ROLE AND CHALLENGES IN EXECUTION OF DIGITAL TOOLS IN SMART AGRICULTURE: A REVIEW

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Abstract: The Internet of Things (IoT), where devices interact and operations are automated and controlled via the internet, has advanced significantly in the digital era. Within agriculture, IoT-based systems provide substantial advantages for crop monitoring and management. As IoT sensors deliver data about farmland and respond according to user commands, the concept of smart agriculture is rapidly gaining importance. This study explores the application of emerging technologies—such as Machine Learning, Deep Learning, IoT, and automation—in agriculture. It examines the tools and systems employed in this domain, along with the potential challenges of integrating technology into conventional farming practices. Both farmers and home growers can benefit from the technological insights offered across the crop cycle.

Keywords: Smart Agriculture, Internet of Things, Machine Learning, Deep Learning, Neural Networks, Support Systems, Engineering.

1. INTRODUCTION

In earlier times, agricultural practices were mainly centered on cultivating land for food production to sustain human life and support animal breeding. This stage, referred to as Traditional Agriculture 1.0, relied heavily on manual labor, draft animals, and basic tools such as sickles and shovels. Due to its labor-intensive nature, productivity remained limited. The nineteenth century marked a turning point with the advent of new farming machinery, most notably steam engines. This initiated the era of Agriculture 2.0, characterized by mechanization and the widespread use of pesticides. While this phase significantly enhanced farm efficiency and crop yields, it also introduced major drawbacks, including chemical pollution, environmental degradation, and resource depletion.
The emergence of Agriculture 3.0 in the twentieth century was driven by rapid progress in computing and electronics. This stage incorporated robotics, automated farming equipment, and diverse technological solutions to optimize agricultural practices. The shortcomings of the second era were systematically addressed by policies and innovations of the third, which emphasized better labor distribution, precision irrigation, reduced chemical dependency, site-specific nutrient application, and advanced pest management techniques.

The present stage of agriculture, often referred to as Agriculture 4.0, represents the latest advancements

in farming methodologies. It leverages modern technologies such as the Internet of Things (IoT), big data analytics, artificial intelligence (AI), cloud computing, and remote sensing. The integration of

these technologies has led to remarkable improvements in agricultural practices, including the development of cost-effective sensor and network platforms that enhance production efficiency while reducing water and energy consumption, all with minimal environmental impact.

In smart farming, big data provides comprehensive real-time insights into field conditions, enabling farmers to make data-driven decisions. IoT devices, equipped with AI-based real-time programming, further support informed decision-making in farm operations. Precision agriculture, as a key component of this era, utilizes advanced tools to remotely monitor crops and automate agricultural equipment. This approach enhances productivity in processes such as harvesting and yield optimization while also increasing labor efficiency.

The shift from conventional farming methods to automated, technology-driven systems marks a true

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agricultural revolution. The integration of IoT and related digital technologies has fundamentally transformed contemporary farming, redefining how agriculture is practiced today.

Smart farming represents a modern agricultural approach that utilizes information and communication technology (ICT) to enhance labor efficiency while improving both the quality and quantity of farm produce. By incorporating advanced ICT tools—such as the Internet of Things (IoT), GPS, sensors, robotics, drones, precision equipment, actuators, and data analytics—this method identifies farmers' requirements and delivers customized solutions to address their challenges. These innovations significantly improve the accuracy and timeliness of decision-making, ultimately boosting agricultural productivity.

International organizations and developing nations alike have advocated the adoption of smart farming technologies to increase crop yields. Continuous and precise monitoring through crop sensors enables the early detection of unfavorable conditions during the initial stages of plant growth. From sowing and cultivation to harvesting, storage, and transportation, intelligent tools are deployed across the entire farming process. The extensive use of diverse sensors has not only enhanced operational efficiency and profitability but also facilitated accurate monitoring. Moreover, as these sensors capture data in real time, the information becomes instantly available online for detailed analysis, offering region-specific agricultural insights.

Smart agriculture and monitoring address a wide range of challenges in crop production, particularly those linked to variations in soil properties, climatic conditions, and soil moisture levels. The central objective is to enhance spatial management practices to maximize crop yields while minimizing the overuse of fertilizers and pesticides. Within this context, Artificial Neural Network (ANN) models play a crucial role in Smart Irrigation Water Management (SIWM), supporting irrigation scheduling decision support systems (DSS) and providing real-time insights into parameters such as irrigation efficiency, water productivity indices, and irrigation water demand and supply.

A promising innovation, particularly in developing countries, is Climate-Smart Agriculture (CSA), which aims to strengthen food security, improve farm system resilience, and mitigate greenhouse gas emissions. Smart agricultural technologies, built upon IoT frameworks, provide immediate applications across diverse processes including irrigation, fertilization, crop protection, quality enhancement, and disease forecasting.

The advantages of smart agriculture include continuous real-time crop data collection, precise soil and crop assessment, remote farm monitoring, efficient management of water and natural resources, and overall improvements in livestock and crop production. As a result, smart agriculture represents the advancement of precision farming by integrating intelligent, technology-driven approaches to gather extensive information on farm operations, thereby enabling remote supervision and timely, data-supported farm management solutions.

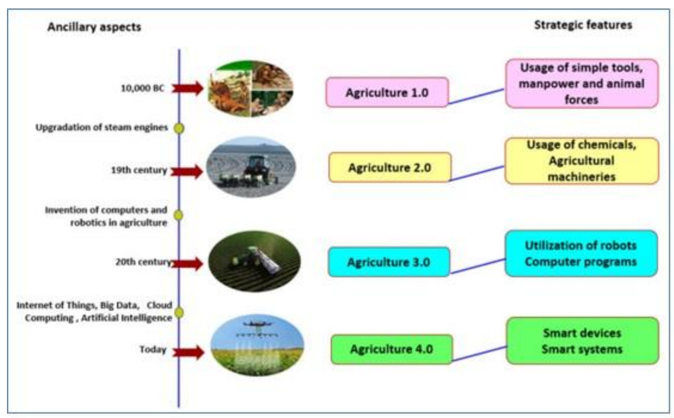

Fig 1: Framework for a system that assists farmers in making agricultural decisions.

The Internet of Things (IoT) refers to a technological paradigm that integrates diverse technologies to enable collaboration, communication, and the wireless transfer of real-time sensor data for processing. This connectivity supports more effective decision-making across multiple research domains. IoT has witnessed rapid growth and is now applied in sectors such as healthcare, defense, industry, and agriculture, among others. Its potential is vast, offering opportunities to advance human civilization and improve quality of life [2]. Successful IoT deployment requires domain-specific knowledge, appropriate hardware infrastructure, and internet connectivity for device interaction. Fundamentally, IoT establishes connections and facilitates data exchange among physical objects, or "smart devices." Although the idea itself is not new, recent advances in hardware have accelerated its adoption [3].

The application of IoT in Auto-ID systems in 1998 drew positive recognition from the U.S. president, which further spurred interest and development in the field. When combined with sensor networks, IoT introduces innovative means of interacting with and observing real-time data in the physical environment, thereby enhancing automation and decision-making. In agriculture, IoT-based intelligent systems have the potential to monitor crop growth and environmental conditions. Beyond raw data collection, however, the critical steps of data mining and analysis are necessary to derive actionable insights [4].

Despite challenges, IoT presents transformative possibilities for agriculture by enabling forecasting, monitoring, and managing the complete lifecycle of agricultural products. In India, where nearly half the population depends on agriculture for their livelihood, the need for such solutions is particularly urgent. To address this, a proposed architectural framework consists of three layers: the physical layer, the IoT layer, and the Com-op layer. Together, these layers create an integrated management system that supports consumer monitoring and automation services. This model can effectively tackle agricultural challenges related to animal control, quality assurance, and supply chain management [5].

1.1 Internet of Things

The Internet of Things (IoT) is an emerging technology facilitating remote connectivity of devices, particularly in the context of smart farming. Its impact extends across various industries, including health, commerce, communications, energy, and agriculture, with the aim of improving efficiency and performance across diverse markets.

Existing applications offer insights into the impact of IoT and reveal practices that are yet to be fully explored. However, considering technological advancements, one can anticipate the pivotal role of IoT technologies are integrated into various agricultural activities, utilizing communication infrastructure, collecting data, employing smart objects, sensors, mobile devices, and cloud-based intelligent information to support decision-making and automate farming operations [6]. The implementation of IoT involves monitoring plants and animals, enabling the remote retrieval of information through mobile phones and devices. Farmers can utilize sensors and instruments to evaluate weather conditions and forecast production levels. In water harvesting, IoT plays a crucial role in monitoring and controlling flow, assessing crop water requirements, determining supply timing, and optimizing water conservation. Through sensors and cloud connectivity via gateways, this technology enables remote monitoring of soil and plant needs, facilitating effective water supply management. Addressing nutrient deficiencies, pests, and diseases manually for each plant is impractical, but IoT technology proves beneficial, marking a significant advancement in modern agriculture. [7].

1.2 Smart Agriculture

Smart farming is a modern agricultural management strategy that employs advanced technologies to improve both the yield and quality of crops. In today's era, farmers can utilize a variety of tools such as GPS, soil analysis, data management systems, and the Internet of Things (IoT). The main aim of research in smart agriculture is to develop decision-support systems that enable more efficient farm management. This approach is essential for tackling issues like population growth, climate change, and labor shortages, covering activities from planting and irrigation to crop health monitoring and harvesting [8].

In IoT-enabled smart agriculture, systems are designed to monitor fields through sensors that track parameters like light, humidity, temperature, and soil moisture, while also enabling automated irrigation. In this context, IoT refers to the use of sensors, cameras, and other devices to transform all aspects of farming into actionable data. Expanding and advancing smart agriculture is critical for minimizing the environmental impact of conventional farming methods. Similarly, in smart cities, IoT devices—including connected sensors, lighting systems, and meters—collect and analyze data to optimize infrastructure, public services, and utilities. Nonetheless, farmers often encounter challenges in adopting these technologies due to their complexity and cost. [9]

1.3 IoT in Advanced Farming Practices

Embracing novel approaches rooted in sensor and IoT technologies has significantly boosted crop yields compared to traditional agricultural methods. The integration of advanced sensor-based technologies in controlled environments is instrumental in elevating both the quality and quantity of agricultural produce.

1.3.1 Greenhouse Farming and Protected Cultivation

Cultivating plants in a controlled environment, dating back to the 19th Century, stands as one of the earliest forms of smart farming. This method gained further traction in the 20th Century, particularly in regions with challenging weather conditions. Plants grown indoors are less susceptible to environmental influences. Consequently, crops traditionally limited to specific conditions can now be cultivated at any time and place through the integration of sensors and communication devices. The success of crop production in controlled environments relies on several factors, including the design and materials of structures to mitigate wind effects, aeration systems, the precision of monitoring parameters, and the implementation of decision support systems. Precisely monitoring environmental parameters poses a significant challenge in greenhouses, necessitating multiple measurement points to predict and control various factors that ensure a conducive local climate. In IoT-based greenhouses, sensors play a crucial role in measuring and monitoring internal parameters such as humidity, temperature, light, and pressure.

1.3.2 Hydroponics

Hydroponics, a facet of hydroculture, entails cultivating plants without soil to optimize the benefits of greenhouse farming. In hydroponic irrigation systems, nutrients dissolved in water are uniformly delivered to plant roots as a solution. Modern systems and sensors have the capability to detect a broad spectrum of parameters, conducting data analysis at specified intervals. The precise measurement and monitoring of nutrient concentrations in the solution are vital for satisfying the requirements of plant growth. A real-time, wireless-sensor-based prototype has tackled soilless cultivation by measuring concentrations of various nutrients and water levels.

An integrated automated smart hydroponics system, incorporating IoT, consists of three primary components: input data, a cloud server, and output data. This system allows remote monitoring of lettuce cultivation over the internet, analyzing real-time parameters such as pH level, nutrient-rich water-based solution, room temperature, and humidity. The deep flow technique in hydroponic systems involves cultivating plants by submerging roots in deep water layers, ensuring a continuous circulation of the plant nutrient solution. Sensors integrated into Raspberry Pi collect data on plant growth elements such as pH, temperature, humidity, and water level in the hydroponic reservoir. This data is automatically processed and monitored in real-time to ensure proper water circulation.

1.3.3. Vertical Farming

Traditional agricultural methods in the industrial sector degrade soil quality at a rate that outpaces the natural regeneration process. The alarming levels of erosion and the extensive use of freshwater in agriculture contribute to a decline in arable land and impose additional pressure on existing water reservoirs. Vertical farming (VF) provides an opportunity to cultivate plants in a precisely controlled environment, significantly mitigating resource consumption while concurrently enhancing production at various intervals. Furthermore, VF necessitates only a fraction of the ground surface, depending on the number of stacks. This approach proves highly efficient in achieving increased yields and reducing water usage compared to conventional farming. In the context of vertical farms, the measurement of carbon dioxide is a crucial parameter, and nondispersive infrared (NDIR) CO_2 sensors play a pivotal role in monitoring and controlling environmental conditions.

2. OBSTACLES IN THE ADOPTION OF SMART AGRICULTURE TECHNOLOGIES

The adoption of technology involves a process influenced by various heterogeneous factors. The integration of technology into farming systems has brought about improvements in accuracy, efficiency, and time management. Despite the enhanced productivity that smart farming offers, there remain challenges in the widespread adoption of these technologies.

2.1 Technology cost

Modern technologies decrease reliance on manual labor and perform tasks quickly with high accuracy. This has led to concerns that machines could eventually replace human workers. However, such a scenario is unrealistic, particularly in countries where agriculture relies heavily on human labor, which is often associated with low-income communities. Moreover, implementing these advanced devices and technologies requires substantial financial investment, making it difficult for farmers to afford them when transitioning from traditional farming methods.

2.2. Inadequate monetary resources

In cases where farmers do not achieve the expected yield due to unforeseen events such as drought, flood, pests, or diseases affecting the crops, financial institutions/individuals have the option to offer sufficient loans to support the farmers.

2.3. Level of education among farmers

The educational level of farmers presents a major obstacle to adopting new technologies, especially in developing countries. Effective use of smart farming tools requires both general education and technical skills. Higher education levels improve a farmer's capacity to process information, make informed decisions, and become proficient in using digital devices and computers. In many developing nations, however, farmers often lack sufficient education and skills due to limited interest in learning or low awareness of emerging technologies. As a result, they tend to rely on traditional farming methods. Another challenge is the perceived complexity of technology; for example, farmers may struggle to interpret icons in mobile applications that are based on conventional symbols. To overcome these barriers, farmers need digital literacy, and agri-tech providers must ensure that the advantages and limitations of technologies are clearly communicated and easily understood.

2.4. Lack of Integration between the Systems

Advances in smart farming technologies should prioritize seamless integration across various systems, including production management, asset management, and decision-support tools. Closing the gap between agriculture and information science requires stronger collaboration among researchers and interdisciplinary teams. The development of information systems increasingly emphasizes improving user efficiency. Effective decision-making depends on the timely availability of accurate, high-quality data; therefore, integrating data is essential for generating comprehensive insights and knowledge.

2.5. Data Management

Farmers often face difficulties in managing and interpreting the data collected by sensors. While weather stations and other devices produce valuable information, farmers may lack the expertise to utilize it effectively or transform it into a more usable format. The complexity of these systems, along with challenges in acceptance and usability, can lead to errors in calculations. To overcome these issues, it is important for farmers, consultants, and other stakeholders to improve accessibility and usability of data within agricultural production systems.

3. LITERATURE REVIEW

Fuentes et al. [23] study evaluated the effectiveness of different deep learning networks, including Faster R-CNN, R-FCN, and SSD, for categorizing diseases in tomatoes. The classification involved applying a Front Viewpoint to RGB images. The Keras framework, utilizing the TensorFlow language, implemented Data Augmentation as the primary methodology. The researchers introduced a method for local and global class annotation, along with data augmentation as the foundation of their approach. The results demonstrated improved accuracy and a reduction in false positives.

Natarajan et al [26] introduced an automated system designed for detecting diseases in cultivated land. Faster R-CNN with feature extraction was employed to identify and categorize tomato diseases in plants. The proposed model underwent training and testing using a dataset comprising approximately 1090 images depicting early and late stages of tomato diseases. The suggested system, utilizing ResNet50, demonstrated effective prediction of early blight, leaf curl, septoria, and bacterial leaf spot even in intricate plant environments.

Alvaro et al [28] produced a deep learning method for the real-time identification of diseases and pests in tomatoes using images captured by cameras. The focus was on three detector families: Single Shot Multibox Detector, Region-based Fully CNN, and Faster Region-based CNN. Each meta-architecture was combined with VGG net and Residual Network. The researchers also proposed a technique for local and global class annotation, along with data augmentation, to enhance precision and reduce false positives during training. The Tomato Diseases and Pests Database, containing images with various inter-class variations such as infection portions in leaves, was utilized for comprehensive model training and testing. The suggested method demonstrated the capability to identify nine distinct diseases and pests while effectively handling complex situations that may arise in the plant's surroundings.

Nagamani et al [30] explored machine learning tools such as Fuzzy-SVM, CNN, and Region-based CNN for the detection of diseases in tomato leaves. Images of tomato leaves exhibiting six diseases and healthy samples were utilized to validate the findings. The images underwent training using techniques such as picture scaling, color thresholding, flood filling, gradient local ternary pattern, and Zernike moments' attributes. The analysis and comparison of Fuzzy SVM, CNN, and R-CNN aimed to identify the most accurate classifier for plant disease detection. In comparison to other methods, R-CNN achieved an accuracy of 96.735 percent

Li et al [12] proposed method, LMBRNet, is introduced as a classifier for identifying diseases in tomato leaves, utilizing Complementary Grouped Dilated Residual feature extraction blocks. Four subsidiaries were created with convolutional kernels of varying dimensions to extract distinctive data on tomato illnesses and tomato leaf receptive fields. To address network degradation and gradient disappearance issues, a residual connection was incorporated. The performance of LMBRNet was tested on public datasets RS, SIW, and Plantvillage-corn. The results on all three datasets demonstrated high accuracy, with scores of 82.32%, 88.37%, and 97.25% on RS, SIW, and Plantvillage-corn, respectively, showcasing the robust generalizability of LMBRNet. When compared to specific datasets, LMBRNet outperformed MobileNetV3S and MobileNetV3L. Despite having a limited number of parameters (4.1M), its metrics were higher than MobileNetV3S (2.9M) and lower than MobileNetV3L (5.4M), indicating better generalization.

Sunil et al [14] proposed Multilevel Feature Fusion Network is presented for the classification of tomato leaf diseases. ResNet50, MFFN, and the Adaptive Attention Mechanism are employed to categorize leaf images. The suggested technique achieved high accuracy, with 99.88% in training, 99.9% in validation, and 99.8% in test accuracy. It outperformed currently employed methods suitable for the dataset. Additionally, the research provides insights into specific pesticides based on the type of leaf disease.

Astani et al [18] aims to swiftly and precisely detect 13 tomato diseases in both farm and laboratory settings using 260 ensemble techniques developed with feature extraction. The accuracy and precision of the suggested method were evaluated under diverse conditions, including laboratory and outdoor scenarios, with challenges posed by two databases, Plantvillage and Taiwan tomato leaves. The best ensemble classifier achieved a disease identification accuracy of 95.98%, effectively addressing challenges such as background clutter, multiple leaves, brightness changes, disease similarity, and shadow conditions. A comparison was made among the 260 recommended ensemble models and various deep learning models. The proposed approach outperformed most advanced deep learning models.

Wspanialy et al [21] trained a model to identify previously unrecognized tomato leaf diseases, and its ability to forecast disease severity was found to be comparable to human assessment. The shape of leaves was identified as having predictive capabilities for disease detection. To enhance dataset diversity and reduce accidental bias in backgrounds, future data gathering initiatives should address limitations in the PlantVillage information set and its image capturing methods. The idea of a diseased-healthy binary classifier as a predictor of healthy leaves was introduced. Beyond identifying diseases not previously trained on, such a classifier can help reduce the effort required to create an extensive dataset for general disease identification. The study also introduced a new dataset featuring proportional disease severity annotations and an associated classifier. Ordinal categories were found to be more effective for diseases caused by viruses and insects, while proportional area measures worked best for estimating severity in bacterial and fungal diseases. Implementing classifiers into an automated examination system can reduce costs, minimize errors, and enhance accuracy, making the findings applicable in practical settings.

Monika et al [27] conducted a research between 2019 and 2020, during which surveys observed the presence of various pests, including Aphids Myzus persicae and Macrosiphum euphorbiae, the serpentine leaf miner Liriomyzia trifolii, the fruit borer Helicoverpa armigera, and the whitefly Trialeurodes vaporariorum. Aphid species M. persicae were found in low hills, whereas mid hills showed tomato infestations by M. euphorbiae. In the mid-hills of Himachal Pradesh, a higher incidence of tomato pest infestations was noted compared to the low hills.

Ashok et al [29] proposed approach establishes a methodology that correlates the pixel intensity of input images and contrasts it with a trained image instance using Convolutional Neural Networks (CNN) for feature extraction. All metrics for adjusting leaf parts are optimized by reducing the error relative to the training set. This study recommends the utilization of image processing methods based on segmentation and clustering to detect tomato diseases. Leaf images are classified using an image classifier that employs Artificial Neural Networks (ANNs), fuzzy logic, and hybrid algorithms to differentiate between disease-affected and healthy leaves. The accuracy of the suggested method is reported to be 98%.

Bhandari et al [31] In addition to healthy leaves, this study aims to visually identify nine infectious diseases in tomato leaves, encompassing early and late blight, leaf mould, 2-spotted spider mite, Septoria leaf, bacterial spot, and mosaic virus. Without segmenting the dataset, EfficientNetB5 was utilized with 10 cross-folds. The classifier achieved accuracy rates of 99.84%, 98.28%, and 99.07% for training, validation, and testing data, respectively. The recommendation is to consider the integration of Gradient-weighted Class Activation Mapping and locally interpretable model-related discussions into agricultural practices for forecasting effectiveness.

Tian et al [32] proposed DL classifier based on private and public datasets of tomato leaf images for identifying diseases. VGG16, InceptionV3, and Resnet50 were trained and evaluated. To identify 9 different diseases and healthy tomato leaves, they installed trained model into Android application called TomatoGuard. TomatoGuard performed better than APP Plantix with 99% testing accuracy.
Martins et al [43] developed a machine learning classifier to evaluate the severity of leafminer fly infestations in tomatoes. The database comprised images capturing signs of pests on tomato leaves in field conditions. These images were manually annotated into three categories: background, leaves, and symptoms of leafminer fly infestation. Three classifiers and four different backbones were compared using metrics like accuracy, precision, and recall for a multiclass categorization. The U-Net classifier with Inceptionv3 yielded the best results, as indicated by a comparison of segmentation outcomes. For estimating symptom severity, the best classifier exhibited lower Root Mean Square Error (RMSE) values and utilized FPN with ResNet34 and DenseNet121 backbones.

Bouni et al [34] identifying and managing plant diseases, which have a considerable impact on food production, population health, plant quality, and productivity, poses a major challenge in agriculture. Manual identification of various plant diseases is time-consuming. The control of tomato diseases demands constant attention throughout the crop lifecycle and contributes significantly to the overall production costs. In this study, automation and pretrained Deep Neural Networks (DNN) were employed for the classification of tomato diseases. Digital image processing is utilized for monitoring plant diseases. Deep Learning (DL) has demonstrated superior performance compared to traditional methods in digital image processing. The article employs transfer learning and a deep Convolutional Neural Network (CNN) to predict tomato diseases. The core of the CNN classifier includes AlexNet, ResNet, VGG-16, and DenseNet. The relative performance of networks is analyzed using the Adam and RmsProp approaches, revealing that DenseNet with the RmsProp methodology achieves remarkable results with 99.9% accuracy.

Tarek et al [35] evaluated the performance of ResNet50, InceptionV3, AlexNet, MobileNetV1, MobileNetV2, and MobileNetV3, all trained on the ImageNet dataset. MobileNetV3 Small and MobileNetV3 Large achieved precision rates of 98.99% and 99.81%, respectively. The effectiveness of each model was assessed by calculating the detection duration on images of tomato leaves using a workstation where all models were deployed. For the construction of an IoT system for tomato disease detection, classifiers were also implemented on Raspberry Pi 4. On the workstation, MobileNetV3 Small exhibited latencies of 66 ms, and on Raspberry Pi 4, it showed a latency of 251 ms. MobileNetV3 Large had a latency of 348 ms on Raspberry Pi 4 and 50 ms on the workstation.

Bhatia et al [36] utilizing an Extreme Learning Machine (ELM) with a sensor-based dataset on Tomato Powdery Mildew Disease, the authors implemented techniques such as Synthetic Minority Over-sampling, Random Over Sampling, Random Under Sampling, and Importance Sampling to balance the TPMD database. Accuracy and the area under the curve were employed for the analysis of ELM. The findings indicate an increase in classification accuracy (CA) and the area under the curve (AUC) for the resampling techniques applied in this study. ELM exhibited superior performance compared to the IMPS approach, achieving an accuracy of 89.19% and an AUC of 88.57%.

Govardhan et al [37] implemented the Random Forest algorithm for the identification and categorization of tomato diseases. Features were extracted from preprocessed images, and the system diagnosed conditions such as Early and Late Blight, Spider Mite, Yellow Leaf Curl Virus, and Target Spot. Identifying tomato leaf diseases can be challenging due to symptoms that often mimic nutritional deficiencies, such as mosaic virus, and can vary based on the plant's age at the time of contamination. The results showed that all testing images achieved optimal image classification, with the system demonstrating 95% effectiveness.

Qasrawi et al [38] utilizing 3000 photos featuring five tomato illnesses—Alternaria solani, Botrytis cinerea, Panonychus citri, Phytophthora infestans, and Tuta absoluta—taken in Tubas, Jenin, and Tukarem, three West Bank communities, the study employed machine learning (ML) classifiers with image embedding and hierarchical clustering. Neural networks, random forests, naive Bayes, SVM, decision trees, and logistic regression were used for prediction and categorization. The proposed model's accuracy was evaluated against a database of tomato plant diseases compiled by plant pathogen specialists. The clustering model achieved an accuracy of 70% for seven diseases, compared to 70.3% and 68.9% for neural networks and logistic regression, respectively. The suggested method demonstrated accuracy in clustering, identifying, and categorizing tomato plant diseases, showcasing the potential benefits of applying ML techniques to agriculture for Palestinian farmers in enhancing their disease control capabilities.

Mokhtar et al [39] suggested the use of Support Vector Machine (SVM) for the identification of two distinct tomato leaf diseases. Both the training and testing phases utilized datasets containing 200 images of leaves affected by Powdery Mildew and Early Blight. Cauchy, Invmult, and Laplacian kernels were employed in the SVM. The proposed approach was selected through grid search, and its performance was evaluated using N-fold cross-validation. Results indicate high accuracy provided by the recommended strategy, with Cauchy and Laplacian kernels achieving 100% and 98% accuracy, respectively, in comparison to the Invmult kernel's 78% accuracy.

Dhaya et al [40] concentrated on Fusarium wilt disease, a common affliction affecting various plants. Fusarium oxysporum, primarily impacting tomatoes, sweet potatoes, tobacco, legumes, and cucurbits, is often soil-borne. The proposed algorithm constructs models by predicting the disease twice to enhance accuracy. The public dataset comprises 87,000 images, with 60% depicting affected leaves and 40% depicting healthy plant leaves. With this extensive dataset, the suggested hybrid approach using Naive Bayes and image recognition accurately detected the disease with a 96% accuracy rate.

IV COMPARATIVE ANALYSIS

Study	Crop	Method	Dataset	Accuracy / mAP	Key Features
Li et al., 2020	Tomato	CNN (Leaf Classification)	PlantVillage	95%	High accuracy for tomato leaf miner
Zhang et al., 2021	Rice	Faster R-CNN	Field dataset	92%	Real-time detection in fields
Singh et al., 2022	Tomato & Rice	IoT + ML Hybrid	Mixed	High reliability	Sensor + image fusion
Kumar et al., 2023	Tomato	YOLOv5	Field images	96%	Fast multi-pest detection
Chen et al., 2023	Rice	Drone + CNN	IP102	90%	Brown planthopper detection

The table shows that deep learning approaches, particularly YOLO-based detectors, outperform traditional ML models. Integration with IoT sensors ensures timely alerts and enhances decision-making accuracy.

4. CONCLUSION

In today's era, there is a growing need for smarter and more efficient methods of crop production to address the challenges of shrinking arable land and increasing global food demands. Ensuring food security through sustainable agricultural practices has become a critical priority. Emerging technologies play a pivotal role in boosting crop yields and promoting farming as an innovative and attractive profession, especially for younger generations. This paper highlights the importance of technologies such as Machine Learning, Deep Learning, and IoT in making agriculture more intelligent and capable of meeting future requirements.

It examines current challenges faced by the agricultural sector and explores future opportunities to guide researchers and engineers. As a result, optimizing the productivity of every farmland unit is essential, achievable through the deployment of sustainable IoT-based sensors and communication technologies that monitor and manage all aspects of agricultural land.

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