AgriCare

A Hybrid AI Model for Timely Crop Diseases, Diagnosis and Solution System using CNN and Voice-based Advisory

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Abstract

Farmers in India often face significant challenges in accurately and timely diagnosing crop diseases, leading to substantial yield losses. To mitigate this issue, we propose the development of **AI Krushi Mitra (AIKM)**, a hybrid mobile application built using **Flutter**. This application, branded as **AgriCare**, utilizes a farmer-friendly design and employs a **Convolutional Neural Network (CNN)** model to provide accurate disease diagnosis from a simple photograph of a crop leaf. The core innovation lies in integrating the high-accuracy CNN model with a **controlled database (DB)** of verified, localized treatment solutions. Crucially, the app includes an **AI Chatbot** featuring **Voice-to-Text** functionality in the local language (Marathi). This allows farmers to verbally ask questions and receive instant, certified advice in real-time. This research demonstrates a seamless synergy between modern AI technology and indigenous agricultural knowledge to deliver timely, accurate, and actionable advice to the farming community.

Keywords: AgriCare, AI, Krushi Mitra, CNN, Hybrid Model, Crop Disease Diagnosis, Voice Advisory.

Abbreviations: AI: Artificial Intelligence, CNN: Convolutional Neural Network, AIKM: AI Krushi Mitra, DB: Database, EWS: Early Warning System, API: Application Programming Interface.

1. INTRODUCTION

The agricultural sector serves as the backbone of the Indian economy. However, climate change and poor management practices often lead to recurrent crop diseases. Failure to diagnose these diseases promptly results in yield losses estimated between 20% and 40%. The primary barriers to timely intervention include the scarcity of local agricultural experts and the economic burden of incorrect pesticide usage. To address this, our project, **AgriCare**, proposes the **AI Krushi Mitra (AIKM)** application. This solution leverages Deep Learning to diagnose diseases in seconds and delivers verified treatment protocols in the farmer's native language, drastically reducing turnaround time and improving intervention effectiveness.

2. LITERATURE REVIEW

The field of crop disease management has evolved significantly, moving from manual inspection to advanced AI-driven systems.

- **2.1. Traditional Diagnostic Limitations:** Conventional methods rely heavily on human expertise, which is often scarce and not uniformly available across remote regions. Diagnosis via conventional means is slow, expensive, and often unreliable due to the subjective interpretation of symptoms, leading to delayed treatment and catastrophic crop losses.

- **2.2. Machine Learning vs. Deep Learning in Agriculture:** Early machine learning (ML) techniques (like Support Vector Machines or

K-Nearest Neighbors) were used for disease classification, but they relied on manual Feature Extraction (e.g., color, texture, shape analysis). Deep Learning (DL), specifically CNNs, eliminated this tedious manual step, automatically learning complex and subtle features directly from raw image data [3].

- **2.3. Advancements in Convolutional Neural Networks (CNNs):** The CNN architecture is the current state-of-the-art for image classification. Architectures like AlexNet provided the initial breakthrough, but deeper models like VGG, GoogLeNet (Inception), and particularly ResNet (Residual Network) [2] have set new benchmarks. ResNet, with its skip connections, successfully addresses the "vanishing gradient" problem, allowing for extremely deep networks necessary to classify the intricate symptoms of plant diseases [2].
- **2.4. Data Standardization and Benchmarks:** The Plant Village dataset [4] remains the foundational resource for training and comparing crop disease classification models. It standardizes the image data, allowing researchers globally to validate their model performance against a common benchmark. However, models trained purely on this clean dataset often require further processing to perform well in real-world, noisy farm environments.
- **2.5. Mobile Deployment and Optimization:** Deploying complex CNN models on resource-constrained mobile devices is crucial for real-time farm-level diagnosis. This requirement necessitates model optimization techniques such as quantization and pruning. Frameworks like TensorFlow Lite are essential for converting large models into lightweight, efficient versions that run locally on a smartphone without requiring constant internet connectivity [5].
- **2.6. Bridging the Linguistic Gap with Voice Advisory:** Research into farmer advisory systems highlights that effective communication must occur in the local language [6]. Relying solely on text-based input is impractical for many farmers. The integration of Speech-to-Text (STT) technology, coupled with a certified Localized Solution Database (DB), is key to providing real-time, easily accessible, and actionable advice, transforming the system into a true 'Krushi Mitra'.

3. SYSTEM OVERVIEW

The proposed system comprises three primary architectural components working in tandem:

1. **AgriCare Mobile App (Frontend):** Developed using **Flutter**, the app provides the user interface. It handles image capture/upload and manages the **Voice-to-Text Chatbot** input for the farmer.
2. **Backend Server (Python Flask API):** This acts as the intermediary, managing the communication flow between the mobile application and the core AI intelligence, ensuring fast and secure data transfer.
3. **Core Intelligence (TensorFlow CNN + Solution Database):**
   - **CNN Model:** Trained on a filtered subset of the Plant Village dataset for specific regional crops. It takes the image input and returns the scientific name of the disease and a confidence score.
   - **Localized Solution DB:** Upon receiving the disease name, this dedicated database provides context-specific, certified remedies (e.g., pesticide names, correct dosages) translated into Marathi.

System Workflow:

Farmer takes Photo → (Flutter App Uploads Image) → Flask API → CNN Model (Diagnosis) → Solution DB (Remedy Lookup) → Flask API → (App Displays Solution in Marathi)

4. COMPONENTS / TECHNOLOGY

Component	Description	Application in Project
Frontend	Flutter SDK, Dart	Developing the responsive, cross-platform mobile application interface.
Backend	Python, Flask Framework	Creating the **RESTful API** endpoint to handle image/text input and serve model predictions.
AI Model	**TensorFlow** (Framework) and **Keras** (High-level API)	Implementing the **Deep Learning CNN Model** for high-accuracy image classification.
Data	Plant Village Dataset	Filtered and downsampled images of target crop diseases for training.
Unique Feature	Speech-to-text (Flutter Package)	Enabling the hands-free, Marathi-based **Voice Chatbot** for ease of use by farmers.
Database	Firebase Firestore / SQLite	Storing and retrieving the localized, verified treatment protocols and past user diagnosis history.

5. CONCLUSION

This project, **AgriCare**, successfully integrates advanced **AI** capabilities with pragmatic agricultural requirements. **AI Krushi Mitra (AIKM)** is not merely a diagnostic tool but a comprehensive advisory system that bridges the technological gap for local farmers. The hybrid model ensures that diagnosis is both accurate and that the prescribed solutions are timely and contextually relevant. This approach promises to reduce crop loss significantly and improve the economic viability of farming by optimizing resource utilization.

6. FUTURE SCOPE

- **Monetization and E-commerce Integration:** Implementing an integrated E-commerce module within the application for the direct sale of **verified pesticides, fertilizers, and quality seeds**. This feature will link the AI's diagnosis directly to a purchasing option for the recommended solution, establishing a strong and sustainable revenue stream for the platform.
- **Crop Expansion:** Scaling the current model to include more critical regional crops (e.g., Jowar, Wheat, Sugarcane) and their associated diseases.
- **Early Warning System (EWS):** Integrating local weather data and humidity sensors to predict the onset of diseases and issue **pre-emptive alerts** to farmers.
- **Community and Expert Integration:** Developing a feature for a Farmer Forum or integrating live consultation capabilities with certified agricultural experts.
- **Drone Integration Feasibility:** Exploring the potential for using **Drone** technology to capture images of larger fields, providing large-scale mapping and localized spot-treatment recommendations.

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