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oNe hEalth SusTainabiLity partnership between EU-AFRICA for food sEcuRity

Deliverable D3.1
Remote Sensing technologies and multi-modal data aggregation protocols

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Abstract	The deliverable provides a detailed description of advanced technologies, including IoT sensors, remote sensing and AI, which are employed in NESTLER project. Specifically, it presents the SynField ecosystem for monitoring environmental parameters in crop cultivation, livestock and aquaculture farming, and introduces a handheld device, which determines the crop quality. Moreover, it demonstrates the enhancement of livestock and aquaculture farming by the use of cameras and microphone coupled with AI to monitor animal health. Regarding remote sensing, satellites and drones are utilized to provide vital data for precision agriculture, optimizing crop yields, identifying environmental stressors and aiding in pest infestation detection. Finally, algorithms that analyse remote sensing data to extract useful knowledge are listed. Generally, it outlines the role of data aggregation from various sources, which allows for comprehensive modelling and improved farm management. Integration of cutting-edge technologies aims to enhance sustainable farming practices, biodiversity conservation, and efficient resource management.

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Definitions, Acronyms and Abbreviations

3D	Three-Dimensional
ADDF	Average Diving Depth of Fish
AI	Artificial Intelligence
API	Application Programming Interface
AQI	Air Quality Index
BSF	Black Soldier Fly
BSFL	Black Soldier Fly Larvae
CCTV	Closed-Circuit TeleVision
CFDS	Chicken Farm Dataset
CH_4	Methane
CLT	Central Limit Theorem
CNN	Convolutional Neural Networks
CO	Carbon Monoxide
CO_2	Carbon Dioxide
COCO	Common Objects in Contex
COFDM	Coded Orthogonal Frequency Division Multiplexing
CV	Computer Vision
CVAT	Computer Vision Annotation Tool
DO	Dissolved Oxygen
EC	Electrical Conductivity
EO	Earth Observation
EMI	Electromagnetic Induction
ESA	European Space Agency
ESD	Electrostatic Discharge.
FDR	Frequency Domain Reflectometry
FFDS	Fish Farm Dataset
GPS	Global Positioning System

GPU	Graphics Processing Unit
I2C	Inter-Integrated Circuit
IoT	Internet of Things
IoU	Intersection over Union
IT	Information Technologies
JSON	JavaScript Object Notation
KDE	Kernel Density Estimators
KNN	K-Nearest Neighbors
LiDAR	Light Detection and Ranging
LMIC	Low- and Middle-Income Countries
LSTM	Long Short-Term Memory
LWS	Leaf Wetness Sensor
mAP	mean Average Precision
ML	Machine Learning
MTBF	Mean Time Between Failures
MV	Machine Vision
NASA	National Aeronautics and Space Administration
NB-IoT	NarrowBand-Internet of Things
NDVI	Normalized Difference Vegetation Index
NH_3	Ammonia
NIR	Near Infrared
NO_2	Nitrogen dioxide
NOAA	National Oceanic and Atmospheric Administration)
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
O_3	Ozone
OLED	Organic Light-Emitting Diode
ORP	Oxidation Reduction Potential
PCA	Principal Component Analysis

PCB	Printed Circuit Board
PDF	Probability Density Function
pH	Potential of Hydrogen
PLF	Precision Livestock Farming
PM	Particulate Matter
PoE	Power over Ethernet
POES	Polar-Orbiting Environmental Satellites
REST	REpresentational State Transfer
RF	radio frequency
RGB	Red Green Blue
ROC	Receiver operating characteristic
RSHF	Reference Speed of Healthy Fish
SAFE	Standard Archive Format for Europe
SAVI	Soil Adjusted Vegetation Index
SDI	Serial digital interface
SDR	Software Defined Radio
SIFT	Scale-Invariant Feature Transform
SMS	Short Message Service
SO_2	Sulfur Dioxide
SS	Semantic Segmentation
SVM	Support Vector Machines
TDS	Time Domain Reflectometry
TVOC	Total Volatile Organic Compound
UAV	Unmanned Aerial Vehicle
UNECE	United Nations Economic Commission for Europe
USGS	United States Geological Survey
VIIRS	Visible Infrared Imaging Radiometer Suite
YOLO	You Only Look Once

Executive Summary

This document consists of the Deliverable "D3.1: Remote sensing technologies and multi-modal data aggregation protocols" of the European Horizon Europe project "NESTLER: oNe hEalth SusTainabiLity partnership between EU-AFRICA for food sEcuRity". D3.1 offers a detailed exploration of how Internet of Things (IoT) sensors and devices, as well as remote sensing solutions, are being utilized in the NESTLER project. This includes their application in environmental monitoring and smart agriculture practices, including crop farming, livestock, and aquaculture monitoring across various regions in Africa.

The keystones of this document are summarized as follows:

1. Extensive analysis of the technological background of various IoT sensors and remote sensing solution, accompanied by an initial market analysis for each.
2. Definition of the data preconditions and requirements for each pilot partner operating in different regions across Africa.
3. Thorough presentation of IoT sensors for environmental monitoring. These sensors are part of the SynField Ecosystem and are utilized within the NESTLER project for monitoring crop farming, livestock, and aquaculture.
4. A device designed for assessing the quality of cassava crops by measuring the starch content. Explanation of the device's development over the course of the project, including the calibration process and field testing.
5. A wireless communication system capable of transmitting data from IoT sensors and devices in the field to a central database over long distances, specifically designed for use in rural areas without cellular infrastructure.
6. Identification of the necessary parameters and selection of suitable devices for the monitoring of livestock and aquaculture, with a particular emphasis on the health of poultry and fish.
7. Design AI algorithms able to monitor the health of poultry and fish. Showcasing those algorithms in two specific use cases, which are Poultry Fleas and Fish Digestion Disorder.
8. Presentation of a remote sensing solution in agricultural monitoring using satellite images and drones. Identification of satellite data intended to be used for the NESTLER project as well as the smart drone solution considered to be used.
9. Development of various AI and analytics-based methods for identifying pest infestations using data from remote sensing.
10. Description of existing algorithms, methods, and services for extracting knowledge from data derived from remote sensing.

The objective of this deliverable is to analyze various IoT sensors and devices employed in environmental and crop farming monitoring, including those used for measuring crop quality. Additionally, it defines the parameters, devices, and techniques utilized in livestock and aquaculture monitoring. Furthermore, it presents the remote sensing solutions, which are satellite and drone imagery, used in the NESTLER project, along with the methods and techniques for extracting information from these sources.

1. Introduction

In the evolving landscape of agricultural technology and environmental monitoring, the integration of cutting-edge systems such as Internet of Things (IoT) sensors, remote sensing solutions, data analysis techniques and advanced Artificial Intelligence (AI) models are revolutionizing the way we approach food production, biodiversity conservation and sustainable agriculture practices. Specifically, IoT sensors and devices enables the real-time tracking of environmental conditions and livestock health, gathering extensive data that farmers can use for immediate field oversight. Additionally, the data can be utilized by advanced AI systems and analytical methods to provide insights, yielding valuable insights that lead to informed decision-making and improved management of resources, ultimately promoting sustainable farming practices. Complementing this, remote sensing technologies provide a bird's-eye view, capturing high-resolution images and multispectral data from satellites and drones. This data, when analyzed, can reveal patterns in crop growth and environmental stressors, such as pest infestation, allowing for precision agriculture techniques that optimize crop yields and minimize environmental impact. Through advanced image processing and analytics, remote sensing acts as a crucial tool for large-scale agricultural strategy and land management decisions. Data aggregation plays a critical role in synthesizing the information from IoT sensors, devices and remote sensing. By combining the detailed, on-the-ground data from IoT devices that monitor specific parameters such as soil moisture, temperature, and crop health with the broader, area-wide insights from remote sensing technologies like satellite imagery, a more layered and contextual analysis is possible. This aggregated data allows for the creation of comprehensive models that can predict outcomes, optimize resource allocation, and enhance overall farm management.

The deliverable explores advanced sensors, technology and services used in monitoring of agriculture, livestock, and aquaculture. It also showcases the potential of remote sensing in data collection, with an emphasis on the use of satellite and drone imagery. Furthermore, it presents services that facilitate the extraction of actionable insights from the data acquired through remote sensing techniques. The data gathered from these diverse sources can be integrated and leveraged by various services with the goal of equipping farmers with actionable insights and knowledge to make informed decisions according to their needs. The deliverable begins by providing an overview and technological background of various sensors and technologies, accompanied by a preliminary market analysis. Following this, it outlines a set of data requirements gathered by different pilot studies, aiming to align the data sources and services offered by the platform with these specified needs effectively.

The deliverable focuses on demonstrating the potential of IoT sensors and devices in capturing critical environmental data, thereby enabling more precise and efficient agricultural practices. It highlights the SynField ecosystem, an advanced IoT-based platform for environmental monitoring. The core of this ecosystem is the SynField node, which can be integrated with a range of sensors and actuators. It's capable of measuring various environmental parameters, including air temperature, wind speed and direction, humidity, leaf wetness, and soil characteristics. Additionally, the ecosystem includes SynWater, a component specifically designed for water quality assessment. It is equipped with sensors to measure several water quality parameters, such as water temperature and pH. Another integral part of the ecosystem is the SynAir node, dedicated to air quality monitoring. It can measure air quality characteristics like Particulate Matter, temperature, and CO2 levels. Overall, the SynField ecosystem represents an integrated solution for comprehensive environmental monitoring, suitable for applications in crop cultivation, livestock rearing, and aquaculture farming. Moreover, the deliverable introduces a crop quality measuring device, specifically tailored for determining the starch content in cassava. This device stands out for its portability, affordability, and user-friendliness, making it well-suited for field applications. It also details the ongoing practical performance assessment of this test instrument, conducted through field experiments at the International Institute of Tropical Agriculture (IITA) in Ibadan, Nigeria. A wireless communication system designed to transmit data from IoT sensors and devices over long distances, especially from rural areas with inadequate cellular infrastructure, is presented. This system has been adapted to be deployable on UAVs (Unmanned Aerial Vehicles), enabling real-time data transmission to a central database. Additionally, the system has been engineered with careful attention to power efficiency, and with specifications for weight and size that ensure it is compatible with UAV deployment.

Furthermore, the document presents sensors and techniques for livestock and aquaculture monitoring, highlighting specific use cases like poultry health and fish monitoring systems. It outlines the essential parameters for measurement and the appropriate technologies for these tasks, which include high-resolution cameras and microphones for livestock. Additionally, it presents advanced AI systems utilized for tracking the health of poultry and fish. These tools and techniques represent the forefront of agricultural technology, aimed at optimizing animal welfare and farm productivity.

Regarding the field of remote sensing, the document highlights the application of those solutions in agriculture, focusing on the use of satellite imagery and drones for data collection and monitoring. These technologies offer ground-breaking methods for observing and managing agricultural environments, providing vital data for crop health assessment, and overall environmental conservation. The document also addresses the issue of pest infestation in crops, particularly describing the various ways that remote sensing technology can help. It specifically mentions the use of satellite imagery for locust detection and presents combined solutions that utilize both drone footage and close-range observations for comprehensive pest infestation detection. Finally, remote sensing data can be utilized via various algorithms and methods to extract vital information from this data, such as crop health and land condition monitoring, and integrates weather remote sensing services. These tools and techniques enable the analysis of temperature variations, precipitation levels, and other meteorological factors, enhancing decision-making in areas like irrigation and pest management in response to climatic changes.

1.1. Intended Audience

The intended audience for this deliverable is diverse and encompasses professionals and stakeholders in the fields of agriculture, environmental science, and technology. It is particularly valuable for agricultural technologists, environmental scientists, and IoT specialists seeking to integrate advanced sensor and remote sensing technologies in their work. The document is also relevant for policymakers and development practitioners who are involved in shaping and implementing sustainable agricultural practices and environmental monitoring policies. Additionally, it serves as a critical resource for academics in these fields, providing comprehensive insights into the latest technological advancements and their practical applications. Finally, this report is useful internally, to the project partners and especially Work Package (WP) 3, WP4 and WP5.

1.2. Relations to other activities

This deliverable primarily relates to all the Tasks of WP3 "Remote sensing technologies and multi-modal data aggregation". The overall objective of the work package is to develop technologies with remote sensing capabilities and to create and utilize IoT sensors and devices that monitor environmental variables and crop quality, alongside developing methods for multi-modal data aggregation. The data sources described in this deliverable are crucial for formulating AI algorithms and automated methods as part of WP4, such as AI algorithms for external weather impact assessment on agricultural farming and for crop yield quality. Last, but not least, the document provides useful feedback to the future integration and validation activities, as well as to the preparation of the pilots in WP5.

1.3. Document overview

The rest of the document is divided into the following sections:

- *Section 2* provides an overview and background on various IoT technologies, devices and remote sensing techniques used in modern agriculture. This section also includes an initial analysis of the market, detailing the current state.
- *Section 3* focuses on detailing the specific data needs for NESTLER pilot projects. It explores how data could be utilized within the project to enhance agricultural practices and environmental monitoring.
- *Section 4* delves into IoT sensors specifically designed for environmental monitoring. It discusses the NESTLER environmental factors and the SynField ecosystem, providing details about the different nodes and systems within this ecosystem and their applications in pilot projects.
- *Section 5* is dedicated to the technologies used for measuring crop quality. It includes various parameters and metrics for crop quality assessment of cassava, the evolution of devices used for this purpose, and the calibration and field tests of these devices.
- *Section 6* examines the wireless communication interfaces used in agricultural monitoring systems.
- *Section 7* focuses on livestock and aquaculture monitoring, outlining the sensors and techniques used for monitoring the health and conditions of poultry and fish. It includes a detailed look at the parameters monitored, the IoT sensors and devices employed, and the overall monitoring systems in place.
- *Section 8* explores the use of remote sensing technologies, such as satellite imagery and drones, in agricultural monitoring. It discusses the role of these technologies in detecting pest infestations and other applications in agriculture.
- *Section 9* addresses the algorithms and methods for interpreting data obtained from remote sensing services.
- *Section 10* provides a summary of key findings and reflects on the implications of these technologies for future agricultural and environmental monitoring practices.

2. Technology Overview and Background

This section provides a comprehensive exploration of the various sensors and remote sensing technologies that are used for agricultural monitoring and management. Specifically, it describes the role of IoT sensors in measuring environmental factors as well as the methodologies behind crop quality measurement devices. Moreover, the data sources and methods for livestock and aquaculture monitoring are analyzed. Lastly, the section also examines the broad field of remote sensing solutions, including data from satellites and drones. Each subsection is designed to provide a detailed technological overview of its respective field, setting the stage for understanding how these advanced technologies are applied in agriculture. In addition, it presents an initial analysis of the market for each of these technological areas.

2.1. IoT Sensors for micro-clima, leaf, soil and water quality monitoring

According to United Nations Economic Commission for Europe (UNECE) environmental monitoring is a tool to assess environmental conditions and trends, support policy development and its implementation, and develop information for reporting to national policymakers, international forums and the public1. Since the key objective in environmental monitoring is to identify, administer and reduce the impact an activity has on an environment, following the respective laws and regulations, a textual or graphical depiction of the state of the affected environment is produced that also identifies resulting environmental changes and potential threats.

According to many relevant use cases [1], an environmental monitoring platform usually encompasses a set of distributed sensors that support wired/wireless connectivity, cloud computing and visibility tools that formulate a system for monitoring conditions, operations and equipment and/or react in case of events that can harm the environment. Following recent technological developments in the field of autonomous interconnected devices and sensors that can collect and communicate data, an environmental monitoring system can utilise IoT equipment for collecting the necessary field data [2].

These IoT enabled monitoring platforms can discover problematic environmental conditions like air pollution [3], flood detection [4], water quality degradation [5] and pest detection [6], that otherwise would be largely unidentified, normalised or underestimated and thus enabling involved actors to take action for the reduction of their negative environmental footprint while warding off other hazardous situations. Consequently, IoT is emerging as a favourable technology that can support the provision of real-time data, statistics and awareness regarding the environmental impact of the monitoring activities [7], as well as facilitate the compliance with environmental protection treaties and frameworks.

2.1.1. IoT technology for environmental monitoring

IoT-based environmental monitoring platform presents a number of advantages such as:

[1] Environmental monitoring (https://unece.org/environmental-monitoring)

- **Enhanced understanding of the monitoring environment's conditions**: With the help of the deployed IoT device network that is supplying continuously real-time data, the operators can understand with greater detail the environment and quantify its characteristics.
- **Advanced efficiency**: Real-time data feeds, from the IoT remote sensors, are enabling the monitoring platforms to identify and take care of any problematic circumstances in a proactive or reactive manner.
- **Improved sustainability**: IoT environmental monitoring systems enable the managing actors to locate areas that can achieve reduced operational environmental overhead, thus facilitate an upgrade towards a more sustainable procedure in the course of time.
- **Environmentally friendly operation**: Following the popularity of the environmental neutral operation principle, companies strive to comply with environmental standards in order to certify that they implement a progressive methodology towards environmental safety. The application of an IoT environmental monitoring platform provides greater assurance that standardized measures and controls are applied during operational procedures, alleviating any environmental concerns.

Concerning the environmental factors that are candidates for observation, they can be categorised into three main fields of environmental monitoring namely micro-clima/ air, soil, and water. Moreover, sensors that keep track of the selected environmental factors values can be classified according to the different measurement elements as follows:

2.1.1.1 Micro-clima/air monitoring

In this category of sensors, we may include sensors measuring:

- **Temperature and humidity**: Their values not only affect agricultural and livestock production, but are also important to human health. Indoor or outdoor measurements can be obtained through humidity and temperature sensors.
- **Air quality**: Air quality monitoring is emerging as one of the most important parameter of environmental awareness, since poor air quality conditions will lead to chronic diseases. Respective sensors measure suspended fine particles, mainly referring to particulate matter with 2.5 or 10 microns diameter (PM2.5 or PM10), formaldehyde, Total Volatile Organic Compound (TVOC) and other harmful substances, as well as carbon dioxide, negative oxygen ions and other parameters.
- **Atmosphere**: Environmental sensors that are included to this category can measure atmospheric pressure, sunlight and noise. Atmospheric pressure data can lead to valid weather forecasts. Moreover, monitoring sunlight is helpful for the evaluation of agricultural production since it affects plant growth and development, while noise levels are relevant to the quality of life of a living environment.
- **Wind speed and direction**: In order to present valid meteorological information, wind speed and direction is monitored with the help of appropriate sensor equipment. With their help, meteorological changes can be analyzed and timely warnings can be issued enabling the successful handling of forecasted meteorological disasters.

- **Rainfall**: Apart from the rainfall values, respective sensors are monitoring evaporation levels. Continuous rainfall will almost certainly lead to flood calamities while abnormal evaporation conditions can easily cause drought. Since both hardships not only influence agriculture production, but also water reserves, industrial production and generally people's living conditions, monitoring their values is frequently requested.
- **Radiation**: Solar radiation levels can be measured from environmental sensors. Considering the fact that the state or evolution of most things on earth is relevant to some degree, directly or indirectly, with the corresponding level of radiation, it is helpful to keep track of its current values.
- **Gas**: Concentrations of various gases in the atmosphere, or in closed spaces, are considered environmental factors and can be monitored with the help of relevant sensors. For instance, carbon dioxide increased concentrations intensify greenhouse effects and climatic change while overmuch levels of ozone affect plant photosynthesis activities and human health. Typical gas sensors can monitor the level of carbon monoxide (CO), carbon dioxide (CO_2), ammonia (NH_3), methane (CH_4), ozone (O_3), and sulfur dioxide (SO_2) gas concentrations.

2.1.1.2 Leaf & Canopy monitoring

In this category we may consider sensors measuring the leaf wetness parameters. Leaf wetness is a critical factor in understanding plant health, disease risk, and microclimatic conditions. Several technologies are used to measure leaf wetness, each with its advantages and limitations. Main technologies for measuring leaf wetness include:

- ***Electronic Leaf Wetness Sensors (LWS).*** These sensors typically consist of a flat surface that mimics the properties of a leaf. The sensor detects moisture on its surface using electrical conductivity or capacitance measurements. When water droplets or condensation form on the sensor, it alters the electrical properties, indicating the presence of wetness. The main advantage of this technology is that provides continuous and real-time data and can be integrated into weather stations and automated systems, while maintenance is simple and low cost. However, the sensor accuracy is rather limited, while sensitivity can vary depending on environmental conditions.
- ***Optical sensors & Infrared Thermography.*** Optical Sensors use optical methods, such as light reflection or transmission, to detect the presence of water on leaves. Changes in light behaviour caused by water droplets can indicate wetness. Infrared cameras can detect differences in leaf surface temperature. Wet leaves typically have different thermal properties compared to dry leaves, allowing the detection of wetness through temperature variations. The main advantages of these techniques are that they are non-contact methods, allowing remote sensing and may cover large areas quickly. However, the equipment costs and the maintenance/ calibration costs make them inappropriate for low income countries.
- ***Wetness Sensors Based on Hygroscopic Materials.*** These sensors use materials that absorb moisture, causing them to change shape, colour, or other properties. The changes in these properties are then measured to indicate the level of wetness. The main advantage is that they can be sensitive to minute changes in moisture. However, they may require frequent calibration and can be less durable and sensitive to environmental changes.

- ***Capacitive Sensors.*** These sensors measure changes in capacitance caused by moisture on the sensor's surface, which can be correlated to leaf wetness. The main advantage is that they can be highly sensitive and responsive and suitable for integration into automated systems. However, they require frequent calibration for specific environments and may be sensitive to factors like temperature and dust.
- **LiDAR Technology.** The last couple of years, LiDAR (Light Detection and Ranging) technology is increasingly being integrated into smart agriculture/precision farming applications to monitor leaf and canopy. LiDAR technology may be used for
  - ***Topography and Terrain Mapping.*** Such as a) elevation mapping, creating detailed 3D maps of agricultural fields, capturing the precise elevation of the terrain. This helps farmers understand the field's topography, which is crucial for water management, soil conservation, and optimizing planting strategies And b) Slope Analysis: By analyzing the slopes and contours of the land, farmers can better plan irrigation, reduce soil erosion, and determine the best planting patterns to maximize crop yield.
  - ***Crop Health Monitoring***, including a) Vegetation Analysis: LiDAR can assess the height and density of crops, providing insights into plant health and growth stages. This data helps in identifying areas with poor growth, allowing for targeted interventions, and b) Canopy Structure Analysis: Detailed 3D models of crop canopies can be generated to study plant structure, leaf area, and biomass. This is particularly useful in monitoring the effects of different agricultural practices on crop development.
  - ***Water Resource Management***. Based on Water resources, LiDAR may support a) Irrigation Planning: LiDAR helps in designing efficient irrigation systems by mapping water flow paths and identifying areas prone to waterlogging or drought. This ensures optimal water distribution across the field and b) Flood Risk Assessment: In regions prone to flooding, LiDAR can be used to model potential flood scenarios, helping farmers take preventive measures to protect their crops.
  - ***Pest and Disease Management.*** LiDAR can detect anomalies in crop growth that may indicate the presence of pests or diseases. Early stage detection allows for targeted treatment, reducing the spread and impact of infestations. Moreover, LiDAR can also be used to identify areas where pests are likely to thrive, enabling pre-emptive actions.

  LiDAR technology used to be too expensive for smart farming. However, in recent years, the cost of technology has decreased significantly, making it more accessible for agricultural applications. While low-cost LiDAR systems are becoming more available, they may have significant limitations in terms of accuracy, range, and data resolution compared to higher-end models. Moreover, LiDAR systems can be affected by Environmental Conditions, such as dust, dirt, and moisture, common in agricultural environments. It's important to choose systems that are robust and designed for harsh conditions. Last but not least, even low-cost/low accuracy LiDAR still have a cost in the range of $1,500, which reflects only the basic hardware without additional integration that may be needed. The total cost may significantly increase if multiple units or advanced data processing capabilities are needed.

2.1.1.3 Soil Monitoring

Soil sensors and technologies play a crucial role in precision agriculture, environmental monitoring, and land management. Since soil sensors are utilised in most cases for measuring factors that affect crop growth, they monitor soil parameters such as temperature, moisture, electrical conductivity, nitrogen, phosphorus, potassium and pH, providing information that is mandatory for the operation of smart agriculture or smart irrigation systems. In detail, we may highlight:

- **Soil Moisture Sensors.** Soil moisture sensors measure the volumetric water content in the soil. The most common technologies include:
  - ***Capacitance Sensors:*** These sensors measure the dielectric constant of the soil, which changes with moisture content. The sensor sends a signal through the soil, and the capacitance value is used to estimate moisture content. The main advantage of this technology is the fast response time and the relatively inexpensive installation. However, they require calibration for different soil types and can be affected by soil salinity.
  - ***Time Domain Reflectometry (TDR) Sensors:*** TDR sensors send an electromagnetic pulse along a probe, and the time it takes for the pulse to return is used to calculate the soil's dielectric constant, which correlates with moisture content. The main advantage of the technology is the high accuracy and reliability and the low influence of the soil salinity. On the other hand, it is a quite expensive solution with complex installation.
  - ***Frequency Domain Reflectometry (FDR) Sensors:*** FDR sensors measure the change in frequency of an electromagnetic field caused by soil moisture. They are accurate and suitable for continuous monitoring, but may be affected by soil salinity and temperature and require calibration for different soil types.
  - **Gravimetric Method:** A traditional method where soil samples are weighed before and after drying to calculate moisture content. The main advantage is the high accuracy. However, it is a labor-intensive method and not suitable for real-time monitoring.
- **Soil Electrical Conductivity (EC) Sensors.** Electrical conductivity sensors measure the ability of soil to conduct electrical current, which is related to soil salinity and nutrient content. The sensor technologies utilized of EC include:
  - ***Electromagnetic Induction (EMI) Sensors:*** These sensors generate an electromagnetic field and measure the induced currents in the soil, which are affected by soil conductivity. The main advantage is that it is a non- invasive technology that can cover large areas. However, it is affected by soil moisture and temperature and requires proper analysis and interpretation of data.
  - ***Contact EC Sensors:*** These sensors use electrodes inserted into the soil to directly measure electrical conductivity. Their advantage is that they provide direct measurement of soil EC. However, they can be affected by soil moisture and require maintenance of electrodes.
  - ***TDR and FDR Sensors:*** Some TDR and FDR sensors can also measure electrical conductivity by analyzing the signal attenuation. Their advantage is that they may measure both moisture and EC from a single sensor, while the main limitation that they require careful calibration for accurate EC measurement.
- **Soil Temperature Sensors.** Soil temperature is crucial for seed germination, root development, and microbial activity. Relevant technologies include:
  - ***Thermocouples:*** These sensors consist of two different metals that generate a voltage when there is a temperature difference between the junctions. They are accurate and reliable,

suitable for a wide temperature range, but they may be sensitive to electromagnetic interference and require careful installation.

- ***Thermistors:*** Thermistors are temperature-sensitive resistors, where the resistance changes with temperature. They are very sensitive, accurate and relatively inexpensive, thus widely used. However, the temperature range is rather limited and require careful calibration.
- ***Resistance Temperature Detectors:*** These sensors measure temperature by correlating the resistance of the sensor element with temperature. They are very accurate and stable over time, but more expensive than thermocouples and thermistors and have slower response time.

- **Soil Water Potential Sensors.** Soil water potential indicates the energy status of water in soil and is a measure of the availability of water to plants.
  - ***Tensiometers:*** Tensiometers measure soil water potential by using a porous ceramic cup filled with water, connected to a vacuum gauge. The gauge measures the tension as water moves in or out of the cup to reach equilibrium with the surrounding soil. They offer direct measurement of soil water potential and they are simple and inexpensive sensors. However, they are limited to measuring water potential near saturation and require maintenance, especially in dry conditions.
  - ***Granular Matrix Sensors:*** These sensors use a porous matrix that equilibrates with the soil water. The electrical resistance of the matrix is measured, which correlates with soil water potential. These sensors are more durable than tensiometers in dry conditions and more suitable for a wider range of soil moisture conditions. However, they require calibration for different soil types and they are less accurate than tensiometers at high water potentials.
  - **Dielectric Sensors (Capacitance-based):** Similar to moisture sensors, these measure changes in dielectric constant related to water potential. These sensors are suitable for continuous monitoring and can provide real-time data. However, they can be affected by soil temperature and salinity and require calibration for specific soil conditions.
- **Multi-parameter Sensors.** These are integrated sensors that can measure multiple soil properties (e.g., moisture, temperature, EC) simultaneously. They are often based on capacitance, TDR, or FDR technologies and provide a comprehensive view of soil conditions. Their main advantage is that they offer comprehensive data from a single installation and they are useful for large-scale monitoring.

Finally, traditional soil sampling followed by laboratory analysis for moisture, EC, nutrients, and other properties may apply. This approach is more accurate and comprehensive and provides detailed analysis of soil composition, but it is not suitable for real-time monitoring.

2.1.1.4 Water level & Quality Monitoring

There are different sensor technologies for measuring the water level, pressure and quality. These parameters are quite important not only for precision agriculture, but also for aquaculture applications. We may highlight:

- **Water level and pressure**: Monitoring of liquid level and pressure can provide important information about rivers, lakes and other water sources like water tanks, wells or springs enabling the operation of flood or drought prevention mechanisms as well as automatic irrigation systems. Technologies that may be deployed include:

- ***Float Sensors.*** Float sensors use a buoyant object attached to a mechanical arm or a potentiometer. As the water level changes, the float moves up or down, translating into a measurable output. The main advantage of these sensors is that they are simple, cost-effective and quite reliable for small to medium water bodies. On the other hand, they have mechanical parts, which may wear out over time and can be affected by debris or vegetation.
- ***Pressure Transducers.*** These sensors measure water level by detecting the pressure exerted by the water column above the sensor. The pressure reading is converted into a water level measurement. They are quite accurate, especially in deep water and suitable for both open water and confined spaces like tanks or wells. However, they requires protection from silt and debris and periodic calibration.
- ***Capacitive Sensors.*** Capacitive sensors detect water level by measuring changes in capacitance as the water level rises or falls along a sensing rod or cable. They are non-contact or semi-contact, depending on design and can be used in a variety of liquids, including corrosive ones. On the other hand, they are sensitive to temperature and composition of the liquid and require regular calibration.
- ***Ultrasonic Sensors.*** Ultrasonic sensors measure the distance to the water surface by emitting ultrasonic waves and detecting the reflected waves. The time taken for the echo to return is used to calculate the water level. They are able to make measurements remotely (non-contact measurement) and they are suitable for a wide range of water bodies. However, they can be affected by temperature and humidity and may have difficulties in very turbulent or foamy water.
- ***Radar Sensors.*** Similar to ultrasonic sensors, they use microwave radar waves, radar sensors measure water level by calculating the time it takes for the radar wave to bounce back from the water surface. Their main advantage is their high accuracy and reliability. They perform well in various environmental conditions, including fog, rain, and darkness. On the other hand, they are more expensive than ultrasonic sensors and not suitable for wide deployment in low income countries.
- ***Optical Sensors.*** Optical sensors measure water level by detecting changes in light transmission or reflection caused by the presence of water. They are non-contact and highly precise sensors, suitable for small or confined spaces. However, they can be affected by turbidity or suspended particles in the water and they are more expensive than other options.
- ***Bubbler Systems.*** Bubbler systems measure water level by releasing a constant stream of air bubbles into the water and measuring the pressure required to maintain the flow. The pressure correlates with the water depth. They are accurate and reliable, especially in moving water. However, they require continuous air supply, maintenance and they are more complex and costly than simpler sensors.

- **Water quality**: Since the survival and growth of all living creatures on earth is tightly connected to water, measuring the levels of water contamination formulates the basic functionality of most environmental monitoring systems. For example, monitoring the levels of pH, electrical conductivity (EC), dissolved oxygen (DO), residual chlorine and turbidity provides valuable information regarding water treatment results, aquaculture industry and sewage treatment. Sensors utilized for water quality include:

- ***pH sensors***, which measure the acidity or alkalinity of water by detecting the hydrogen ion concentration. Typically, they use a glass electrode combined with a reference electrode.
- ***Dissolved Oxygen (DO) Sensors***, which measure the amount of oxygen dissolved in water, which is crucial for aquatic life. There are two main types of DO sensors electrochemical (Clark-type) and optical (luminescent).
- ***Conductivity Sensors,*** which measure the electrical conductivity of water, which is directly related to the concentration of dissolved salts and other ions.
- ***Turbidity Sensors,*** which measure the cloudiness or haziness of water, which is caused by suspended particles. This is typically done using optical methods, such as light scattering or attenuation.
- ***Total Dissolved Solids (TDS) Sensors***, which measure the concentration of dissolved substances in water, often using electrical conductivity as a proxy.
- ***Oxidation-Reduction Potential (ORP) Sensors***, which measure the ability of water to oxidize or reduce substances, providing insight into its chemical properties and contamination levels.
- ***Ammonium and Nitrate Sensors***, which measure specific ions (NH4+ and NO3-) in water, providing crucial information on nutrient levels, which is important for managing eutrophication and agricultural runoff.
- ***Chlorine Sensors***, which measure the concentration of free or total chlorine in water, which is important for ensuring proper disinfection in drinking water and swimming pools.

2.1.1.5 Insect Traps technology

Insect traps technology in combination with automated image processing/photographs analysis and AI may be utilized as supportive mechanism for reducing crop losses and chemical usage. For example, it is viable to build a device that traps insects/pests and identify them using AI technology [8]. Traps may use pheromones to attract pests, which are photographed by a camera in the device. By leveraging large pests' databases, AI algorithms may identify various pest species, such as cotton bollworm, which can damage lettuce and tomatoes.

Once identified, the system may use location and weather data to map out the likely impact of the insects and push the findings as an app notification to farmers. These AI-driven insights enable timely and targeted interventions, significantly reducing crop losses and chemical usage.

NESTLER has analysed these off-the-self solutions. However, they are quite expensive and not directly exploitable from project industrial partners, thus have not been adopted in the project.

2.1.2. Market analysis and sensor providers

The Precision Farming market is expected [9] to grow up from USD 9.7 billion in 2023 to USD 21.9 billion by 2031 in a CAGR of 10.7%. The driving forces behind this expansion of the market include the swift uptake of cutting-edge technologies such as Internet of Things (IoT) and utilization of Artificial Intelligence (AI) in smart farming.

Figure 1: Precision Agriculture Global Market (Source: [9])

Deployment of IoT devices across farms generates vast amounts of data, from soil moisture levels to crop health indicators. When integrated into agricultural data spaces, this data can be analyzed using AI algorithms to deliver precise farming insights. These technologies enable the implementation of precision agriculture techniques that optimize resource use, minimize environmental impact, and maximize crop yields.

The IoT Analytics Market is projected to grow from USD 23.60 billion in 2024 to USD 110.26 billion by 2032, exhibiting a Compound Annual Growth Rate (CAGR) of 21.25% during the forecast period (2024 - 2032) [10], while ***IoT in Agriculture Market*** was valued at USD 15.17 billion in 2023 and it is projected to grow from USD 18.43 Billion in 2024 to USD 71.75 billion by 2032, exhibiting a CAGR of 18.52% during the forecast period (2024 - 2032) [11]. Other less optimistic studies [12], consider that the IoT in Agriculture Market will increase to USD 54.45 Bn by 2031 (Figure 2) at a CAGR of 12.9% CAGR [13].

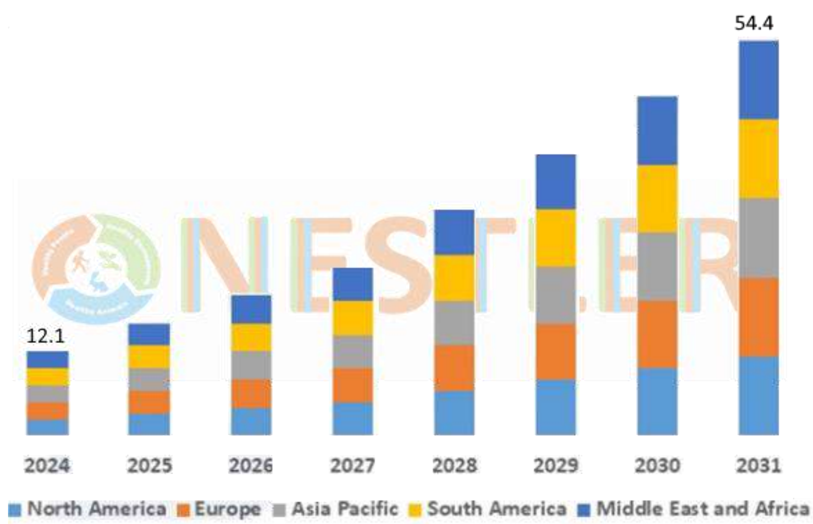

Figure 2: IoT in Agriculture Global Market (Source: [12])

Concluding, regarding the market conditions in the field of environmental sensors that is projected to experience a steady growth over the next years [14], the following table cites vendors with notable market presence in the category of environmental IoT sensors equipment.

Table 1: IoT environmental sensor vendors

Vendor	Type of Environmental Sensor
Davis Instruments[2]	Weather stations, Air Quality Sensors, Data Collection Nodes
Meter Group[3]	Weather monitoring, Soil Sensors, Leaf and NDVI Sensor
Bosch Sensortec[4]	Barometric Pressure, Temperature, Humidity, Air Quality Volatile Organic Compounds, CO, Particulate Matter, Hydrogen)
Honeywell[5]	CO2, CO
Synelixis[6]	Weather stations, Air and Water Quality Sensors, Data Nodes
OMRON Corporation[7]	Temperature, Humidity, Light, Barometric Pressure, Noise, Acceleration, Volatile Organic Compounds
Nisshinbo Micro Devices Inc.[8]	Ambient Temperature, Humidity, Air Pressure, And Illuminance
Murata Manufactoring Co[9]	Temperature, CO_2, Barometric Pressure, Soil sensor (temperature, water content, electrical conductivity)
Disruptive Technologies[10]	Temperature, Water, Humidity, CO_2
Cisco Meraki[11]	Temperature, Water, CO_2
Trapview[12]	Automated Insect Traps

2.2. Crop Quality Measurement

A new handheld device developed at UCL to measure the quality - particularly starch content - of cassava root is evaluated. Cassava, a tropical root crop that serves as a staple for approximately 800 million people globally, holds immense economic significance for developing economies, particularly in sub-Saharan Africa. The surge in global demand for gluten-free flour and biofuel has altered the profile and profitability of cassava, yet, smallholder farmers in the developing world remain largely excluded from this lucrative marketplace. Despite the crop's increasing use and demand, recent studies indicate that cassava production in Africa, accounting for waste, is primarily allocated for food consumption. Although there is potential in the region to increase yield and production capacity enough to meet both domestic and industrial demands, there are key challenges that need to be addressed.

One significant barrier faced by farmers is the reliance on quality standards, notably the minimum starch content, to value their harvest. The average farmer lacks viable means to independently assess this

[2] Davis Instruments: https://www.davisinstruments.com/
[3] Meter Group: https://metergroup.com/
[4] Bosch Sensortec: https://www.bosch-sensortec.com/products/environmental-sensors/
[5] Honeywell: https://sps.honeywell.com/us/en/support/blog/siot/how-to-select-the-right-sensors-in-hvac-systems
[6] Synelixis: https://www.synelixis.com
[7] OMRON Corporation: https://components.omron.com/us-en/solutions/sensor/enverioment_seonsors
[8] Nisshinbo Micro Devices Inc: https://www.nisshinbo-microdevices.co.jp/en/applications/iot-module/environment-sensor/
[9] Murata Manufactoring Co: https://www.murata.com/en-global/products/sensor/library/iot
[10] Disruptive Technologies: https://www.disruptive-technologies.com/applications/environmental-monitoring-sensors
[11] Cisco Meraki: https://meraki.cisco.com/products/sensors/
[12] Trapview: https://trapview.com/

quality, raising the risk in supplying to high-value market hubs where logistics costs are borne by the farmer. Encouraging smallholder farmers to intensify production has proven challenging, with preferences often favouring larger-scale farmers and processors. This places economically disadvantaged farmers in a precarious position, leading them to limit production to established local supply conditions, offering lower margins but minimizing potential losses. On the processor side, the limited supply and capacity, despite national initiatives for economic diversification, hinder the realization of cassava's potential as an industrial raw material in the African context. This presents a significant obstacle to leveraging cassava's growing export potential and achieving economic diversification goals. In navigating these challenges, there is a critical need for innovative approaches and technologies that empower smallholder farmers, improve quality assessment, and enhance the entire cassava value chain to unlock its full economic potential in the global market.

The starch content measuring device developed at UCL offers a cost-effective, swift, and user-friendly solution to the challenge of evaluating cassava samples. This device utilises a non-destructive approach to characterise the samples, and operates by generating a low-power radio-frequency signal, which is injected into the cassava sample using a probe. The device then measures the signal that is reflected back from the sample. The characteristics of this reflected signal are used to estimate the starch content. This estimation is based on a pre-established relationship between radio-frequency reflection and starch content, allowing for a reliable and efficient determination of the starch content in cassava samples that is accessible to farmers.

2.3. Sensors for Livestock and Aquaculture Monitoring

The future of animal farming will be guided by the principles of precision, sustainability, and intelligence. Accurate livestock production can only be attained with the rapid spread of intelligent technology for early warning of illnesses, feeding precision and remote diagnosis [15]. Collecting large amounts of data is made possible by the use of sensors and technology, and these data must be analysed with sophisticated statistical methods before any conclusions can be drawn about the animals' behaviour, health, or welfare. Innovations and information technologies (ITs) are essential for achieving sustainable operations because they enable early and rapid disease detection [16].

2.3.1. Precision Livestock Farming

Precision Livestock Farming (PLF) is generally defined as a management system that offers continuous, automatic monitoring and control of animal behaviour, health, welfare, production and reproduction, as well as environmental impact of the production, in real time [17]. The great potential of PLF is focused on early alerts, which offer the farmer the power to act as soon as the first signs of impaired welfare or health emerge. Accurate prediction models have been developed in the context of PLF that send warning messages to farmers based on information from animal and environmental inputs and can help detect any deviation from the usual pattern. Thanks to the detailed information reported with regard to the status of their livestock, farmers may easily take corrective management measures. In this context, the benefits to farmers include improved decision-making, increased attractiveness for young farmers, and a beneficial effect on resolving the end user's analytical shortcomings through the conversion of raw data to useful information that is currently only obtainable through expert analysis and interpretation.

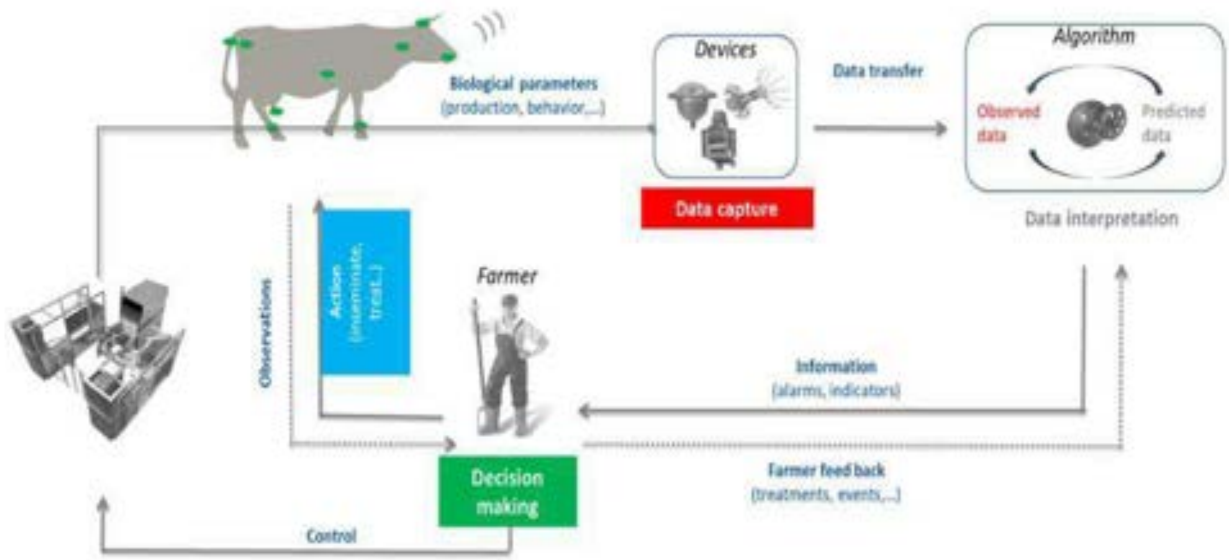

Figure 3: Overview of a PLF system of various components on a dairy farm [18]

2.3.1.1 Sensor Technologies

IoT-enabled livestock management is a technology that uses sensors to gather data about livestock health, environment, and behaviour. Sensors largely represent the "hardware" component of PLF and often closely interact with the animal [19].

Wearable Sensors: As the name suggests, these devices are attached directly to the animals, often in the form of collars, ear tags, or implants. They are designed to monitor various physiological parameters such as body temperature, heart rate, and movement [20]. For example, accelerometers can capture detailed movement data, providing insights into the animals' activity levels, feeding behaviour, or signs of restlessness. Similarly, rumination sensors can track an animal's chewing activity, offering valuable information about its digestive health and welfare.

Environmental Sensors: These sensors are used to monitor environmental conditions that can significantly impact animal welfare. This includes ambient temperature, humidity, air quality, light intensity, and noise levels. By providing real-time feedback on the environment, these sensors can help maintain optimal living conditions for the animals and identify any adverse changes promptly.

The application of sensor technologies in livestock management has opened new avenues for the in-depth monitoring of animals in ways that were previously impossible. However, there are challenges such as the durability of wearable devices, potential discomfort or injury to the animal, ensuring the devices stay on the animals, and the cost and complexity of installing and maintaining environment-based sensors [21].

2.3.1.2 Surveillance Technologies

Advanced surveillance technologies such as CCTV cameras, thermal cameras, and 3D imaging systems can capture a wealth of information about animal behaviour and physical condition. Combined with computer vision and machine learning algorithms, these systems can analyse animal movements, social interactions, body condition, and even detect physical abnormalities.

Moreover, LiDAR (Light Detection and Ranging) technology is increasingly being integrated into PLF to enhance animal monitoring and management. LiDAR works by emitting laser beams and measuring the time it takes for the reflected light to return, creating a detailed 3D map of the environment. In PLF, this can be used for various applications, such as tracking animal movement, monitoring health, and optimizing feeding strategies. LiDAR technology used to be too expensive for PLF, however, in recent years, the cost of LiDAR technology has decreased significantly, making it more accessible for agricultural applications. However, while low-cost LiDAR systems are becoming more available, they may have significant limitations in terms of accuracy, range, and data resolution compared to higher-end models. Farmers need to balance cost with the specific needs of their PLF applications. Moreover, LiDAR systems can be affected by Environmental Conditions, such as dust, dirt, and moisture, common in livestock environments. It's important to choose systems that are robust and designed for harsh conditions. Last but not least, even low-cost/low accuracy LiDAR still have a cost that can be underestimated, which reflects only the basic hardware without additional integration that may be needed. The total cost may significantly increase if multiple units or advanced data processing capabilities are needed.

2.3.1.3 UAV/Drones equipped with surveillance cameras

Fixed cameras providing still images or videos can be used for small-scale animal inspections. Cameras mounted on remotely controlled drones may be used for large-scale surveillance. The outdoor aspect of livestock farming can be eased and modernized mainly with UAVs as the farmer can readily get the birds-eye view of the whole herd, which is impossible to have with conventional methods. UAVs are used in various aspects of livestock monitoring such as detection, counting the numbers, identifying the types, tracking while grazing, health issues monitoring, behaviour monitoring, estimating the herd distribution, monitoring animal's behaviour, etc. [22].

2.3.2. Precision Aquaculture Farming

Precision aquaculture can be defined as a recent initiative that uses different types of advanced strategies and technologies to reduce the environmental impact and to enhance the process efficiency and quality [23]. The connection between digital and physical devices, such as image capture devices, sensors, communication protocols, embedded systems, to record, monitor, and control the main variables related to the aquaculture plant operating in real time characterizes precision aquaculture.

2.3.2.1 Sensor Technologies

In aquaculture, multiparameter sensors with remote monitoring are extensively used to gather information on temperature, pH and dissolved oxygen. Additional types of sensors utilised in aquaculture include current and water flow sensors, which can measure the water levels and currents in real time [24]. Researchers are also using movement and imaging sensors to monitor fish behaviour.

Cameras and imaging sensors observe fish growth, health and behaviour. These sensors can provide real-time photos and videos of fish behaviour, allowing farmers to identify potential issues and take corrective action. They can also monitor fish feeding and ensure sufficient nutrition for proper growth and development.

Sensors can monitor important water quality parameters like pH, dissolved oxygen, temperature, nitrite and ammonia levels. Machine learning models can analyse the sensor data to detect abnormal conditions and predict future changes. This allows farmers to proactively adjust aeration, feeding and water treatment to maintain optimal conditions for fish growth.

2.3.2.2 Camera Technologies

Camera systems can be used to monitor the behaviour of fish in aquaculture farms during production. The computational analysis of images is a useful and promising strategy for extracting information from fish farms due to its non-invasive, automatic and remote monitoring of the environment. Equipment such as surface and acoustic cameras, underwater stereo video systems, sonar systems and others are installed in ponds, tanks and transport systems to observe the fishes.

2.3.2.3 UAV/Drones equipped with surveillance cameras

With the advent of UAVs in aquaculture, new tools such as high-resolution cameras on underwater drones or ROVs can capture images of fish to study their behaviour, growth and health indices [25]. These technologies integrate artificial intelligence (AI) and machine learning (ML) to detect diseases and parasites. Image processing technologies interpret external symptoms, enabling real-time pathogen detection and saving time. Equipped with sensors,

UAVs can monitor environmental conditions, feed, equipment function, fish abnormality and suspicious activity. Drones can be fitted with RGB, multispectral and hyperspectral imaging sensors. Thermal and infrared cameras may also be utilised for specific objectives. UAVs can be deployed to capture images from different ponds in a farm to understand the feeding rate.

2.3.3. Livestock & Aquaculture Monitoring Market Overview

The Livestock Monitoring Market size is expected to grow from USD 6.08 billion in 2023 to USD 11.01 billion by 2028 [26]. The market is characterized by dynamic innovation, with tech integration transforming traditional farming practices. It focuses on optimizing livestock care, disease prevention, and resource allocation to enhance productivity and animal welfare. The increasing focus on early disease detection and real-time monitoring in livestock is expected to significantly drive the growth of the livestock monitoring market. Technological advancement such as herd management system is a key trend gaining popularity in the livestock monitoring market. Current trends include AI-driven predictive analytics, remote monitoring due to the pandemic, sustainability-oriented practices, and block chain adoption for transparency across the supply chain. These trends are reshaping the market landscape, fostering efficient, data-driven livestock management practices. In terms of components, the hardware segment will have the largest market in the upcoming years.

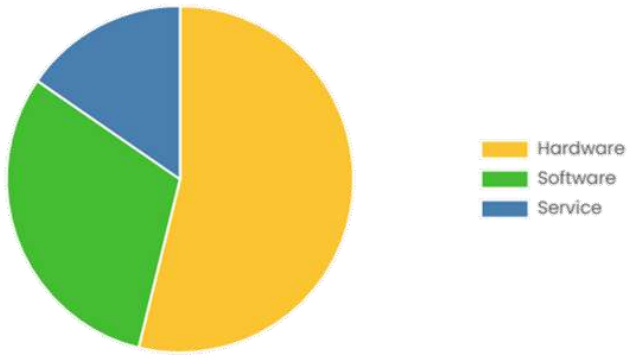

Figure 4:Global livestock monitoring market 2023-2032 (*www.custommarketinsights.com*)

Some of the key players in the global livestock monitoring market are DeLaval Inc.[13], Fancom BV[14], GEA Group Aktiengesellschaft[15], MSD Animal Health[16], Afimilk Ltd.[17], BouMatic[18], and Sensaphone[19]. The global precision aquaculture market size reached USD 481.5 billion in 2022 and is projected to hit around USD 899.57 billion by 2032 [27].

The global smart aquaculture market is primarily driven by the growing global demand for seafood coupled with the need for sustainable and efficient aquaculture practices. Advanced technologies such as Internet of Things (IoT), sensors, automation, and data analytics are increasingly being integrated into aquaculture operations to monitor and optimize parameters such as water quality, feeding, and fish health. These technologies enable farmers to enhance production efficiency, minimize environmental impact, and mitigate risks associated with disease outbreaks. Some of the key players in the global aquaculture monitoring market are AKVA Group[20], Aquaculture Systems Technologies (AST)[21], Deep Trekker Inc.[22], In-Situ Inc. [23],Innova Sea Systems Inc.[24]

2.4. Remote Sensing Solutions

This subsection provides an overview of the data collected through remote sensing, specifically from satellites and drones.

2.4.1. Satellite Data

Enabled from the proliferation of the active satellite systems, Earth Observation (EO) services that are defined as the use of remote sensing technologies to monitor land, marine (seas, rivers, lakes) and

[13] DeLaval Inc.: https://www.delaval.com/en-us/
[14] Fancom BV: https://www.fancom.com/
[15] GEA Group: https://www.gea.com/en/index.jsp
[16] MSD Animal Health: https://www.msd-animal-health.com/
[17] Afimilk Ltd: https://www.afimilk.com/
[18] BouMatic: https://boumatic.com/eu_en/
[19] Sensaphone: https://www.sensaphone.com/
[20] AKVA Group: https://www.akvagroup.com/
[21] Aquaculture Systems Technologies: https://astfilters.com/
[22] Deep Trekker Inc.: https://www.deeptrekker.com/
[23] In-situ: https://in-situ.com/en/
[24] InnovaSea Systems: https://www.innovasea.com/

atmosphere[25], are becoming accessible for integration with platforms that are targeting a multitude of scopes. Through the images obtained from the satellite-based instruments and evaluated and refined regarding several categories of information, a great number of systems and activities can be promoted. Specifically, EO presents an efficient method for surveying Earth's physical, chemical, and biological state while contributing towards an environmental friendly progression of human civilization with the help of monitoring and analysing earths' natural and artificial events and alterations [28]. The knowledge that is provided by EO satellites is extensively utilised in many research domains, especially with regard to the environment. Furthermore, other examples among the fields that EO services are currently utilised are agriculture [29], ecological applications [30], geology [31], and forestry [32], in addition to the areas of monitoring of natural disasters [33], land use and land cover [34], biodiversity [35] and water resources [36].

Moreover, the advancements in satellite EO data accessibility, in conjunction with the ongoing developments in methods and cloud computing services, are bringing about new opportunities by accommodating suitable, precise and trustworthy information for agriculture monitoring platforms while procuring crop-related information from specific regions to nationwide levels [37]. Additionally, EO-data contribute crucial information, regarding current crop conditions that can lead to dependable yield estimations essential for stable market operation, alleviation of possible food supply crisis, and timely activation of humanitarian assistance supporting campaigns.

Regarding EO services that are available, since the capture of the first aerial photograph from Gaspard-Félix Tournachon in 1858 [38], that can be classified as EO image, many significant EO satellite and sensors have been launched, for example Moderate-resolution Imaging Spectroradiometer (MODIS)[26], Landsat[27], Sentinels[28], WorlView[29] and Advanced Very High-Resolution Radiometer (AVHRR)[30].

2.4.2. Drone data

Remote sensing using drones or Unmanned Aerial Vehicles (UAV) has become increasingly popular as a revolutionary technology in various fields [39], [40]. This method involves the use of drones equipped with sensors to gather data about the surface of the Earth. Drones can combine high-resolution imaging and flexibility since they can fly at lower altitudes compared to satellites. Allowing them to capture more detailed and precise data. Moreover, many different sensors can be mounted on drones, from standard RGB cameras to multispectral sensors, thermal cameras, and LiDAR systems. Therefore, drones with the appropriate sensors can be exploited at various applications, including environmental monitoring [41], precision agriculture [42], crop monitoring [43] and soil health assessment [44]. Drones play a crucial role in urban monitoring and planning [45], offering invaluable insights into city development and

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[25] EU Agency for the Space Programme (EUSPA): https://www.euspa.europa.eu/european-space/eu-space-programme/what-earth-observation
[26] MODIS: https://modis.gsfc.nasa.gov/about/
[27] Landsat: https://landsat.gsfc.nasa.gov/
[28] Sentinels: https://www.esa.int/Enabling_Support/Operations/Sentinels
[29] WorldView: https://www.earthdata.nasa.gov/worldview
[30] AVHRR: https://www.eumetsat.int/avhrr

maintenance. Another notable benefit of using drones in remote sensing is their ability to provide real-time data, which is crucial for monitoring dynamic environments. Finally, drones can be characterized as a more economical option compared to traditional aircraft or satellites.

Especially in precision agriculture and crop monitoring, drones and UAVs have been widely used in recent years [46] even though vegetation monitoring has traditionally been performed through remote sensing via satellites. This technology enables precise monitoring of crops, leading to more efficient farming practices and optimized crop yields. It can be used in a wide range of applications. Firstly, by analysing vegetation indices, such as ***Normalized Difference Vegetation Index (NDVI)***, farmers can gain insights about the health of crops, which is particularly vital for early-stage detection of diseases, nutrient deficiencies, or water stress [47]. Additionally, by analysing crop growth patterns, systems that exploits remote sensing images from drones can provide accurate yield predictions [48]. Drones play a significant role in pest and disease detection [49], as they can spot early signs of pest infestation or diseases, allowing for timely and targeted interventions.

Drones in precision agriculture can be characterized as a low-cost aerial camera platform, equipped with GPS and sensors for collection relevant data. Specifically, RGB cameras can provide information about plant growth, coverage, etc., while multispectral sensors expand the utilities of drones by allowing farmers to see things that are not visible in visible spectrum, such as plant health, stress levels and moisture content in soil.

RGB cameras, when mounted on drones, capture light in visible spectrum, like regular digital cameras, providing detailed photographs. These images can reveal various aspects of crop health and field conditions. As the drone flies over the field, the RGB camera continuously takes photos, which can be used from farmers to have an overview of their fields. RGB cameras have considerably higher resolution than the multispectral sensors, which make them suitable to be used for monitoring plants with big leaves, such as corns and maize [50]. However, multispectral imaging can provide more details on the biochemical state of the crops since they can capture light across various wavelengths, including both the visible spectrum and invisible bands such as near-infrared.

Multispectral sensors can gather data by recording how different wavelengths of light are reflected by the crops. This reflection varies based on the health and condition of the plants. The captured images are then processed using specialized software to create vegetation indices, such as the NDVI and NDRE, which helps in providing information about plant health. This technology allows for precise, efficient monitoring of large agricultural areas, allowing farmers to gain insights into potential diseases and pest infestation [51].

The global agriculture drone market [52] [53] is presenting a significant growth, which is primarily driven by the adaptation of precision agriculture, technological advancements, automation and efficiency, cost reduction as well as supportive government regulations. This robust growth trend is expected to continue in the coming years. Specifically, the technological advancements are playing a crucial role in enhancing the effectiveness of drones in agriculture. Improved battery life, advanced sensors, and enhanced data processing capabilities are key innovations that contribute to the increased utility of drones in various agricultural applications. Another important factor is the integration of AI and machine learning in various tasks ranging from data analysis to the development of robust decision-making system, leading to more accurate and insightful practices and approaches in precision farming. In market trends and opportunities, the “Drone-as-a-Service” stands out, offering drone-based services to farmers. This approach can eliminate the need for farmers to own and operate drones. This service further enhances the smart farming and precision agriculture, where drones can automatically perform tasks like data collection, aerial spraying. Regarding the competitive key players of agriculture drones, those are the DJI[31], Parrot Drones[32], PrecisionHawk[33], Trimble Inc.[34], AeroVironment Inc.[35] and AgEagle Aerial Systems Inc.[36] These companies are engaged in continuous product innovation developments to meet the evolving needs of the agriculture sector.

[31] DJI: https://www.dji.com
[32] Parrot Drones: https://www.parrot.com/en/drones
[33] PrecisionHawk: https://www.precisionhawk.com/
[34] Trimble Inc.: https://www.trimble.com/en
[35] AeroVironment Inc.: https://www.avinc.com/
[36] AgEagle Aerial Systems Inc.: https://ageagle.com/

3. Data Preconditions from NESTLER Pilots

At this section, the needs of NESTLER pilots regarding the data are collected. The objective is to collect a set of requirements and information from the various pilots that can be utilized to ensure that the various data sources and services provided by the platform align optimally with these requirements.

Table 2: NESTLER pilots and use cases

Pilot	Country	Use Case	Crop/Animal Type
Crop-based farming	Cameroon	Experimentation with dung-based fertilizers and IoT devices for soil nutrient analysis	Tomato
		Smart irrigation and disease control	
Biodiversity conversation policies and practices	Uganda	Mapping the coffee production system	Coffee
		Environment/Climate change monitoring	
Crop and Livestock farming	Ethiopia	Poultry	Layers & broiler chicken
		Fish	Nile Tilapia
Livestock and Marine farming	Rwanda	Poultry	Layer, broiler & dual-purpose chickens
		Fish	Nile Tilapia
Edible insect farming	Kenya	-	Black Soldier Fly
Crop quality modeling and monitoring solutions and impact on food security	Nigeria	-	Cassava

3.1. Crop-based farming – Cameroon

This pilot is led by AGRI and will be conducted in Cameroon. The main objective of this pilot is to evaluate the quality of crop-based agriculture using Frass fertilizers, IoT devices to analyze environmental parameters, smart agricultural irrigation and pest control measures. To achieve these objectives, the choice of crops is essential, and vegetables are the most appropriate considering local weather conditions Tomatoes are chosen as the most appropriate crops since it is one of the most important seasonal crops grown in Cameroon to supply the entire Central African sub-region. Unfortunately, it is very prone to disease, requires a lot of chemical fertilizers and special monitoring. As it is sensitive to drought, it is grown mostly during the rainy season. In this chapter, an analysis of the data needs from the two use cases under the crop-based farming pilot is provided, including preconditions of each use case as well as a use case data analysis.

3.1.1. Preconditions per Use Case

The use case had the following preconditions

1. Experimentation with dung-based fertilizers and IoT devices for soil nutrient analysis

At this use case the total area of 500 m^2 will be split to assess the effects of different fertilization strategies on plant growth. Specifically, seven different treatments will be performed. The preconditions identified as relevant for this use case are listed below:

a. Demonstrate the influence of frass fertilizers on tomato productivity by acquired different environmental parameters.
b. Environmental parameters regarding the weather conditions will be monitored by IoT sensors and instruments.
c. Soil moisture should be constantly measured by appropriate sensor.
d. Solar radiation data should be obtained.
e. The sensors will continuously monitor and record environmental data.
f. Satellite imagery may be used to provide indicators about the health of tomato crops.
g. Crop disease identification and crop health estimation could be based on images of the crop and the leaves captured from visual and multi-spectral cameras located on drones flying over the field as well as from RGB images from mobile phone.

2. Smart irrigation and disease control

This use case focuses on the impact of smart irrigation and disease control on tomato productivity. The experiments will be conducted in 4 different blocks, which will be differentiated by the quantity and the way of water supply. The preconditions identified as relevant for this use case are listed below:

a. IoT sensors equipped with various sensors and smart devices will measure various key environmental parameters relevant to tomato growing.
b. Soil moisture should be constantly measured by appropriate sensor.
c. Smart irrigation system will be installed on the plots and linked to a mobile application.
d. The automatic irrigation will take place when the soil moisture is below a specific value and will stop as soon as soil moisture has reached a specific value for optimal plant growth.
e. Crop disease identification and crop health estimation could be based on images of the crop and the leaves captured from visual and multi-spectral cameras located on drones flying over the field as well as from RGB images from mobile phone.

3.1.2. Use case Data Analysis

The following table describe, from a general point of view, the features of the potential data that is relevant for the specific pilot.

Table 3: Data analysis for "Crop-based farming" pilot.

Data	Acquisition mean	Data type	Data availability
Environmental Parameters	SynField with appropriate sensors	JSON	streaming
Satellite imagery	Sentinel/Modis	GeoTIFF, HDF, NetCDF	On request
Images	Drone (Multi-spectral or RGB cameras)	.tif, .jpeg	On request
	Mobile phone (RGB camera)	.jpeg, .png	On request

3.2. Biodiversity conversation policies and practices – Uganda

The biodiversity conservation pilot, led by CTPH, will take place in Uganda. CTPH aims to improve the health of wildlife, ecosystems and humans as well as their livestock in and around Africa's protected area. The pilot will take place at areas, where coffee is being grown by communities as an alternative livelihood to help mitigate the Human wildlife conflict arising from crop raids by the Gorillas and other wildlife. There will be analysis of suitable areas for coffee production alongside the spatial distribution of actual and potential zones for coffee, their productivity levels and predicted potential yields using accurate technological interventions. In this chapter, an analysis of the data needs from the two use cases under biodiversity conservation policies and practices pilot is provided.

3.2.1. Preconditions per Use Case

The use case had the following preconditions:

1. Mapping the coffee production system

At this use case, the suitable areas for coffee production will be analysed. Moreover, the actual and potential zones for coffee will be assessed, along with their productivity and potential yields. The preconditions identified as relevant for this use case are listed below:

a. Mapping coffee farms by obtaining GPS coordinates to define the actual size of those areas.
b. Unmanned Aerial Vehicles (UAVs) could be exploited to provide indicators regarding the seasonal crop performance.
c. GIS could be used to visualize the coffee farm areas.

2. Environment/Climate change monitoring

This use case has as goal to effectively monitor the environmental parameters as they are crucial for coffee cultivation. Current and historical climate data will be used in data-driven models to predict future trends and events in coffee production. The preconditions identified as relevant for this use case are listed below:

a. The environmental monitoring will be performed by combining data from IoT sensors and remote sensing.
b. Environmental parameters regarding weather conditions will be monitored by IoT sensors and instruments.
c. The sensors will continuously monitor and record environmental data.
d. Remote sensing techniques could be used to monitor health of coffee crop.
e. Satellite imagery data will be acquired to assess changes in the landscape as well as climatologic variables.

3.2.2. Use case Data Analysis

The following table describes, from a general point of view, the features of the potential data that is relevant for the specific pilot.

Table 4: Data analysis for "Biodiversity conversation policies and practices" pilot.

Data	Acquisition mean	Data type	Data availability
Environmental Parameters	SynField Weather Station	JSON	streaming
GPS coordinates	GPS device	N/A	On request
Satellite imagery	Sentinel/Modis	GeoTIFF, HDF, NetCDF	On request
Images	Drone (Multi-spectral or RGB cameras)	.tif, .jpeg	On request
	Mobile phone (RGB camera)	.jpeg, .png	On request

3.3. Crop and Livestock farming – Ethiopia

The focus on food security is strongly depends on the livestock production systems. The limited supplies and high cost of good quality feed are major constraints. Specifically, in many Low- and Middle-Income Countries (LMIC), various challenges hinder the supply and adoption of improved feed technologies. This pilot is led by EIAR in collaboration with MANA and ICIPE, will be conducted in Ethiopia, exploring the use of insect protein as an alternative feed source to address the various challenges. In this chapter, an analysis of the data needs from the two use cases under the crop and livestock farming pilot is provided.

3.3.1. Preconditions per Use Case

The use case had the following preconditions:

1. **Poultry pilot preparation**

This use case aims to assess various aspects of Black Soldier Fly (BSF) larvae-based feed recipes for poultry. Additionally, the study explores the feed's potential as a scavenging supplement and conducts a partial budgeting analysis in poultry production. For this use case, 4 different experiments will be conducted in poultry on-station and on-farm of the same location. The preconditions identified as relevant for this use case are listed below:

a. Monitoring the environmental conditions of poultry station/farms.
b. Environmental parameters regarding the quality of area will be monitored by IoT sensors and instruments.
c. The sensors will continuously monitor and record environmental data.
d. Poultry health will be monitored by AI-based system that utilizes video and audio.
e. Video should be captured by fixed point in poultry farm/station.
f. Audio should be recorded by microphones in poultry farm/station.

2. **Fish pilot preparation**

This use case has as goal to adapt Black Soldier Fly Larvae (BSFL) production techniques at the pilot site, evaluate the growth performance of Nile tilapia when fed with insect protein from BSFL, and demonstrate the significance of BSFL-based fish feed in enhancing aquaculture farming. For this use case, various experimental setups will be organized at 10 plastic tanks with different treatments in each one at the same location. The preconditions identified as relevant for this use case are listed below:

a. Monitoring the environmental conditions of fish tanks.
b. Environmental parameters regarding the quality of fish tanks will be monitored by IoT sensors and instruments.
c. The sensors will continuously monitor and record environmental data.
d. Fish health will be monitored by AI-based system that utilizes video.
e. Video should be captured by fixed point in fish tanks.

3.3.2. Use case Data Analysis

The following table describes, from a general point of view, the features of the potential data that is relevant for the specific pilot.

Table 5: Data analysis for "Crop and livestock farming" pilot.

Data	Acquisition mean	Data type	Data availability
Environmental Parameters	SynAir	JSON	streaming
	SynField		
Video	Video camera	.mp4, .avi	On request
Audio	Microphone	.mp3, .wav	On request

3.4. Livestock and marine farming – Rwanda

This pilot is led by RAB in collaboration with MANA and ICIPE and it will be conducted in Rwanda. The purpose of the pilot is the development of alternative forms of food sources for the cultivation of livestock and fisheries. In this chapter, an analysis of the data needs from the two use cases under the livestock and marine farming pilot is provided.

3.4.1. Preconditions per Use Case

The use case had the following preconditions:

1. Poultry pilot preparation

This use case focuses on BSF farming to assess the effectiveness of Black Soldier Fly larvae meal as a substitute for traditional protein sources in poultry diets. It aims to evaluate the impact on chicken performance, health, and overall productivity, and to explore the economic feasibility of using BSFL-based feed. The preconditions identified as relevant for this use case are listed below:

a. Monitoring the environmental conditions of poultry stations/farms.
b. Environmental parameters regarding the quality of area will be monitored by IoT sensors and instruments.
c. The sensors will continuously monitor and record environmental data.
d. Poultry health will be monitored by AI-based system that utilizes video and audio.
e. Video should be captured by fixed point in poultry farm/station.
f. Audio should be recorded by microphones in poultry farm/station.

2. Fish pilot preparation

This use case involves BSF farming to evaluate the effectiveness of Black Soldier Fly larvae meal as a replacement for soybean or fish meal in aquaculture feed, particularly focusing on the growth, health, and survival of Nile Tilapia. The preconditions identified as relevant for this use case are listed below:

a. Monitoring the environmental conditions of fish tanks.
b. Environmental parameters regarding the quality of fish tanks will be monitored by IoT sensors and instruments.
c. The sensors will continuously monitor and record environmental data.
d. Fish health will be monitored by AI-based system that utilizes video.
e. Video should be captured by fixed point in fish tanks.

3.4.2. Use case Data Analysis

The following table describes, from a general point of view, the features of the potential data that is relevant for the specific pilot.

Table 6: Data analysis for "Livestock and marine farming" pilot.

Data	Acquisition mean	Data type	Data availability
Environmental Parameters	SynAir	JSON	streaming
	SynField		
Video	Video camera	.mp4, .avi	On request
Audio	Microphone	mp3, .wav	On request

3.5. Edible insect farming – Kenya

This pilot is led by ICIPE in collaboration with MANA and will be conducted in Kenya. This pilot focuses on developing and optimizing the lifecycle of insect production, particularly Black Soldier Fly Larvae, for sustainable agriculture. Additionally, it also aims to investigate the production of Frass fertilizer, made from insect waste, to enhance crop growth. Specifically, various activities will monitor the safety and quality of the produced larvae and insect frass fertilizer and explore the effectiveness of this fertilizer in enhancing crop productivity. In this chapter, an analysis of the data needs from the edible insect farming pilot is provided.

3.5.1. Preconditions per Use Case

The preconditions identified as relevant for this use case are listed below:

a. Environmental parameters regarding the weather conditions will be monitored by IoT sensors and instruments.
b. The sensors will continuously monitor and record environmental data.

3.5.2. Use case Data Analysis

The following table describes, from a general point of view, the features of the potential data that is relevant for the specific pilot.

Table 7: Data analysis for "Edible insect farming" pilot.

Data	Acquisition mean	Data type	Data availability
Environmental Parameters	SynField Weather Station	JSON	streaming

3.6. Crop quality monitoring solutions and impact on food security – Nigeria

The aim of this pilot is to collect comprehensive data to develop a robust yield prediction model specifically for cassava. The potential benefits of the pilot include improved yield prediction, enhanced farm management, tailored support and recommendations, resource efficiency, knowledge sharing, and food security and economic benefits. Various sensing stations will capture crucial environmental data, including rainfall patterns, temperature, humidity and solar radiation. Data indicating the crop quality conditions of crops will also be gathered. In addition to environmental data, the pilot will also focus on gathering farm-level data from the research farms. The collected environmental and farm-level data will then be utilized to develop a yield prediction model for cassava. In this chapter, an analysis of the data needs from the crop quality monitoring solutions and impact on food security pilot is provided.

This pilot is led by IITA and will be conducted in Nigeria.

3.6.1. Preconditions per Use Case

The preconditions identified as relevant for this use case are listed below:

a. IoT station will consist of a SynField module equipped with various sensors and instruments to measure key environmental parameters.
b. Environmental parameters regarding the weather conditions will be monitored by IoT sensors and instruments.
c. Solar radiation data should be obtained.
d. The sensors will continuously monitor and record environmental data.
e. Cheap, accurate and rapid determination of starch content by farmers and processors of cassava

3.6.2. Use case Data Analysis

The following table describe, from a general point of view, the features of the potential data that is relevant for the specific pilot.

Table 8: Data analysis for "Crop quality monitoring solutions and impact on food security" pilot.

Data	Acquisition mean	Data type	Data availability
Environmental Parameters	SynField	JSON	streaming
Starch content	Crop quality device	N/A	On request

4. IoT Sensors for Environmental Monitoring

This section offers a detailed description of the environmental parameters identified by the pilots as critical for collection, along with the IoT sensors of the SynField platform used by the NESTLER project to gather those parameters.

4.1. NESTLER Environmental Factors

The following subsections present the environmental factors that are monitored in each Pilot case by utilizing SynField product line equipment. This determination is based on the data preconditions listed in Section 3 and extensive discussions conducted during the project's initial phase. These discussions included group telecommunications and meetings, as well as peer-to-peer conversations. Accordingly, we have identified the specific environmental factors to be measured in each pilot, along with the appropriate SynField equipment required for these measurements.

4.1.1. Crop-based farming – Cameroon

Table 9: SynField for monitoring environmental parameters for "Crop-based farming" pilot.

Equipment	Quantity	Equipment Code	Environmental Factors
Synfield X3	2	SF-HN-X3	-
Weather Station	2	SF-WS-02	Rain, Wind-Direction, Wind-Speed, Ambient Relative Humidity, Ambient Temperature
Pyranometer	2	SF-SR-01	Solar Radiation (440 - 1100nm spectrum)
Soil Moisture	2	SF-SM-10HS	Soil moisture (Volumetric Water Content)
Electrovalve	4	-	-

4.1.2. Biodiversity conservation policies and practices – Uganda

Table 10: SynField for monitoring environmental parameters for "Biodiversity conservation policies and practices" pilot.

Equipment	Quantity	Equipment Code	Environmental Factors
Synfield X3	1	SF-HN-X3	-
Weather Station	1	SF-WS-02	Rain, Wind-Direction, Wind-Speed, Ambient Relative Humidity, Ambient Temperature

4.1.3. Crop and Livestock farming – Ethiopia

Table 11: SynField for monitoring environmental parameters for "Crop and Livestock farming" pilot.

Equipment	Quantity	Equipment Code	Environmental Factors
Synfield X3	3	SF-HN-X3	-
SynAir	2	SF-SA-01C	NH_3, Particulate Matter (PM1.0, PM2.5, PM4, PM10), CO_2, Temperature, Relative humidity

SynWater	1	SF-SW-01	Water Temperature, pH, Oxidation-Reduction-Potential (ORP), Dissolved-Oxygen (DO), Electrical-Conductivity (EC)
Pyranometer	1	SF-SR-01	Solar Radiation (440 - 1100nm spectrum)

4.1.4. Livestock and marine farming – Rwanda

Table 12: SynField for monitoring environmental parameters for "Livestock and marine farming" pilot.

Equipment	Quantity	Equipment Code	Environmental Factors
Synfield X3	3	SF-HN-X3	N/A
SynAir	2	SF-SA-01C	NH_3, Particulate Matter (PM1.0, PM2.5, PM4, PM10), CO_2, Temperature, Relative humidity
SynWater	1	SF-SW-01	Water Temperature, pH, Oxidation-Reduction-Potential (ORP), Dissolved-Oxygen (DO), Electrical-Conductivity (EC)

4.1.5. Edible insect farming – Kenya

Table 13: SynField for monitoring environmental parameters for "Edible Insect farming" pilot.

Equipment	Quantity	Equipment Code	Environmental Factors
Synfield X3	1	SF-HN-X3	N/A
Weather Station	1	SF-WS-02	Rain, Wind-Direction, Wind-Speed, Ambient Relative Humidity, Ambient Temperature

4.1.6. Crop quality monitoring solutions and impact on food security – Nigeria

Table 14: SynField for monitoring environmental parameters for "crop quality monitoring solutions and impact on food security" pilot.

Equipment	Quantity	Equipment Code	Environmental Factors
Synfield X3	2	SF-HN-X3	N/A
Weather Station	1	SF-WS-02	Rain, Wind-Direction, Wind-Speed, Ambient Relative Humidity, Ambient Temperature
Pyranometer	1	SF-SR-01	Solar Radiation (440 - 1100nm spectrum)

4.2. SynField Ecosystem

SynField platform offers an innovative and flexible platform, capable for smart environmental monitoring as well smart irrigation and water management, with advanced control and monitoring of small and medium-sized crop, livestock and marine farms, as well as water supply networks. Specifically, it offers remote monitoring of climatic, environmental and soil/water conditions such as:

- Air temperature, wind speed and direction, rainfall, humidity, leaf wetness, solar radiation, Particulate Matter, NH_3, CO_2
- Soil conductivity/temperature/moisture

- Water temperature/pH/Oxidation Reduction Potential/Dissolved Oxygen/ EC

Moreover, it provides for remote control of irrigation and water management systems. The control procedure can be based on rules that take into consideration time parameters and sensor values leading into a partially or fully automated operation.

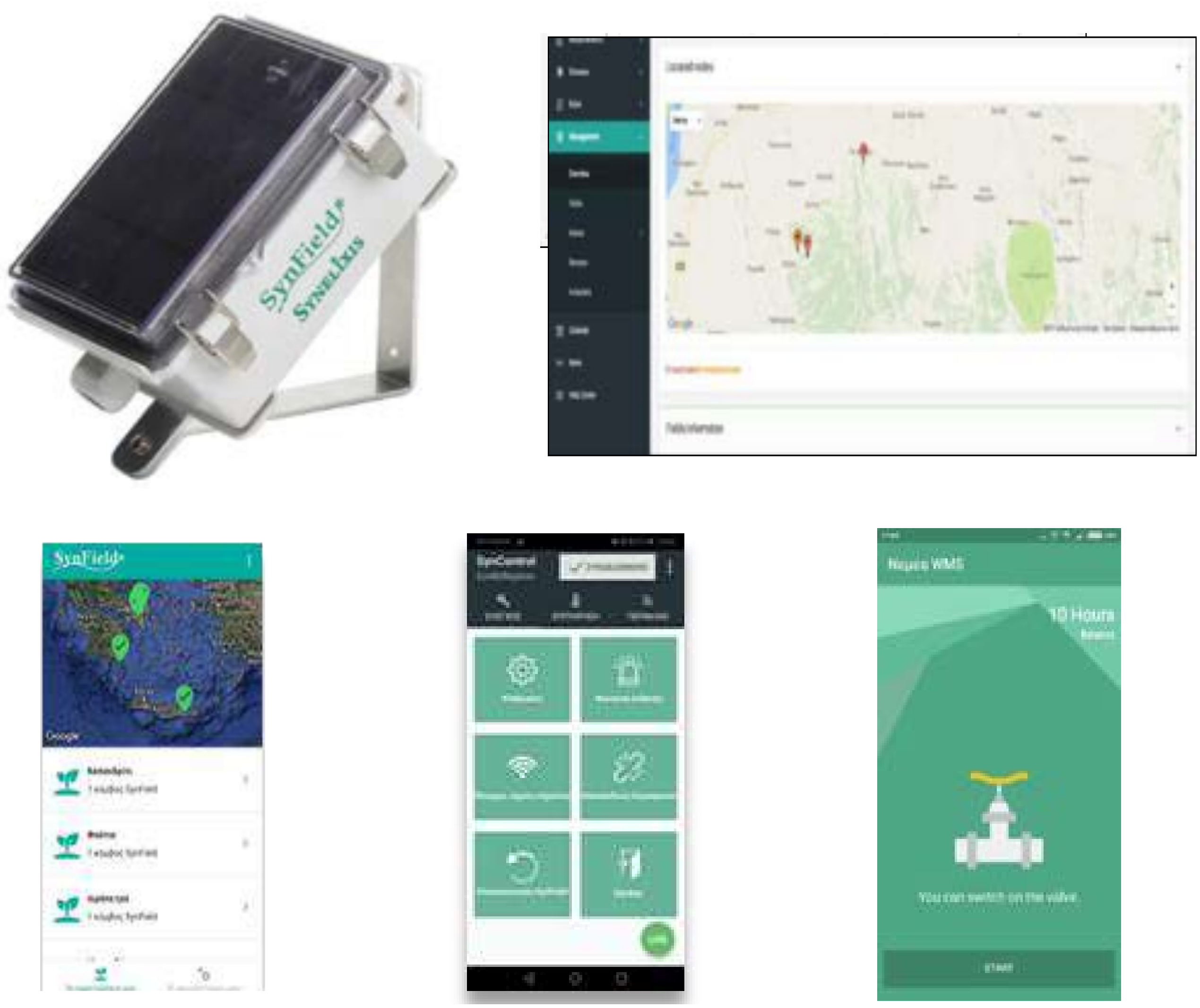

Figure 5: The SynField ecosystem

The SynField ecosystem, which is presented in Figure 5, comprises of:

1. the SynField nodes, which are sensor-logging autonomous systems while providing remote control and can be distinguished to Head Nodes (autonomous) and the Peripheral Nodes (require a Head Node to function properly).
2. the SynField Cloud Server Platform that collects all SynField data and implements the decision making and automated control system.
3. The SynField application for remote monitoring and actuator control.
4. the SynControl application for configuring the SynField nodes in the field.
5. the SynField Water Management application for remotely activating a water well/drilling.

SynField platform main features can be summarized as follows:

- Support any combination of a wide range of analog and digital sensors (vendor independent).
- Automatic/manual remote control of actuators (several types of solenoid valves, pumps start/stop or relay-switches are supported)
- Internet connectivity via mobile network (WiFi connectivity (802.11b/g/n) available upon request)
- Data acquisition, processing & rule based-engine provision
- Energy autonomous nodes (based on solar panel & rechargeable battery).
- Easy on-site setup/control via a mobile application and Bluetooth interface
- User friendly access via web/mobile applications and personalized interface.
- User defined Alarms & Notifications
- Configurable data acquisition/logging frequency
- Automatic SynField Nodes firmware update online (Over The Air) and via Bluetooth
- Outdoor/weatherproof devices (IP65)
- Electrostatic discharges (ESD) and lightning protection

SynField ecosystem is able to communicate with third-party platforms via a REST API so that data acquired from SynField nodes may be utilized by other applications. Moreover, SynField platform is fully compatible with the OneM2M [37]protocol while the Smart Irrigation Business Logic module has been ported over the General Electric Predix platformThe following subsections present the main SynField platform units that are going to be utilized for the environmental monitoring needs during NESTLER's pilot activities.

4.2.1. SynField Head Node

The SynField Head node[38] (Figure 6) is a fully autonomous device with integrated solar panel (on-top of the device) and large capacity batteries.

SynField device directly supports a wide range of analogue and digital sensors (vendor independent) to monitor weather, environmental and soil conditions as well as coordinates water management applications. The SynField Node periodically collects sensor data and forward them to the SynField cloud server via a cellular or Wi-Fi connection. Moreover, they act as controllers that allow remote control of actuators (i.e., electrovalves and relays). Furthermore, the device can be installed and configured easily at the field. Currently there are three SynField Head Node options available (SynField X1, SynField X3 and SynField X5) able to cover efficiently, effectively and economically respective customer requirements. Since regarding NESTLER's pilot activities the X3 is the only version of SynField head node that will be used, the information that is presented below will be focused accordingly.

[37] OneM2M: https://www.onem2m.org/
[38] SynField: https://www.synfield.gr/about/

Figure 6. SynField X3 Head Node

SynField X3 features can be summarised to:

- Ultra-rugged and durable construction
- Eight sensor ports (any type of analog, pulse, Inter-Integrated Circuit (I2C)[39], SDI-12 interface)
- Eight latching actuator ports (any type of solenoid control valves, pumps, latching relays, etc.)
- Supports a plethora of off-the-self sensors (vendor independent) and actuators (valves, relays).
- Integrated quad-band cellular module, NarrowBand-Internet of Things (NB-IoT)[40] compatible
- Supports connection with Weather Station/SynAir/SynWater modules
- Out-of-the-box integrated with the SynField Cloud application, for almost real-time data monitoring
- Almost real-time control of valves, relays and automations using advanced, user-defined rules
- Integrated GPS, barometric pressure, system temperature, battery voltage level and charge current sensors
- Configurable via Bluetooth with the SynField Control application (Android OS)
- Simple setup process via the Bluetooth interface
- Firmware update using the control application
- Built-in solar panel or external charger for all kinds of installations
- Rechargeable high capacity (4000mAh) battery
- On board non-volatile memory (8 Mbyte)
- ESD/lightning protection
- Optimized user interface for desktop and mobile devices
- Dedicated application for mobile devices (Android OS) providing a simplified monitor and control interface.

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[39] I2C: https://community.nxp.com/t5/MQX-Software-Solutions-Knowledge/Introduction-to-I2C-Interface/ta-p/1120762
[40] NB-IoT: https://www.gsma.com/iot/narrow-band-internet-of-things-nb-iot/

A great variety of state of the art, off-the-shelf (vendor independent) sensors and automations can be connected to the SynField nodes (Figure 7), so that the appropriate ones can be selected for the specific cultivation needs. In addition, the SynField system is able of remotely controlling actuator switches, including solenoid valves and start/stop water pumps. Thus, the user, apart from monitoring all the characteristics of the crop and the conditions prevailing in the field, can also initiate appropriate actions by remotely controlling the automations wherever he is.

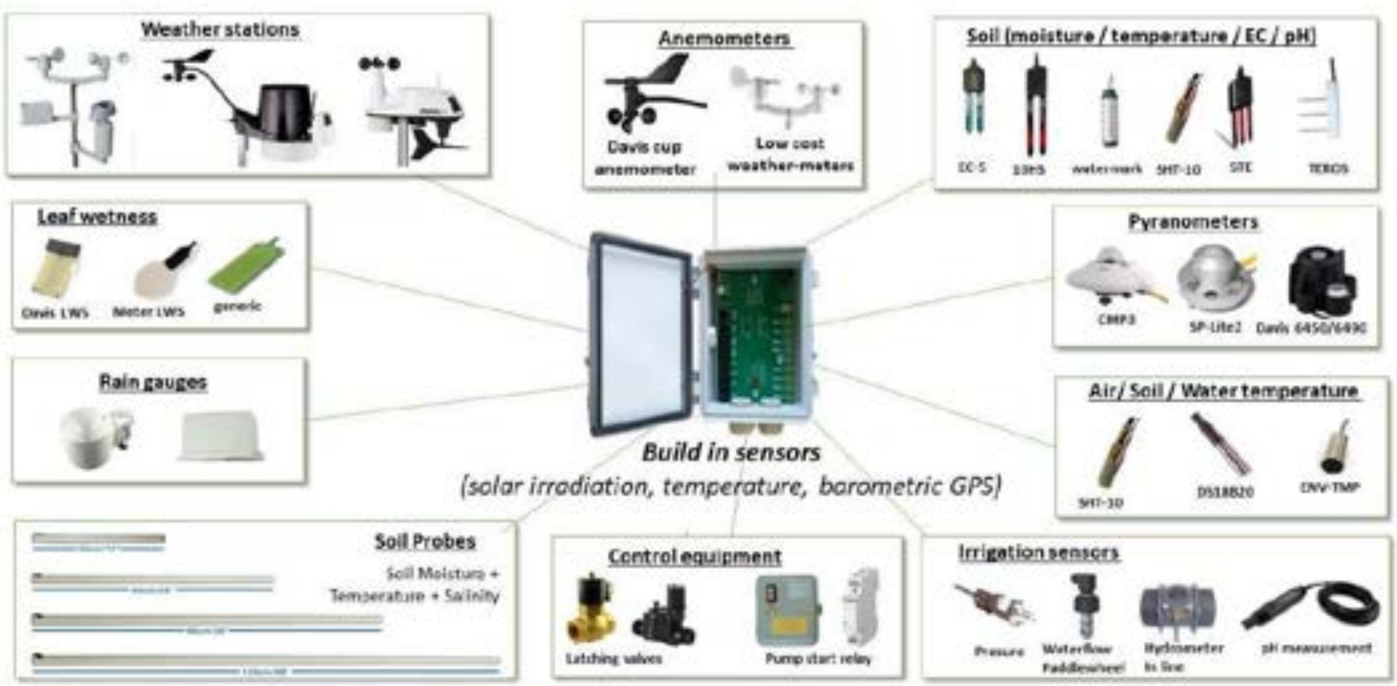

Figure 7. Indicative SynField supported sensors & actuators

The SynField X3 node consists of a single printed circuit board (PCB) that is housed inside the enclosure. The following figure (Figure 8) shows the layout of the device's PCB along with its connectors and switches.

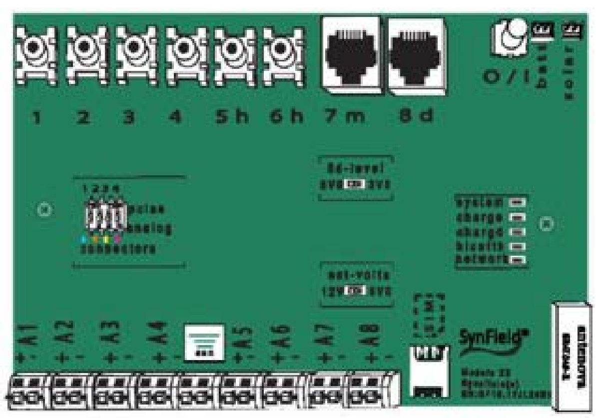

Figure 8 View of the SynField X3 board

Since more than 50 state of the art sensors and actuators41 are already integrated in the platform, the user can access real time data for monitoring the climatic, environmental, and soil conditions using his personal computer or mobile device, through the SynField software applications. Specifically, the following environmental factors can be observed remotely:

- Ambient temperature and relative-humidity
- Wind speed & wind direction
- Rain gauge
- Moisture (soil)
- Electrical conductivity (soil)
- Temperature (soil)
- Leaf Wetness
- Solar radiation
- Liquid flow/pressure (irrigation)
- Flow meters (irrigation)
- Liquid level (tank)
- Distance

Aside from the parameters above, SynField platform, with the addition of SynWater and SynAir peripheral nodes that are described in the following paragraphs, offers the ability to monitor additional environmental characteristics.

4.2.2. SynWater

The SynWater peripheral node[42] (Figure 9) is a versatile sensor device that can accommodate several water quality sensors. The SynWater device cannot operate by itself since it is specifically designed to operate while connected to a SynField head node (X3 and X5 versions). The SynField device will then read sensors values and forward the measurements to the SynField software platform to the cloud. Thus, the data are available, wherever you are, through your desktop or your mobile device, enabling the monitoring of water quality characteristics remotely. Additionally, through the SynField software applications, the user can access historical data measurements and/or configure criteria for alerts so that he will be automatically notified, via email and SMS, in the event that the defined conditions are met.

The SynWater device can support up to 5 water quality sensors. Specifically, Synelixis's professional water quality monitoring node can support measurements from any of the following sensors:

- Water temperature
- pH
- Oxidation Reduction Potential (ORP)
- Dissolved Oxygen (DO)
- Electrical Conductivity (EC)

[41] SynField Supported Sensors: https://www.synfield.gr/features/
[42] SynWater: https://www.synfield.gr/synwater/

Figure 9 SynWater node

Any combination of the above sensors can be utilised since the node recognizes automatically which sensors are connected. Moreover, when a temperature sensor is connected, the readings of the other sensors are temperature compensated.

In addition to the above SynWater sensors, supplementary water related measurements (i.e. water pressure, water level, water flow) can also be obtained from appropriate sensors that can be connected to the respective SynField head node device that the SynWater node is connected to.

It should be mentioned that due to the nature of most water quality sensors implementations and depending on the particular use case's accuracy requirements, it could be recommended to implement a sensor's calibration operation periodically (i.e., on a yearly basis). The SynField/SynWater ecosystem provides a user-friendly procedure for performing the required calibration procedure.

Regarding the SynWater device implementation the following features are supported:

- Ultra-rugged and durable construction
- Low power dissipation. Can be used in solar/battery powered applications[43]
- User-friendly calibration process
- Since each sensor has its own distinct excitation power, the device is enabled to implement a policy that restricts the activation of only one sensor at a time. Consequently, the maximum power consumption of the whole device is equal to the power consumption of its most power-intensive sensor.
- As the on-board digital busses are decoupled from each another (Figure 10), a faulty sensor operation can be isolated, enabling the continuation of the overall operation of the device.

[43] In most cases a solar/battery powered device can operate with a 20 minutes sampling interval. In cases where more frequent sampling is required and/or a very power-hungry sensor is attached, the device may require an external power supply (i.e. external battery or utility power).

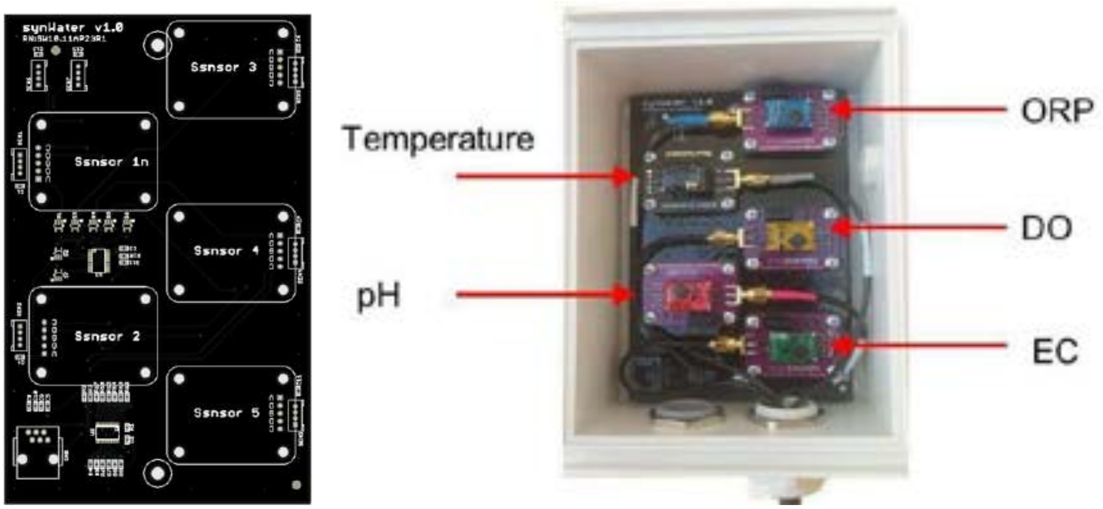

Figure 10 View of the SynWater board

With the addition of SynWater peripheral node(s), the SynField platform is upgraded to an ideal solution for use cases that require monitoring of water quality characteristics such as:

- Aquaculture
- Fish farming
- Smart cities
- Environmental & industrial applications

The following table presents SynWater's sensor specifications.

Figure 11: SynWater sensor specifications

Temperature Sensor Specifications	
Range	-50℃ to 200℃
Accuracy	+/- (0.3 + (0.005*t))
Life expectancy	15 years
pH Sensor Specifications	
Range	0 – 14
Accuracy	+/- 0.002
Life expectancy	~4 years+
Oxidation Reduction Potential (ORP) Sensor Specifications	
Range	-1019.9mV − 1019.9mV
Accuracy	+/- 1mV
Life expectancy	~4 years+
Dissolved Oxygen (DO) Sensor Specifications	
Range	0 − 100 mg/L
Accuracy	+/- 0.05 mg/L
Life expectancy	~4 years
Electrical Conductivity (EC) Sensor Specifications	
Range	5 − 200,000 μS/cm
Accuracy	+/- 2%
Life expectancy	~10 years

4.2.3. SynAir

The SynAir peripheral node[44] (Figure 12) is an adjustable sensor platform that can be configured to integrate a multitude of digital sensors for the detection and/or measurement of air quality characteristics. Since SynAir is not designed to function as a standalone device, it should be connected to a SynField head node (all versions) that will access the sensor and transmit the measurements to the SynField cloud platform. Consequently, with the help of SynField software applications, the aforementioned parameters can be retrieved, enabling remote monitoring of the specific air quality characteristics. Moreover, the user can define criteria for alert notifications, via email or SMS, in case the specified conditions are met.

Figure 12 SynAir peripheral node

The SynAir device can incorporate up to 6 digital I2C air quality sensors. Specifically, for the implementation of environmental monitoring requirements regarding NESTLER's Pilot activities, Synelixis's professional air quality monitoring device integrates sensors for the following factors:

- Particulate Matter (PM1.0, PM2.5, PM4, PM10)
- Temperature
- Relative Humidity
- NH_3
- CO_2

Additionally to the above environmental factors, SynAir's previous versions accommodate sensors capable for measuring barometric pressure, total volatile organic compounds (VOC), CO, CO2, Ozone,

[44] SynAir: https://www.synfield.gr/about-synair/

NO2 and could detect ethanol. Furthermore, SynAir device implementation presents the following features:

- Ultra-rugged and durable construction
- Compliance with the European and U.S. Air Quality Index (AQI)
- Low power dissipation. Can be used in solar/battery powered applications45
- Enclosure fan and high flow vents for increased measurement accuracy
- Since each sensor has its own distinct excitation power, the device is enabled to implement a policy that restricts the activation of only one sensor at a time. Consequently, the maximum power consumption of the whole device is equal to the power consumption of its most power-intensive sensor.
- On account of the fact that the on-board (Figure 13) digital busses are decoupled from each another, a faulty sensor operation can be isolated and thus enabling the continuation of the overall operation of the device.

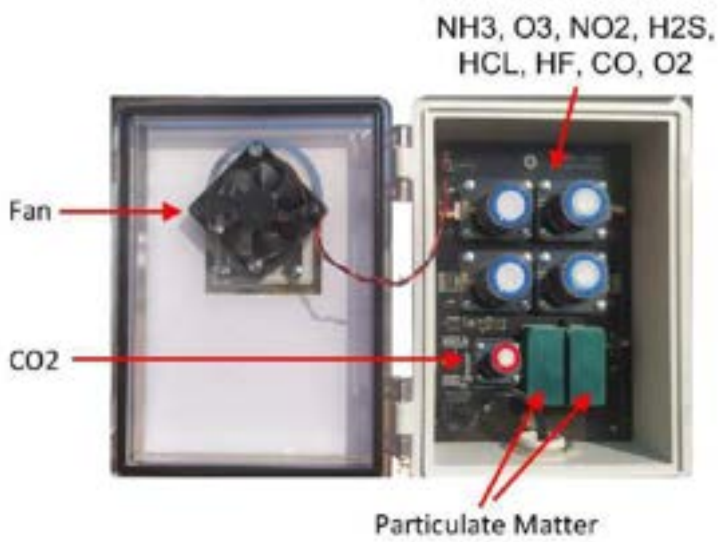

Figure 13 View of the SynAir board

With the integration of SynAir peripheral node(s), the SynField platform is fully equipped regarding use cases that require environmental monitoring of air quality characteristics such as:

- Smart cities
- Precision agriculture and farming

The following table presents SynAir's sensor specifications for Nestler's Pilot implementations.

[45] In most cases a solar/battery powered device can operate with a 20 minutes sampling interval. In cases where more frequent sampling is required and/or a very power-hungry sensor is attached, the device may require an external power supply (i.e. external battery or utility power).

Figure 14: SynAir sensor specifications

Humidity Sensor Specifications	
Relative humidity measurement range	0 – 100%
Accuracy	±3%
Repeatability	0.1%
Temperature Sensor Specifications	
Temperature measurement range	-40 °C - 70 °C
Accuracy	± (0.4 °C + 0.023 x (T [°C] - 25°C))
Repeatability	0.1 C
CO_2 Sensor Specifications	
Range	400 – 10.000 ppm
Accuracy	± (30 ppm + 3%) (25 °C, 400 – 10.000 ppm)
Repeatability	0.1 C
Particulate Matter Sensor Specifications	
Mass concentration range	0 - 1000 μg/m3
Mass concentration accuracy for PM1 and PM2.5	±10 μg/m3
Mass concentration accuracy for PM4 and PM10	±25 μg/m3
NH_3 Sensor Specifications	
Range	0 – 100 ppm
Resolution	1 ppm

4.3. SynField Installation in Pilots

Various SynField devices along with the appropriate sensors have already been shipped to all designated African countries. Moreover, the installations procedures have been started. In Nigeria, the installation phase has reached to a notable level since the SynField X3, the weather station and the Pyranometer have been successfully installed. These devices have started to collect environmental data, essential for the NESTLER objectives. The upcoming period, all the related African countries will install the suitable devices and sensors, starting collected environmental data. Figure 15 and **Error! Reference source not found.** shows the installation of SynField device in field.

Figure 15: SynField Installation in Nigeria

5. Sensor for Crop Quality Measurement

A handheld device able to determine import information about the crop quality of cassava is presented in this section. This device offers a rapid, affordable, and user-friendly means to determine the economic value of cassava for farmers and the bioenergy and bioplastic industries.

5.1. Parameters & Metrics for Crop Quality

The primary quality metric of interest is the starch content of cassava. The bulk of the dried cassava root consists of carbohydrates, over 80% of which is pure starch [54] [55]. In the starch sub-industry, where new applications such as the production of bioenergy and biodegradable plastic alternatives are driving increasing global demand, the availability of a rapid, non-destructive method for estimating the starch content of fresh roots and tubers in the field is highly desirable. Moreover, for these industrial processes, the starch content of cassava determines the actual economic value of the crop and dictates how much the farmers get paid.

5.2. Device & Technique

The cassava starch measuring device works by using radio frequency (RF) return loss measurements. It takes advantage of the natural properties of cassava root samples to estimate their starch content. In simple terms, when the cassava has more dry matter and starch, the device detects lower return loss at specific frequencies, around 30 MHz. This change in return loss indicates a higher starch content. So, by measuring the RF return loss, the device provides a practical way to assess and quantify the amount of starch in cassava roots.

Based on the observed correlation between RF return loss and starch/dry matter content, a portable easy to use handheld device has been developed. This test instrument is designed for the simple and reliable estimation of starch content in cassava roots, particularly in field settings.

The measurement process involves probing cassava samples at a specific frequency, typically 30 MHz. Custom-made probes are employed for this purpose. The return loss at this frequency is then measured and serves as an indicator of the starch content in the cassava roots.

The prototype test instrument is engineered with key objectives in mind: portability, affordability, and user-friendliness. To convey starch content information, the instrument has a display screen to provide the measurement result as well as a basic visual display system consisting of an array of five LEDs. These LEDs categorize starch content into five levels, ranging from "low" to "high", making the measurement result even more accessible to users.

5.2.1. Evolution in the Device Development

The device has gone through three major development evolutions, with three prototype versions, each building on the previous one.

Prototype Version 1

- The first generation of instrument hardware: “minimum viable platform”.

- Intended to prove the concept of a battery operated portable instrument to measure starch content of cassava using the RF return loss method.
- Processor: ATmega328 in the form of an Arduino nano, which allowed for rapid SW development.
- Main signal generator is an AD9850 DDS module.
- Display an array of 5 LEDs to indicate a range of return loss values calibrated to represent starch content in 5 bands, from low to high.
- No data display or wireless capability.

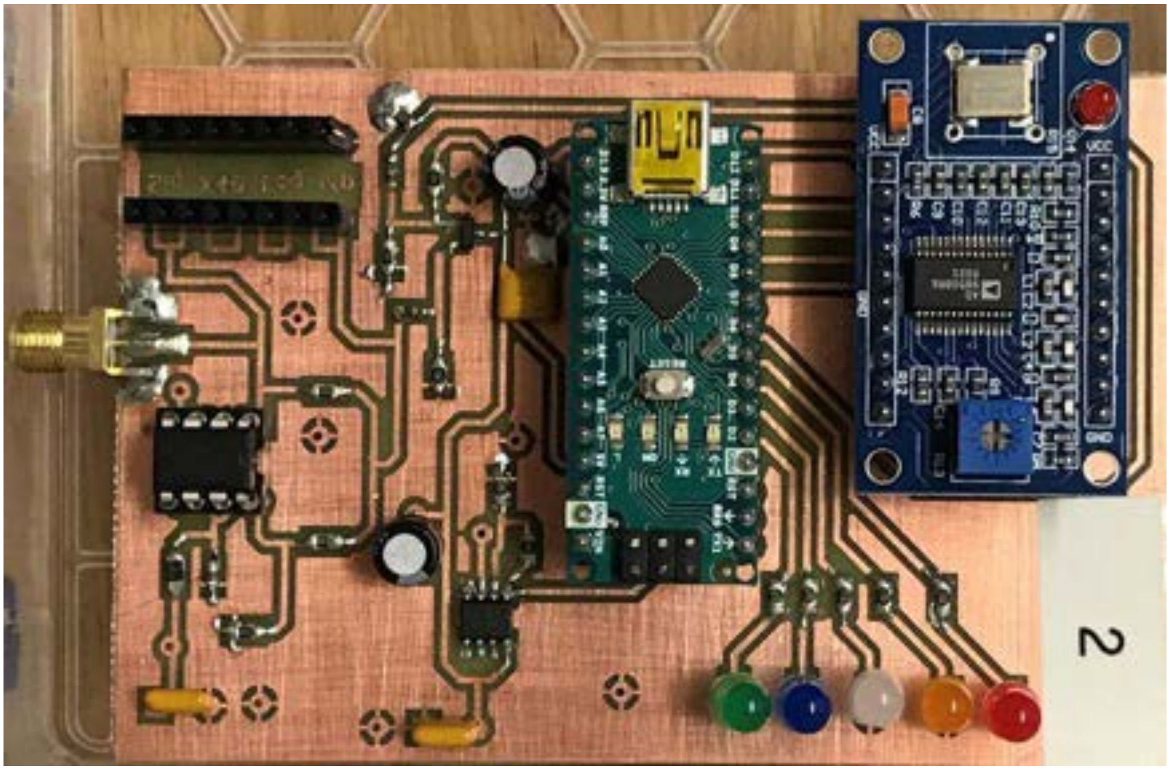

Figure 16: Cassava Quality Measurement Device - Version 1

Prototype Version 2

- Processor evolution to the Heltec processor module:
    - more powerful ESP32 processor
    - Bluetooth connectivity
    - built-in OLED display.
- Temperature sensor added.
- Main signal generator is again a AD9850 DDS module.
- Power supply: Rechargeable Li-Po battery with power management circuitry and external charging via standard micro USB.
- Removable SD card for data storage and 5 data entry keys (later removed in version 3).

Figure 17: Cassava Quality Measurment Device - Version 2

Prototype Version 3

- Processor evolution to Cypress PSoC 6 (CYBLE-416045-02).
- Simplified external circuitry (main signal generator and op-amp integrated into PSoC).
- Removal of AD9850 DDS and op-amp reduces cost.
- Addition of a real-time-clock allows data readings to be time-stamped in the instrument itself, not in the mobile phone, allowing off-line data collection.
- Choice of external, interchangeable OLED display.
- Number of buttons was reduced to only one "test" button.
- Option to allow battery charging from a solar cell.

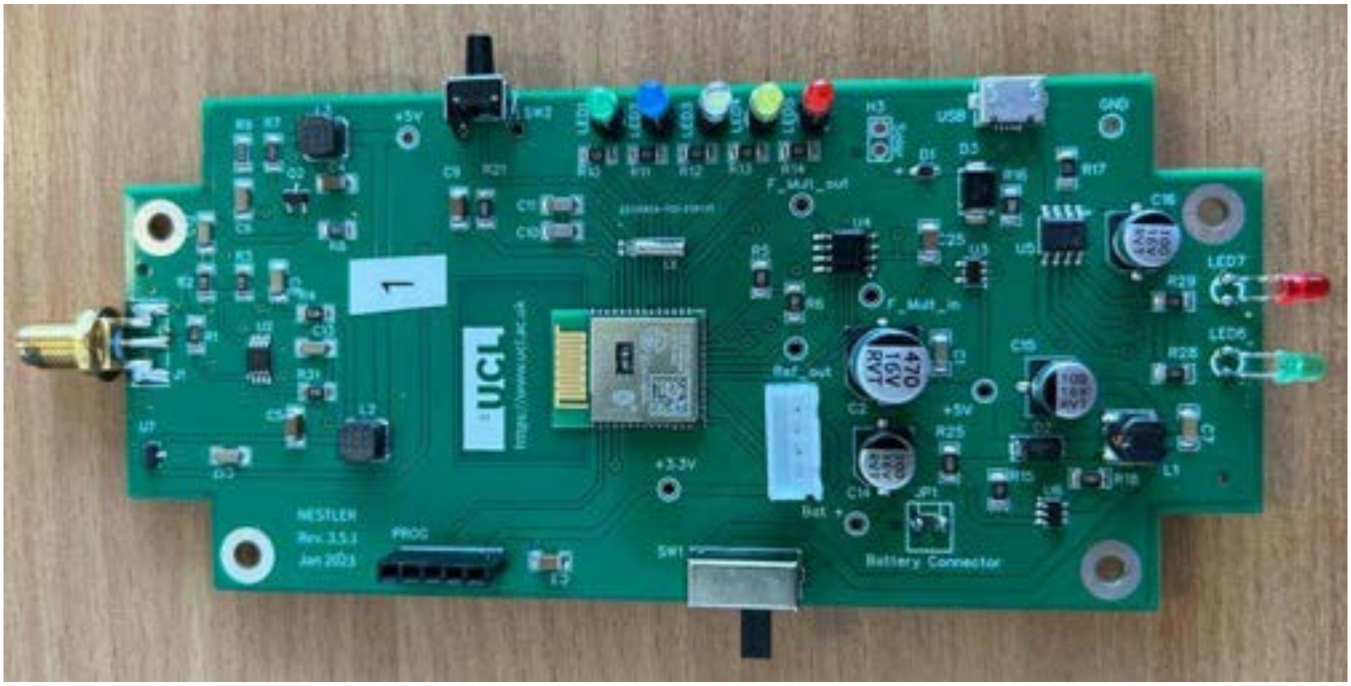

Figure 18: Cassava Quality Measurment Device - Version 3

5.2.2. Device Calibration and Field Tests

The practical performance assessment of the test instrument is being validated through field experiments conducted at the International Institute of Tropical Agriculture (IITA) in Ibadan, Nigeria. Additionally, the evaluation extends to engagement with farmers across key cassava farming communities in the Southwestern region of Nigeria.

These field experiments serve two main purposes: firstly, to improve the robustness of the test instrument, ensuring its durability and reliability in real-world conditions; secondly, to optimize the calibration accuracy of the device. This entails fine-tuning and validating the instrument's measurement capabilities for the precise and consistent estimation of starch content in cassava roots. By engaging both research institutions and end-users in these comprehensive field experiments, the overarching goal is to refine the test instrument, making it a robust, accurate, and user-friendly tool.

Figure 19: Field trials of the device in Nigeria

6. Wireless communication interface

This section introduces an efficient communication system able to transmit data from regions with limited internet connection to the central database. For the experiments, SynField SynOdos devices and handheld device for crop yield measuring are utilized.

6.1. RapidNet Ad-hoc Mesh and Data Aggregator

The developed RapidNet Ad-hoc mesh solution is a self-healing COFDM IP ad-hoc mesh system utilising software defined radio (SDR) platforms. Originally, the system was designed for scenarios lacking traditional communication infrastructure, such as law enforcement, first responders and critical civilian infrastructure protection organizations. Specifically, this system is suitable for situations where there’s no regular way to communicate, like phone lines or cell towers. However, it is also invaluable during the critical “Golden Hour” of incidents, where secure and reliable communication is essential. The system serves as a flexible, easily configurable and standalone communication solution, providing a local area network for first responders or seamlessly integrating with cellular networks for full internet connectivity.

6.2. Modifications of RapidNet

In the NESTLER project, the RapidNet system was modified to address specific scenario, where sensory data collected from various developed IoT devices needed to be integrated into a single transport stream and transmitted over a long distance range from rural areas, where cellular infrastructure is not available, or system throughput is not sufficient.

The focus of the modifications was on seamlessly integrating the RapidNet node with the sensory data aggregator and making the RapidNet nodes applicable for the integration on a UAV. This enabled the creation of full connectivity between the local area networks with the remote locations where access to internet is available, resulting in the live stream of collected sensory data to the centralised NESTLER database. The main emphasis during the development process was on ensuring that power consumption of the airborne RapidNet node will not drain the UAV battery while weight and physical dimensions are suitable for integration on the available UAV. The block diagram of the developed solution is shown in the figure below.

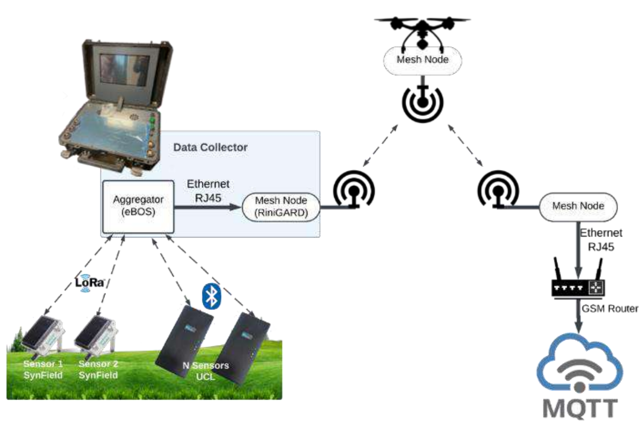

Figure 20: System architecture

6.3. System Integration

A core component of the developed wireless system, the eBOS aggregator, was developed and implemented as part of the integrated solution. In preparation for the case study, ground sensors provided by SYNELIXIS and UCL were connected via BLUETOOTH and LoRa protocols to the eBOS aggregator and then, the aggregated data was streamed via mesh network. The figure below illustrates a schematic diagram of the developed aggregator.

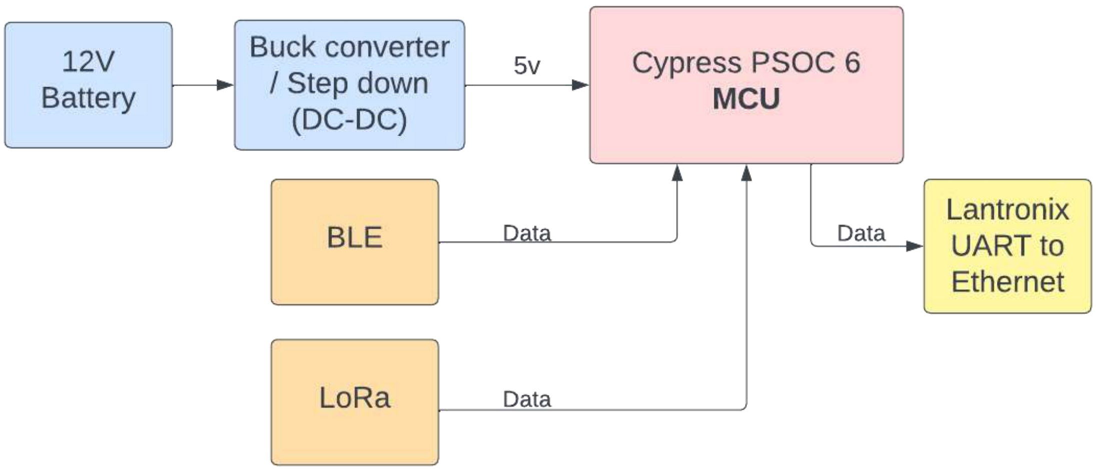

Figure 21: Aggregator architecture

6.4. Initial testing and results

The developed solution was integrated and tested in both laboratory and near-field conditions. Initially, an integration and testing of the various components and their connectivity was performed in the lab. Then, a first demo was conducted in the field, showcasing a seamless communication of UCL and SYNELIXIS SynOdos device (Figure 22) with the eBOS aggregator, which was connected to Rinisoft mesh units and a drone (Figure 23).

Figure 22: UCL Crop Quality and Synelixis SynOdos devices

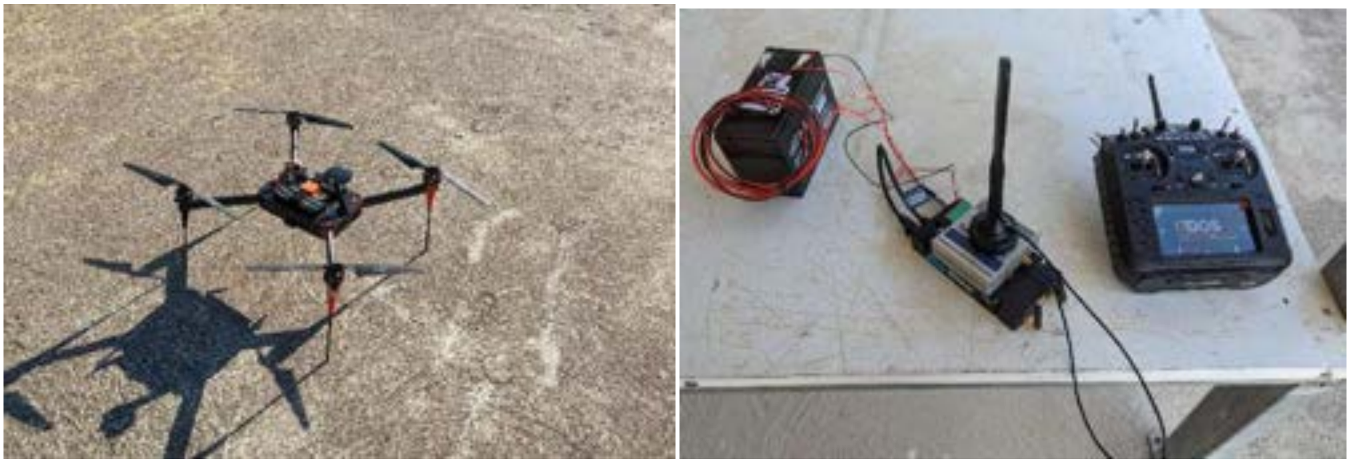

Figure 23: System components at demo site

Preliminary results show operational capabilities as expected, and the requirements for the final use case are being finalised. These preliminary results show operational capabilities of the integrated solution, while the work will continue to further develop and improve the different components as well as finalize the requirements for the final use case.

7. Sensors and Techniques for Livestock and Aquaculture Monitoring

The primary objective of the Task 3.3 is the monitoring of wildlife, livestock, aquaculture well-being, and insects. To meet the task objectives, RiniSoft initially proposed the deployment of wearable devices for the real-time monitoring of large to middle-sized animals as part of solution T3.3. The proposed sensors were designed to track various parameters including geolocation, activity levels, and fundamental physiological metrics. The data collected by these sensors would then be transmitted to the NESTLER Cloud infrastructure for analysis and integration.

However, through extensive consultations with our African partners who oversee the pilot projects, several critical issues were highlighted:

1. **Practicality:** Wearable devices, while technologically robust, presented several practical challenges. These include the difficulty of fitting and maintaining devices on large or active animals, which often require repeated human intervention.
2. **Cost Efficiency:** The cost associated with the production, maintenance, and replacement of wearable devices was identified as a significant barrier, particularly for large-scale deployments.
3. **Scalability:** Wearable devices, due to their nature, pose challenges in scalability. The logistics of deploying and managing numerous devices across large populations of animals were seen as inefficient.
4. **Accessibility:** Frequent access to animals for the purpose of fixing or replacing devices is not always feasible, leading to potential data gaps and increased operational overheads.

In response to the feedback and specific requests from our African partners, we have revised our approach. The revised solution focuses on the deployment of video sensors, which offer several advantages:

- **Ease of Deployment:** Video sensors can be strategically placed in animal habitats with minimal disruption, allowing continuous monitoring without the need for direct animal interaction.
- **Maintenance:** These sensors require less frequent maintenance compared to wearable devices, reducing the need for constant human intervention.
- **Scalability:** Video monitoring systems can be scaled up more easily, providing extensive coverage with a relatively low incremental cost.
- **Affordability:** The cost per unit of video sensors is lower, and they offer a better return on investment due to their longer operational lifespan and lower maintenance needs.

Additionally, based on the directives from our African partners, we have narrowed our focus to specific animal types that are more relevant to their contexts, namely chickens and fish. This specialization allows us to tailor our video sensor technology to the unique behaviors and environments of these animals, enhancing data accuracy and relevancy.

To meet the objectives of the task we propose to develop an AI monitoring system that analyzes video streams to identify potential diseases and specific behaviors indicative of illness or abnormal animal behavior in poultry and fish. To achieve these objectives, the proposed system will consist of two subsystems:

- Chicken Farm Video Monitoring System
- Fish Farm Video Monitoring System

The system is built on a technology that uses primarily video analysis to measure animal health and behavior indicators. Computer vision and artificial intelligence play a key role in the development of the AI Monitoring System. A network of cameras produces a video stream used to identify animals inside farm buildings in real time. The animals do not have to be equipped with any instruments and the system works for any number of animals. It can also effectively measure a wide range of indicators.

Video data was selected because it is a simple approach, which is **not invasive and affordable for application in low income countries of Africa**. In addition, cameras are relatively easy to install and can be scaled for larger flocks. At the same time, significant number of diseases changes the appearance and the behaviour of the bird, which could be captured using visual data. Same argument may be used for fish monitoring, where anomalies manifest themselves in the behaviour and movement of the fishes. For the reasons mentioned above, Machine Vision methods are used as a base for poultry disease detection.

Machine Vision involves the use of various algorithms to enable machines to perceive and understand visual information. Classical techniques such as optical flow and SIFT (Scale-Invariant Feature Transform) have long been fundamental in extracting and analyzing visual data. However, the advent of Deep Learning in 2010th has ushered in a new era, where algorithms driven by neural networks have revolutionized Machine Vision. These newer approaches leverage convolutional neural networks (CNNs) and other deep learning architectures to autonomously learn and extract intricate patterns from images, significantly enhancing the accuracy and efficiency of visual recognition tasks.

For more complex tasks, deep learning often demands substantial amounts of data for effective training, which can pose challenges in data acquisition and annotation. In this context, a combination of classical machine vision techniques with deep learning methodologies becomes particularly valuable. By integrating classical algorithms that offer robustness and efficiency in feature extraction with deep learning's capacity for complex pattern recognition, this hybrid approach can mitigate the need for vast quantities of labelled data. Leveraging the strengths of both methodologies not only enhances the learning process but also reduces the data requirements, making it a pragmatic solution for tackling intricate visual tasks where data availability might be limited or costly to obtain.

In the domain of disease detection among chickens (poultry) and fishes, the absence of comprehensive open imagery datasets depicting various diseases and their discernible impacts on the appearance and behavior of infected animals presents a notable challenge. Discovered datasets focus primarily on more generic problems like animal's detection and counting. For that reason, the final algorithm should be based on a combination of data-driven models for well-established tasks (like detection, tracking, matching, feature extraction) and domain-driven methods that utilize the expert knowledge. That approach can often be formalized as a measure of the deviation from the normal appearance or behavior. For that reason, special attention is paid to one-class classification methods.

In summary, the primary activities in this project stage involved the collection, labeling, and processing of data to create an annotated training dataset. This dataset serves as the foundation for training deep learning models designed for the real-time monitoring and detection of diseases and abnormal behaviors in poultry and fish.

7.1. Poultry Health Monitoring

The Poultry Health Monitoring System is designed to assess the health of poultry flocks through sophisticated analysis of multimedia data. At this stage we focus on the clinical symptoms that can be used for early warning and detection of chicken diseases and try to expound on these symptoms in detail via two dimensions: (1) early disease detection through physiological characteristics, and (2) early disease detection through behavioral characteristics. To detect these characteristics, some monitoring devices will be used, such as microphones and cameras to determine vocalizations; cameras to note birds' activity; and digital cameras to determine the posture of the birds.

The system functions across multiple layers:

- **Data Collection Layer:** Includes IoT devices like cameras and microphones.
- **Data Analysis Layer:** Consists of preprocessing and analyzing modules (Behavior Analyzer, Appearance Analyzer, Vocalization Analyzer) with CNNs for image recognition and classification, Deep SORT for tracking, and additional algorithms for vocalization analysis.
- **Decision-making Layer (Poultry health assessor module):** Applies analytics to the metrics and parameters gathered, leading to actionable insights.

7.1.1. Monitoring Parameters

The AI's architecture and training in the context of monitoring poultry health is meticulously designed to align with the specific types of data collected, predominantly focusing on visual and acoustic information. This system, equipped with state-of-the-art cameras and sensitive microphones, captures a wealth of visual data and sound patterns that are essential for assessing the well-being of poultry. The visual data provides detailed imagery of the chickens, allowing for close monitoring of their physical condition, behavior, and environment. Meanwhile, the acoustic data offers insight into their vocalizations, which can be key indicators of stress, health, or discomfort. The AI, through its specialized architecture, analyzes these diverse data streams, learning to identify patterns and anomalies that might escape human observation. By training the AI specifically on these types of data, the system becomes adept at interpreting subtle signs of health issues or environmental stressors, thereby enabling timely interventions and ensuring optimal poultry health. This alignment of the AI's architecture and training with its data-centric focus ensures a robust, efficient, and highly effective monitoring system in the realm of poultry health management.

Regarding visual information, it is possible to allocate various parameters for tracking and assessing the individual chicken health markers. A sophisticated AI system can track and assess various parameters to gauge the health of individual chickens. Firstly, Object Detection in Frame is utilized to precisely locate each chicken within a visual frame, employing a bounding box to pinpoint their position. This is crucial for individual monitoring and analysis. Next, understanding the Location in Frame Coordinate System provides context to the chicken's behavior, such as their proximity to feeding zones or nesting areas, which can be indicative of their health and wellbeing. Further, the system employs Object Shape Analysis and Color Analysis to detect anomalies in visual features. This advanced analysis enables the identification of specific health markers like changes in plumage thickness or signs of watery eyes. These subtle visual cues are critical in classifying individual health conditions. Additionally, the AI conducts a Structural Integrity Assessment, examining the chicken's overall body condition. This involves looking for signs of emaciation or obesity, which are vital indicators of the bird's health status. Finally, Object Pose Estimation is used for Activity Classification. By analyzing the posture and movement of the chickens, the AI can infer various activities and behaviors, providing deeper insights into their physical condition and overall health. Together, these visual information-based parameters offer a comprehensive, nuanced view of each chicken's health, allowing for precise and proactive management in poultry care.

Moreover, audio information parameters play a pivotal role in the realm of poultry health monitoring, complementing visual data with critical insights. The Overall Acoustic Noise Level of the Herd is a primary parameter, providing a general assessment of the ambient sound environment of the poultry. This can be indicative of the herd's collective behavior and well-being. Additionally, the analysis of Sound Wave Characteristics, including shape, frequency, amplitude, and phase, offers detailed insights into the specific sounds made by the chickens. These characteristics can reveal subtle changes in vocalizations that might signal distress or health issues.

However, the analysis of these audio parameters is not without challenges. One significant obstacle is the Presence of Additional Sound Waves, which involves the difficulty of distinguishing specific chicken sounds amidst a cacophony of background noise. This includes dealing with sound effects like echoes, which can distort the true nature of the sounds. Another challenge is the Variability in Similar Sounds. Chickens may produce sounds that are similar in nature but vary in amplitude, frequency, and speed, making it challenging to accurately interpret their significance. Lastly, Signal Interference poses a considerable challenge. This occurs when overlapping signals with different amplitudes interfere with each other, complicating the process of isolating and analyzing individual sounds. Overcoming these challenges is crucial for the effective use of audio information in monitoring and ensuring the health of poultry.

Within NESTLER, to assess the overall state of poultry flock, the following parameter is suggested to use:

1. **Flock Movement Consistency:** Assessed using optical flow to measure the uniformity of movement across the entire flock. Metrics like variance and kurtosis of motion data give insights into the health of the flock.
2. **Individual Chicken Behavior and Health Markers**, which includes:
   a. **Activity Classification:** Detecting behaviors like feeding, sleeping, or running using CNNs.
   b. **Physical Markers:** Identifying signs of potential illnesses, such as disheveled feathers, bald spots, or other anomalies.
3. **Chicken Vocalization Patterns**:
   a. **Frequency Distribution**: Monitoring shifts or anomalies in vocalization frequencies over time.

b. **Sound Type Classification**: Identifying specific vocal patterns, like alarm calls or feeding sounds, to interpret the flock's mood and health.

7.1.2. IoT Sensors and Devices

When developing a general approach for constructing and AI-based monitoring system, we have identified several fundamental principles for the sensors required by the AI to detect potential illnesses in flock of birds. These principles include:

1. **Non-Invasive Monitoring:** Utilize sensors that detect atypical behaviors without disturbing the animals.
2. **Continuous Operation:** Sensors should work 24/7 and have a high Mean Time Between Failures (MTBF).
3. **Ease of Operation:** The system should be operable without the need for specialized training.
4. **Damage Resistance:** Ensure maximum protection against damage from farm workers or animals.
5. **Cost-Effectiveness and Serviceability:** Aim for low-cost solutions with readily available service centers.
6. **Climate Compatibility:** The system must be operable in equatorial Africa's climatic conditions.

When deciding between the cameras for computer vision (CV) and machine vision (MV) for AI, of course MV cameras are preferable. But this type of cameras does not meet the requirements on simplicity of operation, cost and operability. Due to this fact it was decided to use CV camera. When selecting camera of this type, it is essential to choose the modification with built-in microphone and Power over Ethernet (PoE) power supply. In the NESTLER project, for the monitoring of poultry health, the following sensors and devices will be used:

1. **Video Cameras:** High-resolution Hikvision IP bullet camera DS-2CD2083G2-IU (2.8mm), 8MP, 2.8mm, Microphone, AcuSense, resized to 1920 x 1200 pixels. Video camera should be installed inside the chicken farm at the height of 3-5 meters. The refresh rate of information from the CV cameras is 25 Hz.
2. **Microphones:** Built-in microphone from Hikvision IP bullet camera DS-2CD2083G2-IU with an Environment Noise Filtering is used.
3. **Computing Hardware:** RiniSoft server for data processing and analysis. Server configuration - Intel Xeon E-2236, 6 Core, GPU A2 16 GB GDDR6, RAM 32 GB DDR4, 2 × 960 GB SSD SATA.

Figure 24: Hikvision IP bullet camera DS-2CD2083G2-IU.

7.1.3. Monitoring System

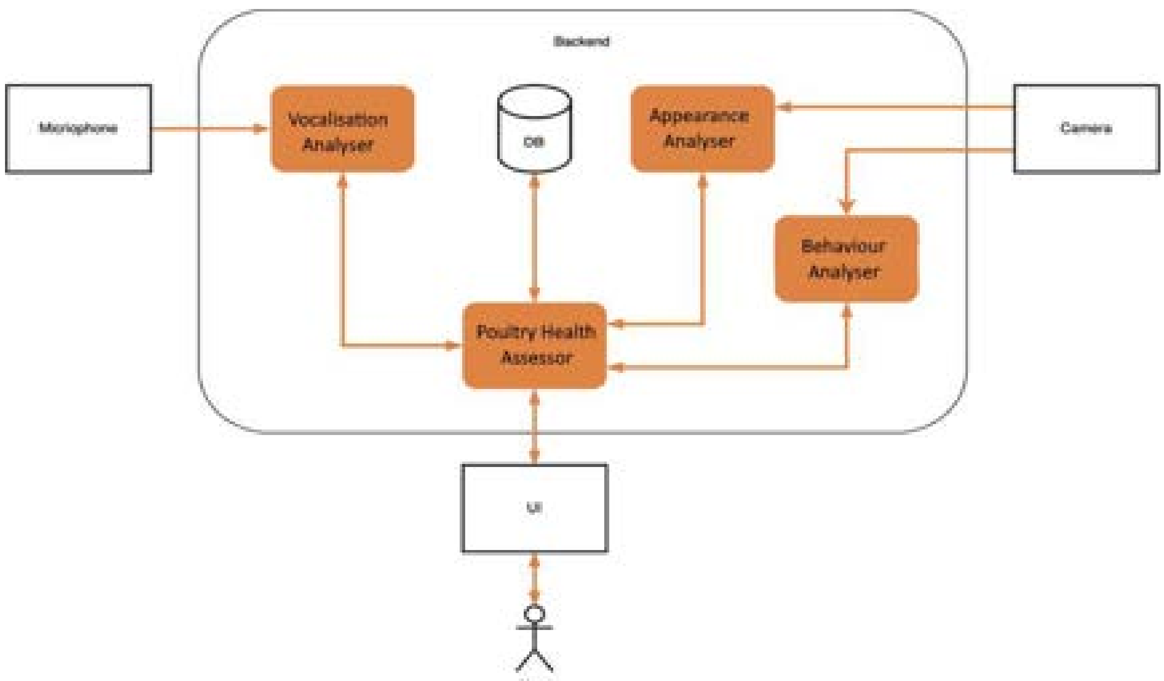

Figure 25: Poultry Health Monitoring System Functional Diagram.

The components and modules of the system are described below:

- *Behavior Analyzer Module:* For flock-wide behavior analysis based on flock's optical flow.
- *Appearance Analyzer Module:* For specific chicken behavior and physical health markers.
- *Vocalization Analysis Module:* For vocal pattern recognition and classification.
- *Poultry Health Assessor Module:* For creating predictions based on the analysis of the data gathered and processed through analyzer modules.

The various artificial intelligence (AI) methodologies and technologies used to monitor and detect diseases within a chicken population would include:

- **Statistical Models:** Used for analyzing the optical flow and vocalizations. Compares current data to historical data to identify anomalies.
- **Convolutional Neural Networks (CNNs):** Used for image recognition tasks, identifying and tracking individual chickens, and recognizing key points for health assessment.
- **Deep SORT Algorithm:** Employed for real-time tracking of individual chickens across frames.
- **Sound Classification using CNNs:** Classifies different types of chicken vocalizations based on their spectrograms.
- **Parameter Aggregation and Prediction:** Combines all the parameters (flock movement, individual chicken data, and vocalization data) into a single health index for the flock. Applies predictive analytics to anticipate disease outbreaks.

7.1.4. Gathering Chicken Farm Dataset (CFDS)

Gathering, labeling, and processing high-quality data is crucial for training deep learning models that are both accurate and robust. This ensures the model's ability to generalize effectively to unseen data and perform optimally in real-world applications.

The poultry dataset for the livestock monitoring task was primarily sourced from RINIS's chicken farm RiniSoft BioLab in Sliven, Bulgaria and various open sources. Consequently, the acquisition of "positive" disease instances was challenging due to the health of the observed chickens and ethical constraints against intentional contamination. Additionally, open-source datasets lacked a comprehensive array of diseased chicken examples. The available examples required detailed filming of each animal, conflicting with the requirement for minimal human interaction.

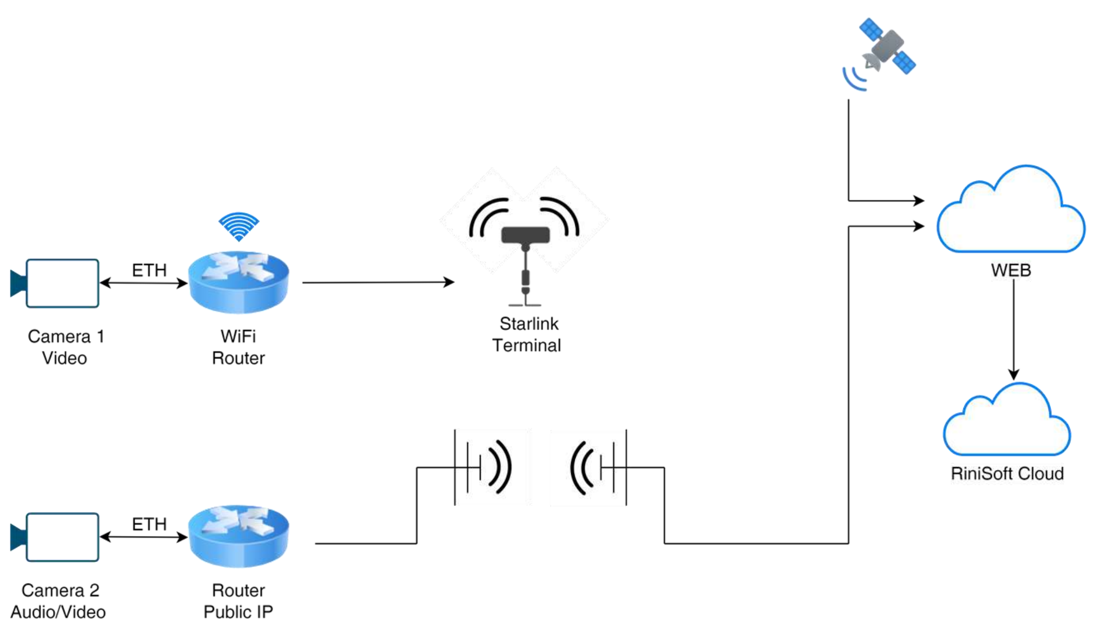

Figure 26: CFDS Collection Diagram.

In addressing the challenge of gauging population health through AI, it is crucial to curate annotated training datasets tailored to individual health threats. The utilization of these samples empowers the AI to learn and predict the emergence of specific diseases within the population, relying on distinctive symptoms discernible through video stream analysis. The requisite volume of annotated data for AI training adheres to the principles outlined in the Central Limit Theorem (CLT).

The CLT posits that as the sample size increases, the distribution of the sample means approaches a normal distribution. In the context of AI training datasets, this implies that a larger volume of annotated data allows for more accurate predictions by the AI.

To curate annotated training datasets specific to individual health threats, diverse data sources, including video streams, can be harnessed. These video streams capture visual symptoms associated with various diseases or abnormal movements. By annotating these videos with labels indicating the presence or absence of specific diseases or symptoms, a comprehensive dataset is created for effectively training the AI. The requirements of chicken farm dataset are listed in Table 26 of Annex A.

It is important to note that datasets should be collected from different flocks of hens (each flock of at least 20 individuals). Each flock should be composed of chickens of the same breed and approximately the same age. Data should be collected for three age groups: 12-16 weeks, 36-40 weeks, 66-70 weeks.

7.1.5. Behaviour Analysis Strategy

Addressing the challenges in tracking individual chickens in a large flock within a confined area, we've shifted our strategy in behavior analysis. Instead of individual tracking, we now focus on analyzing average flock behavior per video frame. This includes patterns in eating, sleeping, and resting. We use models like YOLO to detect chickens in the video frame, crop these detections, and then apply another YOLO model to identify chicken parts and construct skeletons. This process aids in assessing the current actions of each cropped chicken.

For the current implementation, an off-the-shelf implementation of trained YOLOv7 model was used. No changes to the architecture were applied, the model was trained on a combination of COCO dataset and our own small, labelled dataset, which includes a few thousand images with chickens. No tweaks to the training process were applied.

Figure 27: YOLOv7 training tensorboard for poultry health monitoring.

The training of the algorithm took 80 epochs, the convergence was monitored manually, using tensorboard utility, which logs the metrics over training. An example of a training run of YOLOv7 training on joint COCO+Chicken dataset is demonstrated below:

1. The results of the training were evaluated on a combined test set that consists of: 197 annotated chicken images (2560 instances in total)
2. 5000 images from the validation set of COCO, which do not contain any chicken (they were manually checked) are used for false positive assessment.

A chicken was considered as detected for an Intersection over Union (IoU) of 0.3. A slightly higher value was selected due to the necessity of the obtained metrics are listed as follows.

- ROC curve for true- and false-positive rates. The obtained dependency as shown at next figure, That figure shows that a realistic true-positive rate that would not result in an overwhelming number of false positives is **79.8%**, which corresponds to **0.51%** false-positive rate. Lower false positive rate threshold was selected in accordance with the performance of the behavior analytics algorithm, in order to ensure a more stable assessment of the flock activity. Average IoU for true-positives is **0.491 +- 0.026.**

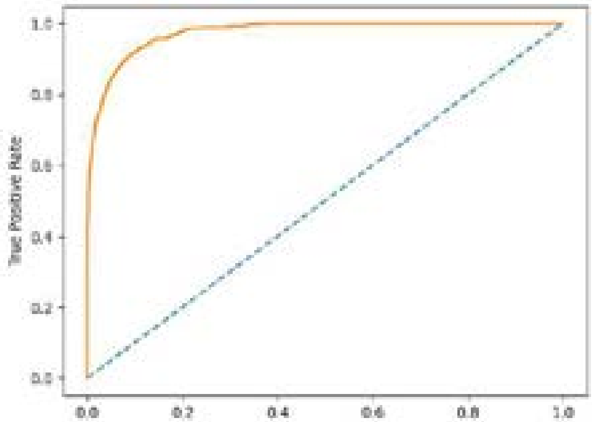

Figure 28: ROC Curve of model for poultry health monitoring.

- Inference rates. Developed neural network was implemented on Pytorch and was tested on a board designed for embedded systems: Nvidia Jetson Xavier. It is a low-power board (20-30W) that has a light-weighted GPU with 384 general-purpose cores and 48 tensor cores. Before the performance tests, the obtained YOLO model was exported to a more efficient presentation, i.e. Tensorflow-1 protobuf graphs. This format allows for 2-3 times faster inference compared to standard Pytorch or Keras formats. Overall, the model inference on 1000 frames took 59.3 +- 1.5 secs.

Further improvement of the detector could be linked to the improvement and enrichment of the visual training dataset and, possibly, implementation of some special training hooks like MixUp, mosaic, SimCLR, etc. These training enhancement methods are widely used to improve the neural network quality.

7.1.6. Optical Flow Analysis for Flock Mobility

We have applied statistical optical flow analysis to detect anomalies in overall flock mobility. Data history and timestamps have been recorded to correlate with specific times of day and year. Currently, this analysis does not employ neural networks; instead, it focuses on collecting statistical outliers and assessing flock health based on threshold exceedances.

The implementation of the algorithms is based on a combination of YOLOv7 detector (described above) and the analysis of the optical flow. We use Farneback optical flow, which we found out as a good compromise between speed and estimation density. YOLO detector is used to filter-out the detections that are not caused by chickens. The algorithm has a set-up (training) time, when it checks the main places of the activity of the birds by using the Kernel Density Estimators (KDE). over the evaluated optical flow. A projection of the resulted KDEs for our Rinisoft chicken on the camera frame is shown on the figures below:

Figure 29: RGB image and estimated speed/position PDF using KDE for poultry health monitoring.

From the figures above it is clear that most of the activities happen in the open areas and near the feeder. This information is captured by the estimated probability density function (PDF) that is defined over time and space.

Figure 30: Night-time image from RiniSoft BioLab.

The space domain is given in pixels of the camera, thus a fixed position is assumed. Time domain is presented as 24-hour periodic space, encoded using sin-cos variables. Therefore, the final PDF is defined for 3 coordinates: (x, y, t), which are implicitly translated to $\left(x, y, sin(tmod24), cos(tmod24)\right)$ (assuming 24-hour presentation of the time). In order to avoid small-scale variations causing significant changes, the space is coarsened, so that the PDF is estimated for every 3 hours and for every 200x200 pixels. For each of the coordinates listed above, 2 probability functions are defined: probability of bird's presence in the given pixel and the expected optical flow. The optical flow PDF is estimated using Parzen's window approach, which is a compromise between evaluation speed and smoothness of the function. The window width is estimated using Silverman's rule.

In order to capture both day and night-time behavior, we propose day/night cameras, which can operate in near-IR spectrum. An example of night-time image is provided below

At operation, the algorithm assesses the movement of the flock using tracking-by-detection approach, combined with Farneback optical flow. Movements and presences are averaged over time and then they are applied to the respective PDF function. Based on the average fitness of each of the detected chickens to the estimated PDF, an average fitness score is computed. This fitness score is used as a parameter for anomaly detection. The score is averaged over chickens, which means that it can be applied for each chicken independently too.

Currently, the existing dataset does not have long video sequences with infected chickens, so the validation of the algorithm is limited. However, some self-validation methods are applied.

- We apply night-time optical flow PDF to day-time activity and compare that against the day-time PDF (simulation of over-activeness and over-feeding). The experiment is conducted on the data from 9AM till approximately 12PM, 1000 activity recordings.

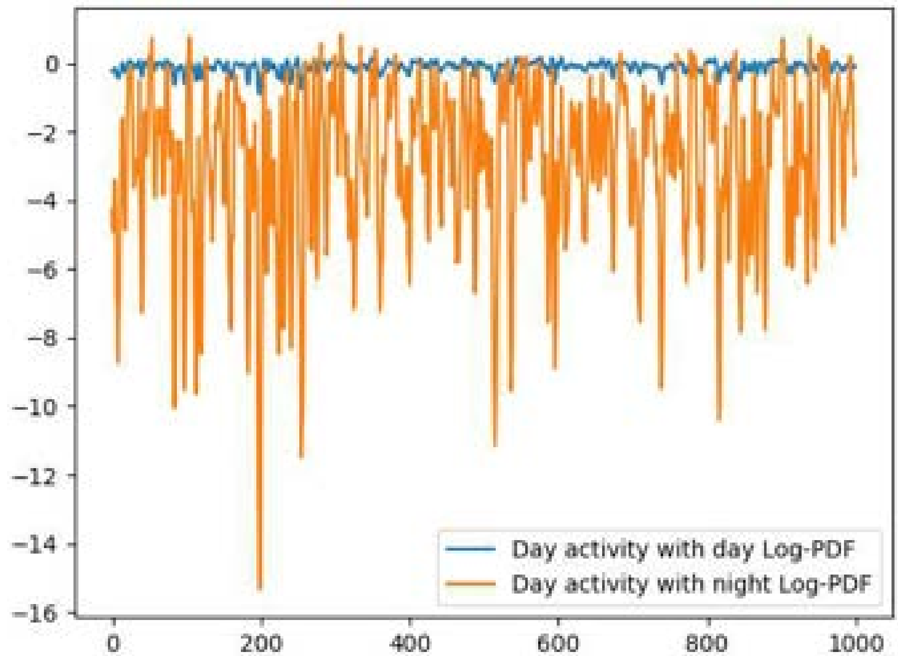

Figure 31: Day-time Data gathered from from RiniSoft BioLab.

- We apply day-time optical flow PDF to night-time activity and compare that against the night-time PDF (simulation of lack of activity and under-feeding). The experiment is conducted on the data from 3AM till approximately 6AM, 1000 activity recordings.

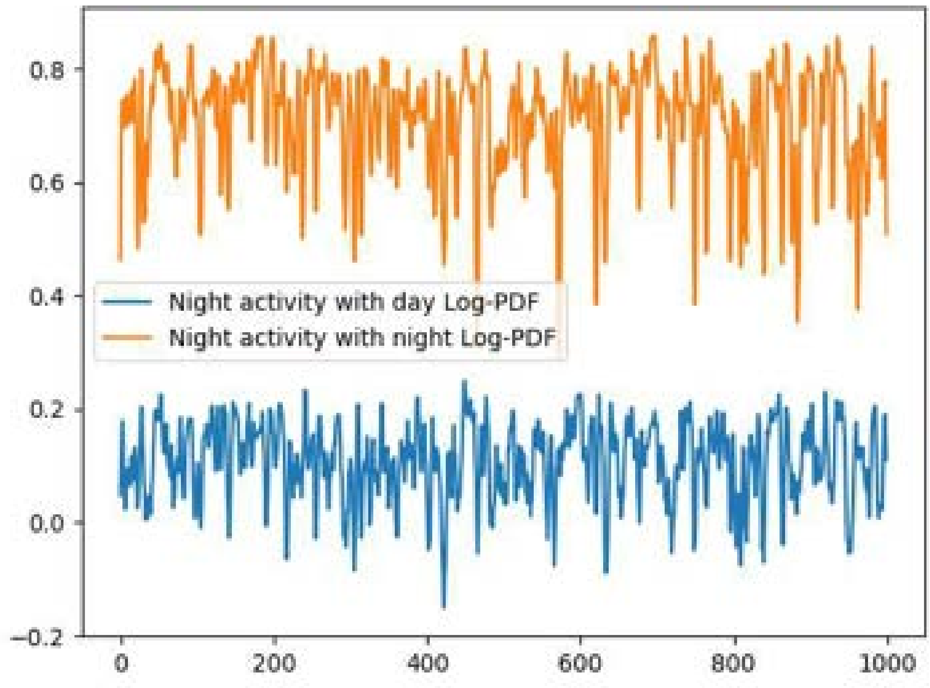

Figure 32: Night-time Data gathered from from RiniSoft BioLab.

The results were somewhat unexpected, revealing that differentiating non-active behavior is more straightforward using the difference between PDF values. This observation could be attributed to the night-time PDF being comparatively "narrow" on average, leading to large negative log-probabilities on night data. In contrast, the day-time PDF, being relatively "wide," tends to capture night-time data with approximately 0-valued log-probabilities. However, the night-time PDF excels in capturing this data more accurately.

7.1.7. Appearance Analyzer

Due to the lack of labeled data on diseased chickens, we have used the DINO v2 self-supervised model to extract features from video stream frames. DINO v2 is a visual transformer that was introduced by Facebook in April 2023 and has shown outstanding results in different machine vision problems. The transformer was trained on a large image dataset, both labeled and unlabeled. The training process was based on self-supervised learning methods, which target to improve the generalization capability of the extracted feature vectors. As a result, DINO v2 extracts visual features that could be applied with no or minimal training to various problems and domains, including object detection, classification, semantic segmentation, image matching, etc. For example, DINO v2 “small” model’s features were used for semantic segmentation (SS) to obtain the result shown below.

Figure 33: Chicken images and respective semantic segmentation.

As it is visible, chickens were properly identified as the same class. This was achieved just by selecting respective semantic classes, with no model pre-training.

For our case, DINO v2 could be used to perform visual analysis of chicken's appearance. As it is a highly problematic task to collect images and videos of different chickens with different diseases, it could be beneficial to apply anomaly detection methods for chickens' visual appearance analysis.

However, metric-based anomaly detection may not be applicable directly. DINO v2 was tested on an open chicken detection dataset, where some sick chickens are present. However, there are no annotations of which chickens are sick and which are healthy. However, 3 instances of sick birds were identified manually. DINO v2 dataset features were projected using PCA.

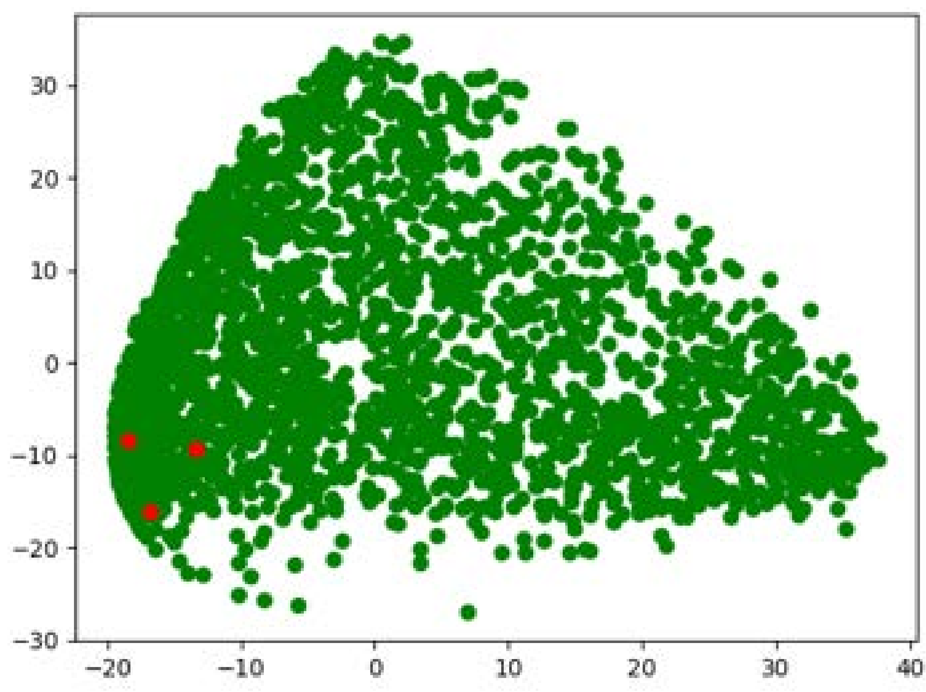

Figure 34: Separation diagram and manually identification of 3 sick chickens.

Green dots correspond to unlabeled instances, red dots correspond to manually selected sick chicken images. There is no clear separation, which could indicate that some additional training may be required to achieve better results.

7.1.8. "Poultry Fleas" Use Case

The presence of skin parasites, primarily fleas, poses a significant problem in chicken farms. Fleas contribute to viral diseases, slow wound healing in equatorial or tropical climates, and feather loss as hens attempt to rid themselves of the parasites. These parasites carry pathogens responsible for brucellosis, encephalitis, salmonellosis, trypanosomiasis, and helminthic diseases. Their bites can also be dangerous to humans. Timely detection of fleas is crucial, as treatment is relatively easy and effective when their numbers are small.

- Experimental Setup
  - To assess the feasibility of flea detection through video stream analysis, four out of 20 hens in the RiniSoft Ltd biolab were intentionally infested with standard fleas (Ceratophillus gallinae).
  - Initial video analysis revealed a characteristic movement (shaking off) in the infested birds, distinguishing them from others.
  - This movement became observable in almost all birds within four days.
- Characteristics of Flea-Induced Movement
  - Deep analysis determined that the duration of this characteristic movement was approximately 700 milliseconds on average.
  - Video clips were annotated to extract frames of this action for training the detection system.
- Dataset Information
  - All videos in the dataset were recorded using Hikvision IP bullet cameras (DS-2CD2083G2-IU, 8MP, 2.8mm, with Microphone and AcuSense).
  - The videos were resized to 1920 x 1200 pixels and saved in MP4 file format.
  - Although vocalizations are not currently analyzed, the recorded data may be used for further analysis in subsequent stages.

7.1.9. Annotation Process and Dataset Augmentation

Annotations were conducted by several team members using the Computer Vision Annotation Tool (CVAT)[46]. CVAT facilitated comfortable annotation of video fragments for training and testing prediction models. Annotations were exported along with video fragments in JavaScript Object Notation (JSON) file format. The annotations adhere to the Common Objects in Context (COCO) format, storing coordinates and object categories for each video. Approximately 83 video fragments (long time, 1 second) were annotated, generating 2075 images, extracted from 187 hours (16,830,000 images) of video footage. The dataset was expanded to around 75,600 seconds annotated video using the standard video editor.

Out of the 75,600 video fragments (LT 1 sec), 23,400 were allocated for training, 2,560 for validation, and 2,560 for model testing. Dataset augmentation involved operations such as brightness change (from -15% to +15%) and cropping (maximum 10%). It's highlighted that instance segmentation annotation is more labor-intensive, requiring the drawing of polygons over each instance of chicken, compared to

[46] https://www.cvat.ai/

drawing rectangles for the dataset used in training detection models. The use of the CVAT tool for annotation is visually depicted in Figure 35.

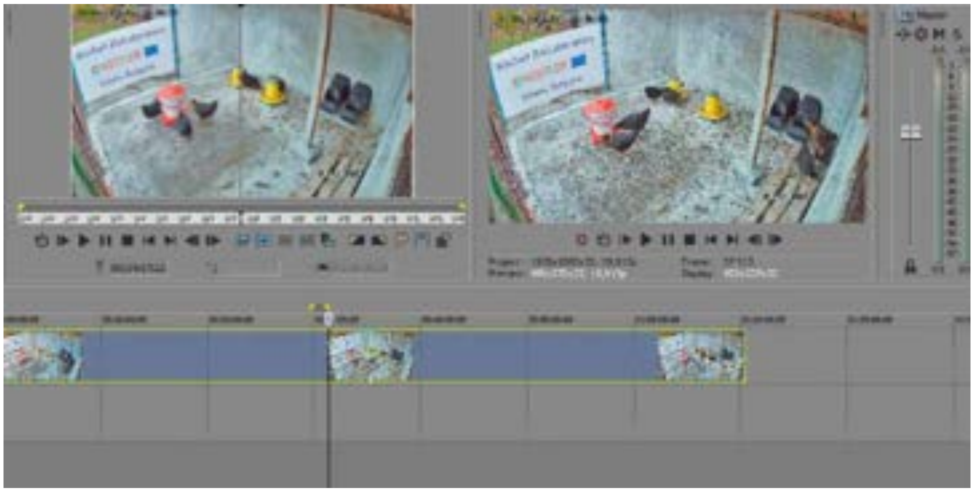

Figure 35: CVAT user interface for labelling CFDS.

7.2. Fish Health Monitoring System

The Aquaculture Monitoring System is designed to assess the health of fish flocks through sophisticated analysis of multimedia data. It functions across multiple layers:

- Data Collection Layer: Uses high-resolution underwater cameras for optical flow capture.
- Data Analysis Layer: Employs statistical analysis and machine learning techniques for real-time health assessment.
- Decision-making Layer (Fish Health Assessor Module): Applies the analyzed data to predict flock health.

7.2.1. Monitoring Parameters

In the advanced realm of aquaculture, a sophisticated monitoring system utilizing video image analysis is pivotal for maintaining the health and well-being of fish. This system encompasses several key Monitored Parameters. Object Detection is the primary feature, enabling the identification of individual fish or groups within the camera's field of view. This is crucial for tracking population dynamics and behavior. Linear Dimensions measurement plays a vital role in monitoring the growth and health of the fish, allowing for the assessment of their size and development over time.

Location Tracking is another essential parameter, where the system determines each fish's position in the pool using the frame coordinate system, providing insights into their spatial distribution and movement patterns. Additionally, the Transparency of the Aquatic Environment is assessed, evaluating water clarity to gauge the environmental quality, which is integral to the health of the fish.

On top of these monitored parameters, the system also calculates Computable Parameters. The Average Speed of a Fish Pack is calculated to understand the overall movement speed of the group. Changes in this speed can indicate alterations in behavior or health. Similarly, the Average Speed of Individual Fish is monitored to detect any atypical behavior or health issues, offering a more granular view of individual wellbeing. Finally, Trajectory Tracking is employed, mapping the movement patterns of fish over time. This helps in identifying any unusual behaviors or stress indicators, contributing to a comprehensive understanding of the fish's environment and health in the aquaculture system.

In the NESTLER project, to assess the overall state of fish flocks, the following parameter are suggested to be used:

- **Flock Mobility Consistency:** Assessed by measuring the stability in optical flow variance over a given time period.
    - **Health Indicator:** Stable variance suggests a healthier flock; significant fluctuations suggest possible health concerns.
- **Individual Fish Behavior Metrics:**
    - **Behavior Classification:** Detected behaviors such as swimming speed and patterns using CNNs.
    - **Mobility Assessment:** Evaluating each fish's movement characteristics.
- **Comparative Behavior Parameter:** Statistical analysis of current behavior metrics against historical data to gauge overall flock health.

7.2.2. IoT Sensors and Devices

The approach for implementing a population health monitoring system in a fish farm, while following the same fundamental principles as the chicken farm, has specific adaptations suited to the aquatic environment.

The basic principles remain consistent with those established for the chicken farm, emphasizing non-invasive monitoring, continuous operation, user-friendly design, damage resistance, cost-effectiveness, and compatibility with local climatic conditions. The key difference lies in the sensor selection, particularly the exclusion of audio sensors.

Given the aquatic environment and the nature of fish behavior, audio monitoring (microphones) is not required. Therefore, the chosen computer vision cameras will be similar to those used in chicken farms but without microphone capabilities.
We use the following equipment in our system:

1. **Video Cameras:** Hikvision IP bullet camera DS-2CD2083G2-I (4mm), 8MP, AcuSense. Video camera should be installed inside the chicken farm at the height of 3-5 meters. The refresh rate of information from the CV cameras is 25 Hz.
2. **Computing Hardware:** RiniSoft server for data processing and analysis. Server configuration - Intel Xeon E-2236, 6 Core, GPU A2 16 GB GDDR6, RAM 32 GB DDR4, 2 × 960 GB SSD SATA.

7.2.3. Monitoring System

The main objective of the fish farm monitoring system is to provide early detection of health problems in fishes by continuously monitoring the reference speed of healthy fish and average diving depth of fish parameters. This proactive approach helps in maintaining the overall health and well-being of the fish population and ensures the sustainable and efficient operation of the fish farm.

"Reference Speed of Healthy Fish" (RSHF) measures the average swimming speed of healthy fish in the farm. This parameter serves as an indicator of fish activity levels. If the swimming speed of the fish decreases significantly, it may indicate a health problem such as infection, parasites, or stress. By comparing the current swimming speed with the reference speed of healthy fish, the monitoring system can detect any abnormal decrease in activity and alert the farm owners or managers.

"Average Diving Depth of Fish" (ADDF) parameter is crucial for detecting gastrointestinal diseases. Fish affected by gastrointestinal issues tend to exhibit abnormal swimming behavior, including changes in diving depth. By monitoring the average diving depth of fish, the system can detect any sudden changes or deviations from the normal pattern. This parameter helps in detecting issues such as swim bladder disorders, digestive problems, or infections that affect the fish's buoyancy and swimming behavior.

By continuously monitoring these two parameters, the fish farm monitoring system can quickly identify any deviations or abnormalities, allowing for early intervention and treatment.

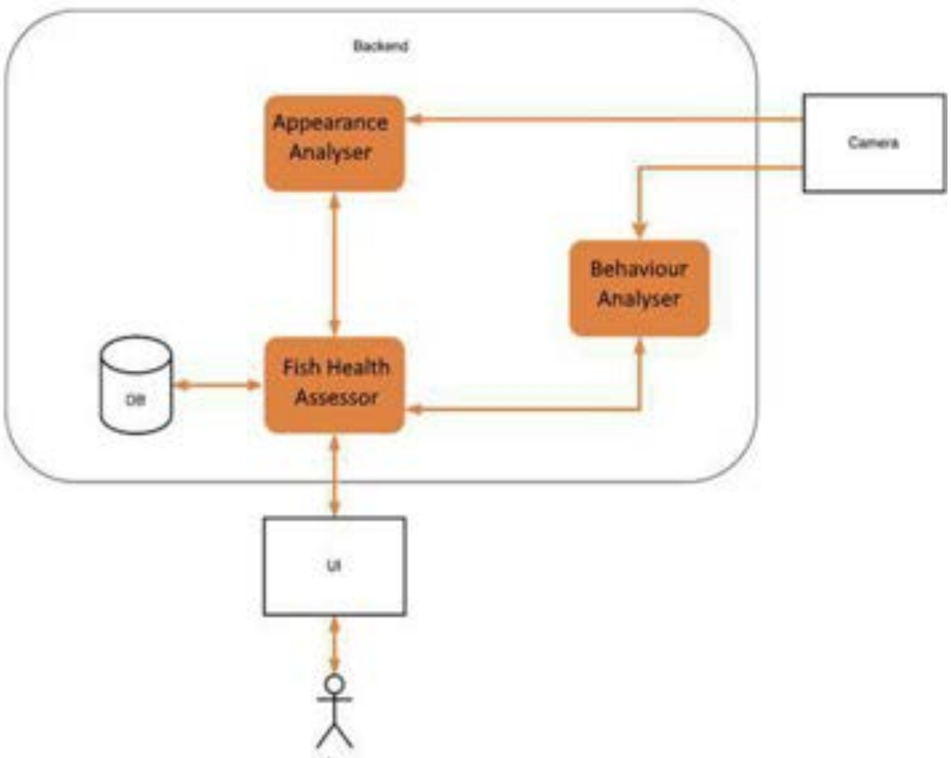

Figure 36: Functional Diagram of Aquaculture Monitoring System.

The components and modules of the system are described below:

- Appearance Analyzer: To analyze the individual fish’s overall physical health markers.
- Behavior Analyzer: For flock-wide behavior analysis based on flock’s optical flow.
- Fish Health Assessor Module: To provide health predictions based on aggregated parameters.

The various artificial intelligence (AI) methodologies and technologies used to monitor and detect diseases within aquaculture population include:

- **Statistical Models:** Used for the analysis of optical flow to measure flock's overall mobility.
- **Convolutional Neural Networks (CNNs):** For fish detection in video frames.
- **Deep SORT Algorithm:** Used for tracking individual fish across frames.

7.2.4. Gathering Fish Farm Dataset (FFDS)

At this stage of the project, the database has been created using data gathered from the RiniSoft biolab. Although the project requirements specified that observations should focus on Nile tilapia, the current database is based on data from observing sturgeon species.

This deviation from the initial project requirements suggests a need to reconsider the relevance of the collected data, given the biological and ecological differences between sturgeon and Nile tilapia.

While video monitoring algorithms share common goals and techniques, they also differ based on the unique characteristics and behaviors of each species.

7.2.4.1 Common Aspects

1. **Object Detection and Tracking:**
   - *Detection:* Identifying the presence of fish in the video frames. Common techniques include background subtraction, frame differencing, and advanced deep learning methods like convolutional neural networks (CNNs).
   - *Tracking:* Following the movement of individual fish across frames using algorithms such as Kalman filters, particle filters, or deep learning-based trackers (e.g., YOLO, DeepSort).
2. **Behavior Analysis:**
   - *Recognizing and classifying behaviour* such as swimming patterns, feeding, schooling, or resting using machine learning models.
   - *Analyzing interaction* with the environment or other fish.
3. **Environmental Monitoring:**
   - *Recording and analyzing environmental parameters* like water temperature, turbidity, and pH using integrated sensors.
   - *Correlating environmental changes* with fish behavior.
4. **Data Annotation and Training:**
   - *Annotating large datasets* to train machine learning models.
   - *Label video data* using semi-automated or automated tools.
5. **Anomaly Detection:**

   Identifying unusual behaviors or health issues.

   Detecting changes in population dynamics or habitat conditions.

7.2.4.2 Differences

While the foundational techniques for video monitoring of sturgeon and Nile tilapia share common ground in object detection, tracking, behavior analysis, and environmental monitoring, the specific algorithms and implementations vary based on the species' unique physical characteristics, behaviors, and habitats. Customizing these algorithms to suit the particular needs of each species will ensure more accurate and useful monitoring outcomes.

The following table summarizes some differences between Sturgeon and Nile Tilapia.

Table 15: Differences between Sturgeon and Nile Tilapia related to video survaillance

Sturgeon	Nile Tilapia
Species-Specific Characteristics	
• Sturgeons are generally larger and have distinct body shapes (elongated bodies and bony plates) which might require specialized detection and tracking algorithms. • Often found in deeper, murkier waters which may affect the clarity of video data.	• Smaller and more agile, requiring algorithms that can handle rapid and frequent movements. • Often found in shallower and clearer waters, which can improve detection but may also introduce reflections and light variations.
Habitat and Behaviour	
• Benthic behaviour (bottom-dwelling) means algorithms must be adept at detecting fish against complex bottom substrates. • Migration patterns may necessitate long-term monitoring solutions.	• More active in the water column and near the surface, necessitating algorithms that can handle varied light conditions and surface reflections. • More prone to schooling, which can complicate individual tracking.
Video Quality and Conditions	
• Sturgeon monitoring might require cameras that perform well in low-light or turbid water conditions.	• Sturgeon monitoring might require cameras that perform well in low-light or turbid water conditions.

At this stage of the project, the primary objective was to optimize the detection algorithms, with the specific fish species being non-essential. In subsequent phases, the focus will shift exclusively to Nile Tilapia. The base algorithms will be adapted to enhance the detection of smaller objects characteristic of this species.

When creating a training dataset for an AI-based fish disease classifier, it's crucial to consider the unique characteristics of the population environment and the capabilities of the project equipment. The information is exclusively available in video format, limited by the water transparency within which the fish swim. The determination of the dataset size is guided by the principles of the Central Limit Theorem (CLT).

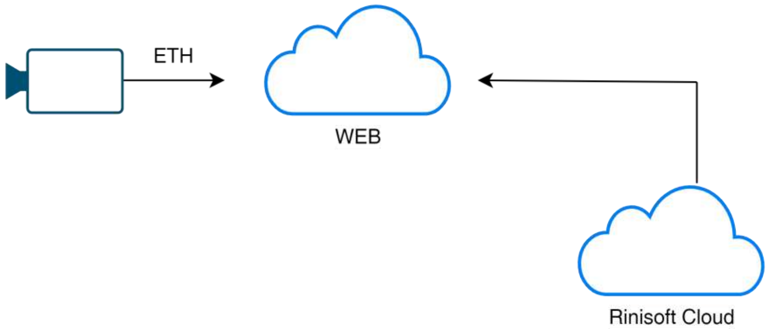

Figure 37: FFDS Collection Diagram

Figure 38: NESTLER Fish Farm

This project encompasses the gathering and dissemination of data through three primary dataset packages. Each package is summarized below, providing a description of the respective volumes of information. The requirements of the aquaculture farm dataset are listed in Table 27 of Annex A.

It is important to note that datasets should be generated for one specific fish species. Each population should consist of at least 60-100 individuals of approximately the same age. Data should be collected for three age groups: fry, juveniles, adults.

7.2.5. "Fish Digestion Disorder" Use Case

Fish health status monitoring is implemented on the fish farm engaged in artificial breeding of sturgeon. The breeding of sturgeon is one of the most attractive in economic and financial terms, as it requires rather low preliminary costs.

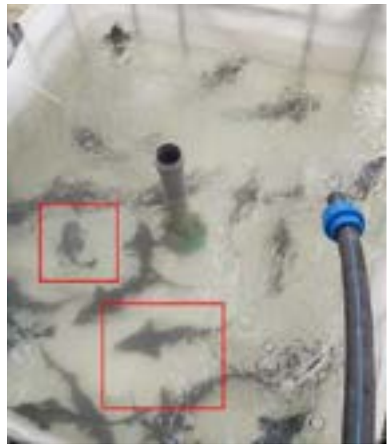

Figure 39: General view of the fish pool

To implement fish health status monitoring, video stream analysis is employed to identify signs of gill and digestive diseases in sturgeon.

7.2.5.1 Gill Diseases:

- Signs:
    - Decrease in the speed of movement by at least 20% of the average in the school.
    - Darkening of color.
    - Appearance of a whitish trace when swimming.

Since sturgeon swim along individual trajectories, it is feasible to detect these parameters for infectious, parasitic, or toxicological gill issues.

7.2.5.2 Digestive Diseases:

- Signs:
    - Unwilled rise of fish to the upper layers of water with accumulated gases in the intestines.
    - Closed circular trajectory of movement on a small radius despite the large amount of available space.

These signs indicate poor-quality nutrition or lack of microelements and proteins. Analyzing the video stream helps identify these signs, allowing preventive measures to be taken to avoid mass fish mortality. Notably, the highest mortality is observed among young fish with sizes up to 15-18 cm, with daily mortality reaching up to 0.5% of the total population.

Monitoring Reduced Activity: To monitor reduced activity, the average speed of an individual fish is compared to the average speed of the population over a 3-day period. A steady decrease below the average speed of the population indicates reduced activity.

Detecting Intestinal Issues: To detect intestinal issues, the level of immersion in water and the defocusing of the outlines of the immersed body can be utilized. This defocusing occurs due to refraction and scattering of light. By knowing the geometric dimensions of the pools, camera parameters, and the level of water transparency, the height of the water column above the fish and the depth of immersion can be determined based on the image captured. An increased number of fish swimming within a depth of 10 cm or less from the water's surface suggests an accumulation of gases in the gastrointestinal tract (GIT), often caused by improper feeding practices.

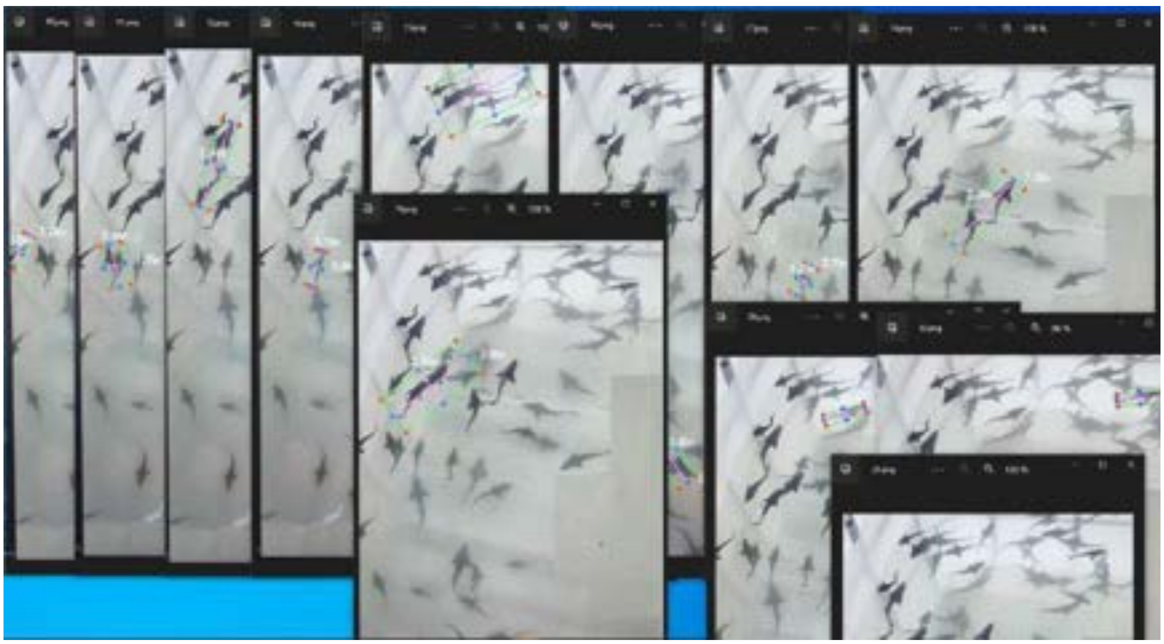

Figure 40: The process of detection and sizing of the fish objects.

Figure 41: Defining the "defocus" level of a fish object.

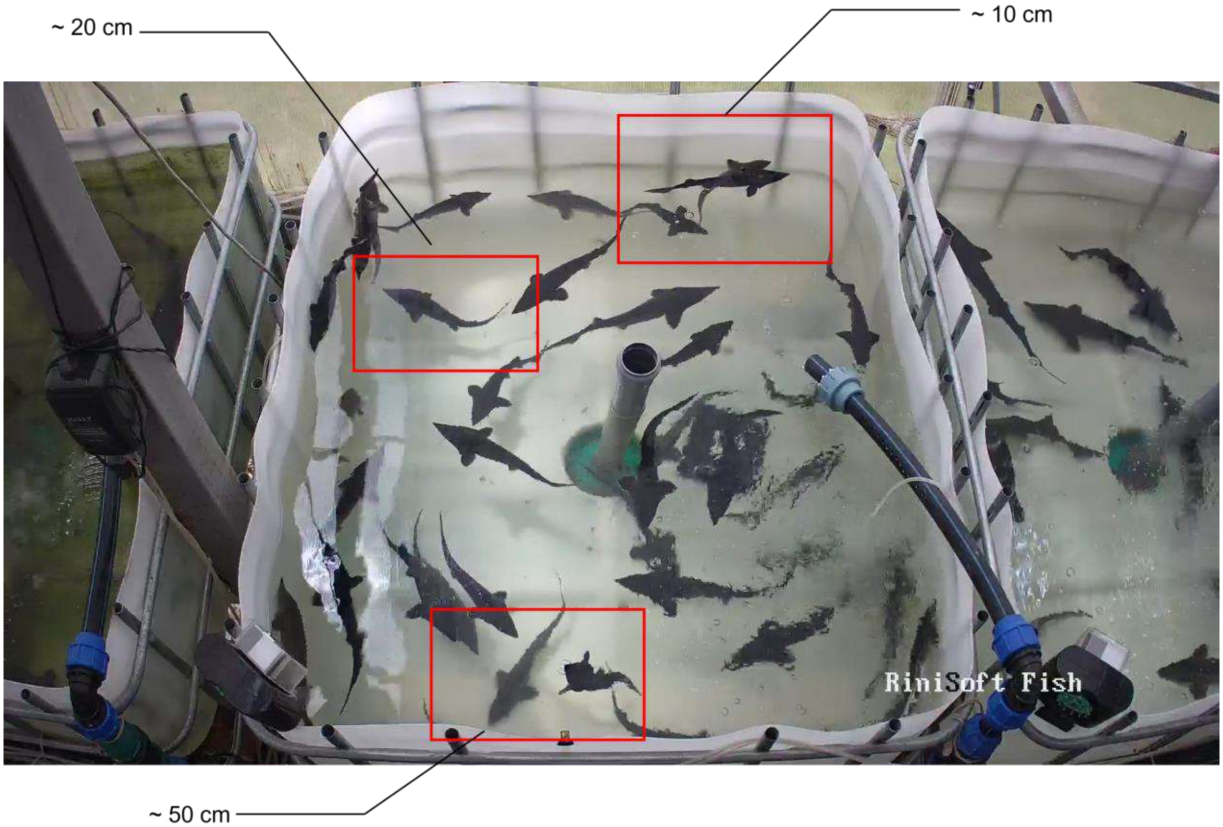

Figure 42: ADDF calculation using video focus for fish health monitoring.

Data Collection Setup:

- A video collection system was established in the swimming pool.
- Camera Positioning:
  - Height: 124 cm above the water surface.
  - Angle of the camera's optical axis to the horizon: 76°.

Fish Population Details:

- Fish Species: Acipenser baerii.
- Number of Fish: 59.
- Size Range: 8 to 14 cm.
- Feeding: Once a day.
- Water Conditions:
  - Temperature: Approximately 10-12°C.
  - pH Range: 7.0 to 7.5.

Fish Characteristics:

- All fish in the population were healthy.
- No signs of disease were observed.

- Individual tendencies for residence were noted; the fish did not swim in schools, simplifying the calculation process by eliminating the need to account for the movement of a multi-element body.

The average speed of a particular fish species was determined using the formula:

$$\langle V \rangle = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} V(t)dt$$

The parameter 'Reference Speed of Healthy Fish,' representing the mean square velocity of population movement, was calculated utilizing the standard formula:

$$v_{msq} = \sqrt{\frac{v_1^2 + v_2^2 + v_n^2}{N}}$$

The calculation was performed with an acceptable probability interval of 10%. This derived value will be employed in predicting the potential occurrence of gill diseases in this specific fish species in the future.

8. Remote Sensing in Agricultural Monitoring

Remote sensing technology, employing satellites and drones, is a pivotal component in modern agriculture, providing comprehensive data for large-scale crop monitoring and management. Satellites offer macro-level views of agricultural fields, enabling the analysis of crop health and regional environmental conditions, while drones provide detailed, close-range imagery critical for precision farming practices. Together, these tools deliver invaluable insights for optimizing crop yields, conserving resources, and enhancing sustainable farming operations. This section presents the use of satellite and drone imagery within the NESTLER project. It details the specific satellite data anticipated for use, along with the capabilities of the Smart NESTLER drone. Additionally, it introduces AI-based algorithms designed to detect pest infestations through remote sensing.

8.1. Satellite Imagery

One of the tasks of the NESTLER project is the exploitation of the advantages offered to the agricultural market by satellite remote sensing technologies. Satellite imagery has become a vital tool that is reshaping the agricultural activities by providing a comprehensive picture of the crop fields. This technology helps farmers assess crop health, identify problems and implement targeted interventions for optimal yields. In addition, it plays a critical role in market forecasting, allowing informed decisions to be made based on trends and potential changes in crop production.

8.1.1. Technological Aspects of Satellite Sensors

The most important criteria for selecting a satellite for a particular project in agriculture are related to the spatial resolution of the sensor, the temporal resolution, and the sensor type.

Spatial Resolution

The spatial resolution of a remote sensing system refers to its ability to distinguish fine details and small objects in the imagery it captures. The choice of satellite imagery resolution in agriculture depends on the specific needs of the task at hand. In general, high spatial resolution provides detailed insights for precision management, medium resolution offers a balance for regional monitoring, and low resolution is suitable for comprehensive, large-scale assessments. The following table presents some of the advantages that each of the different spatial resolutions offers to agriculture management.

Table 16: Advantages of different satellite imagery resolutions to agriculture monitoring.

Spatial resolution	*Advantages to agriculture monitoring*
High (<5 meters/pixel)	• Capture intricate details of small areas. • Allows farmers to closely monitor individual fields. • Facilitates the identification / monitoring of specific crop issues and overall plant health. • Particularly useful for precision farming practices and targeted interventions. • Supports efficient resource management. • Helps farmers address localized challenges effectively.
Medium	• Covers larger areas for comprehensive surveillance. • Ideal for regional monitoring and trend analysis.

(5 – 30 meters/pixel)	• Enables the assessment of broad patterns of crop health. • Useful for monitoring changes in land use over larger regions. • Provides valuable insights for planning and managing agricultural activities.
Low (>30 meters/pixel)	• Covers extensive geographic areas with less detail. • Ideal for monitoring large-scale agricultural trends and assessing general conditions across vast regions. • Useful in detecting large-scale changes in land use. • Facilitates macro-level analyses for agricultural planning. • Serves as a complementary tool to higher-resolution imagery.

Temporal Resolution

Temporal resolution refers to how frequently a remote sensing system can capture imagery of the same area. Since, over time, satellites capture changes in crop growth, enabling farmers to track development stages, this temporal dimension aids in timely interventions and strategic planning for various agricultural activities. The choice of temporal resolution in satellite imagery depends on the specific agricultural application, balancing the need for real-time insights, trend analysis, and long-term planning.

Sensor Type

Satellite imagery is becoming more and more essential in providing farmers with crucial insights; from crop health assessment and monitoring to soil moisture and nutrient level estimation. However, different types of image sensors provide different types of information. For example, optical sensors offer visual assessments of crop health, while multispectral sensors expand the spectrum for more detailed crop analysis, showing information on chlorophyll levels. Thermal infrared sensors provide temperature-related insights, contributing in this way, for example, to a more optimized irrigation plan. This suite of satellite sensor types is able to enhance the overall agricultural efficiency of a field, as presented in the following table.

Table 17: Satellite sensor types.

Satellite sensor types	***Description***	***Advantages to agriculture monitoring***
Optical	Optical satellite data captures visible and near-infrared light, providing visual images of the Earth's surface.	• Visual assessment of crop health, aiding in the identification of potential issues • Support in the classification of different land cover types
Multispectral	Multispectral data captures information across multiple spectral bands, extending beyond the visible spectrum.	• Identification of specific crop types based on their spectral signatures • Assessment of nutrient levels in the soil, contributing to precision agriculture practices

Thermal Infrared	Thermal infrared satellite sensors measure heat radiation emitted by the Earth's surface.	• Support in the water stress estimation in crops by assessing temperature variations. • Irrigation scheduling based on surface temperature-related indicators

8.1.2. Satellite Imagery in NESTLER

In the NESTLER project, it is necessary to observe large agricultural areas and monitor the plant health constantly. Therefore, the satellite data that are foreseen to be used for the NESTLER project and comply with these requirements are presented in the following table and are selected to be 1. of medium spatial resolution to have a balanced area coverage and level of detail and 2. acquired weekly to have sufficient temporal coverage.

Table 18: Satellite sensor data considered to be utilized by NESTLER.

Satellite sensor	*Type*	*Spatial Resolution*	*Temporal Resolution*	*Data format*	*Data since*
Sentinel-2 *(ESA)*	Multispectral	10-60m	5 days	JPEG2000	2015
MODIS *(NASA)*	Multispectral	250m - 1km	1-2 days	HDF	1999
Landsat 8/9 *(NASA/USGS)*	Multispectral	15-30m	~ 8 days (combined)	GeoTIFF	2013
	Thermal	100m			

Other available satellite imagery and products that could be beneficial to NESTLER activities and use cases are the following:

Copernicus Global Land Service Products:

- Part of the European Union's Copernicus program, offering various data services, including land monitoring with medium resolution imagery.

ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) on Terra Satellite (NASA):

- Resolution: 15 meters for visible and near-infrared, 30 meters for shortwave infrared, 90 meters for thermal infrared.
- Applications: Detailed maps of land surface temperature, emissivity, reflectance, and elevation.

8.2. Drone/UAVs (Unmanned Aerial Vehicles)

NESTLER utilizes the full potential of drones in the collection and analysis of agricultural data. By employing these unmanned aerial vehicles (UAVS), NESTLER could effectively gather high-resolution, multi-spectral imagery from vast farming areas. This capability is crucial for various agriculture procedures, such us monitoring crop health and pest infestation. The data acquired by drones can be analyzed using advanced algorithms, providing valuable insights into various aspects of crop management. Essentially, NESTLER's use of drone technology represents a major advance in agricultural practices, offering a sophisticated and sustainable solution to farming challenges.

8.2.1. NESTLER Drone Solution

The NESTLER Drone system designed to conduct aerial imaging for over the field consists of the Smart NESTLER drone, a multi-spectral camera, and a processing unit. The system is composed by the hardware components described in Table 19.

Table 19: Smart NESTLER drone system.

Equipment	Description	Type
Smart Agri Drone	DJI Matrice 600 PRO, ideal for professional aerial photography with an extended flight time and a 5km long-range transmission, intelligent batteries, and maximum payload of 6kg.	drone
Multispectral camera	Parrot Sequoia, multi-band sensor designed for agriculture, featuring excellent precision, flexible integration, and small size and weight, compatible with the Smart NESTLER Drone.	Camera
Processing unit	NVIDIA Jetson Nano 4GB, a small computer which is able to run multiple neural networks in parallel for various ML applications like image classification, which is desired forpest infestation detection.	Processing board

Drone

The DJI MATRICE PRO has been chosen and acquired to serve as the primary drone for incorporating additional modules into the UAV system. A photograph showing it in action during initial testing phases in the laboratory can be found in Figure 43.

Figure 43: Images of Smart NESTLER Drone.

Camera

The UAV is equipped with the Parrot Sequoia+ as its multispectral camera. This camera is capable of delivering absolute reflectance measurements without the need for reflectance targets. Its impressive high resolution (11cm per pixel at 120 meters altitude) makes it highly suitable for Smart Agriculture scenarios. Additionally, the Parrot Sequoia+ offers versatility in triggering and data acquisition, aligning well with the requirements of the NESTLER project. The camera is illustrated in Figure 44.

Figure 44: Multispectral camera of Smart NESTLER Drone.

Since the camera cannot be directly integrated with the chosen drone, a specialized mounting base has been crafted and 3D-printed to facilitate the attachment of the camera to the drone. The design of this custom base is illustrated in Figure 45.

Figure 45: Camera's base of Smart NESTLER Drone.

8.2.2. Data Collection

RGB imaging

Drone with the integrated camera can capture images in the Red, Green, and Blue spectral bands. This type of imaging provides high-resolution, color-rich photographs of the agricultural fields, similar to those taken by standard digital cameras. These images are essential for visual inspections, allowing farmers and agronomists to monitor crop growth, detect physical anomalies, and assess overall field conditions. RGB images are particularly useful for detecting issues that are visible to the naked eye. The images are associated with time information and geospatial/location information provided by GPS.

Multispectral imaging

Drone with the integrated camera can collect data across multiple spectral bands, including both visible light and near-infrared. This capability allows for detailed analysis of plant health and vitality. Those images can be used for calculating indices such as the Normalized Difference Vegetation Index (NDVI), which helps in assessing vegetation density, stress levels, and overall crop health.

The above described data is accompanied with GPS coordinates, allowing for a precise geolocation of the captured data. This precision is crucial for creating accurate maps, monitoring changes over time, and guiding interventions in fields such as precision farming or environmental conservation. The synergy of these technologies in drones offers a powerful tool for detailed and efficient data collection across vast and varied terrains. The combination of imaging technologies and GPS in drones offers a robust tool for collecting comprehensive data across diverse agricultural landscapes, significantly contributing to the efficiency and effectiveness of smart farming practices.

8.3. Pest Infestation Detection with Remote Sensing Solutions

The pest infestation in crop cultivation is a significant problem, posing a major threat to agricultural productivity and food security. Pests, which include a wide range of insects, weeds, rodents, and microorganisms, can cause serious damage to crop since they are feeding on various parts of the plants. This can lead to reduced plant growth and yield. Additionally, pest infestation can also result to long-term soil degradation, increased vulnerability to future infestations, and increased use of chemical pesticides. In economic terms, pest infestations can lead to increased costs for farmers due to the need for pest control measures and can cause fluctuations in market prices due to the unpredictability of crop yields. Consequently, effective pest management is crucial for sustainable agriculture and the stabilization of food supplies.

8.3.1. Monitoring System

NESTLER designs and develops an advanced monitoring system to effectively detect pest infestation in crops. Pest infestation is treated as a visual problem, which is tackled leveraging computer vision and deep-learning methods. In this scope, remote sensing solutions are being explored as proactive method against pest infestation in agriculture. Additionally, advanced deep-learning models able to accurate detect and classify different pests based on their appearance on leaves are trained, evaluated, and utilized by the NESTLER monitoring system. Those AI models are integrated in a mobile application equipped with on-demand features that enable the detection and precise localization of pests within a crop field.

Various pests, each with their unique behaviours and effects, can cause many problems at different crops. Focusing on specific pests is crucial to develop robust technologies for pest detection. By understanding the challenges posted by each type of pest, targeted and effective solutions can be designed. The NESTLER monitoring system should be tailored to focus on and detect the types of pests that are of particular interest to the pilot project's owners. This approach ensures the system's applicability and efficacy in addressing the specific pest management needs of the users.

The types of crops, that the NESTLER monitoring system should be capable of monitoring for pest infestation, are identified based on the review of risks on food security as well as the research on historical case studies that are detailed described and listed in the D1.1 “NESTLER Platform Requirements” [56]. This approach ensures that the system could be able to address the most significant agricultural challenges and is informed by a comprehensive understanding of past pest infestation scenarios and their impacts on crop health and yield.

As it is reported by the stakeholders of the NESTLER pilots, maize and other cereal crops are vulnerable to attacks by fall armyworms. The initial damage appears as ragged holes in the leaves of plants. The larvae of the pest feed on leaves, resulting in plant damage and a consequent reduction in crop yield. Fall armyworm infestations have been reported in Rwanda and Nigeria. Moreover, tomato crops are severely threatened by the tomato leaf miner *Tuta absoluta*, a dangerous pest in Africa. Its larvae feed on various parts of the tomato plant, including leaves, stems, and fruits, creating damaging galleries and burrows. This infestation often leads to over 80% yield loss, significantly impacting the economy by increasing tomato prices and contributing to nutritional insecurity. This pest has had an impact in countries like Rwanda and Nigeria. Coffee crops can suffer from infestations of various pests, including the Antestia bug and aphids. These pests can significantly reduce productivity, leading to decreased income for farmers and increased production costs for the coffee industry, as observed in Rwanda.

Cacao tree plantations are afflicted by black pod disease *Phytophthora palmivora*. Infected fruits develop hard brown spots with a white spore layer, and the disease can also impact leaves, twigs, and roots. In Cameroon, black pod disease is a critical constraint on cocoa yield, causing up to 80% of crop loss under favourable conditions for the disease. Last but not least, locusts, a type of short-horned, are one of the world's most destructive migratory pests. They can damage a wide variety of crops, pastures, and trees by consuming large amounts of vegetation quickly. Their control often involves pesticides that can be harmful to humans. These pests have notably affected regions like Uganda, Ethiopia, and Kenya. Table 20 lists the crops along with the corresponding pests they may be infested with, as reported by the stakeholders of the NESTLER pilots in the D1.1. It should be mentioned that the NESTLER monitoring system focuses on the effective detection of infection or infestation of the aforementioned field crops by the specified pests and diseases.

Table 20: Crops affected by pests based of user requirements of NESTLER pilots.

Field Crops	Pest
Maize and cereal	Fall Armyworms
Tomatoes	Tomato leaf miner
Coffee	Antestia bug, aphids
Cacao	Black pod disease
Various crops	Locusts

8.3.2. Satellite-based Pest Detection

The primary goal of this module is to mitigate the impact of insect pests on food security. Through prior analysis, it has been identified that one of the most dangerous pests is the invasion of locust swarms, causing widespread destruction to crop along their migration route. Various strategies exist for pest control, including the use of chemicals for extermination, mechanical traps and nets, and diverse methods for swarm deterrence. Notably, locust swarms pose a significant threat due to their destructive nature. Another noteworthy consideration is that insects themselves can serve as a valuable protein resource, particularly in regions with limited access to such resources. Enabling accurate forecasting and detection of swarm emergence locations before take-off opens the possibility of using ground equipment to collect insects on an industrial scale for processing.

Predicting the development of locust swarms in expansive territories relies on aerial reconnaissance data obtained through drones, airplanes, or land monitoring satellites. To enhance this predictive capability, the NESTLER project leverages valuable information sourced from a satellite constellation specializing in gathering detailed data on crops in Africa. SENTINEL, as part of this constellation, plays a crucial role in providing specific insights into crop conditions and locust-related factors.

Satellite information is archived in a dedicated database and is accessible in the original UFAX format, ensuring no data loss through uncompressed storage. The suggested approach to identify the likely location of swarm initiation relies on soil conditions and meteorological data. Consequently, the challenge is streamlined into a category of mathematical prediction methods utilizing multivariate analysis within the realm of image processing.

To acquire input data, our sources include agricultural sensors, the Sentinel-2 satellite, and meteorological data. These data undergo thorough pre-processing, which includes atmospheric correction. Within the logical framework, we employ fuzzy logic algorithms to harmonize all essential parameters. As a result, users will obtain output data comprising the coordinates and radius of insect locations, the specific type of insect (indicating its developmental stage), and a certainty degree regarding the presence of insects in the designated area.

The system structure is comprised of several key modules: *Detection Modules*, *Recognition Modules*, and *Decision Modules*, the latter employing Artificial Intelligence (AI) with neural network capabilities.

Insect Detection Module (IDM)

To identify potentially hazardous population of insects, such as locusts, primary analysis will be conducted using images captured by multispectral cameras on Earth remote sensing satellites. Upon detecting objects with suitable entomological signatures, a UAV equipped with an IR camera will be deployed for an additional survey of the area. The information gathered from the UAV will serve to either confirm or deny the presence of entomological threats to the crops cultivated in that particular region.

Insect Detection Modules perform the following functions:

1. *Prediction of Locust Swarm Migration Routes*: Utilizing Sentinel-2 multispectral images to forecast locust swarm migration routes, preventing potential damage to vegetation.
2. *Detection of Optimal Desert Locust Habitat Conditions*: Employing historical, climatic, soil, multispectral, and wind flow data to identify the most favourable conditions for locating locust swarms.
3. *Identification of Temporal and Thermal Signatures*: Enhancing detection accuracy by identifying specific temporal and thermal signatures associated with the chitinous cover of locusts.

4. *Detection of Desert Locust Breeding Grounds*: Identifying breeding grounds of Desert locusts to facilitate the implementation and improvement of control measures, such as chemical and mechanical control. This is particularly effective when locusts are immature and wingless, limiting their mobility.
5. *Integration with NESTLER Cloud for the Food Industry*: Transmitting locust data to NESTLER Cloud for utilization in the food industry, ensuring timely and informed decision-making.

The output of this module should identify the most probable locations where locust swarms originate. The process of prediction is shown in Figure 46.

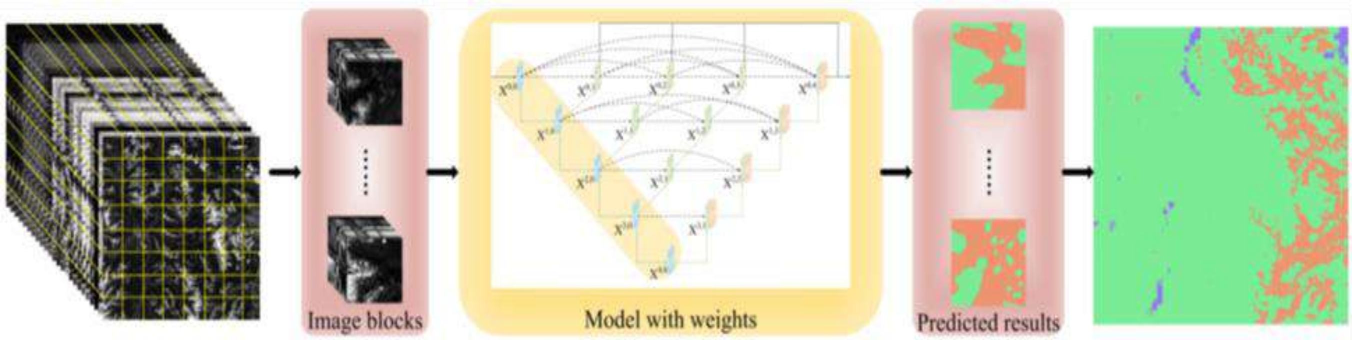

Figure 46: The process of the prediction of the entire Sentinel-2 image [57]

Insect Recognition Module (IRM)

To precisely determine the presence of pests in potential areas, additional reconnaissance is essential, employing UAVs equipped with thermal optical modules. The captured images undergo on-board pre-processing within the UAV and are subsequently transmitted to the NESTLER Cloud for informed decision-making.

Tasks includes:

1. *Confirmation of Pest Swarm Presence*: Utilizing thermal optical modules to confirm the existence of a swarm of pests in the designated areas.
2. *Estimation of Developmental Stage*: Employing image data to roughly determine the developmental stage of the pest flock, providing valuable insights for effective pest management strategies.

Decision Making Module (AI-based)

Utilising data from IDM, IRM, Locus Hub, and Meteo World, this module is designed to accurately ascertain the probable emergence locations, developmental stage, and approximate biomass of locust swarms. Additionally, if information regarding existing technical and human resources is available, it enables the assessment of the economic feasibility of collecting the emerging biomass and determines the optimal timing for such actions. Successful operation of this module requires the design, implementation, and training of a neural network tailored to this specific task.

Training using multispectral data

The neural network training period uses original multispectral data (Sentinel-2 Level-1C products in the SAFE format directly from the European Space Agency's (ESA) Copernicus Open Access Hub) for the past years using our algorithms to predict the location of different locust types based on vegetation indices, meteorological data, soil data and historical data. In the training phase of the neural network, the annotation from 2015 to 2023 includes the following critical data:

- Locust type: hoppers, adults, bands, swarms
- Locust location
- Date of locust emergence

The neural network training utilizes original multispectral data, specifically Sentinel-2 Level-1C products in the SAFE format directly sourced from the European Space Agency's (ESA) Copernicus Open Access Hub. The training process employs proprietary algorithms designed to predict the location of different locust types. This prediction is based on a comprehensive set of features, including vegetation indices, meteorological data, soil data, and historical data.

To validate the accuracy of the predictions, the annotated data and validated historical information are used. This multi-faceted approach ensures that the neural network is trained on a robust dataset and can effectively predict locust occurrences based on various influencing factors.

In the context of Desert locusts *S. gregaria*, the incubation and development periods are intricately linked to both soil and air temperature. The incubation period spans between 14 and 22 days under soil temperatures typically ranging from 27–32 °C in the region. Following incubation, immature Desert locusts undergo various developmental stages while remaining grounded for an additional 35–45 days. Consequently, depending on the developmental stage of the hopper, optimal environmental conditions for egg laying must be met approximately 3–10 weeks prior to the observation date. This nuanced understanding of the temporal relationship between moisture conditions, incubation, and developmental periods enhances the precision of forecasting models and contributes to more effective pest management strategies.

8.3.3. Drone with Multispectral Sensor and On-Field Research for Pest Detection

The utilization of drones equipped with multispectral cameras for pest infestation and disease detection in agriculture represents a significant advancement in crop management and protection. The drones, flying over fields, capture high-resolution images using multispectral imaging technology, which goes beyond the visible spectrum. This technology is particularly effective in identifying changes in plant health that are not immediately apparent to the naked eye or in the initial stage of the development, often a key indicator of pest infestation. The work in [58] presents a method for detecting vine diseases using multispectral images from UAVs combined with a deep learning segmentation approach. The same authors introduce VddNet [59], a vine disease detection network that utilizes multispectral images and depth maps. Additionally, research on the detection of olive trees affected by *Xylella fastidiosa* using multispectral imaging from UAVs has been conducted in [60]. Moreover, the work in [61] presents how pixel-based classification of banana fusarium wilt can be performed using aerial UAVs capturing RGB and multispectral images in the Democratic Republic of Congo.

A drone equipped with a multi-spectral camera can capture images which, when processed through the proper analysis, can provide insights and indicators about the biotic and abiotic stress in crops for the displayed areas of images. Biotic stress refers to the negative impact on plants caused by living organisms such as fungi, bacteria, viruses, nematodes, insects and mites, weeds and parasitic plants, which can lead to diseases and infestations that affect plant health. Abiotic stress, on the other hand, involves non-living climatic and environmental factors like temperature extremes, drought or waterlogging, solar radiation, nutrient deficiencies or excesses, salinity, heavy metals, acidity or alkalinity etc. which can adversely affect plant growth, reproduction and survival. Early-stage detection of these stresses allows for more targeted crop management practices, potentially saving large portions of crops from severe damage. Early-stage detection in plant science and crop sensing refers to the identification of plant diseases or pest infestations during the initial stages of symptomatic phase, when visible symptoms are just beginning to appear but are still minimal or localized. This detection aims to catch the onset of disease or infestation at the earliest visible stage, enabling prompt intervention to mitigate further spread and damage, and typically relies on high-resolution imaging or close inspection to identify these early signs.

Multispectral imaging captures light at multiple wavelengths, including both the visible and invisible spectra (such as near-infrared). Healthy vegetation reflects light differently than stressed vegetation. These changes, although subtle, can be detected by multispectral sensors. Multispectral images can be used to calculate vegetation indices that provide insights into plant health and growth patterns, such as Normalized Difference Vegetation Index (NDVI), the Soil-Adjusted Vegetation Index (SAVI), and the Enhanced Vegetation Index (EVI). Each of these indices serves as a quantitative measure of vegetation health and vitality, providing essential insights into plant growth patterns and stress levels. By analyzing these images, algorithms identify unhealthy and stressed areas, often before the problem is visible to a human observer or in the initial stages of the development. One possible cause of these unhealthy and stressed areas could be the presence of pests and diseases, as plants in situations caused by such factors exhibit changes in their reflective properties.

Many studies have focused on using NDVI to identify areas affected by diseases and insects. The research in [62] demonstrates that NDVI of soybean plants was more associated with pest distributions than other variables, such as soybean plant heights and defoliation estimates. Specifically, it suggests that lower NDVI values often correspond to higher pest activity and associated plant stress. Additionally, the work in [63] focuses on the detection of sugarcane aphid injury to grain sorghum and presents that plant stress increases as plant injury intensifies, leading to lower NDVI values, indicating that NDVI decreases with greater plant injury. The authors in [64] develop a method to identify unhealthy bananas from disease or insects' zones using multispectral UAV data and determining optical vegetation indexes. The results of this paper demonstrate that NDVI is the optimal NIR vegetation index to develop an identification model for banana plants damaged by disease and insect infestations. Moreover, regular NDVI monitoring can track the health of vegetation over time. Specifically, the temporal analysis can reveal emerging patterns of stress or disease, helping to pinpoint affected areas before the disease spreads extensively. Moreover, NDVI time series from Sentinel 2 imagery may be used to detect early signs of pest-induced diseases in vegetation [65]. By applying continuous change detection and classification and trend analysis algorithms, the study effectively identifies and maps subtle vegetation anomalies over time, providing crucial insights into the spatial and temporal dynamics of disease progression caused by pests.

The NESTLER monitoring system leverages drone with multispectral camera to provide indicators of potential pests and diseases in crops. Specifically, this system utilizes a drone equipped with a multispectral camera to capture images, which are then analyzed to calculate various vegetation indices like NDVI. The analysis identifies areas of stress caused by climatic factors, such as extreme heat or water scarcity, as well as zones potentially affected by insects and diseases. If the indicators show concerning levels of stress, detailed field investigations may be necessary to determine the causes of these issues. Users can then visit these areas to conduct further investigations using the NESTLER mobile application, which provides information on whether crops are affected by pests and diseases or not. The proposed solution is presented in Figure 47.

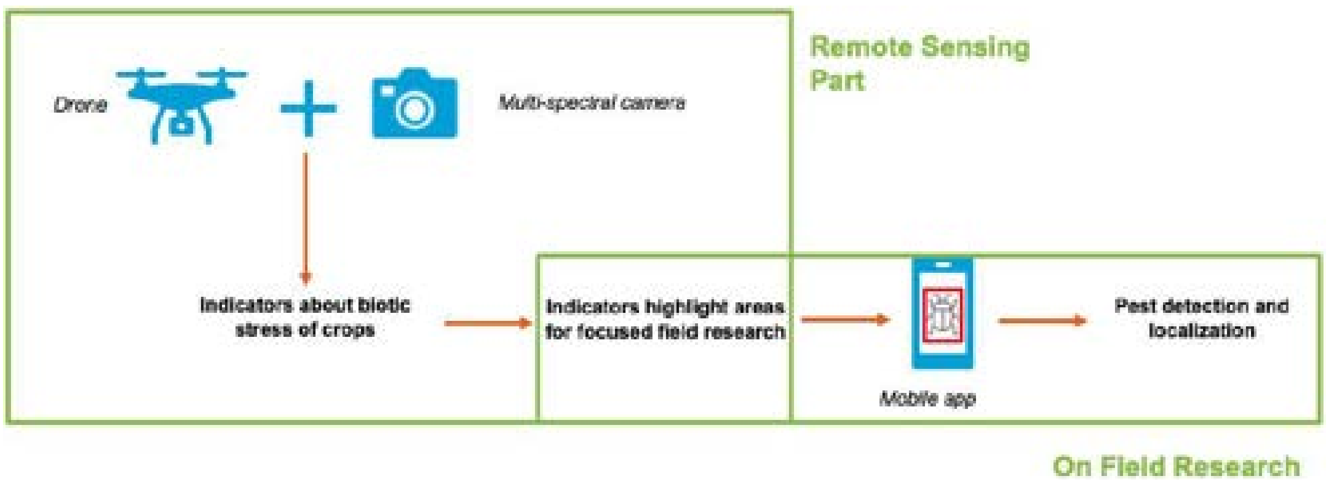

Figure 47: NESTLER monitoring system

Research in this domain suggests that one of the most promising vegetation indices is the NDVI, a straightforward graphical indicator used to analyze remote sensing measurements. It assesses whether the observed target contains live green vegetation.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

where NIR stands for near-infrared light and Red stands for visible red light, is crucial in this context.

Healthy vegetation reflects more near-infrared and green light compared to other wavelengths. However, when plants are stressed, such as by pest infestation or disease, their ability to reflect NIR light diminishes, while the reflection of visible light, particularly red, increases. By analyzing the NDVI data, drones can identify early areas of stress in crops due to pests. In addition, integrating and analysing data from other vegetation indices such NDRE which is more sensitive to changes in chlorophyll content and especially at mid and later crop growth stages, provides a more comprehensive view allowing more correlation with affected areas. Moreover, we might consider investigating NDVI/NDRE time-series to monitor and detect continuous changes in the field. By analyzing these time-series data, we can track the progression of vegetation health over time to pinpoint the onset of any abnormalities that may be caused by pests and diseases.

In the proposed solution, the multispectral camera of the drone would capture high-resolution images in both the NIR and visible spectra. These images are then processed to calculate the NDVI/NDRE for each pixel. The resulting map provides a detailed view of the crop health, highlighting areas of concern [60]. The high mobility of drones allows for frequent and consistent monitoring, ensuring early-stage detection of affected areas. In such cases, field inspection is required to ascertain the cause of the stress, which could be due to pest infestation or other factors affecting crop health. This ground-truthing step is crucial for implementing targeted interventions and managing the issue effectively.

The proposed solution offers early-stage detection by identifying and localizing unhealthy or affected areas as soon as the first signs emerge. With immediate user involvement, who visit the field and use the NESTLER mobile application, potential pest infestations or disease infections can be promptly identified. This early-stage detection is crucial for controlling pest outbreaks, as it allows for timely and localized treatment, thereby minimizing the need for widespread pesticide use.

8.3.4. AI-based Pest Infestation Detection

Based on the NDVI analysis, conducted from multispectral images of drone, the user can visit the field and perform a thorough investigation of the potential pest infestation using the NESTLER mobile application. This application, empowered by robust AI algorithms, offers an advanced level of pest detection and identification. The AI algorithms within NESTLER are trained on publicly available datasets encompassing various pest types. They employ advanced object detection architectures, such as YOLO v8, to accurately identify and classify different pests in real-time. This feature enhances the user's ability to quickly and effectively assess the situation on the ground, complementing the initial drone-based survey.

It's important to note that the technologies employed in the NESTLER application can be used independently of the drone-based NDVI/NDRE analysis. While the combination of aerial surveillance and ground-level AI-assisted inspection provides a comprehensive approach to pest management, each technology offers significant value on its own. In scenarios where drone surveillance is not feasible, the NESTLER app's advanced object detection capabilities can still provide vital insights into pest activity, enabling effective pest management strategies. This flexibility allows for a wide range of applications in different agricultural contexts.

8.3.4.1 Maize & Coffee

The goal of this classification algorithm is to detect pests attacking Maize or Coffee on an image and classify the pests detected based on the name. To reach this goal, we assessed three pre-trained models using transfer learning algorithms with our dataset in order to develop our algorithm.

The dataset that we used can be found on Kaggle website [66]. This Dataset is a carefully curated collection of photos of 14 distinct types of insects often found in agricultural environments. This collection contains useful visual resources for identifying and studying the characteristics of these potentially dangerous insects. Each insect is represented by a series of images that highlight its distinctive features, colours, and patterns.

Amongst the insect types represented in the dataset the following are maize pests:

- Armyworms;
- Corn borers;
- Aphids.

Amongst the insect types represented in the dataset the following are coffee pests:

- Beetles;
- Aphids

Figure 48: Pests attacking maize and coffee

The table below shows the distribution of image classes of the insect types in the dataset.

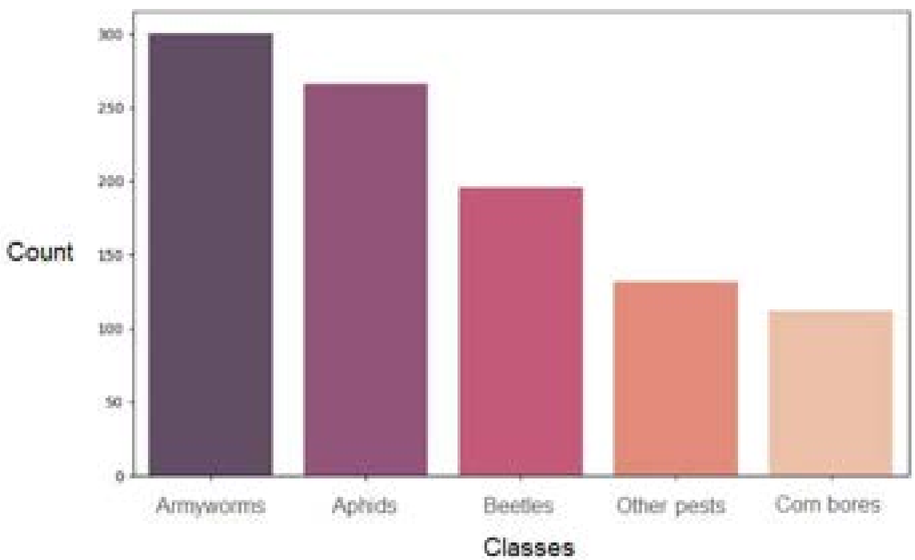

Figure 49: Distribution of image classes in the dataset of maize and coffee

8.3.4.2 Assessment of pre-trained models

We implemented transfer learning using our dataset of insect images on the following three models known for their high performance on image classification:

- EfficientNet [67];
- Resnet [68];
- MobileNet [69].

The performances metrics for each model are displayed on the table below:

Table 21: Performance metrics for trained AI models for pest infestation detection on dataset of maize & coffee

	Accuracy (%)			Weight (MB)
Model	**Training set**	**Validation set**	**Testing set**	
EfficientNet	68	69	72	352
Resnet	92	88	89	37
MobileNet	94	91	88	35
	Precision (%)			Weight (MB)
Model	**Training set**	**Validation set**	**Testing set**	
EfficientNet	70	67	68	352
Resnet	80	79	73	37
MobileNet	90	83	77	35
	Sensitivity (%)			Weight (MB)
Model	**Training set**	**Validation set**	**Testing set**	
EfficientNet	45	53	53	352
Resnet	88	87	83	37
MobileNet	89	86	83	35
	Specificity (%)			Weight (MB)
Model	**Training set**	**Validation set**	**Testing set**	
EfficientNet	76	85	87	352
Resnet	92	90	87	37
MobileNet	91	91	92	35

The above table clearly shows that MobileNet outperforms the two other models. Consequently, we pursue the implementation of the algorithm with it.

8.3.4.3 Fine-tuning of selected pre-trained model

The above clearly shows that MobileNet outperforms the two other models. Consequently, we pursue the implementation of the algorithm with it.

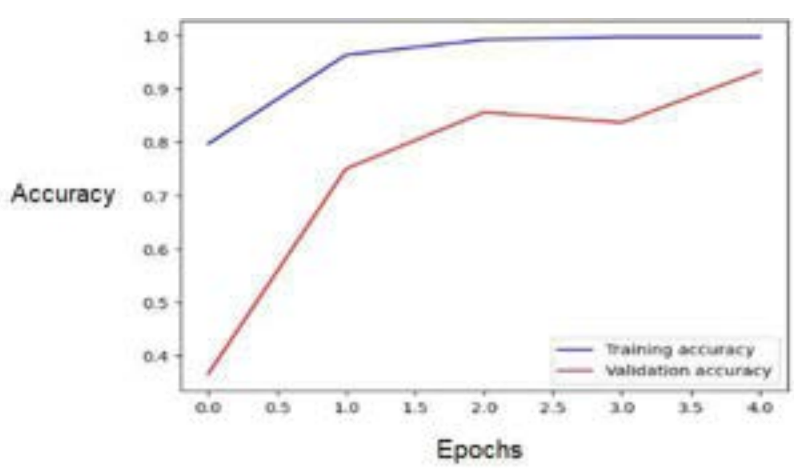

Figure 50: MobileNet accuracy across epochs for pests in Maize and Coffee crops

8.3.4.4 Tomatoes

The detection of tomato leaf miner *Tuta absoluta*, is of paramount importance in tomato cultivation due to its devastating impact on tomato crops. This pest has rapidly spread to many parts of the world, causing significant damage to both greenhouse and open-field tomato production. *Tuta absoluta* larvae feed on tomato leaves, stems, and fruits, leading to substantial yield losses and reduced crop quality. Early-stage detection and management of this pest are crucial, as it can be reproduced quickly and develop resistance to chemical pesticides. Effective monitoring and timely intervention can significantly mitigate the damage caused by the pest, ensuring the sustainability and profitability of tomato farming.

For the effective detection of *Tuta absoluta* in tomato crops, we have developed an advanced object detection model using [70]. This model is trained and rigorously evaluated using an openly available dataset specifically curated for this purpose. The dataset comprises of 1518 images, which are systematically divided into 1278, 169, 80 images in training, validation, and testing sets. Each set contains a balanced mix of images representing two key categories: "Healthy" and "*Tuta absoluta*-infested" samples. In total, the dataset encompasses 2872 number of instances, offering a comprehensive view of both healthy and infected tomato conditions. Figure 51 illustrates the distribution and category of instances across the training, validation, and test sets, providing a clear overview of the data used to train and validate the effectiveness of our YOLOv8-based model in identifying tomato leaf miner infestations. It is observed that the dataset is imbalanced. Consequently, for evaluating the object detection model, reliance on accuracy alone—which can be misleading in cases of class imbalance—is avoided. Instead, the mean Average Precision (mAP) is employed as the primary metric. mAP offers a more reliable measure of model performance across different classes by accounting for both precision and recall, which are essential in datasets where one class significantly outnumbers another [71], [72].

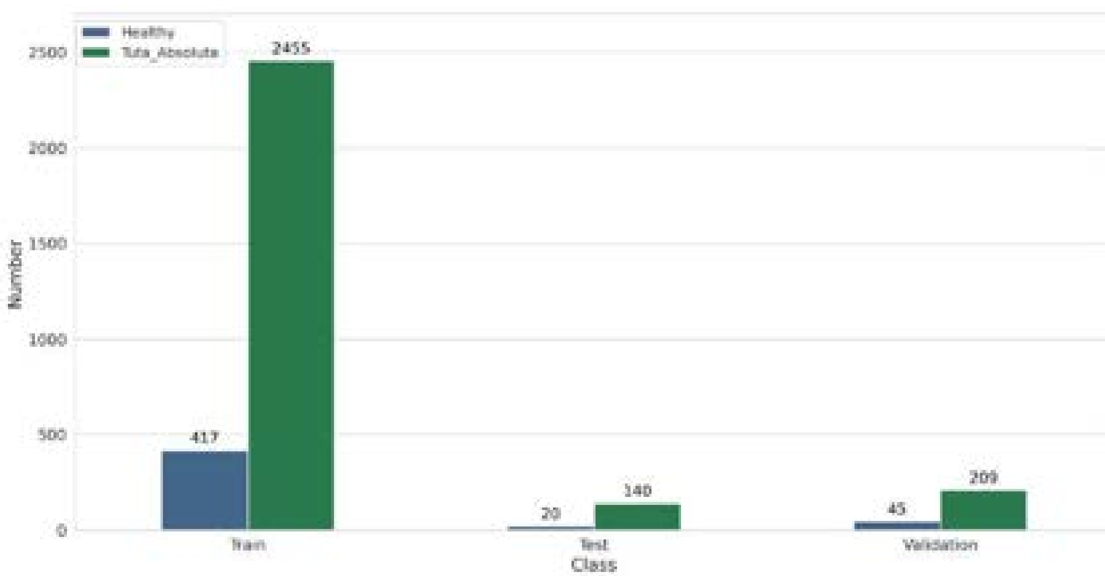

Figure 51: Number of instances per class of *Tuta absoluta* dataset

To enhance the accuracy and effectiveness of the YOLOv8 model for detecting *Tuta absoluta* in tomato crops, we have undertaken a fine-tuning process using our specialized dataset. This fine-tuning was conducted over a span of 20 epochs, a strategic choice that balances the need for thorough learning against the risk of overfitting. During this process, YOLOv8 was exposed to various instances of healthy and Tuta absoluta-infested tomatoes, enabling the model to refine its detection capabilities.

Evaluating the performance of a trained AI model is crucial to assessing its effectiveness. For object detection tasks, it's essential to adopt suitable evaluation metrics to assess object detectors' performance, such as *Average Precision (AP), Mean Average Precision (mAP)*, and visual inspections. The performance of our AI model, that detects the appearance of Tuta absoluta in tomatoes, is evaluated using the *mAP* metric, which provides an overall precision score for the model. The *mAP* of each epoch is visualized in Figure 52. A key component to calculate *AP* and *mAP* is *Intersection over Union (IoU),* which measures the overlap between predicted and ground truth bounding boxes, helping categorize predictions as true positives (*TP*), false positives (*FP*), or false negatives (*FN*) based on an *IoU* threshold, often set at 0.5. Utilizing this categorization, the precision and recall values are calculated based on the equations below:

$$Precision = \frac{TP}{(TP + FP)}$$

$$Recall = \frac{TP}{(TP + FN)}$$

To calculate the *mAP*, it is important to compute the average of the Average Precision (*AP*) scores across all classes.
AP is the average of all precisions on different thresholds regarding the precision-recall curve. It is calculated by the following equation:

$$AP = \sum_{k=0}^{k=m-1} (Recalls(k) - Recalls(k+1)) \times Precisions(k)$$

where m is the number of *IoU* relevant thresholds. Having computed *AP* for all classes, *mAP* is defined as the mean value:

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

where n is the number of classes and AP_k is the average precision of class k.

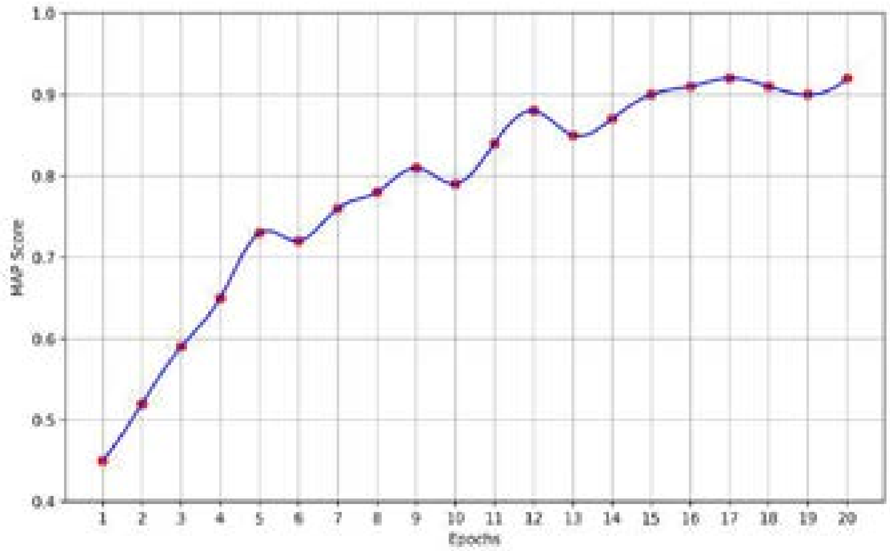

Figure 52: mAP across epochs for training AI model for pest infestation detection of Tuta absoluta

Table 21 presents the performance metrics of an object detection model, specifically YOLOv8, after being fine-tuned to identify Tuta absoluta dataset in tomato crops. Across 80 images, the model detected a total of 160 instances, achieving a mean Average Precision (mAP) of 0.92, indicating a high level of precision in its overall detection capability. For the class labeled 'Healthy', which is the minority class, the model identified 20 instances with an even higher mAP of 0.96, showcasing exceptional accuracy in recognizing healthy tomatoes. This suggests that despite the imbalance, the model is highly effective in identifying the minority class correctly. This performance indicates robust feature learning and discrimination, even with fewer examples. In contrast, the majority 'Tuta absoluta' class, with 140 instances detected, yielded a slightly lower mAP of 0.89, reflecting a very good but marginally less precise detection performance for the pest-infested tomatoes. This could be attributed to the challenges in distinguishing between subtly different states of disease or health, or variations within the 'Tuta absoluta' examples themselves. However, this score still represents a high level of accuracy, indicating effective learning from the larger sample set provided by this class.

Table 22: Performance metrics for trained AI model on Tuta absoluta dataset.

Class	Images	Instances	mAP
All	80	160	0.92
Healthy		20	0.96
Tuta absoluta		140	0.89

Images in Figure 53provide a visual comparison between the ground truth data and the predicted bounding boxes generated by the YOLOv8 model. Ground truth refers to the manually annotated bounding boxes that accurately delineate the areas affected by *Tuta absoluta* or indicate healthy tomato foliage. The predicted bounding boxes are the areas identified by the YOLOv8 model as either 'Healthy' or 'Tuta absoluta' infested. The overlap between these predicted boxes and the ground truth is indicative of the model's precision. The results depicted in Figure 53 below are favourable, demonstrating that the model can reliably detect and outline the areas of interest with high accuracy. The tight congruence of the predicted bounding boxes with the ground truth suggests that the model's training and fine-tuning processes have been successful, enabling it to effectively identify and differentiate between healthy and pest-infested tomatoes.

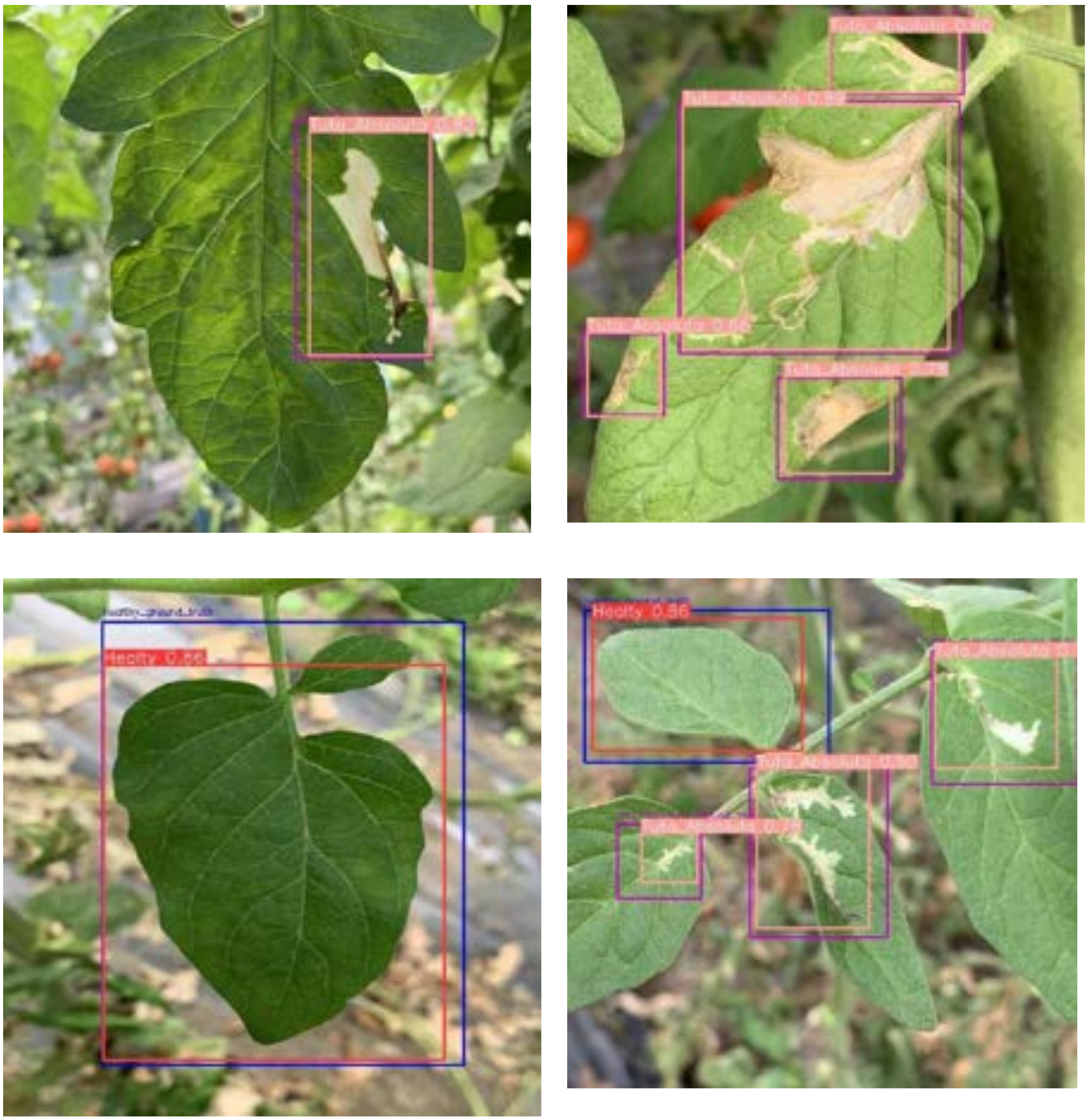

Figure 53: Visual representation of the model's prediction of *Tuta absoluta* identification.

8.3.5. Mobile Application

The Mobile Application which is a plant disease and pests diagnosis tool. It allows farmers to identify plant diseases or pests based on an image of a plant taken with the camera of his smartphone. It then provides treatment recommendations to the farmer in various local African languages. It can run offline allowing farmers in areas without network connection to use it. It is a light app that can run on basic android smartphones such as Android 8 and more. The AI models that have been trained to identify pest infestations are integrated into our mobile application. This integration allows users to harness the power of advanced machine learning techniques for on-the-spot pest detection and management in agricultural settings.

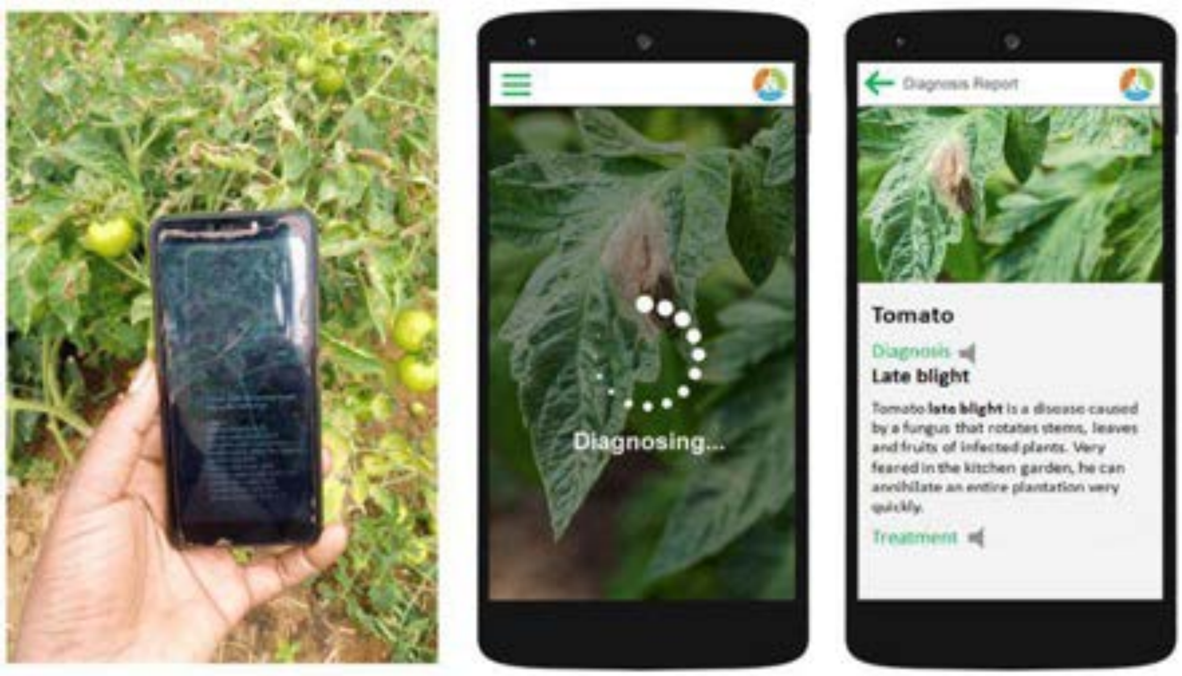

Figure 54: NESTLER mobile application to identify disease on a tomato plant

Technology used

The technologies that we use to develop the mobile application are:

- Mobile app: Java or Flutter;
- AI programming: Python;
- ML framework: TensorFlow or Pytorch;
- Model converter: TensorFlow lite format.

9. Knowledge extraction from Remote Sensing Services

In alignment with the specific data requirements for the proposed use cases, there is the need for consortium partners to monitor the health of specific crop types (e.g. coffee, tomato), as well as to detect changes in land and weather conditions. In this chapter, a description of this thematic information is performed, along with further investigation of existing algorithms, methods, and services on how this knowledge can be extracted from remote sensing-based data.

9.1. Thematic Information and Methods

The analysis and interpretation of remote sensing data rely on a range of algorithms and techniques, each tailored to extract specific types of information. For the abovementioned required field insights, a short overview of the remote sensing algorithms and methods that are foreseen to be developed and utilized in the NESTLER is presented below.

Crop Health Monitoring

The primary focus in the NESTLER project is to understand and monitor the health of specified crop types. In general, crop health monitoring involves the systematic use of remote sensing data to assess the condition, vitality, and potential stress factors affecting crops over agricultural areas. By capturing a variety of spectral and spatial information, remote sensing sensors enable the extraction of crucial thematic information aiming to optimize yields and ensure the sustainability of cultivation practices.

Depending on the required level of detail and field size, either satellite or drone multispectral data can be utilized for the extraction of the below thematic information:

Table 23:Crop health information extracted from remote sensing.

Thematic Layers	*Description*	*Methods/Algorithms*
Crop Health Mapping	Crop field is zoned between healthy and stressed vegetation.	Calculation of spectral indices (e.g. Normalized Difference Vegetation Index, Enhanced Vegetation Index) and application of supervised classification algorithms.
Growth Stage Monitoring	Tracks the growth stages of crops. It can identify anomalies in vegetation patterns due to e.g. diseases or pest infestations.	Time series analysis of spectral indices (e.g. Normalized Difference Vegetation Index, Enhanced Vegetation Index).
Soil Moisture	Monitors soil moisture content, aiding in irrigation management and detection of water stress in crops.	Calculation of spectral indices (e.g. Normalized Difference Water Index) and application of supervised classification algorithms.

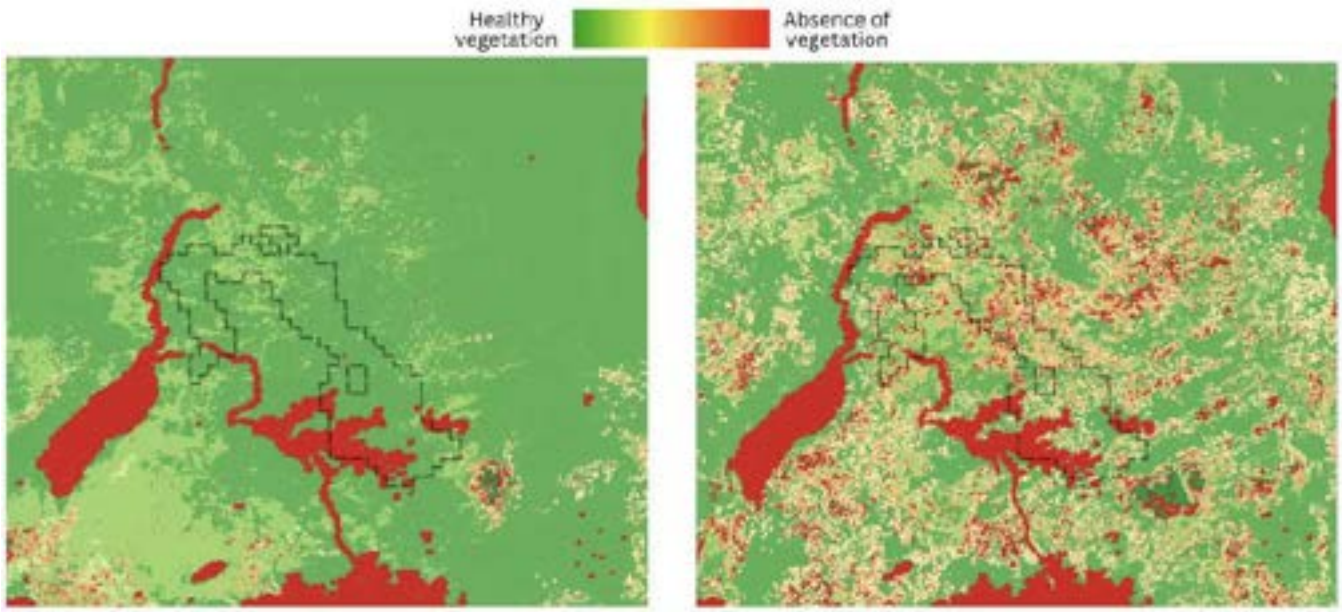

Figure 55: Vegetation health mapping for January 2013 (left) and April 2013 (right) in Uganda.

Land Conditions Monitoring

Shifting the focus to changes in land conditions, the thematic information encompasses the dynamic landscape of agricultural territories. The consortium aims to monitor alterations in land cover, including the identification of crop fields, fallow lands, and potential land-use changes close to the cropland boundaries. By leveraging remote sensing data, the following thematic layers can be extracted within a buffer zone from the specified crop fields/areas by using multispectral or thermal infrared imagery, depending on the required information:

Table 24: Land conditions information extracted from remote sensing.

Thematic Layers	*Description*	*Methods/Algorithms*
Land Cover Change Detection	Detects alterations in land use over time.	Supervised land cover classification (involves training the algorithm with known data points (training samples) to classify unknown areas. Common algorithms include Random Forest, and K-Nearest Neighbors (KNN).)
Land Surface Temperature	Measures the temperature of the Earth's surface, by providing insights into heat distribution.	Application of radiometric calibration to the thermal infrared bands of Landsat 8/9 available imagery, conversion to Brightness Temperature values, and calculation of Land Surface Temperature layer (in °C).
Water Bodies and Wetlands Monitoring	Observes changes in water bodies, including lakes, rivers, and wetlands, supporting in water resource management and potential flood risk assessment.	Calculation of spectral indices (e.g. Normalized Difference Water Index) and application of supervised classification algorithms.

9.2. Weather Remote Sensing Services

Understanding the impact of weather conditions on agriculture forms another critical aspect of thematic information. The use cases require methods to extract knowledge related to temperature variations, precipitation levels, and other meteorological factors to monitor their potential effects on crop growth and health. The thematic information derived from satellite-based weather data aids in making informed decisions regarding irrigation scheduling, e.g. based on temperature, precipitation, and/or humidity forecasts, pest management, and support in mitigation plans to avoid the impact of extreme weather events in the face of changing climatic conditions.

For these reasons, weather satellite data can be added as additional layers to the NESTLER platform. They can work as basemap over the use case areas for visualization purposes, supporting the weather insights derived from the IoT sensors installed in the fields. In the following table, an overview of available weather and climatological services is presented considered to be used in NESTLER.

Table 25: Overview of available weather and climatological services.

Service	*Description*	*Thematic Layers*
OpenWeatherMap	Provision of real-time and forecasting data on the main weather data.	• Current weather (temperature, min temperature, max temperature, atmospheric pressure, humidity, wind speed/direction, cloud coverage, rain) • 3-hour weather forecast for 5 days
answr.space	Provision of natural disaster risk layers derived from 40+ years of historical data.	• Drought Probability • Flood Risk

Figure 56: Flood risk overlayed by agricultural parcels derived from answr.space platform.

10. Conclusion

This report has thoroughly presented the IoT sensors, devices, and remote sensing methods, emphasizing their importance for effective agricultural monitoring in the NESTLER project. It describes the data requirements and preconditions set by pilots in African countries and demonstrates in detail how these needs are met by the IoT sensors/devices and remote sensing methods used in the NESTLER project. Those technologies can be used for crop cultivation, livestock, and aquaculture monitoring.

The remote sensing solutions implemented by the NESTLER project are also elaborated upon. This approach includes the use of satellites and drones. The document presents the potential satellite data intended for project needs, as well as the Smart NESTLER drone, which is equipped with a multispectral camera. Additionally, methods and techniques capable of extracting valuable information from remote sensing data are listed.

It should be noted that the ***SynField ecosystem*** is a Synelixis product that has numerous installations in Greece and abroad, aka in Denmark, Germany, France, Finland, Italy, Lithuania, Netherlands, Spain, Serbia, and India (in collaboration with TATA Advanced Systems). Moreover, in the course of the NESTER project, SynField has been installed in Ethiopia, Camerron, Nigeria, Rwanda, Kenya and Uganda. As a result, the exploitation potential for Synelixis (NESTLER coordinator) is significant. Within the NESTLER project, the SynField Head nodes X3 have been significantly enhanced. Various embedded SW bugs have been corrected and over-the-air-upgrade is now supported. Most important, the SynField head node embedded SW has been extended to support up to 16 peripheral nodes via LoRA connectivity and 4 new low-cost air temperature/humidity and soil moisture sensors have been integrated to support the NESTLER pilots with a sustainable and future proof solution. Moreover, integration with RapidNet Ad-hoc Mesh and Data Aggregator solution has been achieved.

With respect to the ***SynAir***, the subsystem has fully redesigned and the roduct has been reoriented from Smart City Applications to Livestock monitoring applications. The new design supports more sensors, along with a new range of sensors such as O3 and NH3.

With respect to the ***SynWater*** subsystem, this is a fully new product. It has been designed based on NESTLER pilot requirements and specification, and has been implemented to fulfil the specific NESTLER pilot needs. Extensions to SynWater are planned within the second phase of NESTLER project.

The ***Crop Quality monitoring*** system implemented by UCL is a completely new solution that has been design and implemented within NESTLER project. It is important to note that the system has already two circles of design: a proof of concept and a pre-product version.

Additionally, the first version of AI algorithms that process the collected data is described, with some results showcased. Specifically, the AI algorithms for livestock and aquaculture monitoring, as well as for pest infestation detection, are detailed.

The collected data from various IoT sensors and devices as well as the satellite data will be further proceed by the AI algorithms developed in WP4. The final version of remote sensing technologies, multi

-modal data aggregation protocols and AI methods, that utilize this data, will be presented in D3.2 "NESTLER implementation of data aggregation protocols and AI algorithms" due at the end of month 28.

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Annex A

Table 26: CFDS Tab Requirements

Chicken Farm	Number of described classes	Number of annotated images per class (frames, audiofiles)	Total video/ audio content (hours)	System functionality when training with given Dataset
1. Dataset Basic	Classification by flock mobility (average speed of hens): 1 - < Normal 2 - Normal 3 - > Normal Classification based on real-time activity 1 – Resting 2 – Standing 3 – Sleeping 4 – Eating 5 – Itching 6 – Walking 7 – Running 8 – Dead?	1 – 50 000 2 – 30 000	1 – 80 h 2 – 140 h	- Classification of overall flock health by average mobility of hens as an entire flock - Classification of the flock based on the abnormal behavior of hens (insufficient amount of normal activities, excess of abnormal activities)
2. Dataset Standard	Classification by flock mobility (average speed of hens): 1 - < Normal 2 - Normal 3 - > Normal Classification based on real-time activity 1 – Resting 2 – Standing 3 – Sleeping 4 – Eating 5 – Itching 6 – Walking 7 – Running 8 – Dead? Classification by external features 1 – Healthy 2 – Dirty Bottom 3 – Feather fluff	1 – 50 000 2 – 30 000 3 – 30 000	1 – 80 h 2 – 140 h 3 – 90 h	- Classification of overall flock health by average mobility of hens as an entire flock - Classification of the flock based on the abnormal behavior of hens (insufficient amount of normal activities, excess of abnormal activities) - Classification of the flock by the presence of hens with visually distinctive features

3. Dataset Ultra	Classification by flock mobility (average speed of hens): 1 - < Normal 2 - Normal 3 - > Normal Classification based on real-time activity 1 – Resting 2 – Standing 3 – Sleeping 4 – Eating 5 – Itching 6 – Walking 7 – Running 8 – Dead? Classification by external features 1 – Healthy 2 – Dirty Bottom 3 – Feather fluff Classification by vocalization of hens: 1 – Healthy 2 – Abnormally quiet 3 – Abnormally loud 4 – Abnormal sounds (sneezing)	1 – 50 000 2 – 30 000 3 – 30 000 4 – 80 000 5 – 800 files x 90 sec	1 – 80 h 2 – 140 h 3 – 90 h 4 – 250 h 5 – 40 h audio	- Classification of overall flock health by average mobility of hens as an entire flock - Classification of the flock based on the abnormal behavior of hens (insufficient amount of normal activities, excess of abnormal activities) - Classification of the flock by the presence of hens with visually distinctive anomalies - Classification of abnormal vocalization of hens

Table 27: FFDS Tab requirements

Fish Farm	Number of described classes	Number of annotated images per class (frames, audiofiles)	Total video/ audio content (hours)	System functionality when training with given Dataset
1. Dataset Basic	Classification by herd mobility (average speed of fish): 1 – < Normal 2 – Normal 3 – > Normal Classification of location: 1 – Near the surface 2 – At medium depth 3 – At depth	1 – 20 000 2 – 10 000	1 – 50 h 2 – 70 h	- Classification of overall herd health by average mobility of fish as a herd and localization of fish in different position.

2. Dataset Standard	Classification by herd mobility (average speed of fish): 1 – < Normal 2 – Normal 3 – > Normal Classification of location: 1 – Near the surface 2 – At medium depth 3 – At depth Classification based on real-time activity 1 – Resting 2 – Sleeping 3 – Eating 4 – Swimming 5 – Dead	1 – 20 000 2 – 10 000 3 – 30 000	1 – 50 h 2 – 70 h 3 – 60 h	- Classification of overall herd health by average mobility of fish as a herd and localization of fish in different position. - Classification of the herd based on the abnormal behavior of fish (insufficient amount of normal activities, excess of abnormal activities)
3. Dataset Ultra	Classification by flock mobility (average speed of fish): 1 – < Normal 2 – Normal 3 – > Normal Classification of location: 1 – Near the surface 2 – At medium depth 3 – At depth Classification based on real-time activity 1 – Resting 2 – Sleeping 3 – Eating 4 – Swimming 5 – Dead Classification by external features 1 – Healthy 2 – Unhealthy	1 – 20 000 2 – 10 000 3 – 30 000 4 – 30 000	1 – 50 h 2 – 70 h 3 – 60 h 4 – 90 h	- Classification of overall herd health by average mobility of fish as a herd and localization of fish in different position. - Classification of the herd based on the abnormal behavior of fish (insufficient amount of normal activities, excess of abnormal activities) - Classification of the herd by the presence of hens with visually distinctive anomalies