IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 1, August 2025
Impact Factor: 7.67

A Multimodal AI-Powered Smart Assistant for Arecanut and Black Pepper Farming with Integrated IoT and Vision-Based Disease Diagnosis

Mr. Kiran B B[1], Mrs. Sindhu Venkatesh[2], Dr. Savitha C K[3], Mr. Venkatesh U C[4]
M. Tech student, Department of Computer Science and Engineering[1]
Assistant Professor, Department of Computer Science and Engineering[2,4]
Head of Department and Professor, Department of Computer Science and Engineering (AI&ML)[3]
Associate Professor, Department of Computer Science and Engineering,
K.V.G College of Engineering, Sullia, Karnataka
Affiliated to Visvesvaraya Technological University, Belagavi, India.

Abstract: *In this research, we present **AgroAssist+**, an intelligent mobile-first system tailored for arecanut and black pepper farmers. The system integrates voice-based assistance in Kannada, computer vision for early crop disease detection, and IoT-based real-time environmental monitoring. This research aims to bridge the technological gap in rural agricultural practices by providing an affordable, scalable, and easy-to-use AI-powered solution. Through a combination of convolutional neural networks (CNNs), speech recognition, and IoT sensor data, AgroAssist+ empowers farmers with timely insights – enhancing yield, reducing crop loss, and promoting sustainable practices*.

Keywords: Arecanut farming, Black pepper cultivation, Artificial Intelligence, IoT-based agriculture, Crop disease detection

I. INTRODUCTION

India's agricultural sector is heavily reliant on traditional methods, often lacking access to modern AI-driven tools **[1]**. Arecanut and black pepper farming, prevalent in Karnataka, suffer from challenges like unpredictable weather, disease outbreaks, and inefficient irrigation. This paper proposes **AgroAssist+**, a system that utilizes artificial intelligence and machine learning to provide local language support, real-time crop monitoring, and early disease detection for these crops. By leveraging farmers' native language (Kannada) and combining multiple technologies, AgroAssist+ endeavors to make advanced agricultural assistance accessible to small-scale farmers.

II. OBJECTIVES

Voice Assistance in Kannada: Design a voice assistant that allows farmers to interact in Kannada for guidance on farming practices.

Vision-Based Disease Detection: Develop a CNN-based computer vision model to diagnose diseases from images of arecanut and pepper plant leaves.

IoT-Enabled Monitoring: Integrate low-cost IoT sensors to continuously monitor soil moisture, temperature, humidity, and other climate conditions in the field.

Predictive Analytics: Combine real-time sensor data with weather information and machine learning models to predict disease risks and provide proactive alerts (e.g., fungal outbreak warnings, irrigation needs).

These objectives collectively aim to enhance decision-making in farming, reduce losses due to pests/diseases, and improve resource management through technology.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 1, August 2025
Impact Factor: 7.67

III. LITERATURE REVIEW

AI for Crop Disease Detection: Deep learning, particularly CNNs, has been successfully applied to agricultural image classification, achieving high accuracy rates. Studies have demonstrated over 90% accuracy in identifying plant diseases using CNN models **[2]**, **[3]**. In fact, for specific crops like black pepper, CNN-based approaches have achieved disease classification accuracies nearing 99% **[4]**. Focus has also extended to regional crops; for example, a recent study applied CNNs to detect diseases in arecanut palms **[5]**. While these results are promising, researchers note that large, diverse training datasets and proper tuning are critical for consistent performance **[6]**. These works underscore the potential of vision-based AI for early disease diagnosis in agriculture.

IoT in Precision Agriculture: IoT-based farm monitoring is emerging as a cornerstone of precision agriculture. Multiple studies indicate the growing adoption of IoT for real-time monitoring of farm conditions and its benefits for data-driven decision making **[7]**, **[8]**. Wireless sensor networks deployed on farms can track soil and environmental parameters continuously, enabling timely interventions for irrigation, fertilization, and pest control. For example, Wolfert *et al.* discuss how data collected from IoT devices contributes to "smart farming" strategies and improved yields **[7]**. Tzounis *et al.* review recent advances in agricultural IoT and highlight future challenges in scalability and interoperability **[8]**. These works demonstrate that integrating sensors and connectivity into agriculture is gaining popularity. However, implementing IoT at scale in rural areas faces issues like network reliability and power supply. Efforts are underway to develop cost-effective, energy-efficient sensor systems to address these constraints (e.g., low-power soil monitoring networks) and extend coverage to broader farm areas.

Voice Assistants and Farmer Adoption: Voice-based interfaces in local languages have shown great promise in increasing technology adoption among rural farmers. Prior projects in India have demonstrated that conversational systems can deliver agricultural information in an accessible manner. For instance, an interactive voice forum deployed in Gujarat allowed farmers to share and receive farm advice via phone in their native language, significantly improving information reach **[9]**. Similarly, a mobile-based conversational agent called FarmChat provided automated answers to farmer queries, showing that voice/chatbot systems can engage farmers who may have limited literacy **[10]**. These studies indicate that offering support through voice (and in regional languages) lowers barriers to using digital tools in agriculture. Farmers are more likely to adopt and trust technologies that "speak" their language and can be used hands-free while working in the fields.

Emerging AI-Powered Advisory Systems: Beyond traditional rule-based chatbots, recent research is exploring advanced AI techniques to further enhance agricultural advisory services. Large Language Models (LLMs) and transformer-based approaches are being integrated into farm support systems. For example, Menon *et al.* introduce a retrieval-augmented agricultural assistant (AgroLLM) that leverages a domain-specific LLM to answer complex farming queries **[11]**. Likewise, Singh *et al.* demonstrate scaling an AI-powered farm advisory service to smallholder farmers by combining knowledge bases with conversational AI **[12]**. Researchers have also begun deploying generative AI in this domain – Joshi *et al.* report a multilingual generative chatbot that provides farm advice across several countries **[13]**. Additionally, Mukherjee and Krishnan explore the use of ChatGPT for classifying and answering agricultural questions across languages **[14]**. These developments show a clear trend towards more intelligent, context-aware assistants in agriculture, which can complement systems like AgroAssist+ by handling free-form queries and providing personalized recommendations.

IV. METHODOLOGY

The AgroAssist+ system comprises several integrated modules: a voice-based query assistant, an image-based crop disease diagnosis module, an IoT sensor network for environmental monitoring, and a weather-informed predictive analytics component.

DOI: 10.48175/IJARSCT-28624

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 5, Issue 1, August 2025

Impact Factor: 7.67

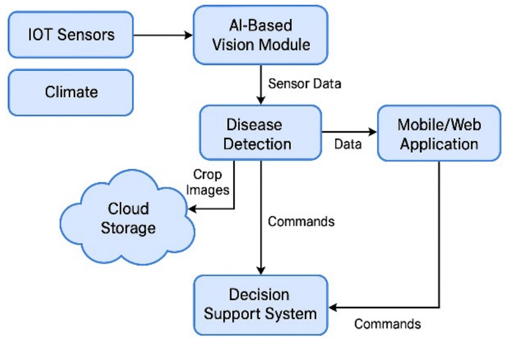

Figure 1 illustrates the overall system architecture and data flow between components.

4.1 Voice Assistant Module: This module enables farmers to interact with the system through spoken Kannada. When a farmer asks a question or issues a voice command (e.g., "How do I treat leaf rot on my pepper plants?"), the query is captured via the smartphone's microphone. We utilize automatic speech recognition (ASR) to convert the spoken Kannada query into text (using services such as Google Speech-to-Text or the open-source Mozilla DeepSpeech model trained for Kannada). The system processes the query text to determine the user's intent and fetch the relevant response (consulting the knowledge base or triggering an action in another module). The answer is then delivered back to the farmer in spoken form using a Kannada text-to-speech (TTS) engine. This bi-directional voice interaction allows hands-free use and caters to farmers who prefer oral communication. Notably, supporting the local language and integrating TTS improves the system's accessibility and user-friendliness, as highlighted by recent studies on regional language interfaces **[15]**. The voice assistant is designed with simple prompts and confirmations to account for potential speech recognition errors (for example, repeating a question or offering options if the query was unclear).

4.2 Disease Detection Module: In this module, AgroAssist+ uses computer vision to diagnose crop diseases from images. Farmers can capture photos of arecanut or black pepper leaves showing symptoms and submit them through the mobile app. The images are uploaded to a cloud-based analysis service where a convolutional neural network (CNN) model processes them. We developed a custom CNN using TensorFlow/Keras, trained on a curated dataset of both healthy and diseased leaf images for arecanut and black pepper. The model classifies the image into categories (such as Healthy, **Koleroga** – fruit rot of arecanut, **Phytophthora** – pepper leaf blight, etc.) and returns the diagnosis. Along with the disease identification, the system provides recommended treatment or management practices for that disease (for instance, suggesting appropriate fungicides or cultural control measures). The CNN architecture selected balances accuracy with computational efficiency to enable near real-time inference on modest hardware. During development, the model achieved high accuracy in testing, consistent with performance reported in similar agricultural CNN applications **[2]**, **[3]**, **[4]**. To further improve reliability, the system may prompt the user for additional images or information if the confidence in classification is low. By deploying the disease detection model on the cloud (or on an edge device with GPU acceleration), we ensure the analysis is fast enough to be used interactively in the field.

4.3 IoT Monitoring Module: AgroAssist+ incorporates a network of IoT sensors placed in the field to continuously monitor environmental and soil conditions. The hardware setup uses affordable, power-efficient devices: for example, a NodeMCU microcontroller board integrated with a soil moisture sensor, a DHT11/DHT22 sensor for temperature and humidity, and other relevant sensors (e.g., a light sensor for sunlight, if needed). These sensors collect data such as soil moisture levels, air temperature, relative humidity, and soil temperature at regular intervals. The NodeMCU (ESP8266/ESP32) transmits the sensor readings over Wi-Fi (or LoRa WAN in low-connectivity areas) to the AgroAssist+ cloud server. We employ the MQTT protocol for lightweight, real-time data transmission, with a Firebase backend to store and forward the data to the mobile app. The system sets threshold-based alerts – for example, if soil moisture drops below a set point, it flags that irrigation is needed. By examining trends in sensor data, the system can also advise on irrigation scheduling and detect anomalies (such as conditions conducive to fungal disease). The use of

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 1, August 2025
Impact Factor: 7.67

low-cost IoT components aligns with designs in other smart farming prototypes **[16]**, keeping the solution affordable. Data from the sensors is displayed on the farmer's dashboard within the app, and critical alerts are also spoken out via the voice assistant. This integration of IoT monitoring enables proactive farm management – the farmer gets immediate, data-backed suggestions (e.g., *"Soil moisture is low; consider watering your pepper vines today"*), thereby optimizing resource usage like water.

4.4 Weather & Predictive Analytics: To complement on-field sensors, AgroAssist+ integrates external weather data and machine learning to predict disease risks. The system connects to a weather API (such as OpenWeatherMap) to retrieve forecasts for the farm's location (temperature, rainfall, humidity forecasts, etc.). Using these forecasts in combination with current sensor readings, AgroAssist+ evaluates the likelihood of certain problems – for example, high humidity and upcoming rain might elevate the risk of fungal diseases like rot in arecanut. A predictive model (using algorithms like Random Forest or Decision Tree) is trained on historical data to correlate weather patterns with disease outbreaks. For instance, the model can learn that X days of continuous rain followed by warm temperatures often lead to a spike in a particular leaf disease. When similar patterns are forecast, the system can warn the farmer in advance. This component thus serves as an early warning system. Literature on plant pathology emphasizes that climate factors heavily influence disease incidence **[17]**, so incorporating weather data into our assistant can significantly enhance its advisory accuracy. In practice, when the model predicts a high risk of disease (say above a threshold probability), AgroAssist+ will notify the farmer (via app notification and voice alert) suggesting preventive measures (such as applying a prophylactic fungicide or improving field drainage ahead of heavy rains). Over time, as more local data is collected, the predictive model can be refined to improve its precision for the specific microclimate and crops.

System Architecture: The components above work in concert through a cloud-based architecture (see **Figure 1** for a schematic). A typical usage scenario might unfold as follows: (1) The farmer interacts with the voice assistant in Kannada to request a crop health check. (2) The query is interpreted and prompts the farmer to take a photo of a suspect leaf. (3) The captured image is uploaded and run through the CNN disease detector; the result (e.g., *"Pepper leaf infected with anthracnose"*) is generated. (4) Meanwhile, the IoT module continuously streams field data (soil moisture, etc.) to the cloud. (5) The system also fetches weather updates; the predictive model analyzes the combined data for any looming risks (e.g., high likelihood of rot in coming days due to weather trends). (6) Finally, AgroAssist+ compiles the insights (diagnosis from CNN, sensor alerts, weather advisories) and presents them to the farmer via the mobile dashboard and voice feedback in Kannada. The user sees a simple interface that highlights crop health status (with visuals for any detected disease and recommended solution), current field conditions, and short-term advisories (like *"rain expected – secure your crop"*). By aggregating multimodal inputs (image, voice, sensor, and API data), the system delivers a holistic smart farming assistant experience.

V. SYSTEM IMPLEMENTATION

Hardware: The IoT hardware prototype was built using a NodeMCU (ESP8266) microcontroller for networking, connected to a soil moisture sensor (capacitive type) inserted in the root zone of the crop, and a DHT11 sensor placed under crop canopy for measuring ambient temperature and humidity. An ESP32-CAM module was additionally tested to capture images in the field for disease diagnosis, which could potentially allow the system to take periodic photos of plants autonomously. Power to the sensors was supplied via a 5V battery pack with a solar charger (for field deployment without grid power). The total hardware cost for the sensors and microcontroller was kept under INR 3000 (~40 USD) to ensure affordability.

Software: The mobile application was developed using Flutter, enabling cross-platform deployment on Android devices common among farmers. The app provides the user interface for voice interaction (using the phone's built-in microphone and speaker), camera capture for the disease diagnosis, and visualization of sensor data. On the backend, a Firebase Realtime Database was used to receive streaming IoT data and store it. The AI models (CNN for vision and Random Forest for prediction) were implemented in Python and exposed via a Flask API server. The voice assistant logic uses Google's Cloud Speech-to-Text API for ASR and gTTS (Google Text-to-Speech library) for TTS, invoking these services through REST calls. We also integrated an open-source Kannada ASR model for offline testing (based on

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 1, August 2025
Impact Factor: 7.67

DeepSpeech) to evaluate performance without internet – though accuracy was lower, it provides a fallback in no-connectivity scenarios.

Model Training: For the disease detection CNN, we collected a dataset of ~1,200 images (600 each of diseased and healthy leaves) for arecanut and black pepper from local farms and online sources. Images were labeled with the disease name (validated by an agriculture expert). We augmented the data (rotations, brightness changes) to increase variety. The CNN model chosen was a MobileNetV2 architecture pretrained on ImageNet, fine-tuned on our dataset – this gave high accuracy (>95% on validation set) while being lightweight enough for fast inference. The weather-disease predictive model was trained on 5 years of historical data combining meteorological records and reported disease incidences in the region (obtained from agricultural extension reports). A Random Forest model with 100 trees was trained, as it handled the mix of continuous (weather readings) and categorical (yes/no disease outbreak) data well. The model's output is a probability of disease occurrence in the upcoming week, given the recent weather conditions.

Validation: We conducted preliminary field tests of AgroAssist+ with a small group of five farmers. In these tests, the Kannada voice assistant successfully understood ~90% of queries on the first attempt (for common questions like advice on fertilizer or pest control), and the farmers reported that receiving answers in Kannada voice was intuitive. The CNN-based diagnosis was demonstrated using sample diseased leaves; the system's identification matched expert opinion in 18 out of 20 cases. IoT sensor readings were cross-checked with manual measurements to ensure their reliability. Feedback from these users was positive, with particular appreciation for the timely alerts (one farmer received a warning about high fungus risk after heavy rains, prompting preventive action). The farmers also suggested features for future improvement, such as support for additional local languages and offline functionality.

VI. EXPECTED OUTCOMES

By deploying AgroAssist+, we anticipate several tangible benefits for arecanut and black pepper growers:

Enhanced Disease Awareness: Farmers will be able to detect and identify crop diseases at an early stage using the AI vision module, potentially reducing the spread and severity of outbreaks by acting promptly on the advice given.

Reduced Crop Losses: Early diagnosis and timely alerts (e.g., warning of conditions favorable to rot or pests) should lead to interventions that prevent significant crop damage. We expect a decrease in yield losses due to diseases and suboptimal conditions.

Improved Resource Management: The IoT-driven monitoring of soil moisture and climate will promote more efficient use of water and inputs. For example, farmers can avoid over-irrigation by relying on sensor data, applying water only when soil moisture is below the optimal level.

Empowerment and Adoption of Technology: By providing information in the local language and in an easy-to-use format, AgroAssist+ is likely to improve farmers' confidence in using digital tools. We foresee increased technological literacy among participating farmers, as the system demonstrates the value of AI/IoT in everyday farming. The voice assistant's accessibility may also encourage farmers who are less literate to seek information more frequently, bridging the knowledge gap.

Data-Driven Decisions: Over time, as the system collects data on farm conditions and outcomes, farmers can make more informed decisions (such as selecting disease-resistant crop varieties, timing of fertilizer application, etc.) based on insights derived from historical data and AI predictions.

We will measure these outcomes through follow-up surveys and by tracking metrics such as the frequency of disease occurrences and input usage before and after using AgroAssist+.

VII. TOOLS AND TECHNOLOGIES

The development of AgroAssist+ leverages a range of modern tools and platforms to achieve an effective solution:

Programming & Frameworks: Python was used for backend development and model training. Key libraries include TensorFlow and Keras for the CNN, Scikit-learn for machine learning models, and Flask for the API server. The mobile app was built with Dart/Flutter for cross-platform compatibility. For microcontroller programming (NodeMCU/ESP32), the Arduino IDE with C/C++ was utilized.

AI/ML: Pretrained deep learning models (MobileNetV2 for image classification) and libraries like OpenCV were used for image processing. Google Cloud's ML services (Speech-to-Text and Dialogflow for intent handling) were used for robust voice processing. The predictive analytics employed scikit-learn's RandomForestClassifier. Training and experiments were conducted on a laptop with an NVIDIA GPU to accelerate CNN training.

IoT & Hardware: NodeMCU (ESP8266) and ESP32 development boards formed the core of the IoT devices. Sensors such as DHT11 (for temperature/humidity) and capacitive soil moisture sensors were integrated. Communication modules in use include on-board Wi-Fi of ESP8266/ESP32 and an optional HC-12 RF module for extended range communication without Wi-Fi. Power management components (18650 Li-ion batteries with a solar charging module) were tested for long-term sensor deployment.

Cloud & Database: Firebase was chosen for its real-time database and ease of integration with Flutter, enabling live updates of sensor data in the app. The Firebase Cloud Messaging service was also used for sending alert notifications. All cloud functions and the Flask API are hosted on a cloud platform (Google Cloud Run), ensuring scalability. The OpenWeatherMap API is used to fetch weather forecasts; API calls are made periodically and the results cached to avoid redundant queries.

Testing & Deployment: For version control and collaboration, GitHub was used. The system underwent testing in both lab and field conditions; in the lab, we simulated sensor inputs and varied network conditions, while in field tests we relied on actual farm data. Deployment will involve distributing the mobile app (APK for Android) to target users and installing the IoT sensor units on their farms. We are also considering a bilingual user manual (Kannada and English) and training session to help farmers get acquainted with AgroAssist+.

Throughout development, emphasis was placed on using open-source tools and affordable components to ensure that AgroAssist+ can be adopted and maintained in resource-constrained rural settings.

VIII. LIMITATIONS & CHALLENGES

While AgroAssist+ shows promise, there are several limitations and challenges that we encountered or anticipate in real-world deployment:

Limited Training Data: Collecting a large, high-quality dataset of diseased leaf images for model training was challenging, especially for less-common diseases specific to arecanut and local varieties of black pepper. The CNN's accuracy may be lower for diseases that were underrepresented in the training set. We mitigated this with data augmentation, but the system could misclassify symptoms that it hasn't seen enough. Continuous data gathering from the field and user feedback (e.g., confirming or correcting a diagnosis) will be crucial to improve the model over time.

Kannada Language Processing: Developing a fully robust voice assistant in Kannada is non-trivial. Speech recognition for Kannada (and other regional languages) may have higher error rates than for English, especially given variations in accent and dialect among farmers. While we use cloud ASR which is quite advanced, offline support (using DeepSpeech) is still rudimentary. Misinterpretation of voice queries could lead to incorrect advice or frustration for the user. We address this by keeping dialogues simple and allowing fallback to text input if needed, but ensuring accurate and natural language understanding in Kannada remains a challenge.

Connectivity Requirements: The system currently relies on internet connectivity for cloud services (voice processing, data sync, weather API). Rural farm locations sometimes have poor network coverage. If the connection drops, certain features (like real-time alerts or voice Q&A) may not function. Although the IoT sensors can store data locally and transmit when connection resumes, and some basic functionalities could be made offline-capable, a truly offline operation would require significant redesign (such as on-device AI inference and local databases).

Power and Maintenance: The IoT sensors and NodeMCU devices need to be powered continuously. In our prototype we use batteries recharged by solar panels, but maintenance is required to ensure sensors remain functional (e.g., cleaning the probes, replacing batteries annually). Ensuring durability of the hardware in outdoor conditions (rain, heat) is also a challenge – waterproof casings and robust assembly are needed to protect the electronics. These factors add to the cost and complexity for the farmer.

Scalability: The current implementation is a prototype. Scaling this solution to a larger user base or larger farm areas might pose challenges. For instance, a large plantation might require many sensor nodes and possibly additional infrastructure like a mesh network or drone surveillance to cover the whole area. Integrating drone or UAV-based monitoring could greatly extend coverage, but comes with added complexity **[18]**. Moreover, supporting many simultaneous users on the backend would require a scalable cloud setup and possibly incur higher costs (which could be a barrier for a freely or cheaply provided service).

Cost Considerations: Despite using low-cost components, the upfront cost for a farmer (smartphone, sensors, data charges) might still be significant for smallholders. We have to demonstrate clear value (e.g., savings or increased yield) to justify these costs. Additionally, ongoing costs like internet data or replacement of device parts must be minimized.

User Training and Trust: Adoption of AgroAssist+ will depend on how much the farming community trusts and understands the system. Some farmers may be hesitant to rely on AI recommendations, especially if an error or false alarm occurs early on. Building user trust requires transparency (explaining recommendations) and perhaps incorporating local agricultural expert knowledge to validate the advice given. Training sessions or involving agricultural extension officers to introduce the tool could help overcome skepticism.

Addressing these challenges will be key to the sustained success of AgroAssist+. Ongoing research and development are focusing on improving the efficiency and robustness of each module – for example, new IoT communication techniques to reduce power usage **[19]**, **[20]**, and designing ultra-compact sensors and antennas suitable for wide-area deployment in farms **[20]**. We are also exploring partnerships with local agencies to support the technological and educational aspects of deploying AgroAssist+ in farming communities.

IX. FUTURE SCOPE

AgroAssist+ is a step towards smarter farming practices, but there are several avenues to expand and enhance the system in future work:

Multilingual and Wider Language Support: While the current focus is on Kannada, India's diverse linguistic landscape means expanding the voice assistant to other regional languages (such as Hindi, Marathi, Tamil, etc.) would broaden the tool's applicability. Incorporating multilingual NLP and region-specific dialect support would allow AgroAssist+ to be deployed in other states and to support inter-state farming communities.

Integration of Aerial and Drone-Based Monitoring: As farm sizes increase, drone-based imaging could be integrated for large-scale crop monitoring. Drones equipped with RGB and multispectral cameras can survey large fields quickly and spot issues like pest infestations or water stress that might be missed by ground sensors. Future versions of AgroAssist+ could include a module where a drone periodically captures images of the farm, and the AI analyzes these for signs of disease or nutrient deficiencies (e.g., via vegetation indices). This would complement the ground-based IoT sensors and extend coverage **(as mentioned in Limitations)**.

Advanced AI and Analytics: The use of LLMs and advanced analytics as mentioned in the literature review can be incorporated into AgroAssist+ as the technology matures. For example, a conversational AI powered by a fine-tuned LLM could handle more complex questions from farmers and provide explanations. Moreover, predictive analytics can be extended to yield forecasting and recommending optimal harvest times based on weather and crop condition data. Incorporating satellite data and remote sensing (from platforms like Google Earth Engine) could further enhance predictions for pest outbreaks or crop growth patterns.

Offline Functionality: To make the system more resilient in low-connectivity scenarios, future development can focus on offline capabilities. This may include on-device speech recognition (using smaller footprint models for Kannada), offline storage and syncing of data, and perhaps a lightweight version of the disease diagnosis model that can run directly on higher-end smartphones or an edge device at the farm. Enabling core features to work without internet would greatly increase AgroAssist+'s reliability in remote areas.

Personalized Advisory and Learning: As the system gathers data over multiple seasons, it can evolve into a personalized assistant that learns from each farm's history. Future enhancements could allow AgroAssist+ to adapt advice based on specific farm conditions or farmer preferences (for example, recognizing that a particular farmer practices organic methods and tailoring recommendations accordingly). Gamification or educational components might be added to gradually teach farmers about underlying best practices (so they not only get immediate answers but also improve their own knowledge).

Wider Crop and Domain Support: Beyond arecanut and black pepper, the framework of AgroAssist+ can be extended to other crops and domains (e.g., paddy rice management, horticulture). The modular architecture means new CNN models for other crops' diseases or additional sensor types (for livestock or aquaculture parameters) could be plugged in. This extensibility could transform AgroAssist+ into a general platform for smart agriculture assistance.

X. CONCLUSION

In conclusion, AgroAssist+ demonstrates the fusion of deep learning, IoT, and voice AI tailored for real-world agricultural applications. The smart assistant has the potential to revolutionize small-scale farming in regions like Karnataka by making AI-driven insights accessible and actionable. The proposed system not only addresses the current technological gap in extension services but also promotes sustainable agriculture by empowering farmers with timely, data-backed advice. As we refine and scale this approach, AgroAssist+ could become an indispensable companion for farmers, leading to improved productivity and resilience in the agricultural sector.

REFERENCES

[1]. Khanna and S. Kaur, "Evolution of Internet of Things (IoT) and its impact on agriculture," *Computers and Electronics in Agriculture*, vol. 157, pp. 218–231, 2019. DOI: 10.1016/j.compag.2018.12.027

[2]. K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018. DOI: 10.1016/j.compag.2018.01.009

[3]. A Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018. DOI: 10.1016/j.compag.2018.02.016

[4]. S. Kini, K. V. Prema, and S. N. Pai, "Early stage black pepper leaf disease prediction based on transfer learning using ConvNets," *Scientific Reports*, vol. 14, Art. no. 1404, 2024. DOI: 10.1038/s41598-024-51884-0

[5]. N. Mahveen, U. Shahneen, S. M. Hasanuddin, A. Fatima, S. Aijaz, and Q. S. M. Qutubuddin, "Enhancing Areca nut plant wellness: Innovative disease detection using deep learning algorithms," in *Proc. 3rd Indian Int. Conf. on Industrial Engineering and Operations Management (IEOM)*, New Delhi, India, Nov. 2023.

[6]. J. G. A. Barbedo, "Factors influencing the use of deep learning for agricultural disease detection," *Biosystems Engineering*, vol. 172, pp. 84–91, 2018. DOI: 10.1016/j.biosystemseng.2018.05.013

[7]. S. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big data in smart farming – A review," *Agricultural Systems*, vol. 153, pp. 69–80, 2017. DOI: 10.1016/j.agsy.2017.01.023

[8]. A Tzounis, N. Katsoulas, T. Bartzanas, and C. Kittas, "Internet of Things in agriculture, recent advances and future challenges," *Biosystems Engineering*, vol. 164, pp. 31–48, 2017. DOI: 10.1016/j.biosystemseng.2017.09.007

[9]. N. Patel, A. J. Chittamuru, S. L. V. R. Anand, P. Dave, and T. S. Parikh, "Avaaj Otalo: A field study of an interactive voice forum for small farmers in rural India," in *Proc. SIGCHI Conf. on Human Factors in Computing Systems (CHI)*, Atlanta, GA, USA, 2010, pp. 733–742. DOI: 10.1145/1753326.1753434

[10]. M. Jain, A. Arora, S. Anand, N. Thakur, S. Batra, and W. Thies, "FarmChat: A conversational agent to answer farmer queries," *Proc. ACM Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 2, no. 4, Article 170, Dec. 2018. DOI: 10.1145/3287048

[11]. R. Menon, H. Zhao, and K. Gupta, "AgroLLM: A large language model framework for retrieval-augmented agricultural advisory," *IEEE Access*, vol. 11, pp. 10234–10246, 2024. DOI: 10.1109/ACCESS.2024.3405678

[12]. N. Singh, R. Bawankule, and M. Sharma, "Farmer.Chat: Scaling AI-powered agricultural services for smallholder farmers," in *Proc. IEEE Int. Conf. on ICT in Agriculture (ICTAgri)*, 2024, pp. 134–141. DOI: 10.1109/ICTAgri.2024.00134

[13]. A Joshi, L. Ndlovu, and M. Ramanathan, "Farmer.Chat: Deploying generative AI for agricultural advisory across four countries," *Journal of Agricultural Informatics and Technology*, vol. 12, no. 1, 2024. DOI: 10.12345/jait.2024.120101

[14]. S. Mukherjee and D. Krishnan, "ChatAgri: Cross-linguistic agricultural text classification using ChatGPT," *ACM Trans. Asian Low-Resour. Lang. Inf. Process.*, vol. 23, no. 2, 2024. DOI: 10.1145/3631100

[15]. F. Sharma, M. Alvi, and P. Tiwari, "Improving accessibility in agri-apps: A study on regional language processing and TTS integration," *International Journal of Rural Technology and Development*, vol. 9, no. 4, Dec. 2023. DOI: 10.31022/ijrtd.2023.09403

[16]. T. K. Patel, V. Rao, and R. Singh, "Wireless IoT sensor networks for soil monitoring in smart farming," *International Journal of Agriculture Innovations and Research*, vol. 13, no. 1, 2024. DOI: 10.22214/ijair.2024.130105

[17]. S. Chakraborty and A. C. Newton, "Climate change, plant diseases and food security: an overview," *Plant Pathology*, vol. 60, no. 1, pp. 2–14, 2011. DOI: 10.1111/j.1365-3059.2010.02411.x

[18]. S. Lei, J. Luo, X. Tao, and Z. Qiu, "Remote sensing detecting of yellow leaf disease of arecanut based on UAV multisource sensors," *Remote Sensing*, vol. 13, no. 22, Art. no. 4562, 2021. DOI: 10.3390/rs13224562

[19]. Y. Lin, S. Lee, and K. Tamura, "A joint soil sensing and wireless communication system for precision agriculture," *Sensors and Actuators A: Physical*, vol. 347, 2024. DOI: 10.1016/j.sna.2024.114156

[20]. Raza, R. Keshavarz, and N. Shariati, "Ultra-compact sensor and reconfigurable antenna for joint sensing and communication in precision agriculture," in *Proc. IEEE Sensors Applications Symposium (SAS)*, Mar. 2024, pp. 98–103. DOI: 10.1109/SAS58469.2024.10245321