Towards Sustainable Farming: A Robust Decision Support System's Architecture for Agriculture 4.0

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***Abstract*—Agriculture 4.0 is a new era in farming that uses digital technologies to optimize crop yields and increase sustainability by collecting, integrating, and analyzing data from various sources. Decision Support Systems (DSS) are critical in collecting vast amounts of data and transforming it into actionable insights. This paper presents a robust DSS's architecture that serves as a user-centric cloud-based Farm Management System that utilizes real-time data from various digital and space-based technologies which are interconnected in a systemic approach. The DSS incorporates artificial intelligence (AI) algorithms and a user-friendly interface to collect data from digital tools and remote sensing systems allowing farmers for timely interventions. The DSS is integrated with an advanced blockchain system for data evidence, integrity, and AI model verification and with a cybersecurity platform to prevent cyber-attacks. It provides well-informed proactive measures and automated visualized decision processes for Integrated Pest Management (IPM) and Integrated Nutrient Management (INM). Overall, our DSS represents a promising solution to the challenges posed by Agriculture 4.0, and opens up new opportunities for sustainable farming.**

I. Introduction

Agriculture 4.0 is revolutionizing the way people cultivate food and addressing global food security challenges by integrating advanced technologies such as artificial intelligence (AI), big data, robotics, cloud computing, remote sensing, and the Internet of Things (IoT) into the agricultural sector [1]. This integration has led to an exponential increase in the amount of data available from farms, enabling farmers to continuously monitor crop growth, soil quality, and weather conditions in real-time and make informed decisions to enhance crop yields and profitability while minimizing the ecological impact of agriculture [2]. Big data can offer farmers predictive insights for farming operations and real-time decision-making capabilities [2], while AI allows computer programs to generate helpful recommendations and insights to support farmers in making informed decisions [3]. Integrated Pest Management (IPM) and Integrated Nutrient Management (INM) are two important components of Agriculture 4.0 that have gained considerable attention in recent years, aiming to reduce the use of pesticides and fertilizers while improving crop productivity [4].

Decision Support Systems (DSS) assist stakeholders and farmers in making evidence-based and precise decisions. Effective DSSs are crucial for processing and analyzing big data, and for providing actionable insights to improve agricultural management [5]. Big data and precision agriculture technologies have led to an exponential increase in available information, making the need for such systems critical [6]. Thus, DSSs play a crucial role in supporting agri-food operators with essential decision-making, farm management, and planning tasks [7], by gathering data from various sources, analyzing it, and presenting the results to the agri-food operator.

Although DSSs are useful for farm management, their adoption is hindered by significant challenges [8]. Farmers often lack experience and knowledge in using DSSs, and the complexity of these systems can make it difficult for them to comprehend the reporting [9]. DSS developers may also fail to fit farmers' requirements and decision-making styles [9]. Additionally, the limited functionality of current DSSs often means that farmers have to use multiple systems to manage different agricultural activities [9]. Moreover, many DSSs prioritize simple reporting over preventative action [9]. Finally, some fundamental factors, such as climate change, soil spatial variability, and crop disease, may be overlooked when generating advice, leading to imprecise outputs [9].

Several DSSs support precision agriculture [10]. Vite.net [11] informs vineyard farmers about vine growth, pest control, and disease management. DyNoFlo Dairy [12] models nutrient budgeting, crop, and optimization to assess nitrogen leaching from dairy farm systems. AquaCrop [13] simulates the impact of rainfall on wheat yield. ATLAS [14] enables crop availability simulation on a landscape with different scenarios for pests, diseases, and biological control. CropSAT [15] uses satellite images to calculate variable rate nitrogen fertilization. Six web-based visual-assisted DSSs were developed for several agricultural use cases [16]. A DSS was refined to assess the soil functions and provide management advice [17]. Visual DSSs

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include tools for vineyard land usage [18], rainfall and yield production [19], real-time in-field sensor data [20], and drip irrigation system design and scheduling, soil, temperature, and water monitoring, and water flow analysis [21].

In this paper we present the DSS architecture of the European Union's Green Deal project PestNu[1] implemented as an efficient and robust user-centric Farm Management System. The PestNu DSS collects data from advanced various digital tools and space-based technologies including Autonomous Mobile Robots (AMR), nutrient analyzers, robotic traps (smart traps), and remote sensing tools such as AgroRadar[2] that is based on Earth Observation (EO) systems using Copernicus data and services. The system incorporates robust AI algorithms and data analytics pipelines to enhance diagnosis, enabling effective follow-up, informed decisions, and automated decision processes for IPM and INM. The DSS features visual analytics and data visualization of the analyzed data and interpretations, along with generating mitigation strategies based on the severity of the diagnosis. The system is interconnected to a blockchain-based system on top of a federated cloud infrastructure that ensures data and AI model result verification. In addition, the DSS offers improved cyber-secure operation by deploying state-of-the-art anomaly mechanisms to reduce DSS vulnerability in cyber-attacks and threats. Finally, the DSS produces simplified reports presenting only critical parameters in a clear and concise manner. The paper's structure is as follows: Section II explains the DSS architecture, followed by a discussion in Section III. Finally, Section IV presents the study's conclusions, along with planned future work.

II. Methodology: Architecture

This section presents the architecture of PestNu's DSS, which comprises three levels: a) data acquisition, b) data processing, and c) data visualization. At the first level, data related to nutrients, pests, and crop anomalies are collected and analyzed from digital and space-based technologies. The digital tools continuously collect data from the environmental sensors, utilize a firewall system to ensure the integrity of the data, and transmit it, under a secure communication channel to the DSS. The second level stores the data in a secure database and uses AI algorithms to analyze the data in order to generate insights on crops, pests, and nutrients status. Cybersecurity and blockchain are implemented to enhance data security and ensure the integrity of the data. Finally, the third level presents the information generated by the AI algorithms in an interactive user interface (UI). The UI provides the farmer with a real-time view of the previous parameters and also offers decision support for applying timely agronomic best practices. The high-level architecture is shown in Figure 1.

A. Data Acquisition Level

At the data acquisition level, the interconnected digital and space-based technologies such as: a) AI-based robotic traps, b) AMR (Agrobots), c) AgroRadar EO-based system, and d) nutrient analyzers collect data which is then fed into the DSS. However, the security of the transmission from the sensors' data to their tools must be ensured.

[1] https://pestnu.eu

[2] https://business.esa.int/projects/agroradar-1

Firewall: A firewall application is used to enhance network security. It inspects data packets to detect and prevent security threats, such as denial-of-service attacks or port scanning. Access control lists are also utilized to control which traffic types are allowed to pass through, and network address translation is employed to hide device IP addresses.

In order to collect real-time data related to pests, crop growth, soil health, and environmental factors such as temperature and humidity, a variety of interconnected digital tools are utilized.

Autonomous Mobile Robot: An AMR navigates in greenhouses, aquaponics, and open fields for effective surveillance of insect and fungal disease and 3D spot spraying. The AMR is equipped with high-precision navigation sensors, a computer vision system, and robotic actuators. It reports its mission (insect and disease detection and spraying actions) in a comprehensive report as a JSON file and is operated via a state machine in the Robot Operating System (ROS), which interfaces with the DSS.

Nutrient Analyzers: Real-time digital analysis of water content is done using Ultraviolet (UV) LED-based nutrient analyzers that measure nitrate/nitrite (NO_3^-, NO_2^-, phosphate (PO_4^{3-}), and ammonium (NH_4^+) levels. The analyzers send 4 byte floats of each nutrient along temperature (float, 4 bytes), humidity (float, 4 bytes) and leak detection (boolean, 1 byte) in JSON format via the Sierra Wireless Octave. The Octave cloud service provides APIs and cloud actions to access the data, which will interface with the DSS.

Robotic Traps: AI robotic traps are used for pest detection and monitoring. The smart traps are equipped with yellow sticky adhesive papers coated with pheromones or chromotropic food lures and a camera that periodically capture images and sends them by IoT networks to a database at the DSS server (in JPG or PNG format). The traps also monitors environmental data, including external humidity, atmospheric pressure, and temperature, as well as the GPS location, data for solar battery percentage, glue paper quality percentage, and pheromone quantity percentage and sends them in a CSV or JSON to the DSS. The communication of the robotic traps with the DSS is established via REST API protocol.

AgroRadar: This system makes use of the Copernicus program's data and services (Sentinel-1, Sentinel-2), presented as GeoTIFF images and leverages Meteosat Second Generation (MSG) EO satellite data. Combining all this, AgroRadar adds a pre-processing layer to the DSS by identifying abnormalities in the fields and generating alerts, in a PDF format, for nutrients and pests stress and by calculating crops sustainability. Moreover, the system models historical data, benchmarking the crops and the regions. In addition, the system collects data related with the emissions, in the production of different crops to calculate their CO_2 footprints in JSON format. The communication of the EO system with the DSS is established via REST API protocol.

The latter tools allow the collection of real-time data, but their communication channels are vulnerable to hacking, interception, and disruption. Thus, secure communication protocols and network security measures are implemented.

Security Channel: To ensure the confidentiality and in-

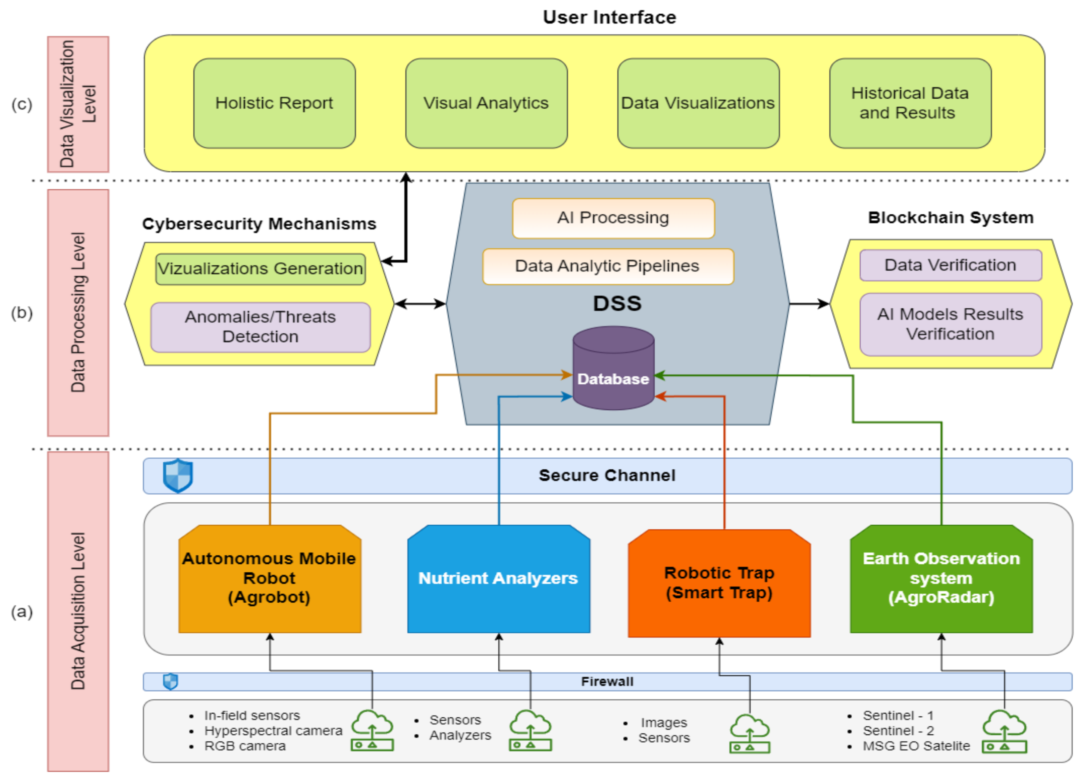

Fig. 1. DSS high-level architecture. (a) At data acquisition level all data from the digital tools are collected. (b) At data processing level, sophisticated algorithms run under blockchain and cybersecurity. (c) At data visualization level, all information is presented via a user-friendly UI.

tegrity of information transmitted from the aforementioned tools, end-to-end security is implemented across all layers of the tools. ARM TrustZone isolates security-sensitive services, tasks, and processes in the CPU and RAM. A dedicated firewall is used for threat mitigation, and policy-based security is applied to IoT controllers and digital tools. SSL/TLS encryption is used at the application layer, and IPSEC/VPN technology is used for network-based encrypted communication.

B. Data Processing Level

The DSS integrates and analyzes multi-dimensional data from digital tools to develop a Farm Management System for circular economy strategies and provide recommendations to farmers. It uses descriptive and predictive AI algorithms to analyze current and historical data from all tools and provide comprehensive summaries and predictions. This analysis is implemented over a secure private cloud infrastructure, incorporating AI models and data analytic pipelines for processing the data from the sources level.

Database: The Database Management System (DBMS) stores and manages the incoming data of the tools, through the Security Channel and stores the AI models results. It also enables communication with the Blockchain for data verification. In the proposed solution, MongoDB [22] is implemented as it supports SSL/TLS network protocols for secure and optimized inter-process communication.

AI Processing: Sophisticated AI algorithms leverage big data collected from digital tools to detect pests and predict future attacks. Deep learning methods analyze AMR's color and spectral images to identify black aphids, whiteflies [23], and Botrytis cinerea [24]. Deep learning algorithms analyze images captured by robotic traps to localize and classify present insects [25]. Self-adaptive models use pest detections and environmental data to forecast future pest presence and attacks. Finally, emission data collected from AgroRadar are processed using Intergovernmental Panel on Climate Change (IPCC) equations to generate CO_2 footprints and a final index representing product sustainability.

Data Analytic Pipelines: The data analytics pipeline generates tailored recommendations based on pest predictions, soil types, and weather patterns. Alerts and cautions are sent to farmers, and preventative measures are taken when nutrient and pest levels approach a given threshold. The threshold can be adjusted by the farmer.

Cybersecurity Mechanisms: To secure the DSS and its data, the SiVi platform[3] is used, which utilizes machine learning algorithms and visualization graphs (see II-C). The platform employs entropy-based traffic anomaly detection to classify data and flow messages as "typical" and "abnormal", allowing for faster classification of potential cyber threats. The SiVi platform also includes supervised and unsupervised algorithms to recognize known and unknown anomalies and

[3]https://sidroco.com/sivi_tool/

threats, ensuring the system's protection. The system's library stores a collection of annotated network attacks, enabling the supervised algorithms to classify incoming traffic, while the unsupervised algorithms can detect global, contextual, and collective outliers.

Blockchain System: A Distributed Ledger Technology (DLT) system is connected to the DSS in order to verify the tools' data and to provide AI model verification. Hyperledger Sawtooth [26] is implemented that consists of three nodes each one running one validator, a REST API, a consensus engine, a set of transaction processors and all are connected in a MySQL database [27]. The components are deployed as Docker containers. Sawtooth forwards each request to the DLT Network for authorization by offering a REST API for interaction of the DLT Network with applications using normal HTTP/JSON protocols. Both data from the digital tools and the AI model results are send from DSS Database, through the DLT API, into the Ledger, to be recorded.

C. Data Visualization Level

The DSS's data visualization system displays information about pests, nutrient levels, soil health, crop growth, and weather patterns to improve sustainability and efficiency for farmers. The system is designed to be simple, effective, and customizable to meet the needs of diverse stakeholders. The system includes a user-friendly graphical user interface (GUI) that provides functionalities for farmers to use available data resources and analysis pipelines.

Holistic Report: A new comprehensive and easy-to-understand holistic report is being developed, which consolidates information from all digital tools, including threshold parameters, locations, and mitigation actions. The report generates warnings and decisions, providing guidance for effective decision-making and implementation in case thresholds are exceeded.

Visual Analytics: Visual Analytics use analytical techniques and interactive visualizations to help farmers analyze complex data. It allows farmers to monitor their crops over time and identify areas that require attention.

Data Visualizations: Data Visualizations uses graphical representation to display various types of data and information. It shows the pheromone level and the glue paper remaining life, used by the robotic trap. It provides colored maps that show the areas of the field with the relative soil health, and crop growth to detect unexpected differentiation. AMR status (e.g., battery level, fertilizer tank level) is also presented to the farmer in order to reduce the time needed to spend on field. Finally, the nutrient levels measured by the analyzers are provided along useful information regarding the condition of the device.

Historical Data and Results: Historical data and results are analyzed using data analytics and visual analytics methods, including temporal plots, clustering views, and graph-based visualizations. The visualization services present the output of data analysis and AI modeling execution, allowing researchers to provide feedback such as marking inaccurate classifications, or editing wrong segmentation contours. This feedback is used to retrain and refine AI models in real-time.

III. Discussion

The three levels for designing a DSS - data acquisition, processing, and visualization - ensure an organized and efficient system. This ensures that the system is efficient, and each level has a specific purpose, making it easier to be managed and maintained. Each level has a distinct function, with data acquisition collecting and securing data, data processing generating accurate results for decision-making, and data visualization presenting insights in a user-friendly way. The use of blockchain and cybersecurity mechanisms in the data processing level enhances the security and reliability of the DSS. Blockchain technology provides a decentralized and tamper-proof method for storing and managing data, ensures that the data stored in the database is secure and cannot be tampered with by unauthorized users. Similarly, cybersecurity mechanisms, such as firewalls and secure channels, ensure that the data transmitted between the different levels is secure and confidential. The data visualization level has a user-friendly UI with the ability to present insights in a comprehensive and simple manner, enabling decision-makers to understand the insights generated easily. The use of historical data and results enables decision-makers to compare and contrast data over time, making it easier to identify trends and patterns. Finally, the DSS improves continuously through feedback, enhancing the precision and consistency of insights.

IV. Conclusion and Future Work

The three-level architecture for designing a DSS is a robust, meaningful, and useful approach to enhancing the security and reliability of the system while enabling efficient and effective data-driven decision-making. The use of DLT and cybersecurity mechanisms ensures that the data is secure and reliable, while the data visualization level offers several advantages such as presenting insights in a comprehensive and simple manner and providing historical data and results. The feedback provided for AI model re-training further enhances the accuracy and reliability of the insights generated, ensuring that the DSS continually improves and evolves.

The proposed DSS has the potential to revolutionize farming practices and enhance sustainability in Agriculture 4.0. In future work, we plan to implement, demonstrate, and field-test the DSS in open fields at CDTA El Mirador and Tilamur in Spain and in aquaponics at University of Thessaly in Greece to provide empirical evidence of its effectiveness in optimizing crop yields, reducing waste, pesticides, and increasing sustainability. We will evaluate the DSS's accuracy and effectiveness in decision-making. Additionally, we will ensure that the DSS generates certified reports that provide farmers with accurate and easily comprehensible information, enabling them to make informed decisions based on digital tools.

Acknowledgment

This paper is supported by European Union's Horizon 2020 research and innovation programme under the Green Deal grant agreement No. 101037128, project PestNu. We thank our partners iKnowHow S.A., T.E Laboratories Limited, Agrorobotica Srl, and Agroinsider Lda for the digital and space-based technologies and University of Thessaly, CDTA El Mirador, and Tilamur S.L. for end-user requirements.

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