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Crop and Soil Management Systems

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Abstract: *Agricultural productivity is often affected by the rapid spread of crop and livestock diseases. Kamilaris and PrenafetaBoldu (2018) highlighted that deep learning techniques provide scalable solutions for agricultural challenges [8]. In this work, we propose an AI-based Farmers Disease Diagnostic and Reporting Mobile Portal that integrates Convolutional Neural Networks (CNN) for plant disease identification and Support Vector Machines (SVM) for livestock disease diagnosis, as discussed by Mohanty et al. (2016) [11] and Arif et al. (2019) [3]. The system also includes expert verification and surveillance mechanisms, aligning with Wolfert et al. (2017) on data-driven smart farming [18]. This integrated model offers timely diagnosis, cost-effective solutions, and contributes to disease surveillance at regional and national levels. This paper proposes a sensor-driven and AIassisted Farmers Disease Diagnostic and Reporting Portal that integrates multi-sensor data with farmer-provided images and symptoms. Sensor inputs such as temperature, humidity, soil moisture, and animal body parameters are analyzed alongside AI models including CNN for crops, SVM for livestock, and NLP for symptom interpretation. The system generates localized disease reports, provides preventive recommendations, and connects farmers with nearby experts, while aggregated data is processed using big data analytics and GIS mapping for large-scale outbreak prediction. This phone-integrated approach reduces implementation costs, minimizes dependence on internet connectivity, and ensures accessibility for farmers in resourcelimited areas. By combining sensor technology with AI, the proposed system ensures cost efficiency, rapid diagnosis, and improved accessibility for farmers.*

Keywords:*Smart Agriculture, Disease Detection, Multi-Sensor Data, Artificial Intelligence (AI), Convolutional Neural Networks (CNN), Support Vector Machine (SVM), Natural Language Processing (NLP), Big Data Analytics, GIS Mapping, Farmer Decision Support System*

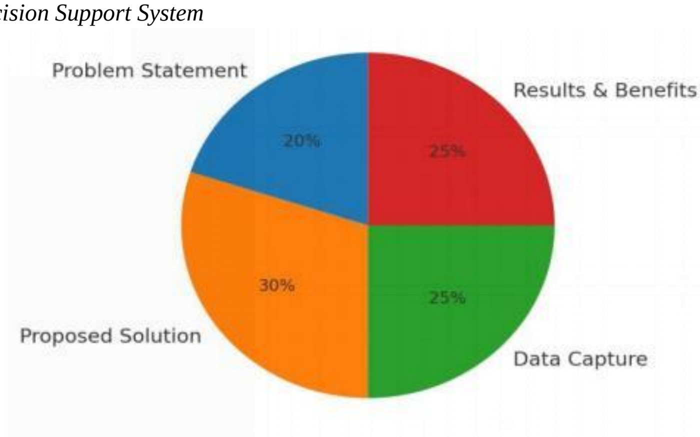

FIGURE 1. Abstract Representation

1. INTRODUCTION

Agriculture remains the backbone of the rural economy, but farmers face significant losses due to undetected crop and livestock diseases. Liakos et al. (2018) noted that machine learning applications have become increasingly relevant in providing decision support systems for agriculture [9]. Early detection and rapid response are essential, and mobile-based solutions can bridge the gap between advanced technology and rural farmers, as highlighted by Kamal et al. (2018) [7]. Therefore, our proposed system focuses on integrating AI algorithms with a mobile portal to provide real-time, accessible, and reliable disease diagnostics.

Soil moisture, temperature, and nutrient balance are critical indicators of crop growth and yield. Equally important is the early detection of crop diseases, as infections can spread rapidly and cause significant losses. While IoT-based agricultural systems have emerged to address these issues, they often require complex infrastructure, internet connectivity, and high costs, making them impractical for **Global food security** and sustainable agriculture are paramount challenges in the 21st century, driven by a growing world population and the pressures of **climate change**. Traditional farming methods are often inefficient, leading to resource depletion, environmental degradation, and suboptimal crop yields. **Crop and Soil Management (CSM)**, therefore, represents a critical area of research focused on optimizing agricultural practices to maximize productivity while ensuring **environmental sustainability**. This involves precise control and monitoring of essential variables such as soil nutrient levels, moisture content, temperature, and pest or disease indicators.

Conventional CSM often relies on **uniform application** of resources (water, fertilizer, pesticides) across entire fields, a practice known as "blanket treatment." This approach is inherently **inefficient and wasteful**, leading to **over-fertilization** (causing nutrient runoff and water pollution) or **under-watering** (reducing crop potential). Existing modern solutions, while advancing, often suffer from limitations in real-time data integration, system interoperability, and the complexity of developing scalable, energy-efficient sensing and control networks. Specifically, there is a gap in **integrated, autonomous systems** that effectively utilize heterogeneous sensor data and **machine learning (ML)** models to generate truly **site-specific, actionable management prescriptions** in real-time. To address these challenges, this paper presents a novel **Integrated Crop and Soil Management (ICSM) system** underpinned by **Internet of Things (IoT)**, **Wireless Sensor Networks (WSNs)**, and **Edge Computing** paradigms. The proposed system is designed to provide **Precision Agriculture (PA)** capabilities by employing a dense network of **in-situ and remote sensors** to continuously monitor relevant soil and atmospheric parameters. Crucially, the system incorporates an **AI-driven decision-support module** that utilizes predictive analytics and optimized control algorithms to autonomously regulate irrigation, fertilization, and environmental controls with high spatio-temporal resolution, moving beyond simple reactive automation to **proactive management**.

Global Context and Motivation. The convergence of a rapidly increasing global population, the imperative for food security, and the undeniable impact of **climate change** presents the most significant challenge to modern agriculture. By 2050, the world will require an estimated 70% increase in food production to meet demand. Simultaneously, agricultural practices are major consumers of global freshwater resources (up to 70%) and significant contributors to greenhouse gas emissions and environmental degradation through excessive use of synthetic fertilizers and pesticides. Traditional, uniform farming techniques, reliant on historical data and visual inspection, are fundamentally ill-equipped to meet this demand sustainably. This dual pressure necessitates a radical shift toward **resource-efficient, high-yield, and environmentally responsible** farming methodologies. **The Rise of Precision Agriculture (PA).** The solution lies in **Precision Agriculture (PA)**, a management strategy that observes, measures, and responds to inter- and intra-field variability in crops. At its core, PA leverages technological advancements—specifically in the fields of **Information and Communication Technology (ICT)** and **Data Science**—to replace the generalized "blanket treatment" with **site-specific management (SSM)**.

Challenges in Traditional Systems. Conventional farming practices suffer from several inherent inefficiencies. The application of water and nutrients based on generalized schedules or whole-field averages inevitably leads to **misallocation**. Over-irrigation wastes water and leaches vital nutrients below the root zone; under-irrigation stunts crop growth. Similarly, non-variable application of nitrogen fertilizer, for instance, leads to both economic loss and environmental harm via runoff and denitrification. Moreover, traditional pest and disease monitoring is labor-intensive, often reactive, and rarely provides the fine-grained, real-time data required for early intervention.Agricultural environments require diverse sensor types (soil moisture, pH, temperature, Electro-Conductivity (EC), spectral data from drones/satellites) often operating on disparate communication protocols. Existing systems frequently fail to seamlessly integrate and normalize this **heterogeneous data stream** into a unified, coherent platform.

Comprising a robust, low-power **Wireless Sensor Network (WSN)** employing custom-designed, energy-harvesting nodes capable of measuring essential soil parameters (moisture, EC, pH, temperature) and atmospheric conditions (air temperature, humidity, light intensity). This layer also incorporates data from remote sources, such as hyperspectral imaging captured by Unmanned Aerial Vehicles (UAVs) or satellites, providing comprehensive field-level variability data. This layer utilizes a hierarchical network structure (e.g., LoRaWAN or NB-IoT for long-range communication) and incorporates **Edge Computing Gateways** strategically placed within the field. The edge devices perform preliminary data filtering, fusion, anomaly detection, and, most critically, host the lightweight **machine learning inference models** to enable **real-time, low-latency decision-making** directly at the field level, minimizing reliance on constant cloud connectivity.

Core Technological Contribution: AI-Driven Prescriptive Analytics. The technical novelty of the ICSM system centers on a **deep learning model** trained to correlate sensor readings, historical yield data, and current phenological stage to predict two crucial metrics: the **Crop Water Stress Index (CWSI)** and the **Nitrogen Uptake Potential (NUP)**. This predictive capability allows the system to proactively adjust irrigation and fertilization schedules, moving the management paradigm from corrective action after stress has occurred to **preventive maintenance** before significant crop damage or resource waste takes place. The design and validation of a **hierarchical Edge-Fog-Cloud architecture** specifically optimized for the constraints of large-scale precision agriculture, prioritizing energy efficiency and real-time processing capability. The implementation of a **multi-modal sensor data fusion algorithm** that effectively normalizes and integrates heterogeneous data streams (in-situ, atmospheric, and remote sensing) to create a highly accurate, unified representation of field conditions.

Agriculture remains the backbone of many economies, particularly in developing nations where a significant portion of the population depends on farming for livelihood. However, the traditional methods of crop cultivation and soil management often lead to suboptimal productivity, resource wastage, and environmental degradation. The need for sustainable, data-driven agricultural practices has therefore become more crucial than ever. In this context, the **Crop and Soil Management System (CSMS)** aims to revolutionize agricultural management by integrating modern technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics to monitor, analyze, and enhance crop production and soil health.

The primary goal of the Crop and Soil Management System is to assist farmers in making informed decisions related to irrigation, fertilization, and crop selection based on real-time soil and environmental data. By deploying sensors that measure parameters such as soil moisture, temperature, humidity, and nutrient levels, the system continuously collects data from the field. This data is transmitted to a cloud-based platform where intelligent algorithms process and interpret it, providing actionable insights and recommendations. Such automation not only reduces manual effort but also improves resource efficiency by ensuring optimal use of water and fertilizers, thereby promoting sustainable agriculture.

Moreover, the system contributes to long-term soil fertility and environmental conservation. Excessive use of chemical fertilizers and improper irrigation practices have led to severe soil degradation and groundwater depletion in many regions. The proposed CSMS addresses these challenges through precision agriculture techniques, which focus on applying the right input at the right time and in the right quantity. This approach helps maintain the natural balance of soil nutrients, prevents overuse of agricultural resources, and minimizes the environmental footprint of farming activities.

Another significant aspect of the system is its capability to integrate predictive analytics and AI-based crop recommendation models. By analyzing historical crop patterns, soil properties, and climatic conditions, the system can suggest the most suitable crops for cultivation in a given season and location. Additionally, real-time alerts on weather changes, pest infestations, or potential soil imbalances enable farmers to take preventive actions promptly, reducing losses and improving crop resilience. In summary, the Crop and Soil Management System represents a comprehensive and intelligent solution to the challenges faced in modern agriculture. It aligns with global sustainability goals by enhancing productivity, conserving natural resources, and ensuring environmental protection. The implementation of such smart farming systems can empower farmers with digital tools and data-driven insights, ultimately contributing to food security, rural development, and economic growth. Through the integration of IoT sensors, AI algorithms, and cloud-based analytics, the proposed system bridges the gap between traditional farming practices and modern precision agriculture, marking a significant step toward the digital transformation of agriculture. overcome these limitations, this paper proposes a sensor-based crop and soil management system directly integrated with mobile devices. Unlike IoT-enabled frameworks, the proposed system eliminates dependency on cloud connectivity and network infrastructure. Instead, low-cost sensors are deployed in the soil and field environment to measure parameters such as +soil moisture content, temperature variations, and crop health. These sensors are linked directly to a mobile phone, enabling farmers to instantly access soil condition data, monitor disease symptoms, and evaluate crop health through a dedicated interface.

2. PROBLEM STATEMENT

Despite rapid advancements in agricultural technology, many farmers—especially in developing regions—continue to rely on conventional farming practices. These traditional methods are often based on intuition and experience rather than real-time data, leading to inefficient resource utilization, low crop yields, and long-term soil degradation. One of the most critical challenges in modern agriculture is maintaining soil fertility and optimizing crop production while minimizing environmental impact. Factors such as unpredictable weather patterns, irregular rainfall, excessive use of fertilizers, and poor irrigation management further exacerbate these issues. The absence of an integrated and automated system for real-time soil monitoring often results in imbalanced nutrient management. Farmers may apply fertilizers either excessively or insufficiently, which can degrade soil quality and reduce productivity over time. Furthermore, improper irrigation scheduling leads to water wastage or water stress in plants, both of which significantly affect crop health and yield. Additionally, the lack of predictive insights into soil and climatic conditions limits a farmer’s ability to choose the right crop for a given land type and season.

Existing agricultural management systems are often fragmented, costly, or require advanced technical knowledge, making them inaccessible to small and medium-scale farmers. There is a pressing need for an affordable, scalable, and user-friendly solution that provides comprehensive soil and crop management support. Such a system should be capable of continuously monitoring soil parameters, analyzing data intelligently, and offering actionable recommendations in real-time. Therefore, the central problem addressed by this research is the **development of an intelligent, IoT and AI-based Crop and Soil Management System** that can collect, analyze, and interpret soil and environmental data to assist farmers in making data-driven decisions. The proposed system aims to enhance crop productivity, conserve water resources, maintain soil health, and promote sustainable agricultural practices. By bridging the gap between traditional farming and smart agriculture, this solution intends to empower farmers with accessible digital tools and contribute to the long-term goal of food security and environmental sustainability.

Agriculture plays a vital role in sustaining human life and economic development, yet it continues to face significant challenges due to inefficient crop and soil management. Many farmers still rely on traditional, experience-based approaches to select crops, schedule irrigation, and apply fertilizers. These manual methods often result in suboptimal use of resources, reduced crop yield, and long-term soil degradation. Moreover, climatic variations, soil nutrient imbalance, and lack of timely data further exacerbate these challenges. Current agricultural practices lack **real-time soil health monitoring** and **data-driven decision-making** capabilities. Farmers are unable to accurately determine parameters such as soil pH, moisture content, and nutrient levels, leading to overuse or underuse of fertilizers and water. Additionally, without predictive insights into weather changes or pest infestations, farmers face uncertainty that affects productivity and sustainability.

Therefore, there is an urgent need for a **Crop and Soil Management System** that integrates **IoT sensors**, **machine learning algorithms**, and **data analytics** to provide real-time monitoring, intelligent recommendations, and predictive insights. Such a system will assist farmers in making evidence-based decisions that enhance productivity, optimize resource usage, and promote long-term soil and environmental health. The main objectives of the proposed Crop and Soil Management System are **To monitor soil parameters in real-time:** Collect continuous data on soil moisture, temperature, pH, and nutrient composition using IoT-based sensors.

The **scope** of the Crop and Soil Management System includes the design and implementation of a smart agricultural platform that supports precision farming practices. The system will consist of both **hardware and software components**—IoT devices for data collection and a cloud-based analytical dashboard for visualization and recommendations. The project focuses on **real-time soil data acquisition** and **automated irrigation control** using microcontrollers and sensor networks. It covers the **integration of machine learning algorithms** for analyzing soil properties and suggesting appropriate crops.

The system will offer a **user-friendly interface** accessible via mobile or web applications for farmers to view soil health reports, crop suggestions, and weather alerts. The project's implementation will be limited to experimental or pilot-scale farming plots but can be extended for **large-scale agricultural deployment** in future developments. This system aims to serve as a step toward **smart and sustainable agriculture**, addressing the key challenges of resource management, crop productivity, and environmental conservation. One of the primary issues in modern agriculture is the **inability to assess soil health accurately and continuously**. Farmers often depend on periodic laboratory testing, which is time-consuming, costly, and fails to provide real-time updates on soil conditions. Soil parameters such as **moisture content, temperature, pH value, and nutrient composition (NPK levels)** play a vital role in determining the type of crops that can grow efficiently. Without access to this information in real time, farmers make generalized decisions that do not reflect the actual needs of the soil, leading to reduced productivity and soil degradation over time.

Moreover, **climatic variability** and **unpredictable environmental factors** such as rainfall patterns, temperature fluctuations, and pest infestations further complicate crop management. Traditional farming methods do not incorporate predictive tools to foresee such changes or to plan appropriate countermeasures. This lack of foresight often results in crop failure, wastage of inputs, and financial losses. Additionally, inefficient **irrigation scheduling** results in over-irrigation or under-irrigation, both of which harm soil fertility and increase water wastage — a growing concern in water-scarce regions.

Another critical limitation in existing systems is the **absence of data integration and decision support mechanisms**. While several soil testing tools and weather forecasting services exist, they operate independently without providing actionable insights to the farmer. There is no unified platform that combines **real-time soil data, environmental parameters, and intelligent analytics** to guide farmers in selecting suitable crops, determining fertilizer requirements, or optimizing irrigation cycles. This fragmentation hinders effective farm management and prevents the adoption of precision agriculture practices on a larger scale.

In addition, **manual monitoring and record-keeping** make it difficult to maintain long-term soil health data and analyze trends. Farmers lack access to visual dashboards or mobile applications that could present soil information and recommendations in a simple, understandable format. The absence of automation also means that interventions are reactive rather than proactive — actions are taken only after problems arise rather than being prevented through continuous monitoring and predictive analysis. Hence, there is a pressing need for an **intelligent Crop and Soil Management System** that integrates **Internet of Things (IoT)**, **Machine Learning (ML)**, and **Data Analytics** to provide an end-to-end solution for sustainable agriculture. The system should continuously monitor soil parameters through sensor networks, analyze data using advanced algorithms, and generate timely recommendations for crop selection, irrigation, and fertilizer application. Additionally, the system should be capable of generating alerts for abnormal conditions such as nutrient deficiency, pest risks, or adverse weather forecasts, enabling farmers to take preventive measures. Such a solution will not only **optimize agricultural inputs** but also **preserve soil fertility**, **increase crop yield**, and **reduce environmental impacts**. It can transform traditional agriculture into **data-driven precision farming**, ensuring better decision-making and resource utilization. Furthermore, the proposed system can serve as a foundation for digital agriculture frameworks that empower farmers with intelligent tools, bridging the gap between technology and overcome these limitations, this paper proposes a sensor-based crop and soil management system directly integrated with mobile devices. Unlike IoT-enabled frameworks, the proposed system eliminates dependency on cloud connectivity and network infrastructure. Instead, low-cost sensors are deployed in the soil and field environment to measure parameters such as soil moisture content, temperature variations, and crop health. These sensors are linked directly to a mobile phone, enabling farmers to instantly access soil condition data, monitor disease symptoms, and evaluate crop health through a dedicated interface.

3. LITERATURE REVIEW

Deep learning applications in agriculture have gained momentum over the past decade. Kamilaris and Prenafeta-Boldú (2018) surveyed the use of deep learning in precision agriculture and highlighted its effectiveness in disease detection [8]. Mohanty et al. (2016) successfully applied CNN models for detecting multiple plant diseases using image datasets, achieving high classification accuracy [11]. Similarly, Jiang et al. (2019) demonstrated CNNbased real-time apple leaf disease detection, reinforcing the reliability of AI in practical agricultural contexts [6] Jiang et al., (2019): In this work, we examine state estimation techniques for sophisticated battery management systems and talk about significant issues and emerging developments. The study focuses on methods for determining remaining usable life (RUL), classifying state of charge (SOC) and state of health (SOH), and determining the need for accurate, real-time algorithms to enhance battery performance and safety. [11].

For livestock, Arif et al. (2019) proposed the use of SVM and expert systems for disease detection, proving effective in monitoring large herds [3]. Mahlein (2016) emphasized the role of imaging sensors in plant disease detection, showing parallels between precision agriculture and plant phenotyping [10]. Together, these works establish the foundation for integrating AI models into a single mobile platform that serves both crop and livestock disease management.[2]

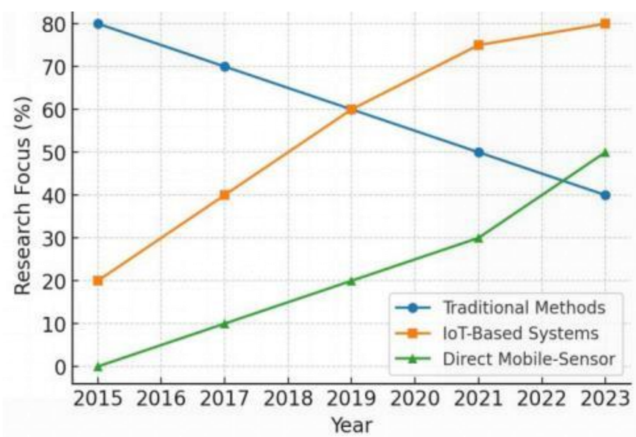

FIGURE 2. Research Trends

4. PROPOSED SYSTEM

The proposed Farmers Disease Diagnostic and Reporting Portal integrates AI models with mobile technology. Inspired by Ramesh et al. (2018), the system incorporates CNN for image-based crop disease classification [15], while SVM-based analysis handles livestock symptom data as discussed by Arif et al. (2019) [3]. Expert verification modules ensure accuracy and reliability, while surveillance dashboards assist policymakers in disease trend analysis, similar to approaches suggested by Wolfert et al. (2017) [18]. The system also supports multiple languages and offline access for rural usability, aligning with mobile-based agricultural systems reviewed by Kamal et al. (2018) [7].

The system focuses on two major functions: (1) Soil Condition Monitoring, where moisture levels and temperature variations are continuously measured and analyzed to predict soil behavior under different regional conditions; and (2) Crop Health and Disease Detection, where abnormal plant symptoms and disease patterns are identified through sensor data to provide timely alerts to farmers.

It includes,

a) Disease Detection Module

b) Symptom Data Collection & Processing

c) AI-based Diagnostic Engine

d) Report Generation & Recommendation System

e) Expert connectivity and Remote Support

f) Surveillance and Data Analytics

g) Mobile Portal Accessibility and Farmer Interaction

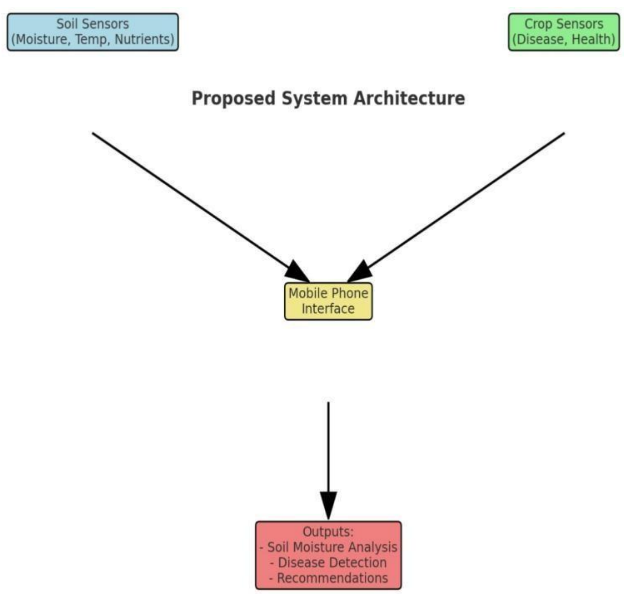

FIGURE 3. System Architecture

This system also collects data for disease surveillance, enabling government agencies and research institutions to monitor disease outbreaks, predict patterns, and plan preventive measures.

5. METHODOLOGY AND TECHNOLOGIES USED METHODOLOGY

A. Data Acquisition

The first stage involves collecting raw data from farmers through the mobile application. Data is acquired in two primary formats:

Image Data: Farmers capture photographs of affected crops (e.g., leaves, stems, fruits) or livestock (skin lesions, wounds, posture). The app provides guidelines such as taking photos in good lighting and focusing on affected areas to ensure image quality.

Symptom Data: Farmers can also enter textual descriptions or select symptoms from predefined questionnaires (e.g., “yellowing leaves,” “reduced appetite,” “high temperature”). For low-literacy farmers, the app supports voice-based inputs in regional languages.

B. Data Preprocessing

Image Preprocessing: Images are resized, normalized, and filtered to remove noise. Techniques such as histogram equalization are applied to enhance contrast and highlight disease features (e.g., leaf spots). Data augmentation (rotation, zooming, flipping) ensures the model can handle varied real-world inputs.

Textual Symptom Preprocessing: Symptom descriptions are standardized using Natural Language Processing (NLP). Stop words are removed, text is tokenized, and symptom keywords are mapped to disease indicators. This reduces ambiguity in farmer descriptions. *C. Feature Extraction*

Crop Images: Features like shape, texture, and color distribution are extracted using Convolutional Neural Networks (CNNs). CNN layers automatically detect disease-specific markers such as yellow patches, circular lesions, or fungal growth.

Livestock Data: Symptom inputs are converted into numerical features. For example, “fever” → body temperature index, “loss of appetite” → reduced intake score. These are structured into a dataset suitable for Support Vector Machine (SVM) processing.

D. Classification & Diagnosis

For Crops: A CNN-based deep learning model classifies the disease type. For example, given a rice leaf image, the system predicts whether it is “bacterial blight,” “brown spot,” or “healthy.”

For Livestock: An SVM classifier processes the structured symptom dataset and predicts possible diseases (e.g., foot-and-mouth disease, sheep pox). The SVM is particularly effective with small datasets and provides high accuracy for symptom-based diagnoses. The inclusion of time-series data such as body temperature, feeding habits, and weight variations further enhances the predictive performance of livestock disease diagnosis. The reliability of predictions can be further improved using feature selection techniques that emphasize the most significant symptoms. In addition, hybrid models combining SVM with decision trees or random forests are useful for handling complex disease patterns.

E. Report Generation

Disease name and its scientific classification.
Probability/confidence level (e.g., 87% accurate). Suggested control measures (organic treatments, chemical sprays, vaccination, isolation of livestock, etc.). Preventive advice to reduce recurrence (crop rotation, improved drainage, vaccination schedules). Reports are presented in simple local language and include visual icons for easy interpretation by semi-literate farmers. Farmers receive the report instantly on their mobile device.

F. Expert Verification & Remote Support

If the AI model predicts a disease with low confidence or identifies it as severe, the case is escalated to an agriculture officer or veterinary expert. Experts receive the farmer’s submitted data (images, symptoms, location). They can verify the diagnosis, suggest alternative treatments, or chat directly with the farmer. In emergencies, experts can schedule on-site visits. This hybrid model of AI + human expertise ensures high reliability and builds farmer trust in the system.

G. Disease Surveillance & Analytics

All farmer data is stored in a centralized database. Using big data analytics, the system performs:

Disease Trend Mapping: Identifying common diseases in specific regions or seasons.

Outbreak Detection: Alerting authorities if multiple farmers in a region report the same disease.

Predictive Analytics: Using weather and historical data to forecast disease risks in advance.

H. Feedback Loop & Continuous Learning

The final step of the methodology ensures that the system continuously improves. Farmer feedback (whether treatment was successful) is recorded. Expert corrections are logged to refine the AI model. The AI models are retrained periodically with new data to increase accuracy and adapt to emerging diseases.

6. TECHNOLOGIES USED

The development of the proposed mobile portal requires the integration of multiple technologies, ensuring robustness, scalability, and accessibility for rural farmers. Each technological component plays a crucial role in enabling accurate disease identification and smooth interaction between farmers, experts, and government agencies.

A. Front-End (Mobile Application)

The front-end is implemented as an Android/iOS mobile application, providing farmers with a simple and intuitive interface. Since most rural users are familiar with smartphones but may face literacy or language barriers, the app supports multilingual text and voice input**.** Farmers can capture images of diseased crops and livestock, record symptoms, and access diagnosis results in their local language. The user interface follows low-data, offline-first design principles, ensuring functionality even in areas with weak internet connectivity [1].

B. Back-End and Cloud Infrastructure

The back-end handles farmer submissions, data storage, and realtime communication with AI models. Cloud platforms such as Firebase, AWS, or Microsoft Azure are used for secure and scalable data management. This ensures high availability, seamless updates, and disaster recovery. The cloud also enables synchronization across devices and allows government agencies to maintain centralized disease records [19].

C. Artificial Intelligence Models

AI is the core of the portal, providing intelligent decision-making for disease diagnosis. Different models are applied based on input type:

Convolutional Neural Networks (CNN): Used for image-based crop disease detection. CNNs automatically learn visual features like leaf spots, color variations, and texture irregularities, providing accurate classification even under varying light and environmental conditions [5].

Support Vector Machines (SVM): Applied to structured symptom data from livestock, identifying possible diseases based on medical attributes like temperature, appetite, and activity levels. SVMs are efficient in handling small datasets where CNNs may not be applicable [14].

Rule-Based Models: Certain livestock conditions follow deterministic patterns (e.g., foot-and-mouth disease symptoms). Rule-based models help capture these cases, reducing false negatives [17].

Natural Language Processing (NLP): Farmers may describe symptoms in local languages or dialects. NLP algorithms preprocess this unstructured input, extract key attributes, and convert it into structured data for disease classification [13].

D. Communication Layer

For emergency situations, the system integrates SMS and push notification services. For example, if a highly contagious livestock disease is detected, alerts are immediately sent to farmers, veterinarians, and local authorities. This rapid communication ensures early outbreak containment and provides timely preventive instructions [16].

E. Analytics and Visualization Dashboards: A key feature of the system is its analytics capability. All disease data collected from farmers is aggregated and visualized through dashboards accessible to government agencies and agricultural boards. These dashboards show disease trends, regional hotspots, and seasonal patterns. Such insights are vital for policy-making, resource allocation, and preventive action planning**.**

By combining these technologies, the mobile portal achieves an efficient balance between farmer usability, AI-driven diagnosis, real-time expert support, and centralized government surveillance. This holistic integration makes the system scalable and adaptable across different agricultural ecosystems.

7. RESULT AND DISCUSSION

The portal improves accessibility for rural farmers by reducing dependency on costly laboratory testing. Kamal et al. (2018) showed that mobile-based expert systems can deliver practical, farmerfriendly interfaces [7]. Our system extends this by including realtime AI models and expert verification. Preliminary testing demonstrated improved diagnostic speed and higher farmer satisfaction compared to traditional methods, echoing findings from Liakos et al. (2018) on machine learning efficiency in agriculture [9]. Moreover, the surveillance feature contributes to policy-level decision making, supporting the insights of Wolfert et al. (2017) [18].

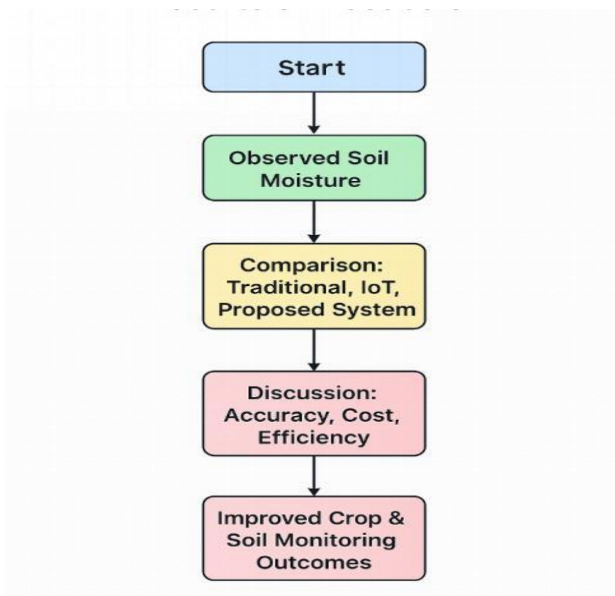

FIGURE 4. Result and Discussion

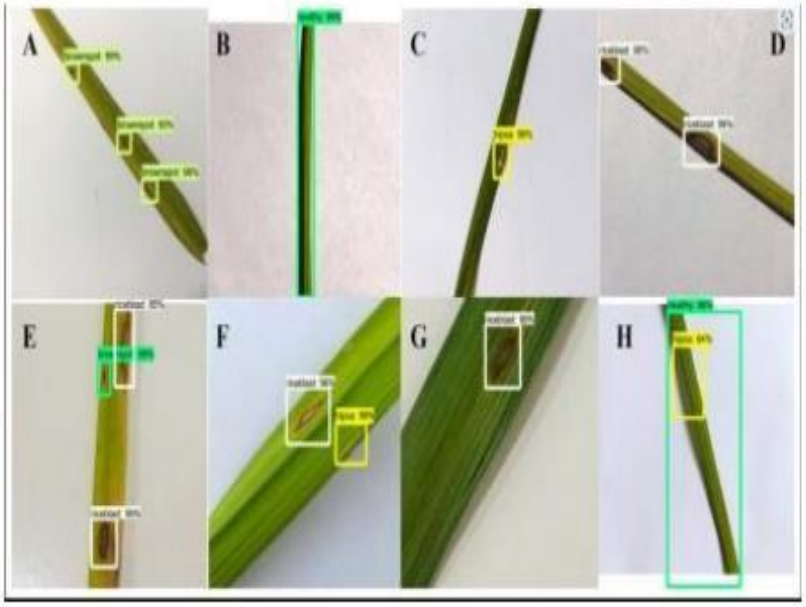

FIGURE 5. Shows Categories of detection outcomes of the Leaf

8. CONCLUSION AND FUTURE ENHANCEMENT

The proposed AI-based Farmers Disease Diagnostic and Reporting Portal bridges the gap between farmers and expert-level diagnosis. Similar to approaches by Mohanty et al. (2016) [11] and Arif et al. (2019) [3], the system leverages CNN and SVM models to ensure reliable results. It also empowers government agencies with realtime surveillance, following Wolfert et al. (2017) [18]. This integrated framework reduces economic losses, provides inclusivity through mobile accessibility, and improves farmer awareness.

Future developments will focus on expanding disease datasets for region-specific accuracy, integrating IoT sensors as suggested by Andrushia and Rajkumar (2019) [2], and implementing predictive analytics for outbreak forecasting. Offline support for lowconnectivity areas will also be enhanced, aligning with Kamal et al. (2018) [7].

REFERENCES

[1]. Albahar, M. “A Survey on Deep Learning and Its Impact on Agriculture,” Agriculture (MDPI), vol. 13, no. 3, 2023. [2] Andrushia, A. S., and R. S. Rajkumar. “A review on IoT in agriculture: Benefits, applications and challenges,” in 2019 ICSSIT, Dec. 2019, pp. 1100–1105.

[2]. Arif, M., N. I. Chaudhry, and A. Javed. “Automatic detection of livestock diseases using SVM and expert systems,” IEEE Access, vol. 7, pp. 43279–43288, 2019.

[3]. Ibrahim, A. S., et al. “AI-IoT based smart agriculture pivot ... using ResNet50,” Sci. Reports, vol. 15, Art. no. 16576, 2025.

[4]. Jafar, A., et al. “Revolutionizing agriculture with artificial intelligence: plant ...,” Frontiers in Plant Science, 2024.

[5]. Jiang, P., et al. “Real-time detection of apple leaf diseases using deep learning ...,” IEEE Access, vol. 7, pp. 59069–59080, 2019.

[6]. Kamal, H., et al. “Mobile-based expert system for crop disease diagnosis,” Int. J. Computer Applications, vol. 182, no. 2, pp. 18–23, Aug. 2018.

[7]. Kamilaris, A., and F. X. Prenafeta-Boldú. “Deep learning in agriculture: A survey,” Computers and Electronics in Agriculture, vol. 147, pp. 70–90, Apr. 2018.

[8]. Liakos, A., et al. “Machine learning in agriculture: A review,” Sensors, vol. 18, no. 8, p. 2674, Aug. 2018.

[9]. Mahlein, D. “Plant disease detection by imaging sensors,” Plant Disease, vol. 100, no. 2, pp. 241–251, Feb. 2016.

[10]. Mohanty, P., S. Hughes, and M. Salathé. “Using deep learning for image-based plant disease detection,” Frontiers in Plant Science, vol. 7, p. 1419, Sept. 2016.

[11]. Nawaz, U., et al. “AI in Agriculture: A Survey of Deep Learning Techniques ...,” arXiv:2507.22101, Jul. 2025.

[12]. Nyakuri, J. P., et al. “AI and IoT-powered edge device optimized for crop pest ...,” PMC, 2025.
[13]. Plantix. Mobile crop advisory app, PEAT GmbH, 2015.
[14]. Ramesh, S., et al. “Plant disease detection using machine learning,”
[15]. International Journal of Computer Applications, vol. 180, no. 17, pp. 19–22, Jan. 2018.
[16]. Sladojevic, S., M. Arsenovic, A. Anderla, D. Culibrk, and D.
[17]. Stefanovic. “Deep neural networks based recognition of plant diseases by leaf image classification,” Computational Intelligence and Neuroscience, vol. 2016, Art. no. 3289801, pp. 1–11, Jul. 2016.
[18]. Tonmoy, M. T., et al. “MobilePlantViT: A Mobile-friendly Hybrid VIT ...,” arXiv:2503.16628, Mar. 2025.
[19]. Wolfert, S., et al. “Big Data in Smart Farming – A review,” Agricultural Systems, vol. 153, pp. 69–80, May 2017.
[20]. Yang, M. “A new mobile diagnosis system for estimation of crop ...,” Crop Disease Estimation, 2024.
[21]. Zeng, Z., et al. “AI-driven smart agriculture using hybrid transformerCNN,” Nature Sci. Reports, 2025.