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Option: Advanced Information System

TITLE

Un Système d'Information Avancé pour une Agriculture Intelligente

Defended by:

Thabet Righi

Before the jury composed of:

Chairman	Pr. Abdelkamel Ben Ali	University of El Oued
Supervisor	Pr. Mohammed Charaf Eddine Meftah	University of El Oued
Examiner	Dr. Mohammed Anouar NAOUI	University of El Oued
Examiner	Dr. Benbrika Mohammed Kamel	University of El Oued
Examiner	Pr. Lakhdar LAIMECHE	University of Tebessa
Examiner	Dr. Mourad BOUZENADA	University of Constantine

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Dedication

To my beloved family,

To my brothers, sisters, and dear friends who stood by my side through every step — thank you for your support and encouragement.

But above all…

To my mother, the heart of our home, the source of endless love, comfort, and prayers.

To my father, my first teacher and role model, whose wisdom, patience, and unwavering belief in me guided my path.

With your love, prayers, and support, I reached this milestone.

To you, and to everyone who shared this journey with me, I dedicate this achievement with gratitude and pride.

Thabet Righi

Résumé

Ces dernières années, l'agriculture a connu une transformation majeure vers la modernisation et l'utilisation de technologies avancées, en particulier dans le domaine de l'agriculture intelligente. Cette tendance reflète les progrès considérables dans des domaines tels que l'informatique, l'Internet des objets et l'intelligence artificielle. Malgré de nombreuses études et projets visant à développer l'agriculture intelligente, ils se concentrent souvent sur des aspects spécifiques sans considérer l'image complète du secteur agricole.

L'objectif de cette thèse est de présenter deux contributions majeures. Dans la première contribution, nous partons de la proposition de concevoir une approche globale englobant le secteur agricole à ses différents niveaux, général et spécifique, en mettant l'accent sur une vision moderne de la technologie de l'information, en se concentrant sur l'Internet des objets, l'intelligence artificielle, et les techniques d'amélioration. Nous cherchons à améliorer l'intégration entre les nombreux aspects diversifiés de l'agriculture intelligente.

Dans le contexte de la deuxième contribution, nous nous concentrons sur les défis de l'agriculture moderne, tels que la propagation des maladies des plantes et le manque de contrôle en temps réel. Nous avons présenté un système intelligent de surveillance agricole et de détection des maladies utilisant des techniques de reconnaissance d'image, renforçant ainsi l'efficacité du diagnostic et la réponse rapide aux problèmes agricoles.

De cette manière, ces propositions visent à créer un système d'information agricole avancé qui soutient l'agriculture intelligente. Nous cherchons à améliorer la prédiction et la prise de décision dans l'analyse complète des données, telles que les données climatiques, environnementales et financières. Notre objectif est d'utiliser ces données pour tirer des leçons cruciales sur les maladies, le manque d'eau et les conditions climatiques défavorables, conduisant à des décisions agricoles durables et efficaces dans un environnement intelligent. Le système peut améliorer la qualité des cultures et réduire les coûts totaux de production, en faisant de lui une valeur ajoutée pour l'agriculture intelligente.

Mots-clés : Agriculture intelligente, Internet des objets, Détection des maladies, Système d'information agricole avancé

Abstract

In recent years, agriculture has undergone a significant transformation towards modernization and the use of advanced technology, especially in the field of smart agriculture. This trend reflects tremendous progress in areas such as computing, the Internet of Things, and artificial intelligence. Despite numerous studies and projects aimed at developing smart agriculture, they often focus on specific aspects without considering the complete picture of the agricultural sector.

The purpose of this thesis is to present two main contributions. In the first contribution, we start with the proposal to design a comprehensive approach that encompasses the agricultural sector at its interconnected levels, both general and specific, with a modern vision of information technology. This involves a focus on the Internet of Things, artificial intelligence, and enhancement techniques. We aim to improve the integration between the various diverse aspects of smart agriculture.

In the context of the second contribution, we focus on the challenges of modern agriculture, such as the spread of plant diseases and the lack of real-time control. We have introduced an intelligent system for monitoring agriculture and detecting diseases using image recognition techniques, thereby enhancing the efficiency of diagnosis and the rapid response to agricultural problems.

In this way, these proposals aim to create an advanced agricultural information system that supports smart agriculture. We seek to improve prediction and decision-making through the comprehensive analysis of data, including climate, environmental, and financial data. Our goal is to use this data to extract crucial lessons about diseases, water shortages, and unfavorable climate conditions, leading to sustainable and effective agricultural decisions in a smart environment. The system can improve crop quality and reduce the overall costs of production, making it an added value for smart agriculture.

Keywords: Smart agriculture, Internet of Things, Disease detection, Advanced agricultural information system

ملخص

في السنوات الأخيرة، شهدت الزراعة تحولًا هامًا نحو التحديث واستخدام التكنولوجيا المتقدمة، خاصةً في مجال الزراعة الذكية. يعكس هذا الاتجاه التقدم الهائل في مجالات أنظمة المعلومات المتقدمة، مثل الحوسبة، وإنترنت الأشياء، والذكاء الاصطناعي. رغم وجود العديد من الدراسات والمشاريع التي استهدفت تطوير الزراعة الذكية، إلا أنها غالبًا ما كانت تعتني بجوانب محددة دون النظر إلى الصورة الكاملة للقطاع الزراعي.

تقديم هذه الأطروحة يهدف إلى تقديم مساهمتين رئيسيتين. في المساهمة الأولى، ننطلق من اقتراح تصميم نهج شامل يتضمن القطاع الزراعي بمستوياته المترابطة، العام والخاص، وجوانبه المختلفة ضمن رؤية حديثة لتكنولوجيا المعلومات، مع التركيز على تقنيات الربط بين انترنت الأشياء والذكاء الاصطناعي وتقنيات التحسين. نسعى إلى تحسين التكامل بين العديد من الجوانب المتنوعة في مجال الزراعة الذكية.

في سياق المساهمة الثانية، نركز على تحديات الزراعة الحديثة، مثل انتشار الأمراض النباتية ونقص التحكم في الوقت الحقيقي. قدمنا نظامًا ذكيًا لرصد الزراعة وكشف الأمراض باستخدام تقنيات التعرف على الصور، مما يعزز فعالية التشخيص والاستجابة السريعة لمشكلات الزراعة.

بهذه الطريقة، تهدف هذه المقترحات إلى إنشاء نظام معلومات زراعي متقدم يدعم الزراعة الذكية. نسعى إلى تحسين التنبؤ واتخاذ القرار في التحليل الشامل للبيانات، مثل البيانات المناخية والبيئية والمالية. نهدف إلى استخدام هذه البيانات لاستخلاص دروس حاسمة حول الأمراض ونقص المياه وظروف المناخ غير الملائمة، مما يؤدي إلى اتخاذ قرارات زراعية مستدامة وفعّالة في بيئة ذكية. يمكن للنظام تحسين جودة المحاصيل وتقليل التكاليف الإجمالية للإنتاج، مما يجعله قيمة مضافة للزراعة الذكية.

الكلمات المفتاحية: زراعة ذكية، إنترنت الأشياء، اكتشاف الأمراض، نظام معلومات زراعي متقدم

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AAIS: Advanced Agricultural Information System

AIS: Agricultural Information System

FMIS: Farm Management Information System

IoT: Internet of Things

SA: Smart Agriculture

AI: Artificial Intelligence

General Introduction

General Introduction

In the introduction of this thesis, we will start by outlining the context and problematizing the research work, followed by an overview of the thesis's contributions. Finally, we will describe the organization of the thesis.

1. Context and Problem

Smart Agriculture (SA) is a rapidly evolving field that utilizes advanced technologies to enhance agricultural productivity and sustainability. However, the complex nature of agricultural systems and the diverse challenges faced by farmers necessitate the development of sophisticated information systems to effectively manage and optimize agricultural operations. This thesis aims to address this need by proposing an Advanced Information System (AIS) for SA.

The research work is motivated by the recognition that traditional agricultural practices often fall short in addressing the intricate demands of modern farming. The challenges faced by farmers include:

- **Predicting and preventing crop diseases:** Diseases pose a significant threat to agricultural production, leading to substantial economic losses. Traditional methods of disease detection and control are often reactive and resource-intensive, emphasizing the need for proactive and data-driven solutions.

- **Optimizing resource management:** Agriculture consumes a significant amount of water and energy, making resource optimization crucial for both environmental and financial sustainability. Traditional irrigation and fertilization practices often lack precision, leading to inefficiencies and potential environmental damage.

- **Making informed decisions:** Farmers face a multitude of decisions daily, ranging from crop selection to pest management. These decisions significantly impact crop yields, profitability, and environmental sustainability. Traditional decision-making processes often rely on limited data and intuition, making them susceptible to errors.

The proposed AIS aims to address these challenges by providing a comprehensive information system that integrates various technologies and methodologies, including:

- **Data collection and analysis:** The AIS will utilize sensor networks to collect real-time data on various parameters such as soil moisture, temperature, humidity, and crop health. This data will be analyzed using advanced machine learning algorithms to identify patterns and trends.

- **Predictive analytics:** The AIS will employ predictive modeling techniques to forecast crop yields, disease outbreaks, and resource requirements. These predictions will enable farmers to take proactive measures and optimize resource allocation.

- **Decision support:** The AIS will provide farmers with data-driven decision support tools that consider various factors, including crop growth models, weather forecasts, and market trends. These tools will assist farmers in making informed decisions that maximize productivity and minimize environmental impact.

The implementation of the proposed AIS is expected to yield significant benefits for both farmers and the environment:

- **Reduced crop losses:** Accurate disease prediction and timely intervention will minimize crop losses due to diseases.

- **Optimized resource utilization:** Data-driven irrigation and fertilization strategies will reduce water and energy consumption, promoting environmental sustainability.

- **Improved decision-making:** Data-driven decision support tools will enhance farmers' ability to make informed choices, leading to increased productivity and profitability.

The development and implementation of the proposed AIS represent a significant step towards advancing SA practices and ensuring sustainable agricultural production. The AIS has the potential to revolutionize the way farmers manage their operations, leading to a more productive, sustainable, and resilient agricultural sector.

2. Objectives

The thesis delves into the four distinct visions of the advanced information system (AIS) for smart agriculture:

- **Business Vision:** This vision outlines the processes and activities that the AIS must support to enable a fully integrated smart agriculture ecosystem.

- **Functional Vision:** This vision articulates the specific functions and capabilities the AIS must possess to effectively support smart agriculture processes.

- **Application Vision:** This vision envisions the comprehensive application elements of the AIS, encompassing a range of tools and functionalities tailored to smart agriculture.

- **Technical Vision:** This vision outlines the technical architecture (hardware, software, and underlying technologies) that will underpin the seamless integration of IT infrastructures and tools in the smart agriculture domain.

3. Contributions

In light of the aforementioned challenges, this thesis presents two contributions, each addressing a specific issue in the realm of smart agriculture:

- Towards a comprehensive approach for an advanced agricultural information system (AAIS):

Responding to the need for a comprehensive approach to designing an advanced agricultural system, this contribution proposes a comprehensive framework that integrates various levels of the agricultural sector. It includes stakeholders from both the public and private sectors. By leveraging modern information technology principles, with a specific focus on the Internet of Things (IoT), this research aims to enhance seamless integration across diverse aspects of smart agriculture.

- An Intelligent Agriculture Monitoring Framework for Leaf Disease Detection Using YOLOv7:

This contribution proposes an intelligent system for agricultural monitoring and disease detection. Harnessing the power of YOLOv7 technology, to address the pressing issue of plant diseases and the lack of real-time monitoring this system enhances diagnostic efficiency and enables a rapid response to agricultural challenges. By addressing these challenges, this research aims to contribute to the development of sustainable and effective smart agricultural practices.

These contributions pave the way for the establishment of an advanced agricultural information system that empowers smart agriculture. The system encompasses predictive and decision-making aspects through comprehensive data analysis, incorporating climate and environmental data. The goal is to extract critical insights into diseases, water scarcity, and unfavorable climatic conditions, enabling well-informed and sustainable agricultural decisions in a smart environment. With the potential to improve crop quality and reduce overall production costs, this system adds significant value to the landscape of smart agriculture.

4. Thesis Organization

This thesis is composed of four chapters, some of which are based on works that have been published or submitted to international journals and conferences.

- **Chapter 1:** Overview of Advanced Information Systems

This chapter provides an overview of advanced systems and the Internet of Things (IoT). It defines and describes the characteristics and components of advanced systems and the IoT.

- **Chapter 2:** Review of Research of Advanced Systems in Smart Agriculture

This chapter reviews the work and contributions of researchers in the field of advanced systems in smart agriculture. It compares the different approaches that have been taken to address the challenges of smart agriculture.

- **Chapter 3:** Proposal for a Comprehensive System for Smart Agriculture

This chapter proposes a comprehensive system for smart agriculture. The system integrates multiple levels of the agricultural sector, including stakeholders from both the public and private sectors. It uses modern IT principles, with a particular focus on the Internet of Things (IoT), to improve the effectiveness of smart agriculture.

- **Chapter 4:** Proposal for an Intelligent Disease Detection System Using YOLOv7

This chapter proposes an intelligent disease detection system using YOLOv7 technology. The system addresses the critical issue of plant diseases and the lack of real-time monitoring. It uses YOLOv7 technology to enhance the effectiveness of diagnosis and enable rapid response to agricultural challenges.

- **Conclusion**

The thesis concludes by summarizing the contributions and highlighting future prospects.

Chapter 1:
Overview of Agricultural Information Systems (AIS)

1. Introduction

1.1. Background

1.1.1. Context of Agricultural Information Systems

An agricultural information system can be defined as a system in which agricultural information is generated, transformed, transferred, consolidated, received, and fed back in a manner that allows these processes to function synergistically. This synergy underpins the effective utilization of knowledge by agricultural producers, enhancing decision-making and productivity. Such a system is composed of several key elements: components (subsystems), information-related processes, system mechanisms, and system operations. The components include both hardware and software aspects, along with physical sensors that collect vital data. Information-related processes involve the generation, transformation, storage, retrieval, integration, diffusion, and utilization of agricultural data. System mechanisms, such as interfaces and networks, ensure smooth communication and data flow, while system operations focus on control and management activities. Agricultural information serves as a critical input to agricultural education, research and development, and extension activities, enabling stakeholders to address challenges, adopt innovations, and optimize resources.[1] The integration of real-time data and Internet of Things (IoT) technologies further enhances these systems, allowing for precise monitoring of field conditions, timely interventions, and improved resource efficiency.

Agricultural information systems (AIS) (Figure 1) are defined as information systems that generate, transform, and consolidate agricultural information to enhance knowledge utilization by agricultural producers [2]. These systems comprise various subsystems, processes, mechanisms, and system operations, AIS users include government decision-makers, policymakers, universities, researchers, extension workers, and farmers by enabling the collection, processing, and dissemination of agricultural data, these systems support critical activities such as policy formulation, educational outreach, research development, and practical on-farm applications.[3][4]

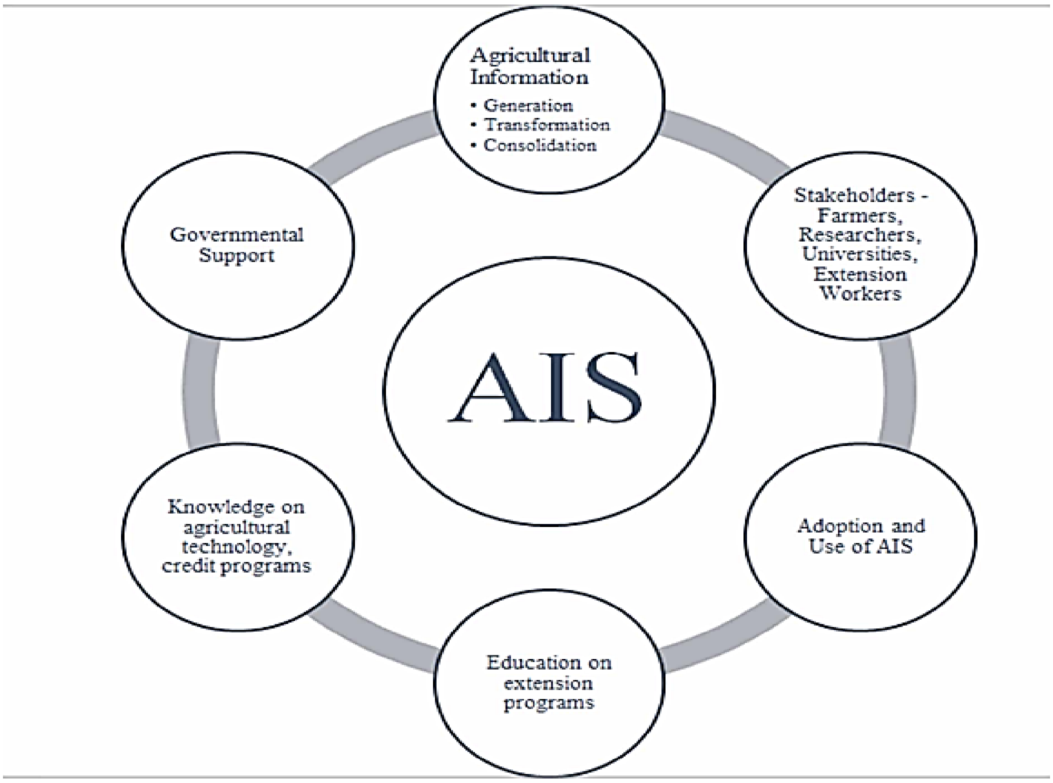

Figure 2. Agricultural Information Systems [4]

1.1.2. Current Challenges in Agricultural Management

The agricultural sector faces a multitude of challenges that demand innovative solutions to ensure food security and sustainability. Increased global food demand and population growth pose a significant challenge, requiring agricultural practices to optimize resource utilization and increase yields. Precision agriculture techniques offer a promising approach to addressing this challenge.[5] Climate change and its impact on agriculture present another pressing issue, as extreme weather events and shifting climate patterns threaten crop yields and agricultural practices.[6] Climate-smart agriculture, which incorporates practices such as crop management, sustainable agriculture, agroforestry, precision agriculture, and the development of climate-resilient crop varieties, enhances soil health, improves water use efficiency, reduces erosion, boosts carbon sequestration, conserves biodiversity, and optimizes resource use.[7]

Sustainable water use for irrigation is considered one of the primary priorities in agriculture in arid regions. In the face of water scarcity and climate change, significant efforts have been dedicated over time to developing policies aimed at increasing water use efficiency. The focus is particularly on improving water resource management, as better results can be achieved with less water through advanced irrigation management techniques. Typically, improving management refers to optimizing water allocation and enhancing the efficiency of irrigation systems, thereby maximizing the use of these limited resources.[8].

Integrated pest management (IPM) represents the future of agriculture at a time when the sector faces unprecedented challenges in pest management. In this context, the adoption of IPM practices and innovation emerges as a key pillar of a flexible and sustainable food production strategy. Improving pest management is a significant challenge in modern agriculture, where environmental and climatic challenges demand innovative solutions to ensure high productivity and food quality, while minimizing negative environmental impacts.[9]

Soil presents one of the main challenges in agriculture, as a decrease in soil organic carbon content, soil health degradation, and the loss of soil resilience can lead to reduced crop productivity. Additionally, the loss of rich topsoil due to water, wind, or plowing erosion diminishes soil fertility. Unsustainable management practices, such as excessive tilling of sensitive soils and removal of crop residues, exacerbate this issue. Therefore, sustainable soil management and conservation are critical to increasing crop productivity and ensuring agricultural sustainability.[10]

Finally, these challenges in precision agriculture (Figure 2)are crucial for maintaining productivity and food security. They require the development of smart systems and innovative approaches to improve crops, agricultural production, and climate conservation. To achieve this, it is essential to adopt advanced smart farming systems that integrate technology and data to ensure agricultural sustainability and enhance efficiency.

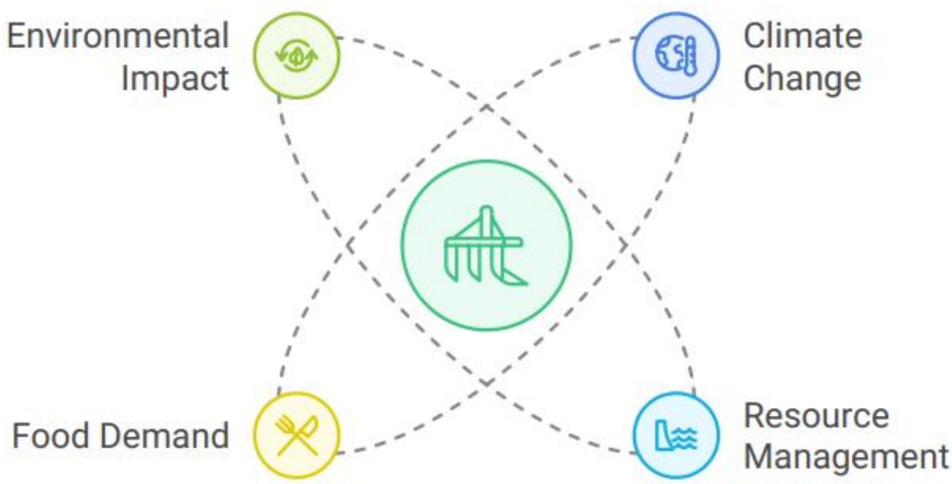

Figure 2. Challenges in Agricultural Management

1.2.2. Importance of Advanced Systems in Agriculture

Advanced agricultural systems are revolutionizing the agricultural sector by providing significant benefits that enhance productivity, sustainability, and resilience in the face of growing challenges (Figure 3). Agricultural technology plays a pivotal role in enabling farmers to overcome these challenges and improve their operations. Among its key advantages is increased crop productivity through precision farming techniques that reduce waste and improve operational efficiency. It also helps reduce water, fertilizer, and pesticide usage by supporting informed decision-making, thereby minimizing environmental impact, agricultural technology mitigates the impact of farming on natural ecosystems by reducing the use of harmful chemicals and limiting their runoff into rivers and groundwater, decreasing risks of environmental and public health issues. It improves working conditions for farmers by streamlining operations and ensuring safety, increasing efficiency, and reducing costs. With climate forecasting powered by artificial intelligence, farmers can accurately determine planting and harvesting schedules, reducing crop losses due to unexpected weather conditions. Biotechnology contributes to developing crops that are resistant to diseases, pests, and harsh climatic conditions, further boosting productivity and reducing waste, Moreover, agricultural sensors provide real-time data on factors affecting crop growth, such as soil moisture and temperature, enabling precise and effective management. The overall result is safer farming practices, higher-quality food for consumers, and a reduced environmental and ecological footprint. [10]

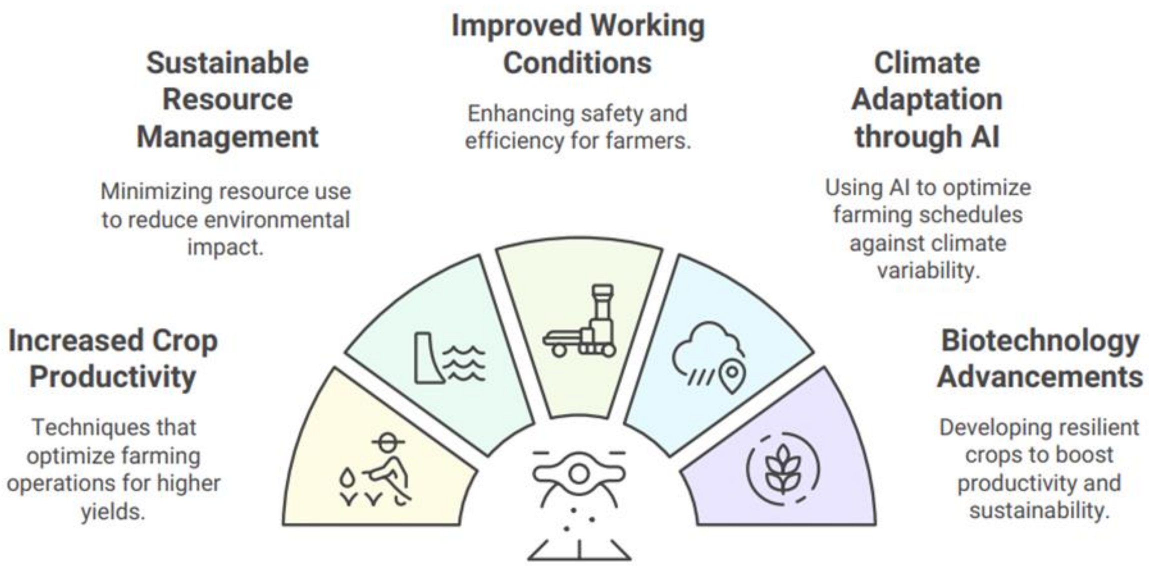

Figure 3. Revolutionizing Agriculture: The Impact of Advanced Agricultural Systems

2. Definitions and Characteristics

2.1 Information Systems (IS)

An information system is an interconnected set of components used to collect, store, process, and transmit digital data, transforming it into useful information (Figure 4). The system comprises hardware, software, data, people, and processes working together to support various objectives such as improving customer service and increasing operational efficiency. Although the terms "information system" and "computer system" are often used interchangeably, they are not the same. While computer systems are a part of information systems, they do not encompass all elements such as people and processes. Similarly, "information technology" (IT) focuses on the technical aspects of hardware and software, whereas an information system emphasizes how individuals use technology and data to manage and make decisions within an organization. In addition to decision-making, information systems play a crucial role in knowledge management and enhancing communication. They facilitate data sharing across different departments, providing consistent data for analysis by various teams. Information systems support a wide range of business functions such as accounting, finance, marketing, human resources, operations, and supply chain management. Moreover, they enable innovative business models and opportunities, including e-commerce, social media, and artificial intelligence applications.[14]

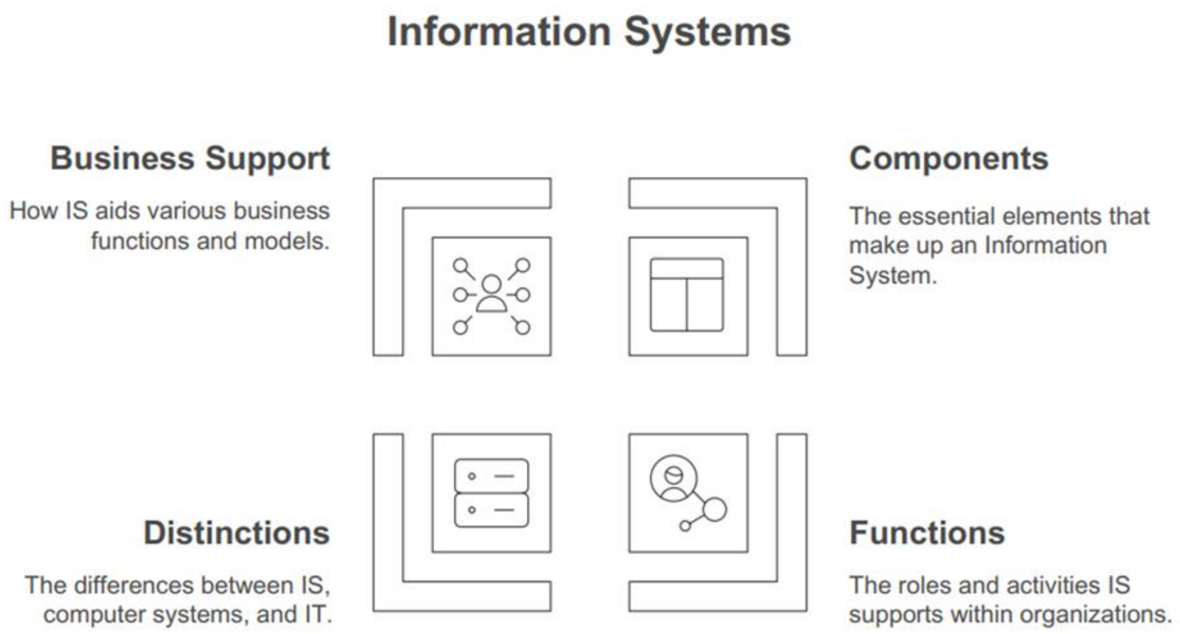

Figure 4. Information Systems (IS) [14]

2.2 Agricultural Information Systems (AIS)

The agricultural information system is defined as an organized structure through which agricultural information is created, organized, and transmitted in an integrated manner [11]. This system comprises several key elements that work synergistically to enhance agricultural producers utilization of knowledge. These elements include collecting agricultural data, converting it into valuable information, and standardizing it to ensure its effective circulation and use [12] (Figure 5).

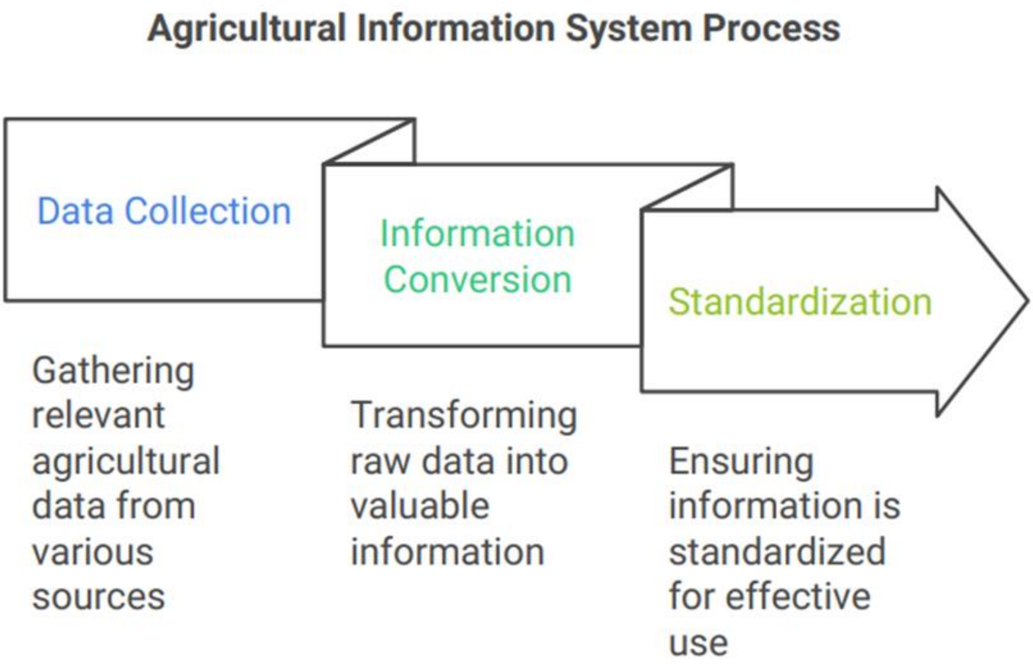

Figure 5. Agricultural Information System Process [12].

Agricultural information is regarded as one of the primary inputs for supporting agricultural education, research and development, and extension activities (Figure 6). The diverse use of this information necessitates addressing the varying needs of multiple user categories. These users include government decision-makers, agricultural policymakers, planners, researchers, teachers, students, program managers, field workers, and, most importantly, farmers [13].

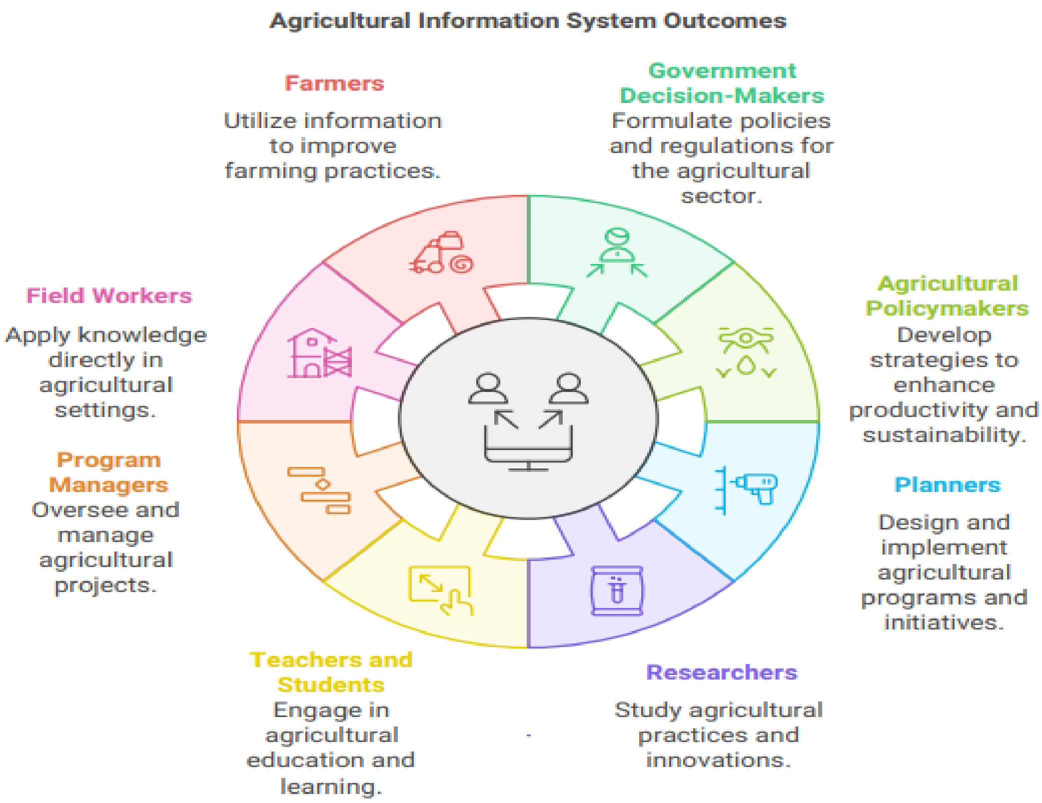

Figure 6. Agricultural Information System Outcomes [13].

2.3 Farm Management Information Systems (FMIS)

Farm Management Information Systems (FMIS) are meticulously designed systems that provide information and communication solutions aimed at collecting, processing, storing, and disseminating data in the required format to support farm operations and functions. These systems are available as desktop-based software or mobile applications and can be internet-connected, relying on cloud-based platforms. Data is gathered from various agricultural processes, such as operational, financial, and marketing activities, then organized, integrated, and processed to support farmers' management decisions. Commercial FMIS typically offer a range of key functionalities, including field operations management, adoption of best practices, financial and inventory management, product traceability, reporting, site-specific management, sales and purchases, machinery management, human resource management, quality assurance, and portfolio risk management (Figure 7). These systems enhance agricultural efficiency and empower farmers to make informed and sustainable decisions.[15]

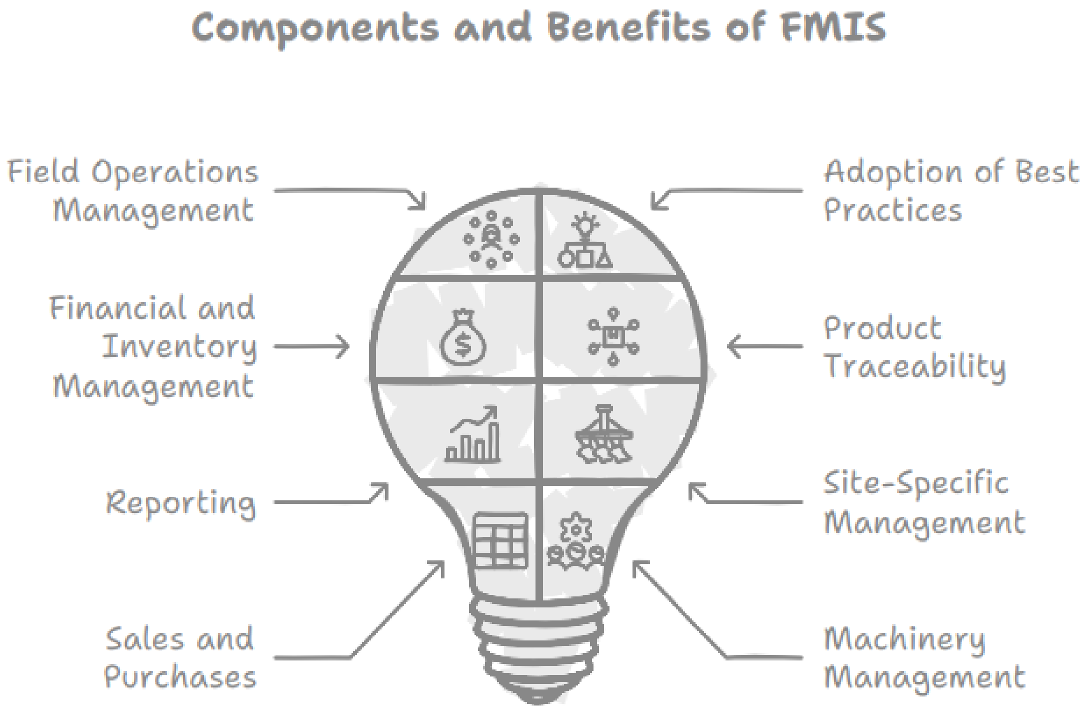

Figure 7. Components and Benefits of FMIS [15].

2.4 Internet of Things (IoT) in Agricultural Advancements

The Internet of Things (IoT) represents the new era of future information and communication technology, enabling a network of interconnected devices such as sensors, cameras, and electronic devices. These devices are programmed to work together within an independent monitoring and control network. Today, IoT has become an integral part of our daily lives, used to control devices such as televisions, air conditioners, refrigerators, washing machines, and electronic doors/locks. The IoT network relies on five key components: sensors or electronic devices, cloud servers, the internet, local area networks (LAN), and software applications. The process begins with IoT devices connecting through the LAN to transmit data to a cloud server, which then delivers the data to the software application via a two-way connection .IoT plays a significant role in advancing modern agricultural technologies by monitoring crops, enhancing yield production, and improving storage, transportation, and distribution methods. It helps reduce production costs, minimize resource and product waste, and maximize farm productivity (Figure 8). IoT is a high-tech, capital-intensive technology that enables farmers to produce sustainable food with high quality at lower costs. In agriculture, IoT supports farmers in various ways, most notably by helping them produce high-quality crops at reduced costs. Additionally, it enhances the storage, transportation, and timely distribution of agricultural products to consumers, lowering expenses and increasing profits.[16]

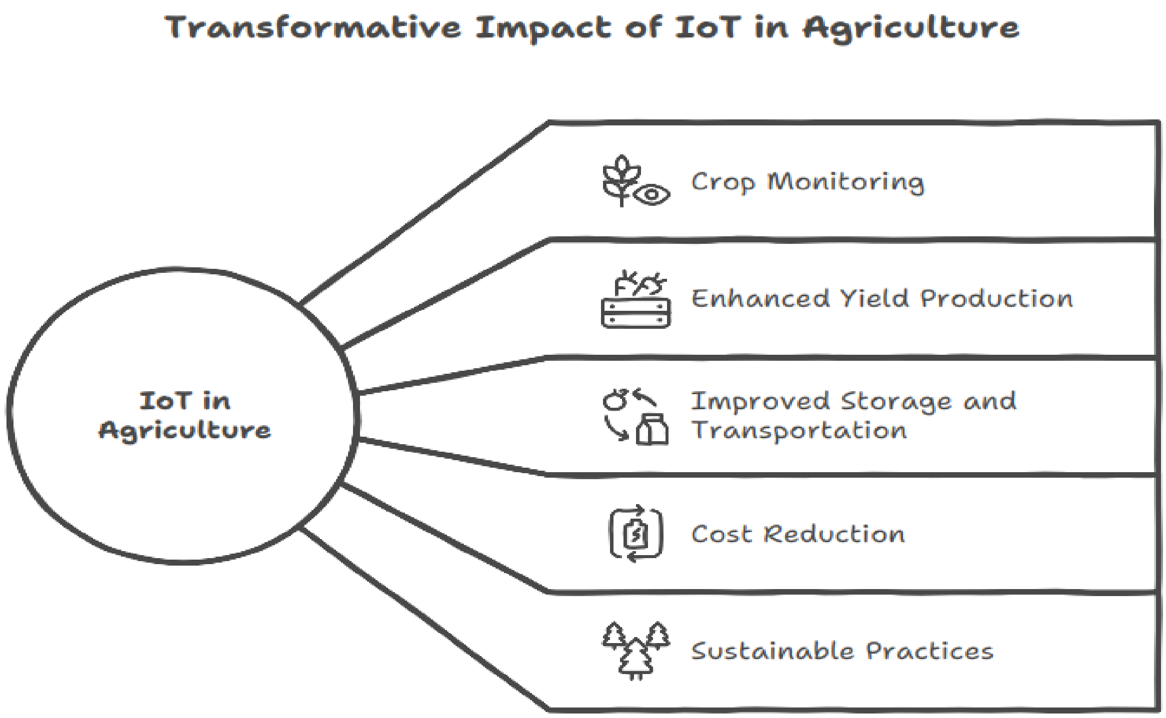

Figure 8. Transformative Impact of IoT in Agriculture [16].

2.5 Internet of Things Artificial intelligence in Agricultural Advancements

Artificial intelligence (AI) is a multidisciplinary field of study aimed at simulating human intelligence in robots, enabling them to mimic human cognition and behavior, including learning and problem-solving. AI technologies are now being utilized by researchers and agricultural extension specialists to address challenges in agricultural productivity. These technologies assist farmers in increasing yields by helping them select appropriate crop varieties, adopt improved soil and nutrient management practices, combat pests and diseases, estimate crop production, and predict commodity prices. AI relies on advanced techniques such as deep learning, robotics, the Internet of Things (IoT), image processing, artificial neural networks, wireless sensor networks (WSN), and machine learning to tackle complex agricultural challenges. These technologies enable farmers to monitor various aspects of their farms in real time, such as weather conditions, temperature, water usage, and soil conditions, empowering them to make well-informed, data-driven decisions. Furthermore, AI contributes to the development of smart agricultural practices that minimize farmers' losses while providing higher yields and promoting agricultural sustainability. [17,18,19,20]

3. Conceptual Framework of Agricultural Information Systems (AIS)

3.1 Objectives of Agricultural Information Systems (AIS)

The primary objectives of an agricultural information system are to meet farmers' needs for information and support, enhancing agricultural productivity and sustainability. Among these objectives is providing real-time agricultural advice, delivering accurate and tailored recommendations to farmers based on crop types, best practices, and local conditions. The system also aims to supply real-time market prices, enabling farmers to access precise information about the prices of their agricultural products and supporting them in making informed decisions regarding sales and fair price negotiations (Figure 9). Additionally, the system focuses on offering continuous weather information, including updates, forecasts, and warnings, to assist farmers in planning their agricultural activities and mitigating risks. Furthermore, it seeks to enhance farmers' knowledge and skills by providing educational resources, training programs, and instructional materials that improve their proficiency in adopting modern agricultural practices and technologies.[20]

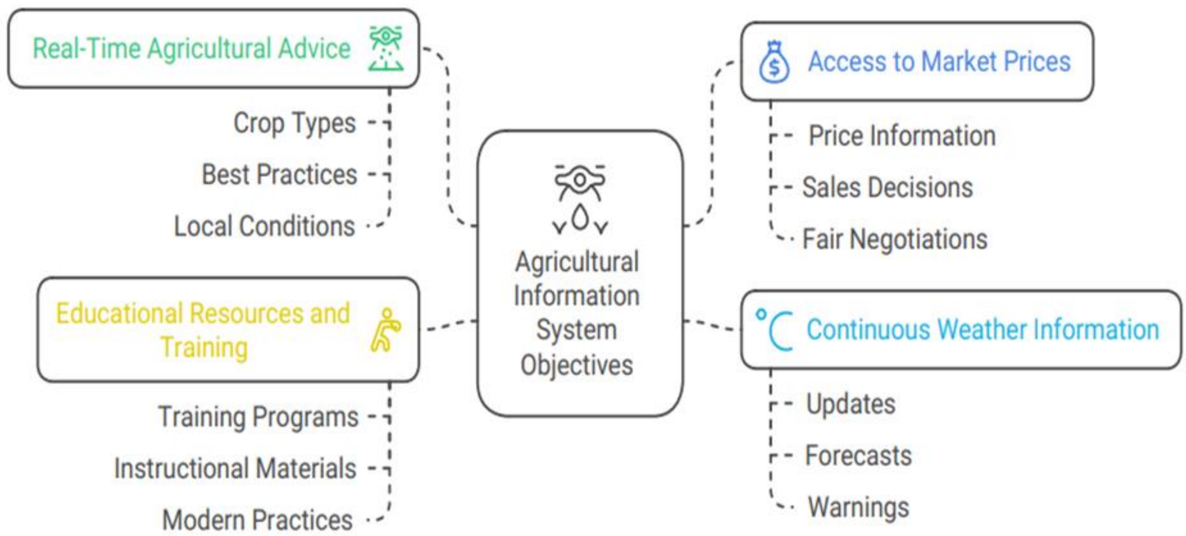

Figure 9. Agricultural Information System Objectives [20]

3.2 Key Advantages of Systems Analysis and Information in Agriculture

Systems analysis in agriculture offers key advantages that enhance productivity and sustainability. One of its primary benefits is improving decision-making processes, as comprehensive data access enables farmers to make informed, data-driven decisions, resulting in greater efficiency, reduced costs, and increased yields. Additionally, systems analysis helps identify inefficiencies by detecting bottlenecks and areas where resources are underutilized. This enables farmers to make precise adjustments and optimize their operations. Moreover, systems analysis contributes to sustainability and resource management by allowing farmers to minimize the use of inputs such as water and fertilizers, thereby reducing waste and ensuring the adoption of sustainable agricultural practices that preserve the environment while boosting operational efficiency.[22]

3.3 The Future of Advanced Information Systems Analysis in Agriculture

The future of Advanced Information Systems and analysis in agriculture holds great promise with the continuous evolution of technology and its integration into various tools. The potential applications of Advanced Information Systems and analysis in this field are vast, and they are expected to revolutionize agricultural practices (Figure 10). Below are some key trends:

1. **Big Data Analytics:** With the growing availability of agricultural data, farmers can leverage advanced analytics to gain deeper insights into their systems. This will enable data-driven decision-making and the continuous improvement of agricultural practices.
2. **Integration of the Internet of Things (IoT):** By incorporating IoT devices such as sensors and drones, farmers can collect real-time data on various aspects of their farms. Systems analysis will play a pivotal role in processing this data and extracting actionable insights.
3. **Artificial Intelligence and Machine Learning:** Machine learning algorithms and AI technologies help predict crop yields, manage risks, and optimize resource allocation. Systems analysis will underpin these technologies, enhancing precise and efficient decision-making.

Systems analysis significantly contributes to improving resource allocation, crop management, farm operations, and sustainability. Real-world examples, such as precision agriculture and irrigation management, demonstrate the practical benefits of these analyses. As technology continues to advance, the future of systems analysis looks bright, with big data analytics, IoT integration, and AI-driven tools set to bring about a transformative impact on agriculture.[22]

Future Trends:

1. **Artificial Intelligence:** AI-powered systems will analyze massive amounts of data, enabling automated agricultural decision-making, improving efficiency, and reducing costs.
2. **Precision Agriculture:** Systems analysis will remain a cornerstone of precision agriculture, enabling tailored practices for specific areas within fields to optimize resources and minimize environmental impact.

3. **Data Sharing:** Farmers, experts, and researchers will increasingly collaborate by sharing data, fostering the development of innovative solutions that enhance productivity and sustainability.

In conclusion, systems analysis has revolutionized farm management by enabling data-driven decision-making, improving operations, and promoting sustainability. With advancements in technology and agricultural sciences, the future holds immense potential for further progress in systems analysis. By adopting these technologies and analytical approaches, farmers can elevate agriculture to new heights, ensuring a more productive and sustainable industry.[22]

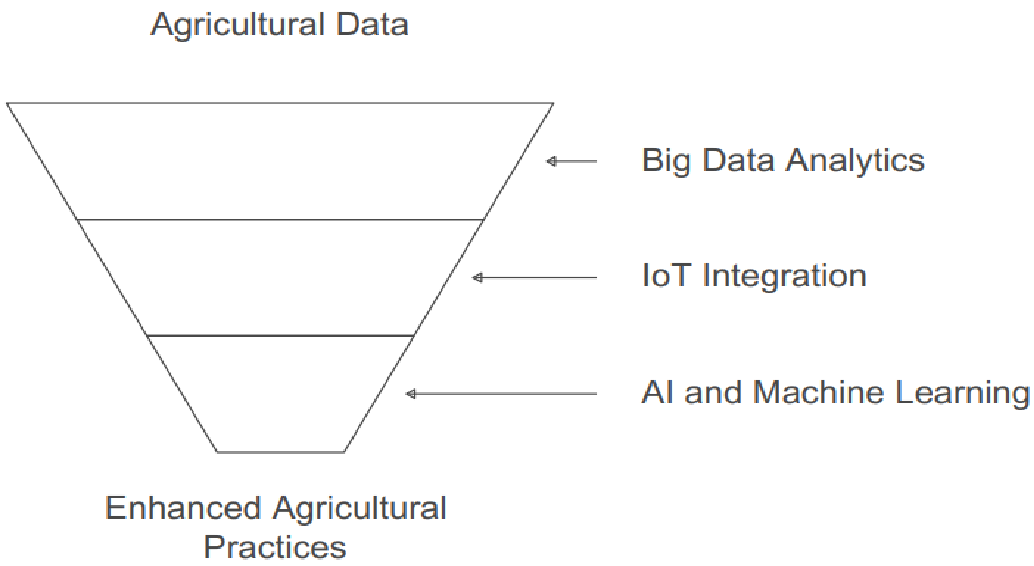

Figure 10. Transforming Agriculture with Technology Advanced Information Systems [22]

4. Conclusion of Agricultural Information Systems (AIS)

The agricultural information system is a vital tool for supporting the agricultural sector, enabling the efficient utilization of knowledge and resources to achieve sustainable productivity. By integrating technology and streamlined processes, this system enhances informed agricultural decision-making, addresses agricultural challenges, and paves the way for a smarter and more sustainable agricultural future.[1] This brings us to the review of related works in Chapter 2, where we explore advanced information systems in the field of smart agriculture, highlighting key studies and reviewing them to provide a comprehensive understanding of the field and its role in developing innovative and efficient agricultural solutions

Chapter 2:
Review of Research of Advanced Systems in Smart Agriculture

1. Introduction

Modern agriculture has witnessed significant advancements through the development of advanced information systems, with research focusing on improving productivity and resource management via technology. These efforts include the adoption of precision farming, the Internet of Things (IoT), and artificial intelligence (AI) to enhance operational efficiency and sustainability.

This chapter highlights key research contributions that developed tools like sensors, drones, and real-time monitoring systems to support decision-making. It also explores machine learning techniques that have enabled crop yield predictions and risk management in agriculture.

The chapter concludes with a brief comparison of the reviewed studies, emphasizing strengths, challenges, and potential areas for future development toward smarter and more sustainable agriculture.

2. Review of Works on Advanced Information Systems in Agriculture

- The Architecture of an Agricultural Data Aggregation and Conversion Model for Smart Farming:

In their work "The Architecture of an Agricultural Data Aggregation and Conversion Model for Smart Farming," Žuraulis and Pečeliūnas (2023) address the challenges caused by the lack of standardization in data extracted from various agricultural machinery, which often limits its effectiveness in unified analysis. The authors propose an innovative model for agricultural data aggregation and conversion (Figure 11), which integrates data from multiple sources with varying formats into a standardized structure. This model enables its practical use in smart farming solutions. Utilizing technologies like Python, PostGIS, and machine learning algorithms, the model processes and classifies the data efficiently. Additionally, it supports real-time, location-based data updates, thereby facilitating precision farming practices. The study concludes that this model improves efficiency, reduces waste, and contributes to more sustainable agricultural operations. [23]

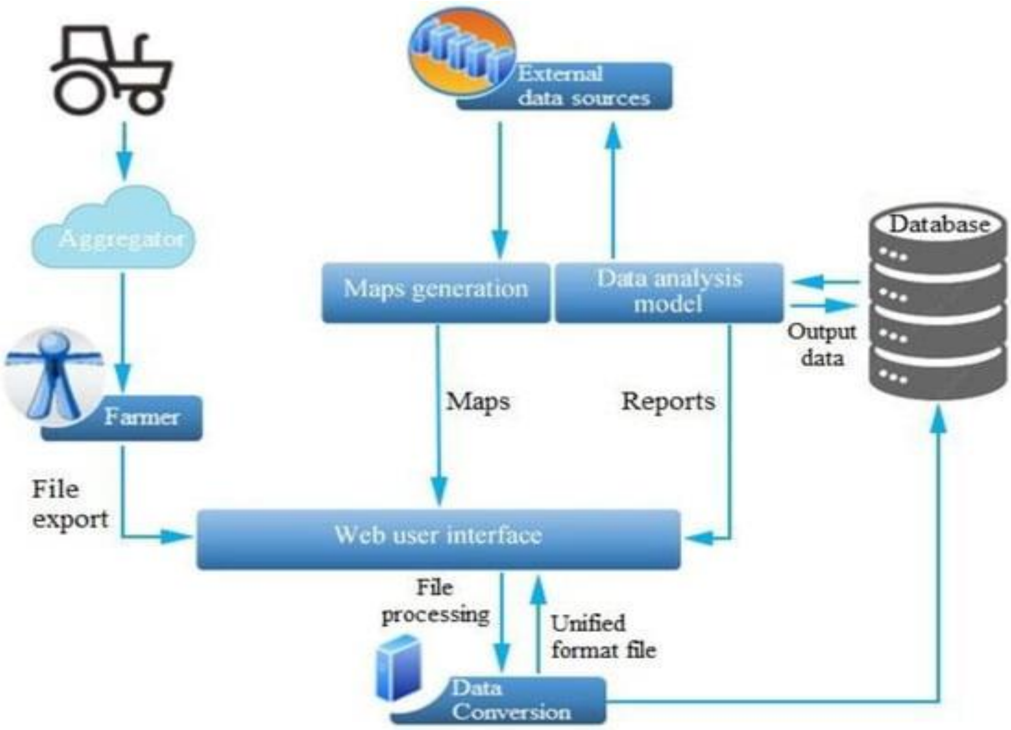

Figure 11. Agricultural data exchange scheme.[23]

- Reference architecture design for developing data management systems in smart farming:

In their paper "Reference Architecture Design for Developing Data Management Systems in Smart Farming", the authors address the limitations of traditional data management systems in handling the complexity, volume, and variety of data in agricultural operations. They propose a reference architecture tailored for smart farming data management systems, developed using domain analysis and architectural modeling approaches. This reference architecture provides a structured framework that highlights common and variable features across smart farming domains, enabling a more efficient design process. The study evaluated the proposed architecture through two case studies, demonstrating its practicality and effectiveness.

The architecture achieved a modular reuse rate of 82.6% across the case studies, underscoring its versatility. This research pioneers a focused approach to designing data management systems for smart farming by integrating domain-specific architectural insights. The findings suggest that the proposed reference architecture can serve as a blueprint for developing new systems in diverse agricultural domains, emphasizing data management and overall system design in smart farming.[24]

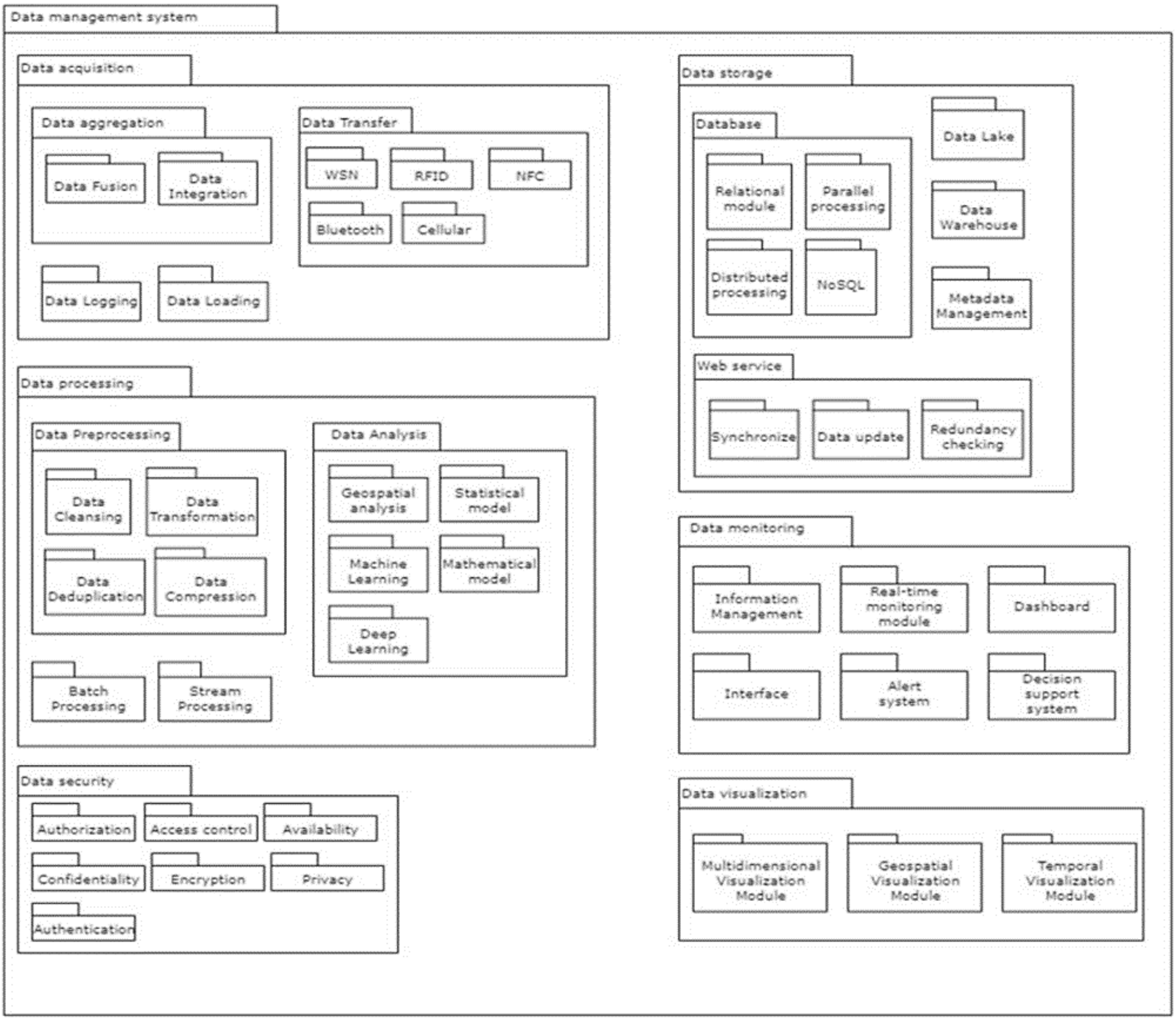

Figure 12. The reference decomposition view of smart farming data management.[24]

- Architecture Design Approach for IoT-Based Farm Management Information Systems:

In their paper "Architecture Design Approach for IoT-Based Farm Management Information Systems" Köksal, Ö., & Tekinerdogan, B. (2019) focusing on the integration of IoT technologies into Farm Management Information Systems (FMIS) to advance smart farming practices. The study highlights how FMIS automates critical processes like data acquisition, monitoring, planning, and decision-making, thereby enhancing farm operations. The authors propose a systematic architecture design approach to address the diverse functional and quality requirements of IoT-based FMIS, such as communication protocols, data processing, security, and performance. Using a feature-driven domain analysis, the research develops a reference architecture and reusable components tailored to the needs of different agricultural contexts. This methodology is demonstrated through case studies on smart wheat production in Konya and smart greenhouses in Antalya, Turkey. The approach is structured in two phases: domain engineering, which creates reusable artifacts like feature models and reference architectures, and application engineering, where specific FMIS implementations are built using these artifacts. The study underscores the efficiency of reusing domain-engineering outputs to optimize the development process, making IoT-based FMIS more adaptable and effective in supporting diverse farming scenarios.[25]

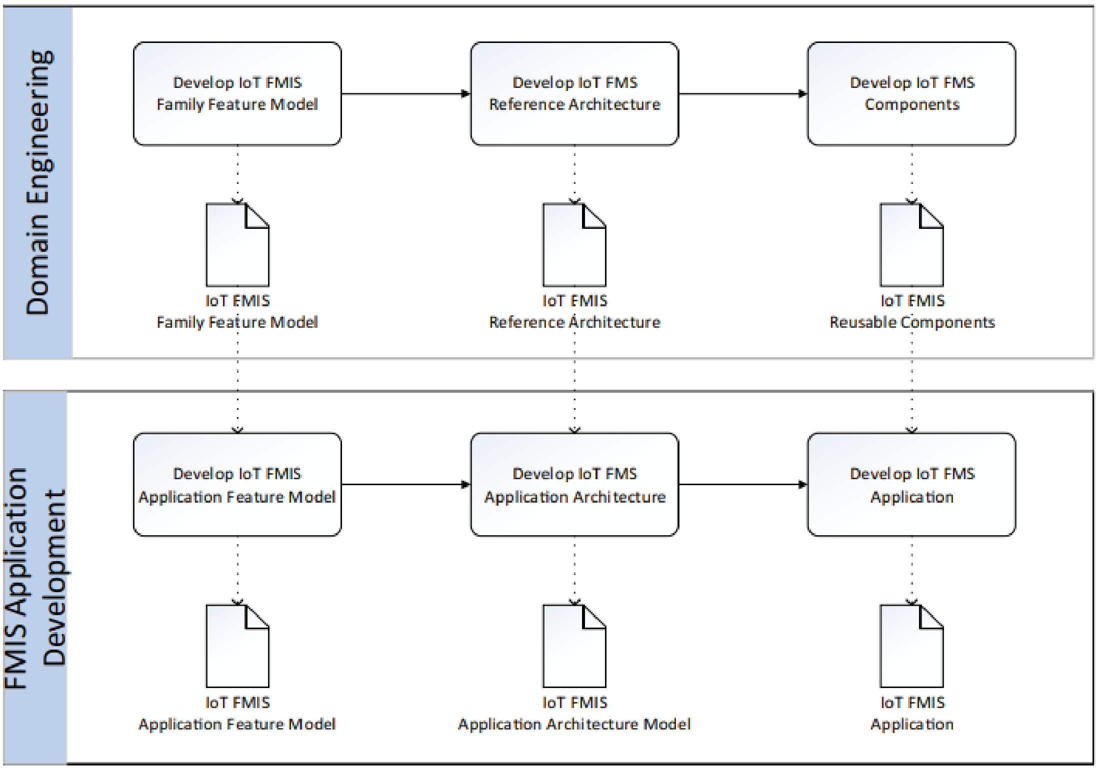

Figure 13. FMIS development approach [25].

- A Full Integrated System for Agroclimatic and Pest Monitoring at Farm and Landscape Scales in Campania Region:

Martino, R., Nicolazzo, M., & Langella, G. (2019), in their paper "A Full Integrated System for Agroclimatic and Pest Monitoring at Farm and Landscape Scales in Campania Region," explore the integration of Industry 4.0 principles, precision agriculture, and smart farming into agro-environmental management. They emphasize the need for solutions that implement Knowledge Management 4.0 methodologies within agricultural systems. The study proposes an ontology-based conceptual map that transforms raw data into actionable information, supporting the development of advanced Farm Information Systems (FIS).

The data-to-information cycle is divided into four phases: data collection, data processing, data analysis and evaluation, and information usage. The first and last phases involve "light digitization," typically reliant on Online Transaction Processing (OLTP) tools, whereas the intermediate phases involve "heavy digitization," requiring advanced Online Analytical Processing (OLAP) capabilities, often beyond the direct management scope of farmers. The conceptual map guides the modular design of FIS, starting with simpler OLTP components and gradually incorporating more complex OLAP functionalities.

This staged approach allows decision-makers to evaluate the sustainability of FIS implementations in terms of financial, cultural, and professional resources. The study also highlights the role of cloud computing and widespread connectivity in facilitating OLAP adoption, providing practical examples of application scenarios. This framework enables the creation of scalable and efficient agricultural information systems that meet diverse farming requirements.[26]

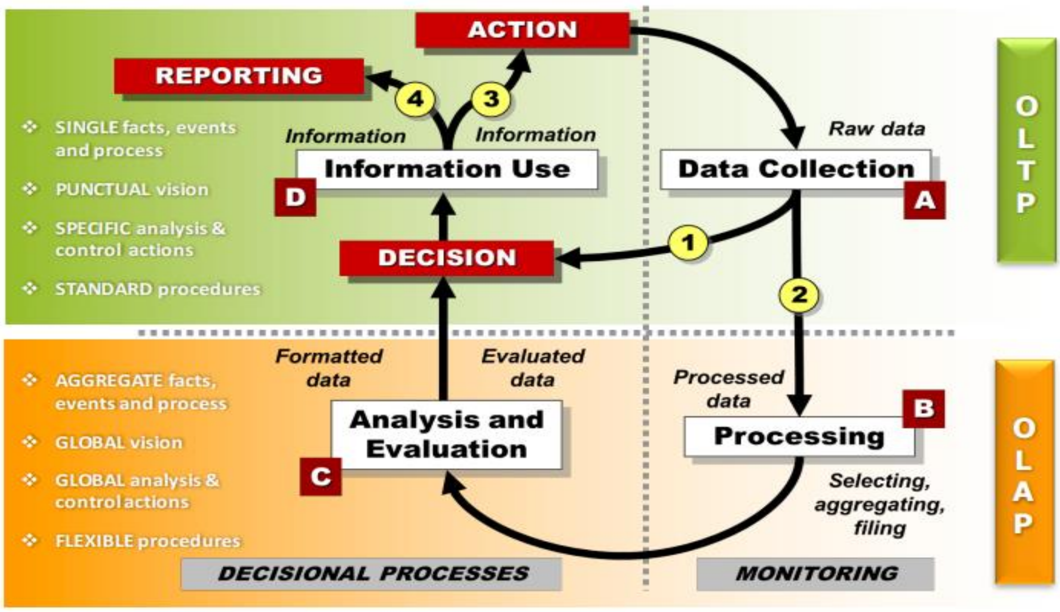

Figure 14. Data-Information Life Cycle: Integration of OLTP and OLAP Components.[26]

Intelligent Agriculture and Its Key Technologies Based on Internet of Things Architecture:

J. Chen and A. Yang (2019), in their paper "Intelligent Agriculture and Its Key Technologies Based on Internet of Things Architecture" present a framework for leveraging Internet of Things (IoT) technologies in modern agricultural production. The paper outlines the construction of a smart agricultural system utilizing IoT functionalities such as sensing, identification, transmission, monitoring, and feedback to optimize agricultural operations. By integrating data visualization and cluster analysis techniques, the authors identify key technologies essential for advancing intelligent agriculture.

The study highlights how IoT-driven smart agriculture can enhance production efficiency, improve crop yields, and ensure the quality of agricultural products. It underscores the role of IoT in automating and streamlining agricultural activities, which reduces time costs for farmers and promotes scientific and efficient farming practices. Additionally, the paper explores the potential of IoT technologies in aquaculture, emphasizing their significance in inductive recognition and intelligent operations. This research provides valuable insights into the adoption of IoT for developing smart, precise, and sustainable agricultural systems.[27]

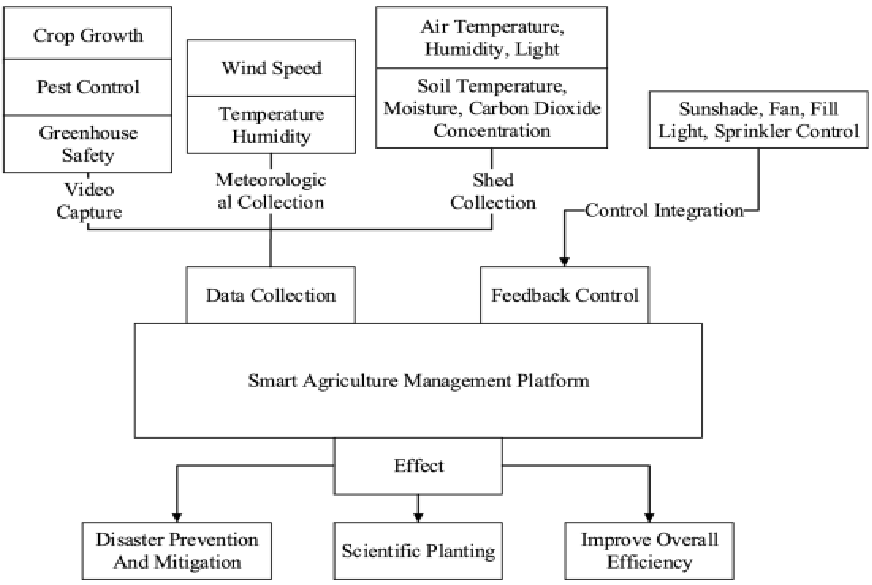

Figure 15. Intelligent agricultural management platform.[27]

- Design of a Data Management Reference Architecture for Sustainable Agriculture:

Giray, G., & Catal, C. (2021), in their paper "Design of a Data Management Reference Architecture for Sustainable Agriculture" published in Sustainability, address the critical role of efficient data management in smart and precision agriculture. The study highlights how diverse data collected through various sensors are stored in disparate systems and processed using advanced technologies like machine learning and deep learning to achieve operational efficiency, full automation, and high productivity. Given the complexities in data management processes, the authors propose a reference architecture tailored for sustainable agriculture.

This architecture was developed through a structured methodology encompassing domain scoping, domain modeling, and reference architecture design. Four case studies were conducted to validate its applicability, demonstrating that the proposed architecture is practical and effective for sustainable agricultural practices. The study is the first of its kind to focus on sustainability within the context of data management reference architectures, leveraging Design Science Research (DSR) methodology.

The findings suggest that this architecture can enhance sustainable agriculture research by providing a robust foundation for designing intelligent systems for smart and precision farming.[28]

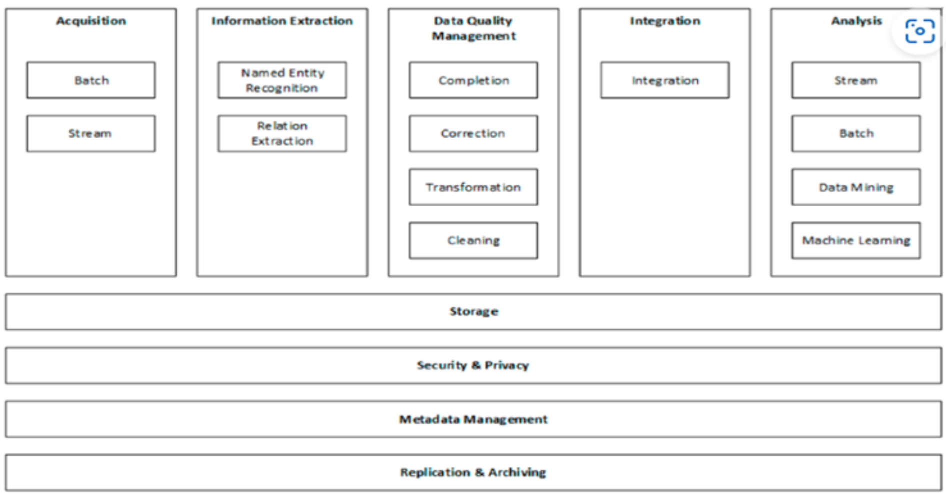

Figure 16. Decomposition view of the data management reference architecture.[28]

- A Farm Management Information System Using Future Internet Technologies :

Dimitris S. Paraforos and his colleagues (2016), in their study "A Farm Management Information System Using Future Internet Technologies" published in

IFAC-PapersOnLine, detail the development of a cloud-based Farm Management Information System (FMIS) named ifarma6, created by Agrostis Agricultural Information Systems. Designed for individual farmers and agricultural cooperatives, this system supports precision agriculture through the integration of modern mobile and digital technologies. The FMIS facilitates comprehensive management by organizing farm data hierarchically, encompassing fields, crops, agricultural tasks, and related inputs. It also includes tools for managing farm entities, assigning costs and efficiencies to resources like labor, machinery, and materials, and performing financial analyses based on recorded transactions. Successfully tested on winter wheat, ifarma6 demonstrated its ability to streamline operations by tracking all relevant costs and providing actionable insights. This innovative application exemplifies the transformative potential of future internet technologies in advancing precision agriculture and farm management practices.[29]

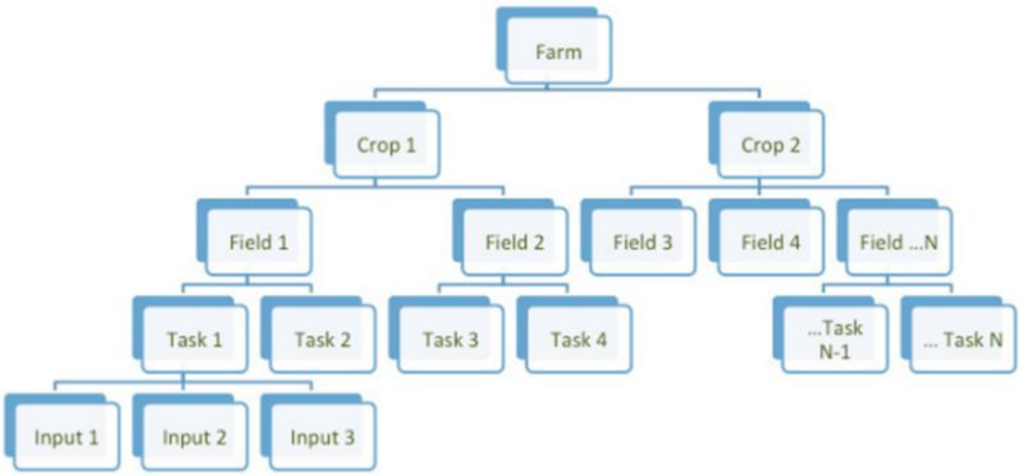

Figure 17. Farm entities model of ifarma.[29]

- Architecture framework of IoT-based food and farm systems: A multiple case study:

Cor Verdouw et al. (2019), in their study "Architecture Framework of IoT-based Food and Farm Systems: A Multiple Case Study" published in Computers and Electronics in Agriculture, explore the transformative potential of the Internet of Things (IoT) in the agriculture and food sectors. Recognizing the significant challenge posed by the diversity within these fields, the study introduces a comprehensive architectural framework for modeling IoT-based systems. The framework incorporates a coherent set of architectural viewpoints and guidelines to design system architectures specific to various IoT applications. It was validated through multiple case studies conducted as part of the European IoT 2020 project, encompassing different agricultural subsectors, farming methods (conventional and organic), adoption stages (early adopters and pioneers), and supply chain roles.

The framework organizes systems into four hierarchical layers (Figure 18). The Management Information Layer focuses on overarching processes for long-term control of entire enterprises (e.g., farms) with timeframes spanning months to days. The Operations Execution Layer deals with task definition, control, and execution over medium time horizons (days to minutes). The Production Control Layer addresses task implementation by equipment and personnel in short time intervals (minutes to milliseconds). Finally, the Physical Object Layer represents real-world entities, including IoT-enabled devices such as sensors, actuators, fields, stables, animals, plants, machinery, and logistics like trucks and containers.[30]

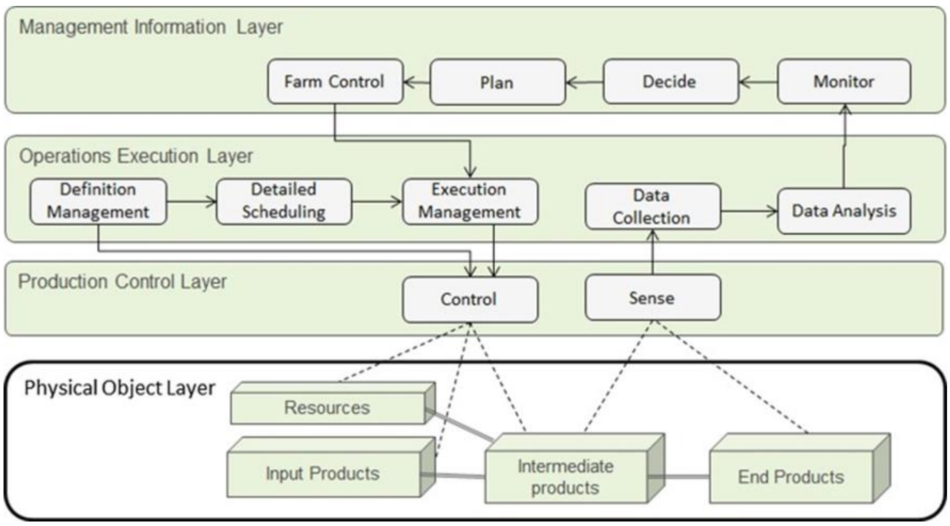

Figure 18. the four layers of the Business Process Hierarchy View.[30]

A smart farming system, designated AgriSys, has been put forward, which is capable of analyzing the agricultural environment and intervening to sustain its operational efficiency. This system tackles common farming challenges like temperature, humidity, pH levels, and nutrient support. Moreover, it addresses desert-specific problems including dust, infertile sandy soil, persistent winds, exceptionally low humidity, and notable diurnal and seasonal temperature variations. The principal aim of the system's interventions is to maintain the suitability of the agricultural environment, consequently reducing the complexity of the control unit [33].

Ms. Shraddha pioneered the concept of integrating crop growth models (CGMs) within an IoT application system. This system is engineered to gather real-time data based on current conditions, employing wireless technologies such as sensors and a Raspberry Pi device. The acquired data is subsequently relayed to cloud-based storage for later retrieval and analysis. Via a cloud-based application, recommendations and updates are delivered to the farmer through an Android mobile application, following successful system login and verification. The application can also detect diseases by capturing images of affected crops, which are then analyzed using image processing technology to pinpoint the specific malady [34].

An IoT-based smart agriculture monitoring system was established, deploying a variety of sensors on the farm, such as temperature sensors, humidity sensors, and PIR (Passive Infrared) sensors. Data gathered from these sensors is connected to a microcontroller via RS232. Incoming data is continuously monitored against predefined threshold values. If a data point surpasses its threshold, an alarm buzzer is triggered, and a corresponding valve begins to flash. This alarm notification is sent as a message to the farmer, and power to the implicated system is automatically cut off after sensing. The sensor readings are generated and shown on a web page, offering the farmer detailed descriptions of environmental parameters. In manual operation mode, the user can activate or deactivate the controller by interacting with a button on the developed Android application [35].

An IoT-Based Smart Farm Monitoring System was proposed, which integrates hardware components with programmable add-ons. The hardware segment comprises installed frameworks, and the Arduino IDE is the programming software used. The Arduino IDE shows readings from various integrated hardware sensors. The system utilizes specialized sensors for temperature and humidity, PIR detection, and soil moisture. Data collected by these sensors is processed by an Arduino Uno ATmega328 microcontroller. The gathered data can be displayed on an Arduino-compatible screen. A GSM module is integrated with the Arduino to enable communication with a media department, which furnishes updates to farmers every 10 seconds regarding the environmental conditions of their agricultural plots [36].

An architectural model for smart farming was put forward, which also considers a vital non-functional requirement: the constraint of energy consumption. Furthermore, the technologies integrated within the four layers of this architectural model—namely the sensor layer, network layer, service layer, and application layer—are examined. The discussion also covers the challenges faced by smart agriculture monitoring systems [37].

A smart agriculture management system has been actualized using several sensors (Temperature, LDR Sensor, Humidity, Moisture Sensor, Smoke Sensor) connected to a microcontroller that serves as a central node. Access to these sensors is provided through a web application developed with modern technology and the Python programming language. This design allows the user to efficiently manage and monitor agricultural parameters, leading to enhanced operational results [38].

The "Implementation of Wireless Sensor Network for Real-Time Monitoring of Agriculture" project outlines a smart farm monitoring system that utilizes sensors like wind speed and direction sensors for monitoring, along with an automatic control system for light, soil moisture, humidity, and soil temperature. These sensors are linked to an ATmega microcontroller. The gathered information is then sent to the farmer's phone as an SMS message via a GSM module connected to the microcontroller [39].

A Smart Agricultural System delivers information relevant to plant irrigation, thereby aiding in water conservation. This system employs a soil moisture sensor and a DHT11 sensor (for temperature and humidity), which are linked to the internal ports of a microcontroller. Upon detecting changes in ambient temperature or humidity, these sensors record the variations and send an interrupt signal to the microcontroller. Simultaneously, an alarm is activated if the water level at the station decreases. Data transmission to an Android device is facilitated using a Bluetooth module. The entire system is managed and implemented by an Arduino Uno Board (ATMEGA328) controller [40].

"Smart Precision based Agriculture using Sensors" describes an intelligent system engineered to establish an optimal environment for crop cultivation. Sensors identify soil moisture and ambient moisture levels, and this data is transmitted via a Zigbee network to a remote computer. The remote computer is then capable of controlling an on-site motor and humidifier fan [41].

"Internet of Things in Agriculture - A Decision Support System for Precision Farming" details the creation of a decision support system for precision agriculture that utilizes data from multiple sources to furnish critical information. Specifically, data obtained from a variety of sensors via LoRaWAN (Long Range Wide Area Network), in combination with weather data and crop-specific information, is integrated to support informed decisions, primarily aimed at optimizing water usage and safeguarding crops from unfavorable weather conditions [42].

In response to this, we previously proposed [72] a comprehensive reference framework for an advanced agricultural information system. This system is engineered to encompass the agricultural sector across its interconnected levels (public and private) and its various operational dimensions (Monitor, Prediction, Optimization, Control), all within a modern information technology structure grounded in the Internet of Things (IoT), artificial intelligence, and optimization technologies [73].

In 2018, researchers suggested the development of convolutional neural network models for plant disease detection and diagnosis, using simple leaf images of healthy and diseased plants via deep learning methodologies. Konstantinos P. Ferentinos et al. conducted model training with an open database of 87,848 images, covering 25 different plant species across 58 distinct 'plant, disease' group classifications, including healthy plants. They trained various model architectures, and the results indicated a 99.53% success rate in identifying a mixture of plant and disease or a healthy plant [74].

In 2021, Amreen Abbas et al. introduced a deep learning-based method for detecting tomato diseases. Their strategy involved using a Conditional Generative Adversarial Network (C-GAN) to produce structural images of tomato leaves, subsequently training a DenseNet121 model on both artificial and real images through transfer learning to classify tomato leaf images into ten different disease categories. The model underwent thorough training and testing on the publicly accessible PlantVillage dataset. The proposed method achieved notable accuracy rates of 99.51%, 98.65%, and 97.11% for classifying tomato leaf images into 5, 7, and 10 classes, respectively [71].

In 2020, Anjanadevi B et al. formulated an optimized and customized Deep Convolutional Neural Network (DCNN) model for plant disease classification. This model was trained using the PlantVillage dataset, primarily utilizing images of tomato, maize, and potato plants for training and testing. The dataset contained images of both healthy and diseased tomato leaves. The experimental outcomes of the proposed model were compared against other architectures, such as MobileNet and DarkNet-19 ResNet-

101. The proposed network was also trained on an object classification task for monitoring the operational condition of pin insulators, attaining an overall accuracy of 85.3% in these experiments [75].

In 2021, Abhishek Mohandas et al. introduced a system for detecting and identifying plant leaf diseases using object detection techniques in image processing. They employed the YOLOv4 framework, based on convolutional neural networks, for real-time object detection. Their work concentrated on various leaf diseases affecting vegetables and fruits such as tomato, mango, strawberry, bean, and potato, with a focus on real-time detection of these leaf diseases [76].

In 2021, Midhun P. Mathew et al. utilized the YOLOv5 algorithm to detect bacterial spots in sweet pepper plants using a deep learning approach. Their proposed method included collecting a dataset from Kaggle and annotating it with the LabelImg tool. Using this data, they trained a custom YOLOv5 model and subsequently tested it, achieving faster and more accurate results compared to earlier versions of the same algorithm.

In 2021, Mahnoor Khalid et al. suggested a method for detecting healthy and unhealthy money plant leaves using deep learning. This method involved creating a dataset of thousands of images of money plant leaves, categorized as either healthy or unhealthy. These images were gathered in a controlled environment, and a public dataset with precise dimensions was used. A deep learning model was trained to identify healthy and unhealthy leaves. Subsequently, a YOLOv5 model was trained to detect the smallest disease spots on both the exclusive and general datasets. The search conducted using YOLOv5 successfully identified diseased spots accurately and quickly, achieving an accuracy of up to 93% on the test set [77].

These works present diverse architectural and technological frameworks aimed at developing agricultural information systems. These studies focus on leveraging the Internet of Things, machine learning, cloud computing, and domain-specific methodologies to address challenges in smart agriculture, sustainable agriculture, and precision agriculture. Despite their common goal of enhancing efficiency and sustainability in agriculture, they exhibit differences in their approaches, validation technique, and technology adoption. This comparison identifies key similarities and differences across the works, providing insights into their contributions, focus areas, and implementation strategies.

The studies represent diverse efforts to develop advanced agricultural information systems, focusing on utilizing modern technologies such as the Internet of Things (IoT), machine learning, and cloud computing to enhance smart and sustainable agriculture. While sharing common general objectives, the approaches vary; some studies emphasized sustainable data management (e.g., Giray & Catal's study), while others focused on integrating IoT into farm management systems (e.g., Köksal & Tekinerdogan's study). Most research utilized case studies to validate the proposed frameworks and adopted different architectural models, such as layered structures. The comparison highlights the similarities and differences among these works, contributing to a comprehensive understanding of modern agricultural systems development trends.

The comparison is summarized in the table below (Table1):

Table 1: Comparative Summary of These works present

Study	**Focus Area**	**Technologies Used**	**Validation**	**Architectural Approach**
Žuraulis & Pečeliūnas	Data Standardization	Python, PostGIS, Machine Learning	Conceptual/Modeling	Data Aggregation Model
Giray & Catal	Sustainable Agriculture	Machine Learning, Deep Learning	Case Studies (4)	Reference Architecture
Köksal & Tekinerdogan	IoT-based FMIS	IoT, Feature-Driven Domain Analysis	Case Studies (2)	Domain-Driven, Two-Phase Design
Martino et al.	Agroclimatic Monitoring	OLTP/OLAP, Cloud Computing	Conceptual Framework	Knowledge Management 4.0
J. Chen & A. Yang	IoT in Agriculture	IoT, Data Visualization, Cluster Analysis	Conceptual Framework	IoT-Driven Smart Agriculture
Dimitris et al.	Farm Management System	IoT, Cloud Computing	Practical (ifarma6)	Hierarchical Farm Entities Model
Cor Verdouw et al.	IoT Food Systems	IoT, Architectural Viewpoints	Case Studies (IoT 2020)	Four-Layer Hierarchical Framework

Chapter 3:
Towards an organizational approach for an advanced agricultural information system (AAIS)

1. Introduction

The Internet of Things (IoT) holds a transformative potential to reshape numerous aspects of contemporary life, ushering in enhanced efficiencies across a multitude of sectors, from interconnected transportation and intelligent urban landscapes to the wide array of components integral to the IoT paradigm. However, it is within the agricultural domain that technologies like IoT can arguably exert their most profound influence. Precision agriculture, notably, has emerged as a significant IoT application area within farming [31]. The agricultural sector itself has undergone substantial evolutions, increasingly integrating diverse machinery to boost crop production. The diligent and comprehensive monitoring of field conditions, which encompasses environmental variables and soil attributes, along with crop vitality, are indispensable factors for securing yields of superior quality. Recent years have witnessed remarkable technological strides in agriculture, leading to augmented productivity and improved crop resilience [32]. As a beneficial consequence, these advancements also contribute to enhancing the quality of life for agricultural laborers by reducing physically demanding work and alleviating monotonous tasks.

Intelligent, interconnected components are unlocking exponentially greater opportunities and capabilities, far surpassing and redefining the limitations of conventional products. These sophisticated, connected products are distinguished by three core elements:

- **Physical Components:** These refer to the mechanical and electrical constituents of a product. For example, in a vehicle, this would encompass the engine block, tires, and batteries.
- **Smart Components:** This classification includes sensors, microprocessors, data storage devices, control systems, software, and, typically, an embedded operating system paired with an enriched user interface.
- **Connectivity Components:** This entails ports, antennas, and communication protocols that enable wired or wireless connections with the product.

Motives

Governmental strategic roadmaps are increasingly prioritizing the deployment of a wide range of resources and technologies to fortify the agricultural sphere. This focus is driven by agriculture's critical role in enhancing national food security, diversifying the national economy to lessen dependence on petroleum-derived revenue, and correcting trade deficit imbalances. Specifically concerning the agricultural sector, the Algerian government is actively working to encourage agricultural investment and foster agro-industrial development through the adoption of cutting-edge technologies, with a particular emphasis on digitalization and the Internet of Things.

The strategic blueprint primarily concentrates on removing bureaucratic obstacles that hinder economic activity. This objective is set to be realized through the creation of an advanced information system, designed to operate as a "one-stop shop" and guarantee transparency across all transactions. Concurrently, the government is committed to modernizing the sector by improving its information and statistical systems.

Consequently, dedicated initiatives by the nation's higher authorities (Algeria) have been aimed at strengthening the developmental underpinnings of the agricultural sector. This has spurred the enforcement of the agricultural guidance law of 2008. Reaffirming the strategic importance of agriculture, the government emphasizes that “agriculture must evolve into a veritable engine of comprehensive economic growth through production intensification, encompassing strategic agro-food divisions, and by fostering the integrated development of all rural territories.”

The Algerian government's strategic vision has solidified around the necessity of formulating robust agricultural policies designed to reduce vulnerabilities and promote the establishment of sound, rational governance within agriculture and rural areas. This requires the proactive engagement and empowerment of all stakeholders, encompassing both public and private entities. This policy direction was primarily actualized through a thorough reassessment of the support system, based on the principles outlined below:

1. Redirecting support towards agricultural production disciplines of strategic importance, in line with their significance in the local dietary framework (e.g., cereals, pulses, milk, meat).

2. Channeling support towards collection networks and supply chains that serve a variety of agricultural products (e.g., cereals, milk, potatoes, industrial tomatoes, seeds, and seedlings).

3. Giving precedence to the conservation and advancement of the seed and seedling sector for both animal and plant production.

4. Establishing clear objectives for supporting agricultural investments, complete with robust monitoring and follow-up mechanisms managed by the agricultural administration.

5. Securing and stabilizing farmers' incomes while protecting consumer interests through the endorsement of control measures (such as storage grants and intervention reference prices) for crops with a wide consumer base (e.g., cereals, milk, potatoes, meat, onions).

6. Executing interventions in rural areas that are cohesive and tailored to the specific characteristics of agro-ecological zones (e.g., desertification control, watershed management).

7. Fulfilling the support and accompaniment requirements of small-scale farmers and livestock breeders via dedicated rural renewal programs.

The enhancement of intervention tools and support strategies for agricultural and rural development aims to:

- Foster a supportive and secure operational climate for farmers and active participants in the agro-food industries, coupled with the establishment of a suitable support policy.

- Formulate and strengthen control mechanisms and procedural guidelines.

- Boost the capacities of public institutions, bureaus, and agricultural cooperatives to effectively engage in the execution of development programs and control procedures.

The problématic

A significant body of studies, research initiatives, and projects has explored various dimensions of smart agriculture. Nevertheless, these have largely represented partial efforts, failing to adopt a comprehensive view of the agricultural sector that includes its public and private facets and its entire operational lifecycle. This situation leads to the following questions:

- Why is there a discernible lack of a holistic reference framework for the creation of an advanced agricultural information system, one that could act as a fundamental reference and guide for all initiatives in this area?
- What are the clearly defined goals of such a referential framework?
- What are the specific levels of the intended information system required for the thorough management of the agricultural sector?
- What constitutes the most suitable methodology for developing an advanced information system capable of effectively managing smart agriculture?

Contributions

This chapter enriches the current research landscape by proposing an integrated approach for the creation of an advanced agricultural information system, specifically engineered for the holistic management of the agricultural sector. This approach is organized around the following key axes:

Objectives of AAIS:

- Prediction and Optimization
- Monitoring, control, and decision support.

Levels of AAIS:

- State level (Public): Involving governmental and regulatory oversight.
- Executive level (Farmers): Concentrating on operational management at the farm scale.

The periods of the agricultural season:

- Pre-season: The preparatory stage preceding cultivation.
- The growing season: The phase of active crop development.

- Post-season: Activities that follow the harvest.

Methodology for AAIS:

- Activities vision: Defining the scope of agricultural operations.
- Functional vision: Specifying system functionalities.
- Application vision: Outlining software and tool requirements.
- Technical vision: Detailing the underlying technological infrastructure.

The subsequent sections will delve into these aspects in greater detail. Initially, significant works in this domain will be examined, followed by a comparative analysis. Thereafter, the proposed approach and its constituent elements will be thoroughly presented. Subsequently, the design and applied engineering framework suggested for managing the agricultural sector will be explored, culminating in a concluding summary.

Contribution of the Proposed Approach

Our contribution to the design of an advanced agricultural information system for agriculture is anchored in the proposal of a comprehensive framework designed to tackle the multifaceted challenges inherent in the agricultural sector. This proposed framework encompasses diverse operational layers of the agricultural landscape, taking into account both the public sector at the state level and individual farmers at the executive tier. By harnessing contemporary information technology principles, with a pronounced emphasis on the Internet of Things (IoT), our research strives to facilitate seamless integration across the varied dimensions of smart agriculture. The framework also delves into the temporal aspects of the agricultural season, classifying it into pre-season, growing season, and post-season periods. To steer the implementation of the advanced agricultural information system (AAIS), we outline a structured methodology that integrates an activities vision, a functional vision, an application vision, and a technical vision. Through these contributions, our goal is to enhance the effectiveness and sustainability of smart agricultural practices, thereby tackling critical issues prevalent in this field.

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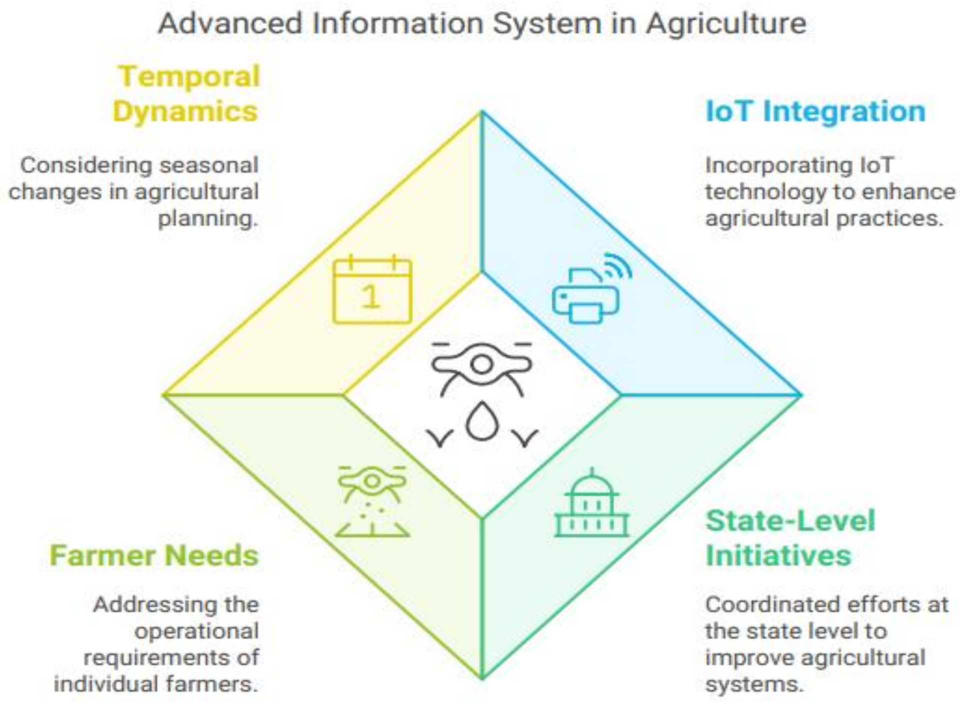

Figure 19. Advanced agricultural information system (AAIS)

2. The proposed approach

It is timely to reassess all interventions within the sphere of smart agricultural production, where information plays a crucial role in the precise and intelligent management of diverse agricultural activities. In this framework, responsibilities, and consequently the flow of information, frequently overlap between public and private sectors. As noted from our review of previous works, current solutions are often fragmented, partial initiatives that do not conform to an effective, all-encompassing reference approach. The application of such partial works typically leads to disjointed or heterogeneous benefits from different applications, thereby reducing the overall effectiveness of these efforts. Consequently, this section will introduce a comprehensive reference approach for an advanced information system specifically designed for smart agriculture, structured as detailed below:

We put forward a methodology for the creation of an advanced agricultural information system (AAIS) that is built upon the following fundamental principles:

Objectives of AAIS:

- **Prediction and Optimization:** Prediction entails forecasting future events based on established rules or reasoning. This definition inherently connects forecasting with future occurrences. Essentially, forecasting seeks to estimate events after a specific time 't', by utilizing knowledge and observations gathered before that instant 't'. From a methodological perspective, the forecast will depend on a model that encapsulates, as precisely as possible, the system's knowledge and the relationships between observations (measurements) and the variables to be predicted. Prediction in this framework centers on analyzing data (e.g., temperature, air and soil hygrometry) and images captured and stored in databases to derive essential information, facilitating an anticipated and accurate response. Optimization in the agricultural context refers to minimizing resource usage while maximizing profitability, a principle applicable at both public (state-managed) agricultural project levels and private farmer levels. In agricultural systems, managing crop growth is a vital factor. Historically, this often relied on a farmer's experiential knowledge, intuition, and forecasting skills, honed through trial and error. Precision farming, therefore, strives for maximum efficiency, requiring a more stable and dependable system for monitoring and controlling the agricultural process. Prediction introduces a novel machine learning paradigm that has attracted considerable interest from researchers in smart agriculture. It involves the forecasting of parameters used in agricultural optimization problems. Subsequently, the optimizer devises an optimal decision for the agricultural activity based on these predicted values.

- **Monitoring and Control:** Intelligent agricultural monitoring and control systems amalgamate data, sophisticated analytical models, and data analysis tools, all sourced from diverse monitoring and sensor devices. These systems are engineered to support both routine and non-routine decision-making. They also aid supervisors of agricultural activities, at both public and private echelons, in making prompt and decisive judgments, which are often difficult to determine prospectively. While these systems draw upon internal information from process management systems and local information repositories, they also integrate data from external sources, such as climatic and environmental information.

Levels of AAIS:

The effective implementation of a smart agricultural process, across its various stages, is not a solitary undertaking. From an informatics viewpoint, it entails a collection of information sourced from multiple origins, distributed and managed within a cohesive vision and a well-articulated agricultural strategy. This strategy must be harmonized and balanced within a broader vision focused on achieving food security and agricultural self-sufficiency. This can only be accomplished by considering both public and private sector participation in managing the agricultural process through a comprehensive information system.

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- **State level (Public):** At this tier, the agricultural sector is managed by the state or the relevant ministry (public sector). The aim is to define a general agricultural program consistent with national food security and self-sufficiency objectives, and to ensure a balance in product supply to satisfy market demands. This also includes harnessing and managing natural resources relevant to agriculture, such as dams, wells, and water resources, in addition to monitoring and providing climatic and environmental data.
- **Executive level (farmers):** At the individual scale, managing the local agricultural process for a farmer (agricultural establishment, peasant) means adapting operations to local conditions and aiming for specific objectives geared towards private profitability, all within the scope of the state's comprehensive agricultural plan.

The periods of the agricultural season:

The agricultural season represents a segment of the year defined by particular weather patterns, environmental conditions, and daylight duration. It is directly correlated with the climatic and environmental conditions of a specific agricultural region, thus differing from one region and country to another (Figure 20). The growing season is that portion of the year when local conditions (such as rainfall, temperature, and daylight) allow for normal plant growth. Each plant or crop has a distinct growing season, dependent on its genetic adaptation. Therefore, in this proposed framework, we recommend considering three distinct stages in agricultural season management.

These stages vary from an informatics perspective regarding their objectives, utilized techniques, and tools (Table 2), and are defined as follows:

- Pre-season
- The growing season
- Post-season

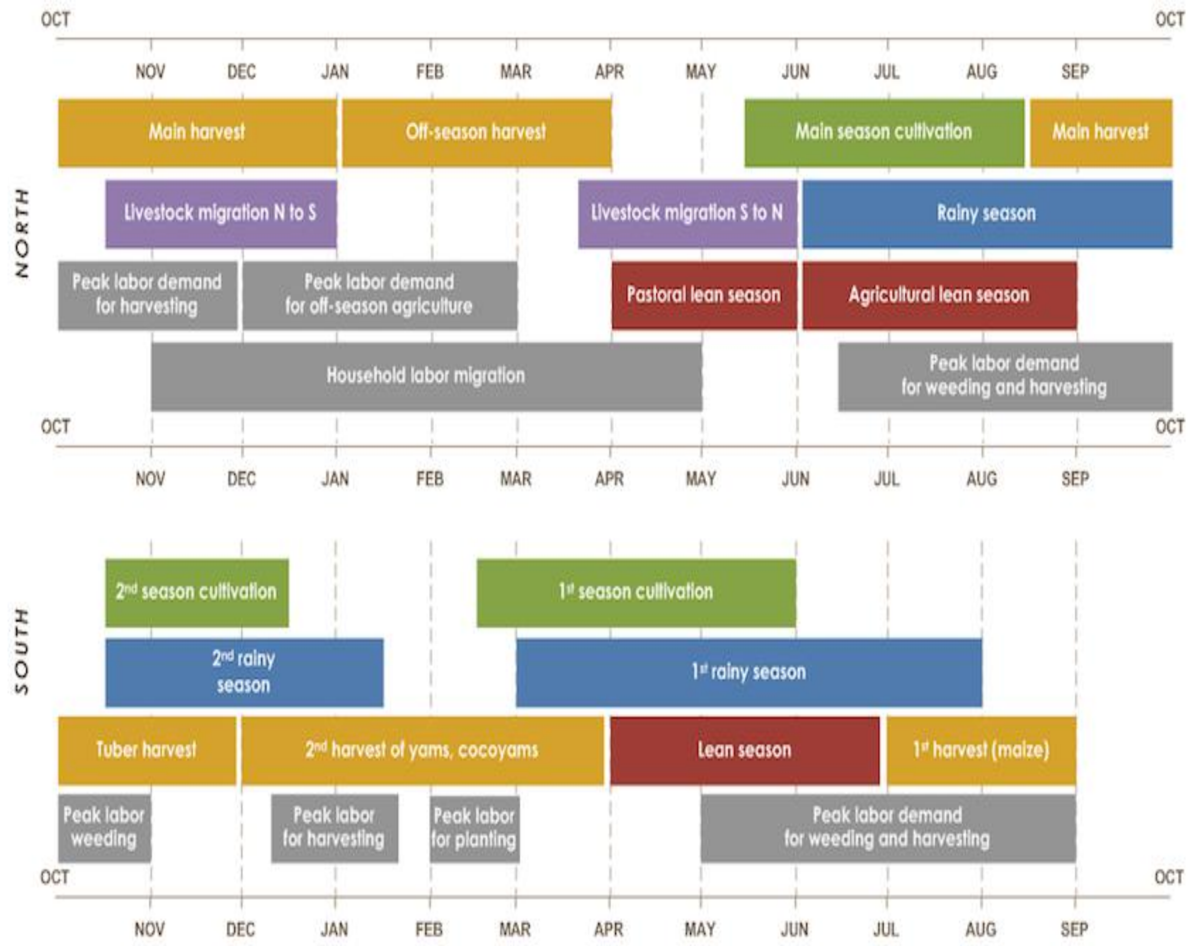

Figure 20: Seasonal Calendar (2020) – Africa

Methodology for AAIS:

The methodology for crafting an advanced agricultural information system must carefully articulate the following four visions:

- **Activities Vision:** This outlines the processes and activities that the AAIS must facilitate for smart agriculture, viewed from a purely agricultural executive standpoint.

- **Functional Vision:** This specifies the functions the AAIS needs to perform to support smart agriculture processes, derived by transforming the activities identified in the previous stage into informational functions.
- **Application Vision:** This details all the application components of the AAIS designed for smart agriculture, based on the established informational functions.

  Technical Vision: This describes the technical architecture (including hardware, foundational software, and employed technologies) that forms the basis for integrating infrastructure and IoT tools for smart agriculture

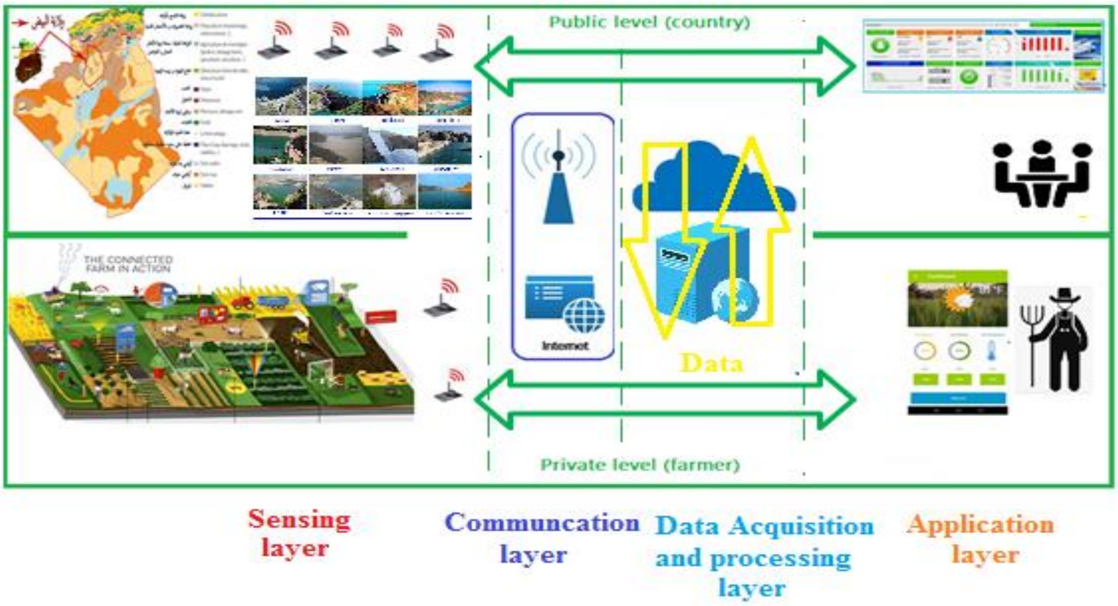

Figure 21: Technical vision describing the technical architecture.

Furthermore, the data flow is organized into four distinct forms, which can be described as:

- **Sensing Layer:** LPWA (Low Power Wide Area) technologies are exceptionally well-suited for IoT connectivity in scenarios with resource constraints, such as Smart Farming and Connected Agriculture.
- **Communication Layer:** IoT Gateways establish vital connections between various connectivity paradigms (e.g., ISM & Cellular networks).
- **Data Acquisition and Processing Layer:** Within this logical tier, software-based information processing is carried out, guided by a functional vision for the

intelligent management of agricultural operations. This processing takes place in storage and processing media on servers and in cloud computing environments.

- **Application Layer:** Following the selection of the communication mechanism and the design of control nodes, the development of control applications that interface with these nodes to manage equipment and sensors proceeds. In our proposed solution, we have utilized two types of control applications: a web application and a mobile application. The interface of the Web Client application features gauges for real-time display of measurements, graphs for showing historical measurement data, and interfaces for managing electrical outputs and organizing measurements and various activities.

The second type of control application is a mobile application offering remote control functionalities via GSM technology. The mobile application facilitates remote control operations, alert configuration, and real-time notification reception. Its interface is structured with fragments, where each fragment is represented by a class (view) and another class (controller). This design supports Responsive Design, enabling fragments to be reconfigured based on the screen's orientation and size.

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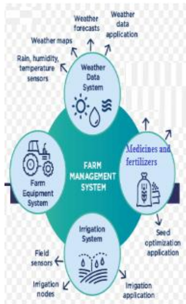
Table 2: The Proposed approach: levels, stages, objectives and tools

Levels	Objectives	Pre- season		Growing season		Post- season	
		Prediction and optimization	**Decisions**	**Monitoring and Control**	**Decisions**	**Monitoring and Evaluation**	**Decisions**
Public Level	-Alimentary security - Agricultural and Alimentary balance. - Economic profit	-State of environmental conditions -State of resource availability -State of markets and prices	The agricultural map and plans (List of agricultural crops, areas, quantities, ...)	Monotoring of : -State of environmental conditions -State of resource availability -Agricultural situation Control of : -Public agriculture -Public resources (dams, wells....)	-Rectification of the map and the Agricultural Plans. - Risk management. - Farm management: Disease prevention Treatment of diseases Watering Ventilation Lighting Fertilizers Operations on plantations.	-Evaluate the quantity and quality of the products -Expense évaluation	-Commercialization -Fabrication -Stockage
Private Level	-Economic profit.	-State of environmental conditions -State of resource availability -State of markets and prices	The agricultural map and plans (List of agricultural crops, areas, quantities, ...)	Monotoring of : -State of environmental conditions -State of resource availability -Agricultural situation Control of : -Local agriculture -Local resources.	- Farm management: Disease prevention Treatment of diseases Watering Ventilation Lighting Fertilizers Operations on plantations.	-Evaluate the quantity and quality of the products -Expense évaluation	-Commercialization -Stockage
Techniques and Tools	- Internet of things - Artificial intelligence - Expert systems -Data bases - Algorithm and optimization techniques						

System Architecture

This section details the overall architecture of our integrated system, which consists of the following two primary modules:

1. **An IoT Infrastructure:** The IoT infrastructure is composed of the following elements:
    - A sensor array (e.g., soil moisture, climatic humidity, temperature, wind speed, light intensity) and related equipment, networked together.
    - A collection of APIs distributed across smart devices and the control application (web and mobile), which expose the functionalities inherent to these smart objects.
    - Communication protocols that enable the coordination of diverse communication pathways between smart devices and applications.
2. **A Decision Support System Hosted on a Server, Utilizing Collected Data:** The decision-making system includes the following components:
    - Multiple interconnected farms (each utilizing IoT infrastructure).
    - A central server that stores data aggregated from the various farms. This data is initially kept in a dedicated storage unit for each farm before being sent to the server.
    - Data analysis and processing techniques designed to extract relevant information from the diverse datasets collected and stored on the server.

The system architecture is illustrated in the subsequent diagram, followed by a thorough description of all components within this architecture.

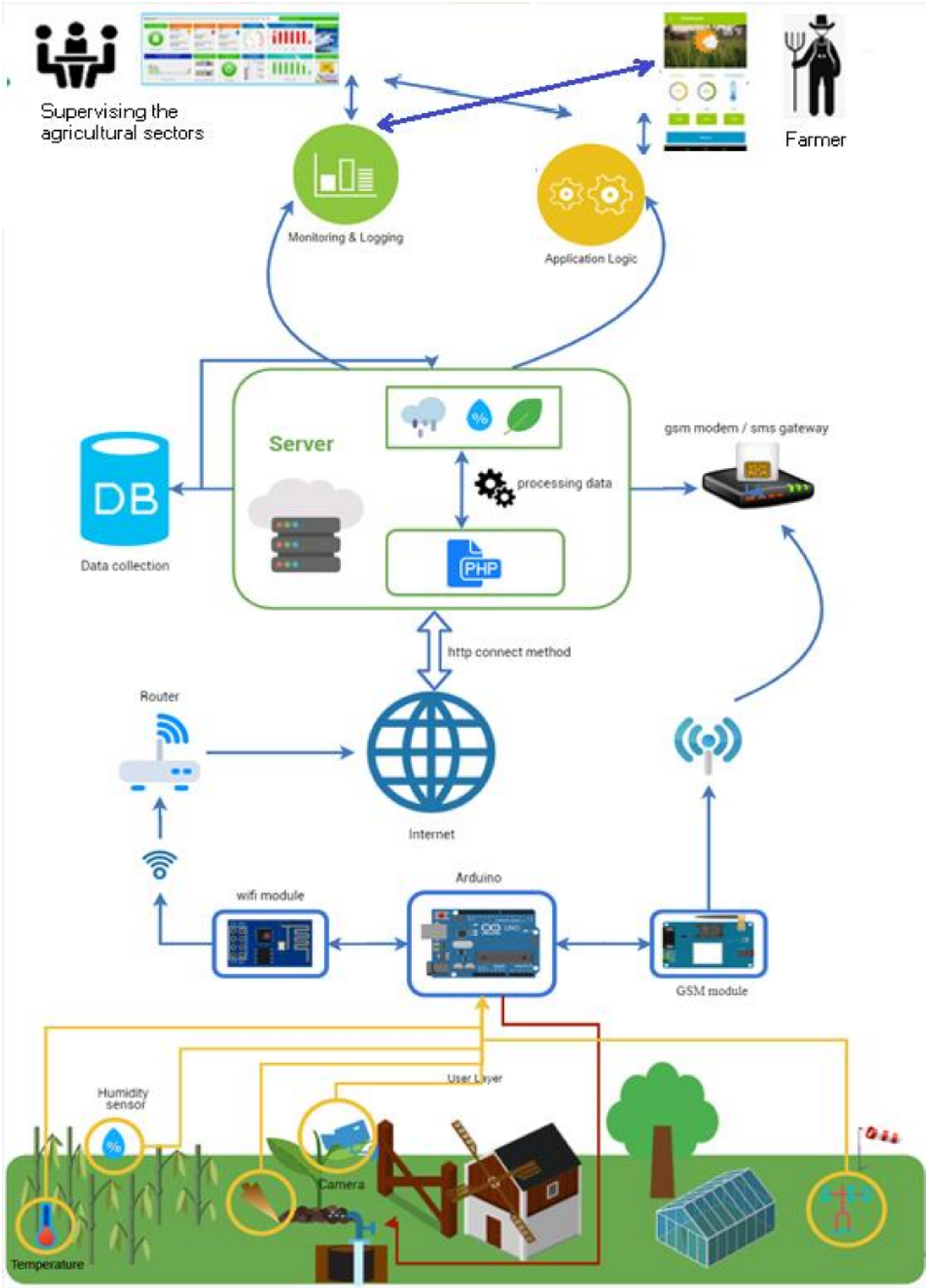


Figure 22: System Workflow: Sequence, Connections, Devices, and Farm-Level Activities

Communication mechanisms

In our system, the primary mode of communication is the internet, with interactions conducted via established internet communication protocols. For the selection of a communication medium, three potential solutions were considered:

- Web services (SOAP)
- Representational State Transfer (REST) Architecture.
- Protocols specific to the Internet of Things (COAP, MQTT).

In scenarios where internet connectivity is unavailable, an alternative communication method has been planned. For this purpose, SMS (GSM) technology, renowned for its efficiency and reliability, is employed. This provides a dependable solution for farmers in instances of internet service disruption.

1. System Flow

The data flow within the proposed approach, as shown in Figure 23, involves the following three stages:

- Data collection.
- Data storage.
- Data exploitation.

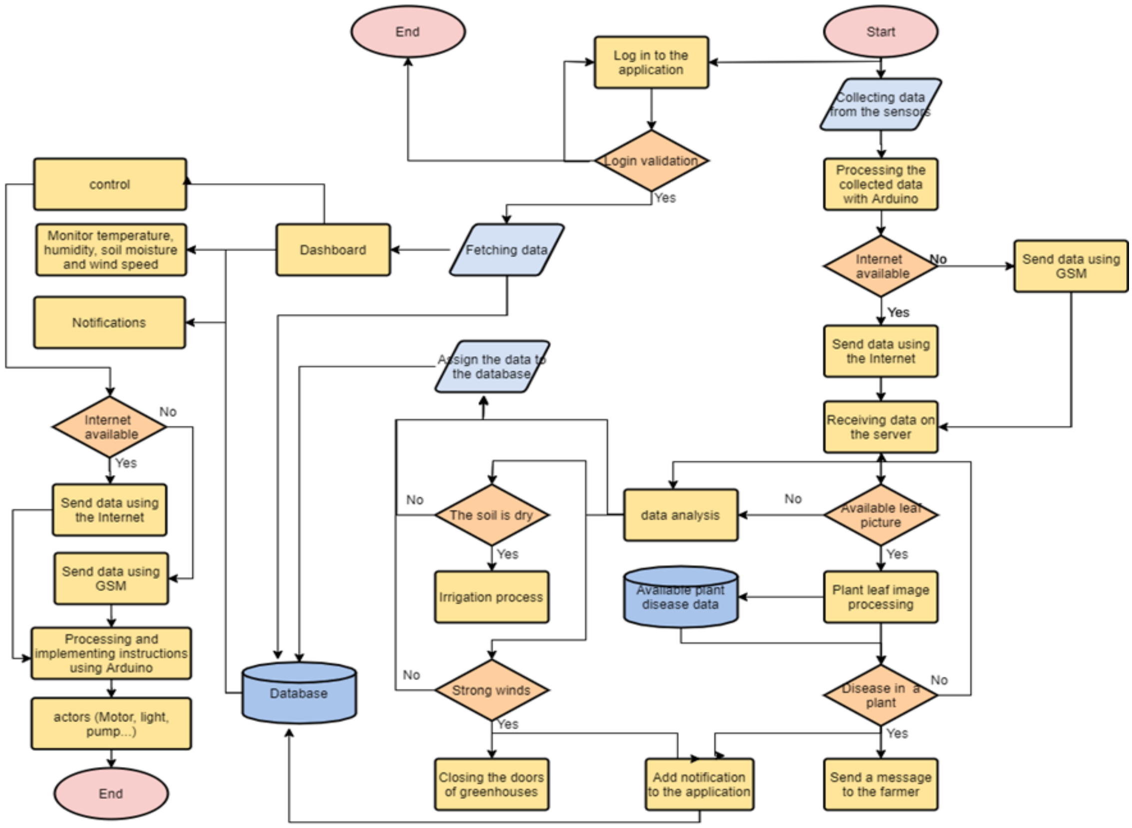


Figure 23: System Flow

The control node functions as the orchestrator for all equipment and sensors within the infrastructure; it serves as the intermediary between control applications (web and mobile) and the sensor network. The control node can be either a microcomputer (such as Raspberry Pi) or a microcontroller (such as Arduino). A significant difference between a microcomputer and a microcontroller is data storage capacity. Microcontrollers generally have very limited storage space, insufficient for storing data from multiple diverse sensors. While one alternative is to store data directly on a central server, this method is often impractical due to the limited performance capabilities of microcontrollers. Conversely, a microcontroller is an excellent choice if the main goal is remote control without requiring an integrated decision-making system, especially given its lower cost, which makes it accessible to a wider range of farmers.

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System Hardware Design

The system utilizes several devices that form the infrastructure, situated within agricultural areas and resource locations. From these points, they gather data and manage specific farm operations. These devices are grouped into five categories:

1. **Sensors**

- **Soil moisture sensor:** This sensor is linked to the Arduino and is employed to measure the soil's moisture content.
- **Temperature and Humidity sensor:** A DHT11 sensor, engineered to measure atmospheric temperature and humidity, is connected to the Arduino to read the gathered data.
- **Wind speed and direction sensor:** This unit consists of two sensors: one for measuring wind speed and another for determining wind direction. Both sensors are connected to the Arduino board, and the collected data is subsequently read and analyzed.
- **Light sensor (LDR - Light Dependent Resistor):** This sensor gauges the intensity of ambient sunlight to distinguish between light and dark conditions, sending this data to the Arduino

2. **Actors**

- **Motors:** These are electromechanical devices set up to control various physical operations based on system decisions, such as activating the opening and closing of greenhouse doors or managing irrigation faucets.
- **Pump:** Irrigation pumps are managed by the system to conserve water and improve the efficiency of the irrigation process.
- **Light:** Illumination systems for the farm and greenhouses are automatically regulated by the system to optimize energy use.
- **Camera:** This device is tasked with capturing images of plants and sending them to the system for analysis. The camera is directly linked to the Arduino board.

System Software Design

1. Software Requirements

- *Laravel:*

This is an open-source framework based on the PHP programming language, used for creating web applications efficiently and rapidly. It provides robust security features for applications and employs a design pattern that separates business logic from the user interface, which simplifies error tracking and the application maintenance process.

- *PLANT-AI*:

This is an algorithm created by Soumyajit Behera, designed to identify plant diseases by classifying leaf images. It performs leaf image classification to detect various plant diseases using different types of Convolutional Neural Network (CNN) architectures to identify diseased foliage [46].

2. Software Components

The program was developed based on the principle of separating the user interface, logic, and storage, ensuring each component is isolated from the others while permitting inter-component communication. The program is composed of five basic components:

- *User Interface:*

This is the direct point of interaction for the farmer. The interface shows farm-related information (e.g., temperature, humidity, soil moisture) and enables the farmer to control farm operations (e.g., watering, lighting) through this interface.

- *Logical layer:*

This is the central layer of the program that interfaces with all other system layers. It coordinates all operations within the system and is implemented using the PHP programming language.

- *Data layer:*

This layer handles data management. It stores and retrieves data from the MySQL database and connects this data with the logical layer.

- *GSM Gateway:*

This service oversees telephone-based communications. It was used to send and receive SMS messages containing data from the farm (via Arduino) and to send commands to the farm. This library acts as an alternative to internet-based communication, allowing data exchange between the program and the farm via SMS when internet connectivity is not available.

- *Image processing interface:*

This component processes plant images sent from the farm via the internet using the HTTP protocol. Upon arrival at the server, the image is forwarded to the image processing server, which uses the PLANT-AI algorithm. The processed results are then sent back to the server and displayed on the user interface.

3. Experimentation & Results

Results The primary sensors (temperature and humidity sensor, lighting sensor, etc.) were connected to the Arduino device. Subsequently, the system control code was uploaded to the Arduino Micro Device, which was then linked to a dedicated server hosting the proposed intelligent agricultural system. The results presented below demonstrate the data acquired from the system. The developed application shows temperature and humidity readings. Figure 24 illustrates the web application interface as seen on a computer, while Figure 25 displays the application on a mobile phone, showcasing its compatibility and responsiveness across various devices.

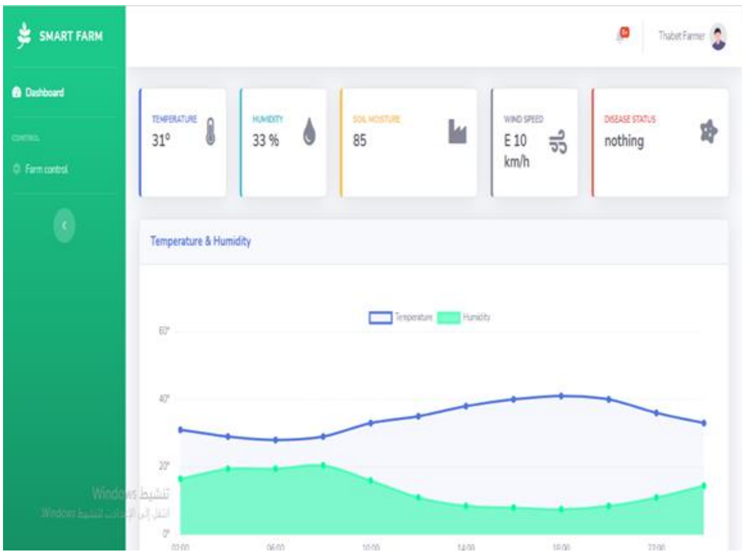

Figure 24: Web Application Interface Displaying Temperature & Humidity

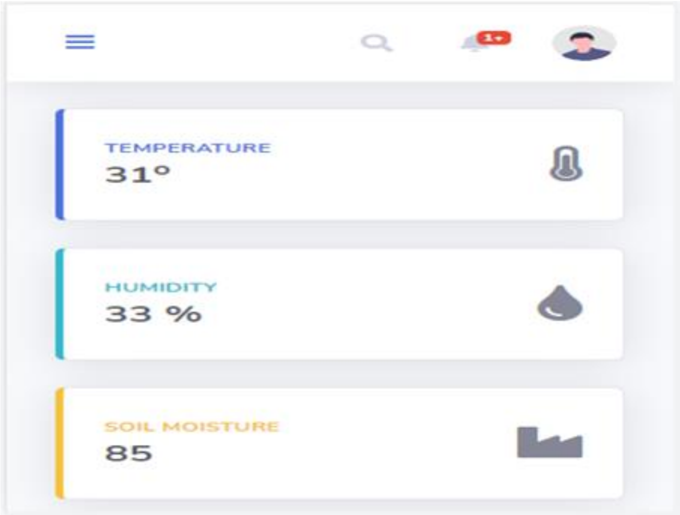

Figure 25: Mobile Application Interface Displaying Temperature & Humidity

Figure 26 : Graph of temperature and humidity.

3. Conclusion

In this chapter, a smart farm system has been introduced, providing solutions to support both farmers and supervisors in the public agricultural sector of developing countries. This system enables the monitoring and control of agricultural activities, contributing to farm development, production enhancement, and the optimization of time and effort. From a technical standpoint, the proposed approach utilizes the Internet of Things and a sensor network. Web technologies were instrumental in developing a responsive application compatible with a broad array of devices, facilitating remote monitoring and control of the farm. This significantly improves the farmer's capacity to manage farm operations and track crop progress effectively.

The contribution of this chapter lies in the proposal of a holistic approach for designing and creating an advanced agricultural information system (AAIS) dedicated to managing the agricultural sector. This approach empowers the AAIS to address the agricultural sector through the following dimensions:

Objectives of AAIS

- Prediction and Optimization
- Monitoring, control and decision support.

Levels of AAIS:

- State level (Public):
- Executive level (farmers);

The periods of the agricultural season:

- Pre-season
- The growing season;
- Post-season.

Methodology for AAIS:

- Activities vision
- Functional visio
- Application vision
- Technical vision.

Chapter 4:

An Intelligent Agriculture Monitoring Framework for Leaf Disease Detection Using YOLOv7

1. Introduction

As a cornerstone of human societal advancement, agriculture holds paramount importance for society, economic frameworks, and the environmental equilibrium. It functions as the principal source of food production, delivering the essential nourishment required by an ever-expanding global population. Agriculture plays an indispensable part in ensuring food security through the cultivation of a wide array of crops, fruits, vegetables, and the raising of livestock [47].

Given the critical nature of agriculture, it is crucial to promote sustainable practices that effectively tackle the challenges presented by a growing global populace, shifting climatic conditions, and volatile economic landscapes [48]. Consequently, ongoing development and innovation within the agricultural sector are essential for guaranteeing a resilient, productive, and environmentally responsible food system for future generations [49].

Digital farming, also referred to as precision agriculture, utilizes sophisticated technology and digital tools to optimize numerous facets of agricultural practices. The primary goal is to boost efficiency, productivity, and sustainability in farming operations, thereby increasing crop yields, improving resource efficiency, lowering costs, and lessening environmental impact [50]. By leveraging technology and data-driven insights, farmers are equipped to make more informed decisions, adapt to changing conditions, and contribute to sustainable and resilient agricultural methods [51].

In this pursuit, Artificial Intelligence (AI) has taken on a vital role in progressing digital farming, offering sophisticated tools and capabilities for data analysis, prediction, and the optimization of many agricultural operations. AI algorithms analyze data from varied sources to monitor crop health, identify diseases, and evaluate overall plant conditions [52, 53]. AI-powered systems can proficiently identify and distinguish among crops, weeds, and pests. This information allows for the targeted application of pesticides and herbicides, facilitating the early detection of pest or disease outbreaks. This, in turn, permits timely intervention and consequently minimizes adverse environmental effects [54, 55].

A major concern in agriculture is the detection of plant diseases. Early identification of diseases is vital for preventing their spread to other plants, thereby avoiding significant economic losses. The consequences of plant diseases can differ greatly, depending on the specific pathogen, the affected crop type, and the stage at which the disease is identified and managed. Such diseases can negatively impact both the quality and quantity of harvested crops, with effects ranging from minor symptoms to the devastation of entire plantations, severely affecting the agricultural economy [56].

Tomatoes are acknowledged as one of the most widely consumed fruits globally [57]. They constitute a major agricultural crop, ranking as the second largest worldwide, and are a significant source of income for farmers and horticulturists [58, 59]. Tomatoes can be grown in various dry soil types [60, 61]. Farmers and horticulturists grow tomatoes for culinary uses or commercial purposes. However, they sometimes face challenges in achieving optimal plant growth, and tomatoes may not ripen at the correct harvest time or develop fully on the plant. In some cases, tomato plants are vulnerable to various diseases, such as blight, rot, or other fungal and bacterial infections, which can appear as black spots or changes in the fruit's coloration [60].

A proposed solution to this problem is the implementation of an agriculture monitoring and plant disease detection system, using tomatoes as a model to assess the effectiveness of the proposed system in detecting plant diseases. Deep learning techniques are considered state-of-the-art methods for computer vision tasks [62]. These techniques have been applied in numerous fields, including agriculture. The use of machine learning techniques in agriculture has significantly increased agricultural productivity, especially with recent progress in deep learning [63, 64].

Among these advancements is the employment of Convolutional Neural Networks (CNNs) for diagnosing and detecting plant diseases [65]. This involves training artificial neural networks to learn and recognize patterns within large datasets, enabling the accurate identification of diseases based on visual symptoms [68, 67, 66]. CNNs are trained on comprehensive datasets composed of images of both healthy and diseased plants. These models learn to automatically extract relevant features from these images, allowing them to distinguish between healthy and infected plants based on visual cues [70, 69].

In this chapter, our main focus is the application of an optimized YOLOv7 algorithm [71] within our proposed system for the real-time detection of diseases in tomato plants, based on a deep learning approach. This aims to enable detection before the disease spreads significantly within the plant, thereby lessening the risk of substantial plant damage.

This chapter offers two primary contributions:

1. We introduce a system that identifies and monitors plant diseases in real-time within an agricultural environment, utilizing deep learning techniques.
2. The second contribution focuses on improving the accuracy of the YOLOv7 method for plant disease detection. These improvements signify an advancement in the agricultural field by enhancing the performance of plant disease detection, reducing disease spread, and ultimately boosting production yields for farmers.

The remainder of this chapter is organized as follows: Section 2 presents related works pertinent to this project. Section 3 provides a comparative analysis of the selected studies. Section 4 elaborates on the system's operational methodology and its handling of training and test data. Section 5 presents the results obtained from our experiments. Finally, Section 6 concludes the chapter.

2. Methodology

As depicted in Figure 27, the plant monitoring and growth tracking system is envisioned as a three-stage process, covering pre-planting, growth and planting, and post-planting phases.

Pre-planting stage:

During the pre-planting phase, vital information regarding the chosen plant species and soil characteristics is gathered. Predictions about the anticipated plant product are made based on data obtained from previous crop cycles (Previous Records – 1).

Growth and planting stage:

The growth and planting phase entails the continuous observation of plant development and health. This is accomplished using sensors and cameras to collect data on critical parameters such as temperature, humidity, wind speed, lighting conditions, and the visual state of plant leaves (WBSN: Pathological Data – 2). This data is sent to a cloud-based system through the gateway device (3), where it is analyzed using deep learning techniques. Edge devices (4) perform immediate local processing and temporary data storage before transmitting the sensed monitoring data through LTE to the centralized database (5). In the cloud data center (5), the data undergoes fusion, preprocessing, feature selection, and disease prediction through classification models to provide evaluations of the plant's growth status and to identify any existing diseases.

Post-planting stage:

In the post-planting phase, the system oversees the harvesting process. The core of the plant growth monitoring system, especially during the second phase, concentrates on tracking plant development and health through advanced techniques. This is achieved via a network of sensors and devices that gather data on various parameters, including temperature, humidity, wind speed and direction, and lighting conditions. Additionally, images of plant leaves are captured by cameras and processed using deep learning algorithms to detect any signs of disease or abnormalities in the plants. The system issues emergency alerts (6) and stores health status information and results for monitoring and logging by the farmer (7).

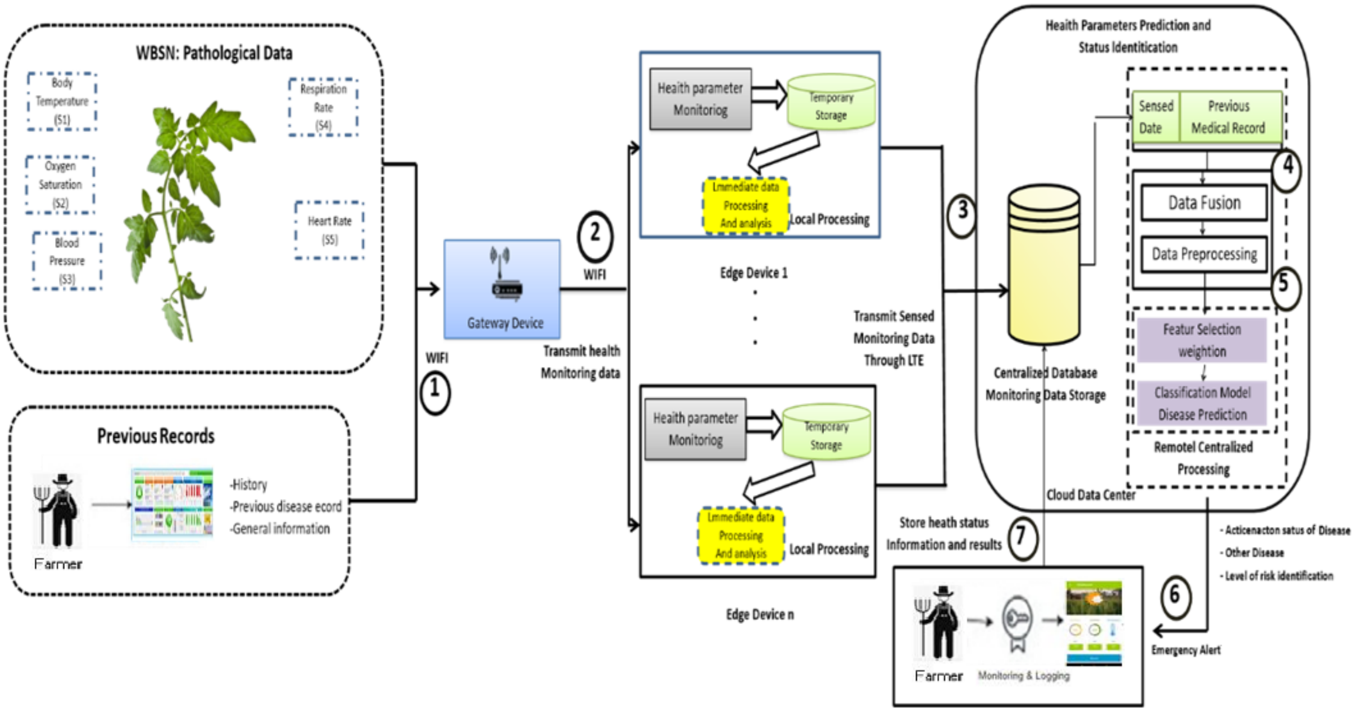

Figure 27: System overview: Sequence of work, Connections, Devices, and activities.

4.1. System overview

The proposed system utilizes an enhanced version of the YOLO (You Only Look Once) object detection model, specifically YOLOv7. This model has been carefully trained to identify plant diseases by analyzing a comprehensive dataset of images showing diseased plant leaves. A convolutional neural network (CNN) is employed to extract significant features from these images and then classify them into distinct disease categories. The image processing sequence starts with the capture of plant leaf images using cameras strategically placed within the agricultural setting. These images are subsequently transmitted to the cloud-based monitoring system. This system processes and analyzes the images using the improved YOLOv7 model to detect any indications of disease or irregularities in the plants. The methodology is thoroughly described, and the proposed solution is examined, covering data collection, preprocessing, model selection, training, and evaluation. The research depended on the YOLO (You Only Look Once) model, specifically YOLOv7 [09], for object detection, which is founded on deep learning approaches and is detailed extensively. During the preprocessing stage, novel improvements were introduced to achieve better results. The effectiveness of the proposed model was assessed by applying various techniques and comparing the outcomes. Figure 28 shows the sequential steps used in the detection and classification of plant diseases. After data collection, the dataset was divided into training and testing sets, with an 80/20 split, respectively. Following this, the optimized YOLOv7 model was trained, and its training plots were generated to evaluate its suitability and performance.

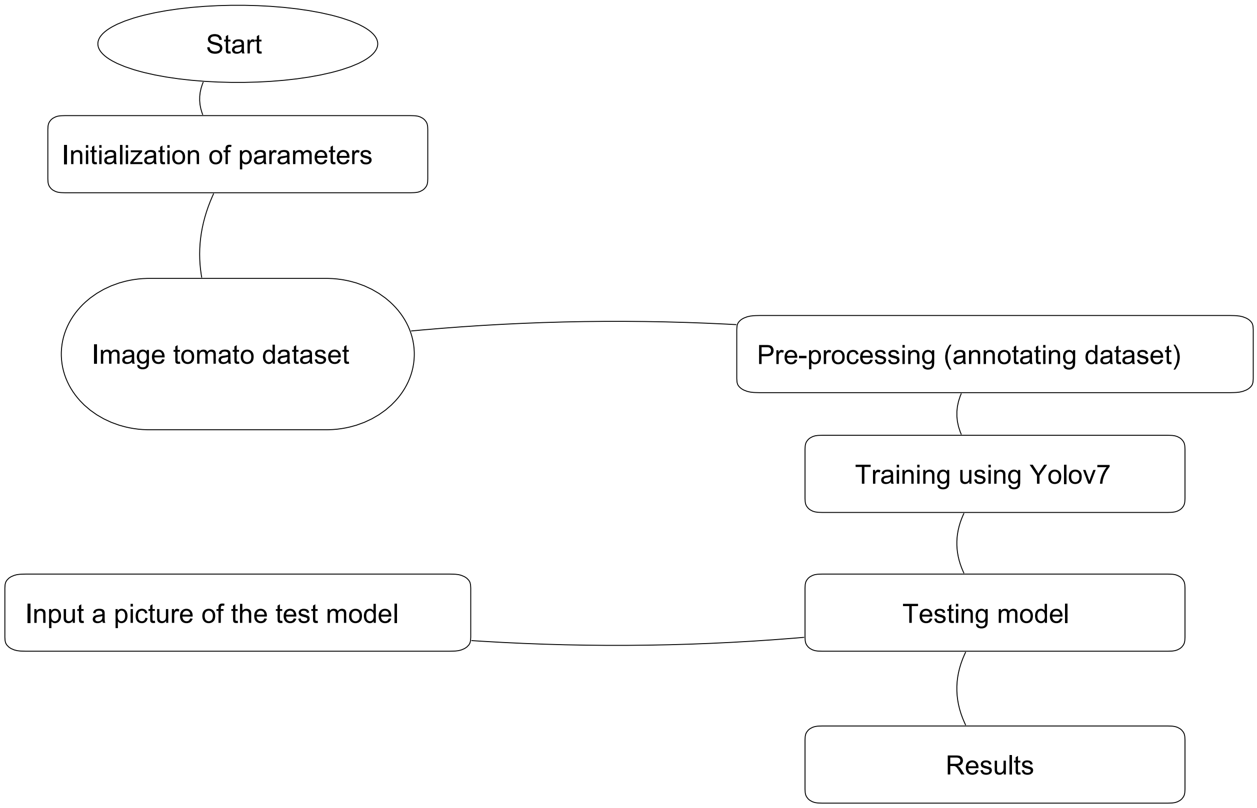

Figure 28: The model training and testing process.

4.2. Dataset Preparation and Preprocessing

This research employed a publicly available dataset from Kaggle, which specifically centered on tomato leaf images [78]. The images were obtained from datasets dedicated to plant disease detection. These datasets classified diseased tomato leaves into 2 distinct types of plant diseases. Each category contained 1000 images of diseased tomato leaves designated for training (Table 3). Figure 29 presents visual examples of different kinds of tomato plant diseases found in the datasets.

Table 3: The classification of diseases in the utilized datasets.

Class	Total
Bacterial-spot	1000
Septoria leaf spot	1000

(a) Bacterial Spot 1

(b) Bacterial Spot 2

(c) Septoria Leaf Spot 1

(d) Septoria Leaf Spot 2

Figure 29: Pictures of different types of tomato plant diseases in the datasets.

Image annotation is a vital step for the precise identification of leaf diseases. This procedure involves adding detailed annotations to the images before their use in training a machine-learning model. For this research, the LabelImg tool was utilized for image annotation. Initially, the LabelImg tool was installed using the pip3 command in a Python environment. Once installed, the tool offered a user-friendly graphical interface, allowing users to browse image folders. The YOLO annotation method was chosen for this research. Subsequently, images were loaded into the tool one by one. A bounding box was carefully placed around the plant disease in each image, as shown in Figure 30. This bounding box helps the machine learning model to accurately identify the exact location of the disease on the leaf. After placing the bounding box, a textual comment was entered to describe the specific plant disease within the selected box. This annotation process was iteratively applied to all images in the dataset. Upon completing the annotation for each image, a corresponding text file was generated. This text file included explanatory data, such as the bounding box's location and dimensions, the type of plant disease, and any other relevant information. These annotations were then used to train the machine learning model to accurately identify and classify different types of tomato plant diseases.

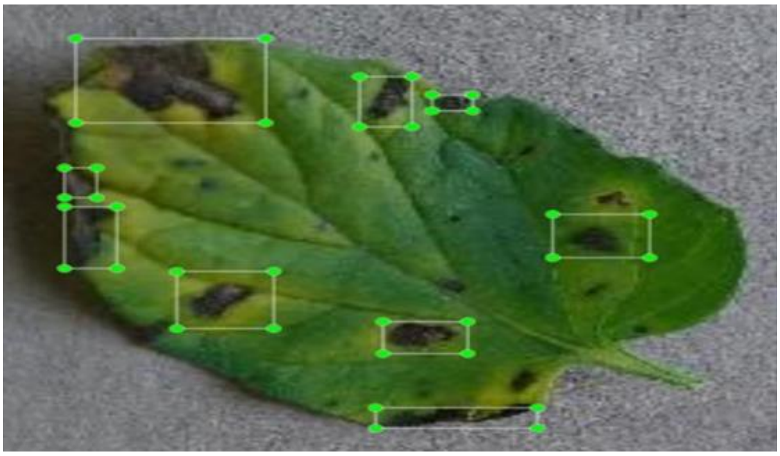

Figure 30: The annotation process of tomato leaf disease with the labImg tool.

4.3. Data Augmentation for Enhancing Dataset

To achieve superior outcomes and refine the training process, data augmentation techniques were employed to generate images of diseased tomato plant leaves, based on images of healthy tomato leaves. This approach effectively increased the number of images in the dataset, thereby improving the robustness of the training process. Using image processing operations, a method was proposed to synthesize images of diseased tomato leaves (Figure 31). The diseased spots were carefully extracted from images of healthy tomato leaves through image processing techniques. Subsequently, an algorithm was developed to blend these extracted disease spots onto images of healthy tomato leaves and to simultaneously create YOLO annotation files, thereby enhancing the accuracy of image descriptions. This involves establishing a correspondence between the disease spots and the healthy tomato leaves, which has produced promising results in terms of improving the training process and boosting overall accuracy.

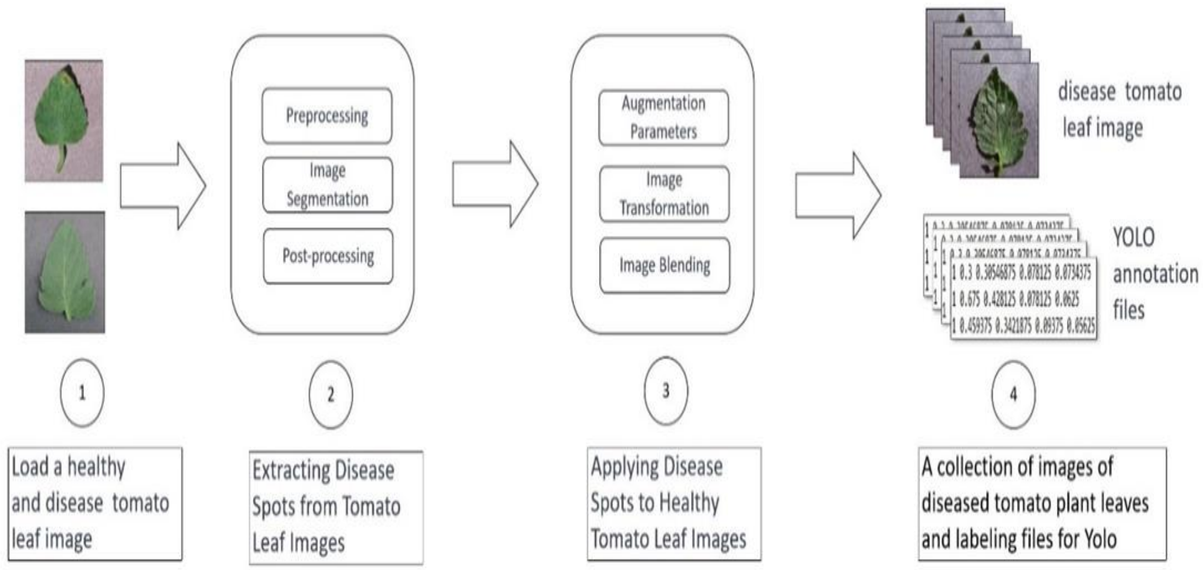

Figure 31: Data Augmentation for Tomato Disease Detection: An Overview and Step-byStep Approach.

Extracting Disease Spots from Tomato Leaf Images

At the start of this procedure, a set of images showing tomato leaves affected by diseases was gathered. These images were obtained from a publicly available dataset on Kaggle. They were carefully chosen and categorized based on the clarity of the diseased areas, thereby improving the machine learning model's ability to accurately identify leaf diseases. Subsequently, a series of processing operations were applied to these images to enhance their quality and prepare them for model training. The process of extracting disease spots consists of three main stages (Algorithm 1).

Algorithm 1 Extracting Disease Spots from Tomato Leaf Images

procedure DATASETCOMPILATION
  Let D be the dataset of tomato leaf images affected by diseases.
  $D = \{d_1, d_2, \ldots, d_n\}$, where d_i represents an image.
procedure IMAGESELECTIONANDSORTING
  Let C be the clarity measure of a diseased spot in an image.
  $C = \{c_1, c_2, \ldots, c_n\}$, where c_i represents the clarity score of d_i.
  Sort D based on C in descending order.
procedure PREPROCESSINGIMAGES
  for each image d_i in D **do**
    $d_i = \text{resize}(d_i, 640, 640)$
    $d_i = \text{denoise}(d_i)$
    $d_i = \text{color\_correction}(d_i)$
procedure IMAGESEGMENTATION
  for each image d_i in D **do**
    $d_i = \text{grayscale\_conversion}(d_i)$
    $d_i = \text{thresholding}(d_i)$
    Resulting binary image: $d_i = \{0, 1\}$, where 0 represents background and 1 represents diseased spots.
procedure NOISEREMOVALANDENHANCEMENT
  for each image d_i in D **do**
    $d_i = \text{remove\_noise}(d_i)$
    $d_i = \text{morphological\_operations}(d_i)$
    $d_i = \text{contour\_extraction}(d_i)$
    $d_i = \text{boundary\_refinement}(d_i)$
procedure ACCURATEDISEASESPOTIMAGES
  The result is a set of images that accurately represent the disease spots: $D' = \{d'_1, d'_2, \ldots, d'_n\}$, where d'_i represents an image with refined disease spot boundaries.

- **Pre-processing Infected Leaf Images:** In this initial phase, images of diseased tomato leaves are uploaded, and a sequence of processing operations is performed. These operations involve resizing the images to a standardized 640×640-pixel dimension, followed by noise reduction techniques to improve image clarity, and color correction procedures to ensure color uniformity while removing distortions (Figure 32).

Figure 32: Picture of diseased tomato leaves after pre-processing.

- **Image Segmentation**: During this phase, grayscale conversion of the images is carried out to enable a clearer distinction between diseased spots and the background. Subsequently, the images are divided into distinct regions using thresholding techniques. This results in binary images, represented in black and white, which effectively isolate the diseased spots.

- **Noise Reduction and Image Enhancement:** Any remaining noise is removed at this point, and image quality is further improved by applying morphological ellipses. Individual disease spot regions are then extracted from the segmented images by using contour detection. Non-spot areas are meticulously filtered out from the spot region to fine-tune and sharpen the boundaries of the disease spots, ensuring an accurate representation. Consequently, a set of images is obtained that faithfully depicts the disease spots (Figure 33).

Figure 33: Binary image of diseased tomato leaves after segmentation.

Figure 34: A sample extracted from a tomato leaf showing a diseased spot.

Applying Disease Spots to Healthy Tomato Leaf Images

Following the extraction of diseased spots from tomato leaves in the initial phase, these spots are utilized in the second phase. This phase involves generating images of healthy tomato leaves that incorporate these extracted diseased spots (Algorithm 2). This procedure entails creating diseased images by performing a series of sequential operations structured in three steps. In the first step, images of healthy tomato leaves and the extracted diseased spots are uploaded. The intact (healthy) images are then resized to dimensions of 640×640 pixels. Next, a set of enhancement parameters is defined for use in the diseased image generation process; these parameters include positioning, measurements (size), and rotation.

In the second step, these enhancement parameters are applied to each diseased spot in conjunction with each healthy image. The enhancement parameters are varied randomly for each image. This means that the location, size, and angle of each diseased spot are mapped based on these parameters. The modified spots are then integrated with the intact images. In the third step, the coordinates of the diseased spots are extracted from the image and appended to a text file associated with each image. This file, known as the "YOLO annotation file," contains the coordinates of the diseased spots within the image. Steps two and three are iteratively repeated for all healthy images, thereby creating a dataset of diseased images containing the altered spots, along with their corresponding YOLO annotation files (.txt). This approach ensures that the coordinates of the diseased spots are accurately aligned with the healthy images, consequently improving the precision of the training process and the model's ability to effectively identify diseases in tomato leaves.

Algorithm 2 Generating Images of Healthy Tomato Leaves

```
procedure GenerateHealthyImages
    Let D be the set of diseased spots extracted in the first stage.
    Let H be the set of images of healthy tomato leaves.
    Let E be a set of enhancement parameters.
    E = {e1, e2, ..., en}, where ei includes positioning, measurements, and
  rotation.
    for each healthy image hi in H do
        hi = resize(hi, 640, 640)
        for each enhancement parameter ej in E do
            Apply ej to each diseased spot in D on hi randomly.
        Save the modified image with diseased spots.
        Create a YOLO annotation file with coordinates of diseased spots.
```

4.4. YOLOv7 Model Optimization

YOLOv7 signifies the most recent progress in the YOLO (You Only Look Once) series of object detection models. As a single-stage object detector, YOLOv7 analyzes entire image frames in a single forward pass, making it computationally efficient and reducing the need for multiple sequential running operations [52]. The YOLOv7 model utilizes a backbone network to extract features from input image frames. These features are then combined and refined in the network's neck before being passed to the head. In the head, YOLOv7 predicts the locations and classes of objects within the image frames. Specifically, YOLOv7 predicts the bounding boxes for each object, along with a confidence score that indicates the likelihood of the object being present within the predicted bounding box [79]. Due to its advanced performance in terms of speed and accuracy, YOLOv7 has become a popular choice for numerous real-world object detection applications. By utilizing an efficient single-stage architecture, YOLOv7 offers a powerful and scalable solution for real-time object detection tasks.

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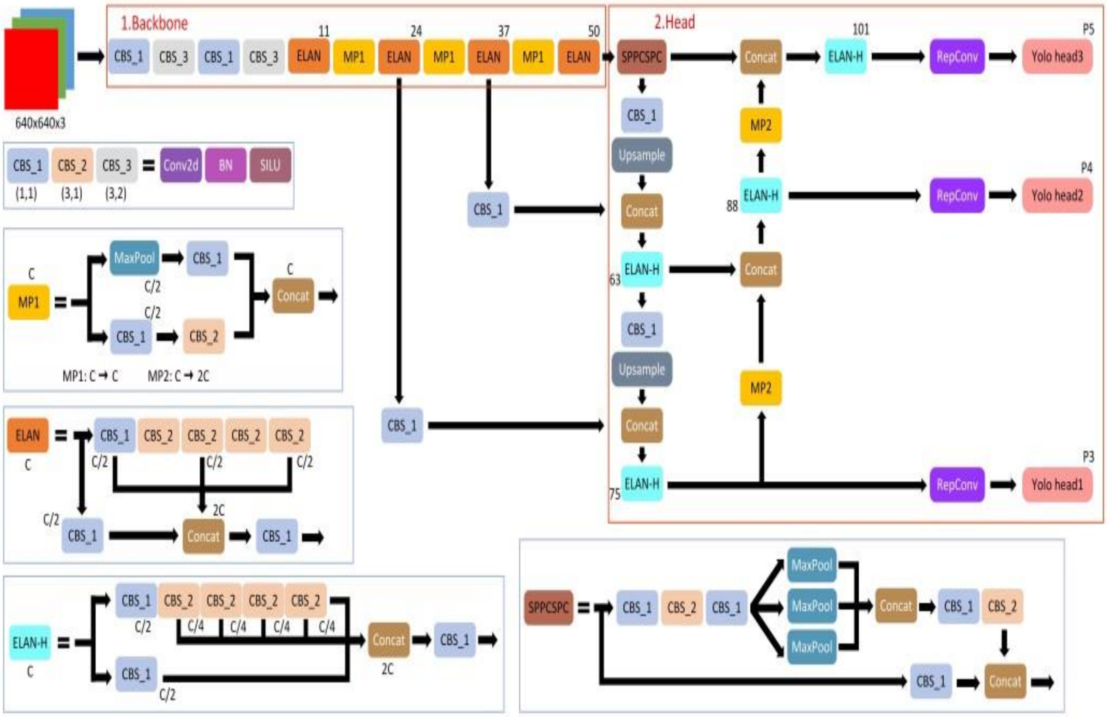

Figure 35: The structure of YOLOv7[59].

The latest version in the YOLO series, YOLOv7, demonstrates object detection performance varying from 5fps to 160fps, achieving a notable accuracy of 56.8% AP (Average Precision), thereby outperforming all other real-time object detectors operating at 30 fps or higher on a GPU [71]. During the training phase, the YOLOv7 algorithm was chosen due to its exceptional accuracy and quick object detection capabilities. In this chapter, experiments are conducted to propose a method for improving the detection efficiency of the YOLOv7 model. The architecture of YOLOv7 is illustrated in Figure 35. To preserve the integrity of the model's backbone, experiments are carried out on the head and backbone adjustments, carefully considering the experimental results and comparative analyses to determine the optimal configuration. The modifications are divided into two steps: the first part involves altering the convolutional layers, and the second part includes experimenting with pooling layers. Initially, a series of convolutional layers are integrated into the model's architecture. These convolutional layers play a key role in extracting features from the input images and identifying objects within them. This process can be mathematically represented as shown in equation 1.

$$fconu = Conu(f(i,j,height))(i,j,height \in N) \quad (1)$$

The pooling layers are adjusted following the convolutional layers. Pooling layers are used to decrease the spatial dimensions of the feature maps, thereby making the model more computationally efficient. This can be shown as in equation 2.

$$fconu = Conu(fconcat) \quad (2)$$

3. Experiments and Results

5.1. Preparing project for training

In this study, a custom YOLOv7 model was trained, featuring modifications to its architecture, which mainly comprises two key components: the backbone (spine) and the head. The backbone is a Convolutional Neural Network (CNN) made up of 38 layers. It is structured as a sequence of convolutional and pooling layers, which progressively increase in depth and width, allowing the network to identify increasingly complex features within the input images. The backbone is crucial for extracting features from the input data, an essential preliminary step for object detection. The main component, following the backbone, includes an SPPCSPC (Spatial Pyramid Pooling and Cross Stage Partial Connection) layer, a series of additional convolutional layers, and a final detection layer. The SPPCSPC layer, a spatial hierarchical pooling and concatenation layer, enables the network to learn features at multiple scales. This is a vital aspect for object detection, as objects of different sizes may appear in the same image. Subsequent convolutional layers further refine the features learned by the SPPCSPC layer. The final detection layer is responsible for predicting the bounding boxes and object classes within the image, a fundamental part of object detection. The disclosure process within the YOLOv7 model is a significant phase. It encompasses the final detection layer, which is tasked with predicting bounding boxes and object classes within the input image. This layer uses information learned throughout the network, including hierarchical spatial features obtained by the SPPCSPC layer and enhanced features from the additional convolutional layers. The function of the final detection layer is to accurately locate objects of interest by defining their bounding boxes and assigning corresponding class labels. This capability allows the YOLOv7 model not only to detect objects within images but also to classify them, making it a powerful and versatile tool for various object recognition and localization tasks.

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5.2. Custom Model Training

In this phase, the training process is commenced using the command python train.py. The parameter for customizing the training is device, specifying the GPU used for training. The data/custom.yaml parameter furnishes descriptive data for the annotations, incorporating the modified enhancements. Subsequently, the custom model parameter is passed within cfg/training/yolov7x-custom.yaml. Following this, the yolo7x training file parameter is provided, and the training process begins. Upon completion of training, several output files are produced. These files contain results from image testing, graphical representations of performance, and the weights/best.pt file, all situated within the train/run directory.

Figure 36: Detection process for tomato plant diseases

5.3. Results

In this section, we conduct a thorough analysis of the obtained results and present the observations derived from the preceding research phases. We discuss the training methodology utilized for the YOLOv7 object detection model and present the outcomes of the performance analysis. YOLOv7 is a cutting-edge model recognized for its speed and accuracy in real-time object detection. The model was trained using a specific dataset, and various evaluation metrics were employed to assess its performance. We present these findings in Table 4, which includes accuracy and mean average precision (mAP), metrics that comprehensively evaluate the model's effectiveness.

Table 4: Performance Metrics for YOLOv7 Object Detection Model.

Metric	Accuracy	mAP
Result	96%	99%

Table 4 encapsulates the performance metrics attained during the evaluation of the YOLOv7 model. The mean average precision (mAP) evaluates the model's performance across different object classes. Collectively, these metrics underscore the efficacy of the YOLOv7 model in accurately detecting and classifying objects in real-time scenarios. In the subsequent sections, we will delve deeper into these results and discuss their implications within the realm of object detection tasks. Additionally, we will explore potential avenues for enhancement and suggest future research directions to further improve the performance of YOLOv7 in object detection applications. Our analysis thoroughly examined various performance metrics, including mean average precision (mAP), precision, and recall. Figure 37 displays graphs illustrating the F1-confidence relationship, showing the F1 score of the YOLOv7 object detection model at varying confidence thresholds. This metric, proficient at balancing precision and recall, proves indispensable for assessing the overall model performance.

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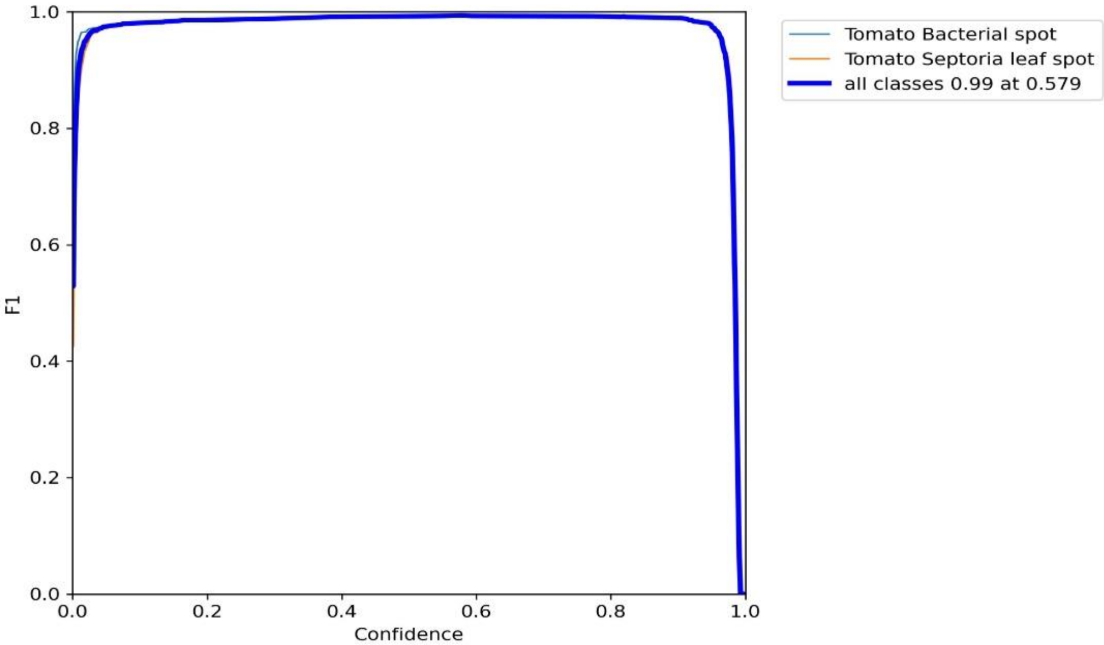

Figure 37: Graphs presentation with illustrating the F1-confidence graph.

We noted a consistent rise in the F1 score of the YOLOv7 model corresponding with an increase in the confidence threshold. This significant trend aligns with theoretical expectations, as a higher confidence threshold implies that the model's predictions are made only when there is a high degree of certainty. Identifying the optimal confidence threshold is a crucial decision and depends on the specific requirements of the application in question. In the provided visualization, the F1 score for the YOLOv7 model achieves a remarkable value of 0.99 at a confidence threshold of 0.579. This indicates the model's proficiency in correctly identifying 99% of the objects within the dataset with a confidence level of at least 57.9%. In summary, the F1-confidence graph serves as an invaluable tool for the comprehensive evaluation of object detection models. Its effectiveness lies in vividly demonstrating how the F1 score of a model changes across different confidence thresholds, thereby enabling an informed choice of the optimal threshold tailored to a specific application.

$$Precision(P) = TP/(TP + FP) \tag{3}$$

$$Recall(R) = TP/(TP + FN) \tag{4}$$

In the context of object detection evaluation, several key terms are employed to gauge model performance. These include True Positive (TP), signifying the number of instances accurately identified by the model. False Positive (FP) pertains to cases where the model incorrectly identifies instances, for instance, distinguishing between healthy and unhealthy leaves when the identification is mistaken. Conversely, False Negative (FN) represents the number of cases the model failed to detect. To assess the overlapping accuracy between predicted and ground truth bounding boxes, the Intersection over Union (IoU) is computed. Additionally, a threshold value, indicated by 'K', sets the IoU threshold for classifying detections as true positives or false positives.

In Figure 38, we present "Confidence according to the R graph," which contrasts recall growth across different experiments based on the training techniques used. This graph offers an alternative depiction of the precision-recall curve, providing insightful observations about the model's recall performance. The "Confidence according to the R graph" shows how the confidence of the custom YOLOv7 model changes with increasing recall. Recall signifies the percentage of true positives correctly identified by the model. The graph illustrates that the confidence of the custom YOLOv7 model increases proportionally with recall growth. This suggests that the model becomes more confident in its predictions as it successfully identifies an increasing number of true positives. Specific results observed for the custom YOLOv7 model in this graph include: At a recall of 0.5, the custom model achieves a confidence of 0.95, meaning 95% confidence in its predictions when detecting 50% of true positives.

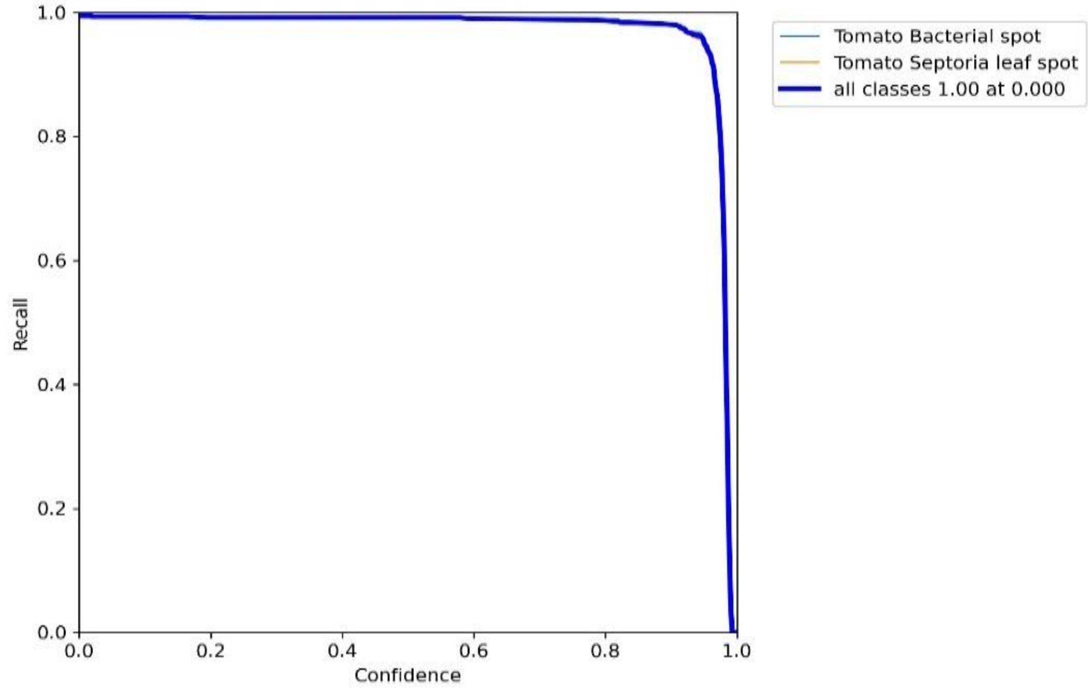

Figure 38: Confidence according to R Graph.

At a recall of 0.75, the custom model attains a confidence of 0.98, indicating 98% confidence when identifying 75% of true positives. At a recall of 0.9, the custom model achieves a confidence of 0.99, reflecting 99% confidence when detecting 90% of true positives. These specific outcomes in the graph also underscore the reliability of the custom model, reaching confidence levels of 0.95, 0.98, and 0.99 at recall levels of 0.5, 0.75, and 0.9, respectively. These findings suggest that the custom model excels in accurately identifying objects with a high degree of confidence. In Figure 39, "Confidence according to the P-curve graph" is shown, illustrating the progression of precision across various experiments, categorized based on the utilized training mechanisms. This graph allows us to analyze and understand how different training techniques affect the precision of the custom YOLOv7 model. Precision, in the context of the P-curve, denotes the percentage of expected positives that are genuinely true positives. The specific results observed for the custom YOLOv7 model in the graph are as follows: At a precision of 0.5, the confidence of the custom model is 0.95. This implies that the model is 95% confident in its predictions when capable of filtering out

50% of false positive results. At a precision of 0.75, the confidence of the custom model is 0.98. This suggests that the model is 98% confident in its predictions when able to filter out 75% of false positive results. At a precision of 0.9, the confidence of the custom model is 0.99.

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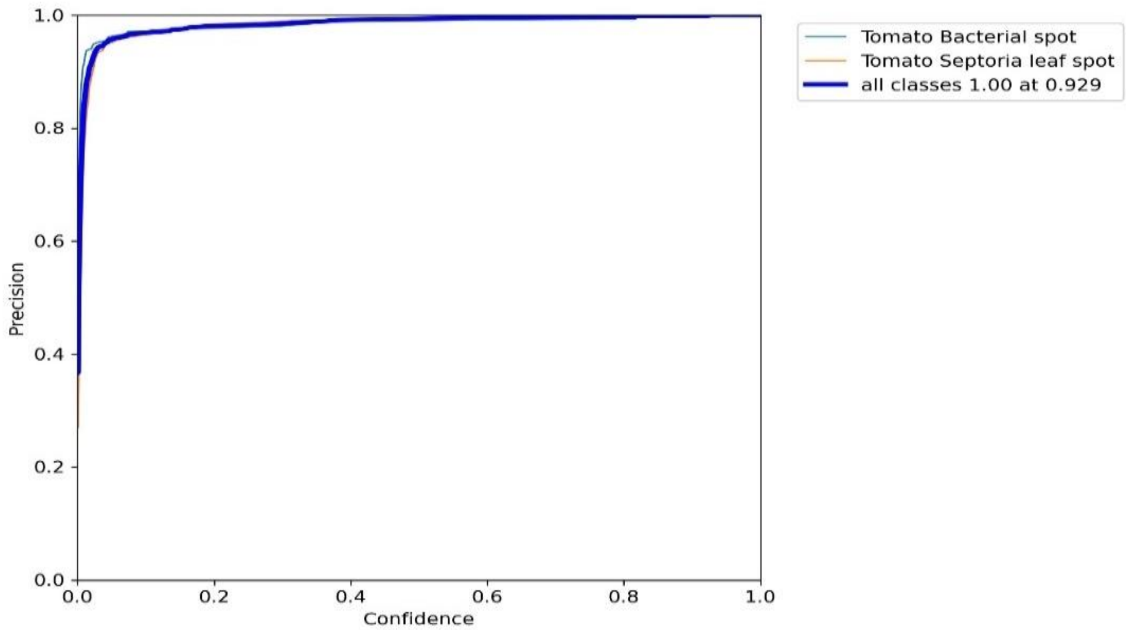

Figure 39: Confidence according to R Graph.

This signifies that the model is 99% confident in its predictions when capable of filtering out 90% of false positive results. The specific results in the graph demonstrate that the custom model can achieve confidence levels of 0.95, 0.98, and 0.99 at precision levels of 0.5, 0.75, and 0.9, respectively. This highlights the high reliability of the custom model in accurately detecting objects. Figure 40 displays the confusion matrix, illustrating discrepancies between actual and predicted values, with a particular focus on tomato bacterial spot and tomato septoria leaf spot. This matrix offers valuable insights into the model's accuracy in classifying these specific categories, highlighting instances of correct predictions (true positives) and misclassifications (False Positives and False Negatives). Tailored for tomato bacterial spot, tomato septoria leaf spot, False Positives (FP), and False Negatives (FN), the matrix's diagonal values show the accuracy for each class: tomato bacterial spot (0.78), tomato septoria leaf spot (1.00), and FN background (0.31). While the model excels in accurately classifying tomato septoria leaf spot with 1.00 accuracy, it encounters challenges in classifying tomato bacterial spot (0.78) and FN backgrounds (0.31). Potential contributing factors include the quality and diversity of training data, model complexity, and other considerations. These findings emphasize the model's strength in identifying tomato septoria leaf spot and suggest areas for improvement in accurately classifying tomato bacterial spot and FN background. Further investigation and potential modifications to training data and model complexity could enhance its performance in these specific categories.

In contrast, the YOLOv7 model presented in this study achieved an accuracy of 96% and a mean average precision (mAP) of 99%, outperforming most prior works in both accuracy and detection efficiency. This performance improvement can be attributed to the model's optimized architecture, enhanced feature extraction layers, and improved bounding box regression. The superior mAP value indicates robust multi-class detection capabilities, enabling YOLOv7 to effectively identify diverse plant diseases in real-time environments. Consequently, the results affirm that the proposed YOLOv7-based system not only meets but exceeds the detection accuracy and speed achieved in earlier studies, establishing it as a promising framework for intelligent and sustainable agricultural monitoring systems.

6. Conclusion

In modern times, agriculture is acknowledged as one of the most crucial economic sectors, a reliance that societies have upheld since ancient times. With recent technological progress, agriculture has seen the integration of modern technologies, such as the Internet of Things and Artificial Intelligence, aimed at boosting productivity and monitoring agricultural operations. In this vein, the Smart Farm System was proposed, offering a comprehensive solution to assist farmers and agricultural sector supervisors in monitoring and enhancing agricultural activities and farm development. The system is founded on Internet of Things technology, sensors, and web-based technologies. A responsive application, compatible with all devices, was created. This application enables farmers to control and monitor their operations remotely, thereby promoting more efficient farm and production management.

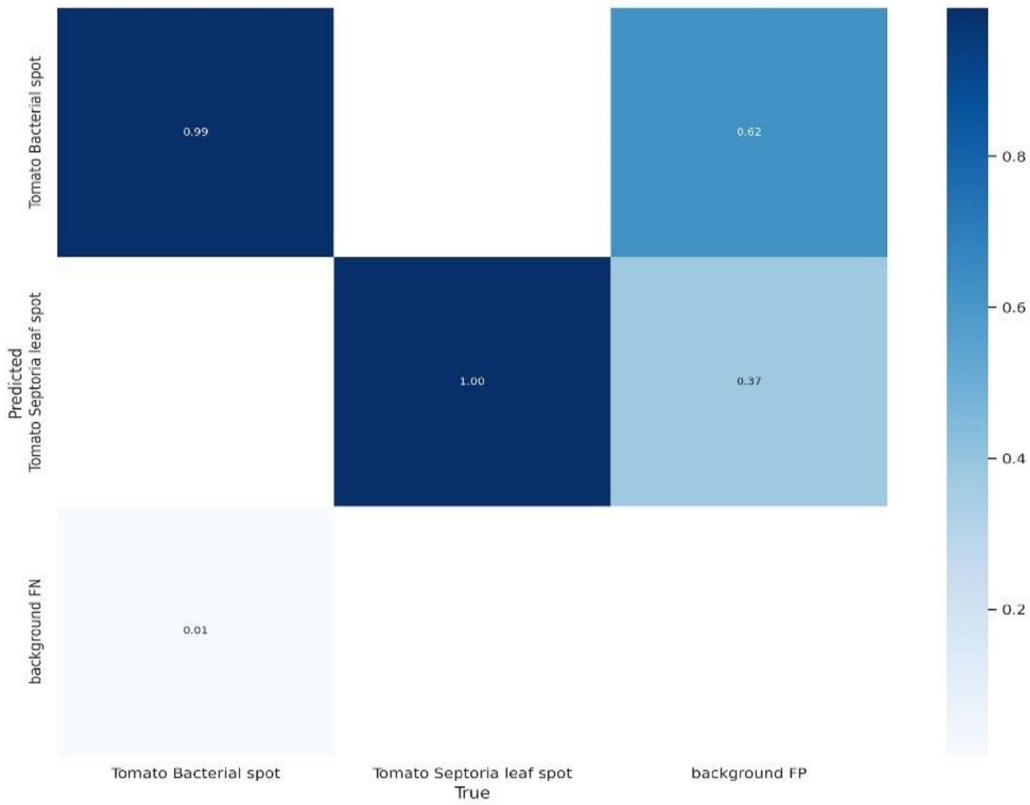

Figure 40: Confusion matrix displaying the variations between the actual and predicted value.

The principal contribution of this research involves the design and development of a comprehensive agricultural information system within the proposed framework. A rule-based policy is formulated for the real-time detection of plant diseases through real-time plant leaf monitoring via local edge devices. Images of plant leaves are sent to central cloud servers in real-time for disease detection using enhanced YOLOv7 technology. The proposed system was evaluated using a dataset of infected tomato leaves, where an accuracy of 96% was attained. The algorithm performs commendably, encouraging further exploration and development in the application of real-time detection and monitoring using YOLOv7 during the cultivation phase. Expanding the model to include other types of plant diseases in future research and broadening the scope of applications using blockchain technologies for health-related purposes [47], positions this system as an important advancement towards enhancing the agriculture sector through modern technology. It holds the potential to contribute significantly to the improvement of the agricultural economy in the future.

Conclusion

Conclusion

This research developed and designed an advanced agricultural information system (AAIS) aimed at improving agricultural practices by integrating cutting-edge smart technologies. The system leverages the Internet of Things (IoT), sensors, advanced system-based solutions, and artificial intelligence to provide a comprehensive platform for monitoring, controlling, and optimizing agricultural operations effectively.

The system supports multiple levels of management, from public administration at the state level to individual farmers, and covers the entire agricultural cycle pre-season, growing season, and post-season. It emphasizes predictive analytics, real-time monitoring, and decision-making support, enabling more efficient and sustainable farm management.

Additionally, an advanced crop disease detection system using YOLOv7 technology was integrated into the system, enhancing its capabilities to address critical agricultural challenges such as crop health monitoring and disease detection. This contributes to streamlining agricultural operations, increasing production efficiency, and minimizing resource waste.

By integrating business, functional, application and technical perspectives, the Advanced Agricultural Information System (AAIS) offers a systematic and comprehensive approach to smart agriculture in precision agriculture by enhancing sustainability, improving crop quality and reducing production costs, making it an invaluable tool for modern agriculture. Future research will focus on improving the design of advanced information system architectures that can be easily adapted to diverse agricultural regions. By adding advanced mechanisms for real-time disease tracking and predictive intervention strategies, it will enhance its diagnostic and preventive capabilities. The research will also explore the development of advanced machine learning models to enhance crop yield predictions with greater accuracy and adaptability across different agricultural contexts and crop types.

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