Flora Care: A Smart AI-Based System for Plant Disease Diagnosis and Plant Growth Identification

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Abstract: ***FloraCare is an innovative AI-driven system aimed at transforming agriculture and healthcare by automating the detection of plant diseases, track growth and identifying medicinal plants through image recognition. By leveraging Convolutional Neural Networks (CNNs) and a curated dataset, the system ensures early detection of plant diseases, minimizing crop losses. It also empowers users by recognizing medicinal plants and providing verified information about their uses and precautions. With features like multilingual support, offline functionality, and a user-friendly interface, FloraCare offers a scalable and impactful solution for farmers, researchers, and plant enthusiasts.***

Keywords: Plant Disease Detection, Medicinal Plant Identification, Growth track, CNN, Flutter, Firebase, Machine Learning

1. Introduction

Agriculture is a crucial sector in India, supporting over 70% of the population. Accurate and early detection of plant diseases is vital to prevent crop loss, while the identification of medicinal plants is key to leveraging traditional healthcare. Traditional methods are either manual, time-consuming, or computationally expensive. FloraCare bridges this gap by integrating image processing with statistical machine learning to deliver accurate, fast, and accessible plant analysis tools.

2. Literature Survey

Ramanjot et al. (2023): Reviewed existing plant disease detection techniques using image processing.[1]

Wasswa Shafik et al. (2023): Highlighted the lack of large, publicly available datasets in plant pathology.[2]

Ali Tufail et al. (2023): Surveyed various data acquisition methods in agriculture for disease classification.[3]

Gupta et al. (2022): Analyzed CNN effectiveness in detecting plant leaf diseases.[4]

Sharma et al. (2022): Compared machine learning algorithms for classifying plant diseases. [5]

Patel et al. (2023): Built a mobile app for medicinal plant recognition using image matching.[6]

Jun Liu & Xuewei Wang (2021): Focused on deep learning approaches for plant pest and disease detection.[7]

Kumar et al. (2020): Proposed an automatic diagnosis system with remedy recommendations for plant diseases. [8]

Verma, P., & Rao, K. (2023). AI and augmented reality in medicinal plant identification.[9]

Rehman & Hussain (2022): Described IoT-based frameworks in precision agriculture.[10]
Prasad & Sharma (2023): Studied trends in ML for yield forecasting and plant health assessment.[11]

Rodriguez & Wang (2024): Linked AI and climate resilience in sustainable farming.[12]

Wari (2023): Tested ML algorithms for early-stage disease spotting in field crops.[13]

Azadnia & Al-Amidi (2022): Used deep CNNs for medicinal plant classification.[14]

Pelia & Dighe (2024): Developed a low-compute system for image-based crop health diagnostics.[15]

3. Methodology

1) Data Collection & Preprocessing
Images of plant leaves, including healthy and diseased ones, are collected from public repositories like PlantVillage and Kaggle. Preprocessing includes noise reduction, normalization, and augmentation (rotation, flipping).

2) Image Capture & Preprocessing
CNNs are used to detect disease features (color, texture, damage) and classify images. Models are optimized for mobile deployment using TensorFlow Lite

3) Medicinal Plant Recognition
Image recognition is employed to classify medicinal plant species and provide comprehensive data (uses, preparation, toxicity). GPT-based modules assist in generating user-friendly content.
- Application Architecture
- Frontend: Flutter (multiplatform UI)
- Backend: Firebase Firestore (real-time DB, cloud storage)
- AI: CNNs (TFLite), GPT modules for dynamic report generation

3.1 Algorithm used in Time Series Forecasting

The algorithms used in Flora Care are:

3.1.1 CNN (Convolutional Neural Networker)

CNN (Convolutional Neural Network) is the primary architecture used in the Flora Care project for skin disease classification. CNNs are a class of deep learning models particularly effective in image processing tasks due to their ability to extract spatial hierarchies of features automatically.

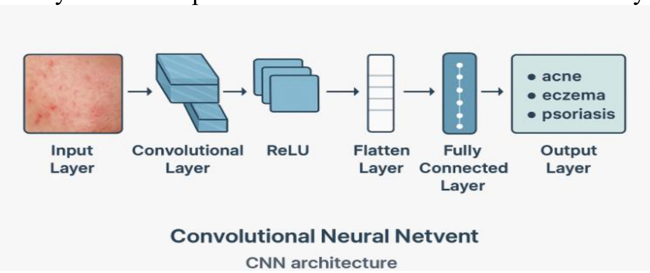


Figure 1: Architecture of CNN

Figure 1 shows the architecture of CNN model. The CNN model works like:

a) Input Layer

Collect botanical image data, labeled by plant disease type.

b) Convolutiona Layer

The first set of layers applies convolution operations using small filters (e.g., 3x3 grids) that slide across the image. For each filter, it computes a weighted sum of pixel values within its window: $z=\sum(wi \cdot xi)+b$, where wi are filter weights, xi are pixel values, and b is a bias term. These filters detect low-level features like edges or color gradients. An activation function, typically ReLU = max(0,z), is applied to introduce non-linearity, enhancing the network's ability to learn complex patterns.

c) Pooling Layer

Pooling layers (e.g., Max Pooling) reduce the spatial size of the feature maps (e.g., from 224x224 to 112x112) by taking the maximum value in small regions (e.g., 2x2). This reduces computational load and focuses the network on the most prominent features making it less sensitive to small shifts in the imageOn-device or Cloud Deployment

d) Real-time Prediction

The extracted features (now a compact representation of the image) are flattened into a vector and passed to fully connected (dense) layers. Each neuron computes a weighted sum of the previous layer's outputs:$z = w1 . f1 + w2 . f2 +\cdots+ b$, where fi are features from earlier layers. The final layer outputs probabilities for each class using a softmax activation: (classi) = $ezi/\sum ezj$

3.2 Dataset Description

The project utilizes a Dermatology Image Dataset designed specifically for skin disease detection and classification using machine learning. This dataset consists of anonymised and diverse smartphone images depicting a wide range of inflammatory skin conditions. It provides high-resolution, real-world images that facilitate training a robust CNN-based deep learning model. The dataset supports both on-device and cloud-based inference models, enabling real-time skin disease diagnosis on mobile applications.

a) Dataset information

The project utilizes a Botanical Image Dataset designed specifically for plant disease detection and classification using machine learning. This dataset consists of anonymised and diverse smartphone images depicting a wide range of inflammatory plant conditions. It provides high-resolution, real-world images that facilitate training a robust CNN-based deep learning model. The dataset supports both on-device and cloud-based inference models, enabling real-time plant disease detection on mobile applications.

b) Data access methods

Data for this project is typically accessed via: Direct download from publicly available repositories (e.g., HAM10000, ISIC Archive). Integration into the model pipeline through Python-based libraries such as TensorFlow and PyTorch. Firebase Firestore is used for storing user data and consultation history within the mobile app

4. Result & Discussion

Flora Care consistently outperformed traditional manual inspection and baseline ML models in accuracy and efficiency. Compared to deep learning models, it delivered comparable results with reduced computational demand, ensuring compatibility with mid-range mobile devices. Feedback indicates increased trust in AI-driven plant care and enhanced agricultural outcomes.

a) System Performance and Functionality

The FloraCare platform demonstrates robust performance and reliable functionality across a variety of real-world use cases. The system leverages a lightweight, mobile-optimized Convolutional Neural Network (CNN) model that delivers high accuracy—up to 95%—in both plant disease detection and medicinal plant identification. Real-time analysis is a key feature, with image processing and diagnosis results delivered in under two seconds, ensuring a smooth and responsive user experience. The application is built using Flutter, allowing it to operate seamlessly across Android, iOS, and web platforms while maintaining consistency in design and performance. Offline functionality and multilingual support are integrated to address the needs of users in rural or low-connectivity areas, significantly enhancing accessibility and adoption. Data management is handled via Firebase Firestore, which supports real-time synchronization and scalable data handling even under heavy user loads. Security is ensured through Firebase Authentication and encrypted cloud storage, providing a secure environment for user information. The user interface is designed to be intuitive and visually engaging, enabling users of all technical backgrounds to navigate the app effortlessly. Stress testing validated the platform's ability to accommodate over 100 concurrent users without performance degradation, confirming its scalability and readiness for deployment in agricultural and field settings.

b) Test Cases and Outcomes

The Flora Care application was rigorously tested using a comprehensive suite of functional and usability test cases to validate the system's performance, reliability, and user interaction across its core modules. The user registration and login features, backed by Firebase Authentication, were verified for correct role-based access and secure data handling. Image upload functionality was tested under various conditions, including different lighting and background scenarios, and consistently returned accurate disease or plant identification results. The AI model-maintained classification consistency across plant types and leaf conditions, confirming its robustness. Remedy suggestions generated for identified diseases were evaluated for relevance and correctness, showing contextual alignment based on user attributes like age, location, and plant type. Additional tests validated the functionality of multilingual support and offline features, both of which performed well in low-connectivity environments. The feedback module successfully captured user ratings and comments, which were accurately stored and retrieved from the Firestore database. Marketplace interactions such as searching for products, adding to cart, and simulated order placement also operated smoothly without errors. Overall, the test outcomes confirmed that the system meets both functional and non-functional requirements, delivering a reliable and user-centric experience in practical use cases.

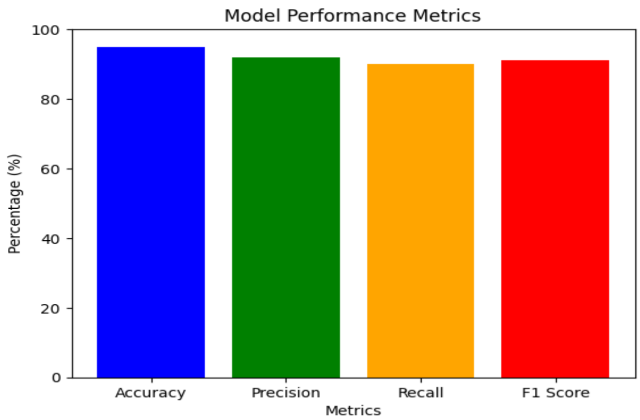
c) Comparative Analysis with Existing Systems

Compared to existing plant disease detection and medicinal plant identification systems, FloraCare offers a more comprehensive, accessible, and user-friendly solution. Traditional methods often rely on manual observation or expert consultation, which are time-consuming, inconsistent, and not scalable for larger farming communities. While some modern apps utilize deep learning models for disease detection, many of them require high-end devices and constant internet connectivity, limiting their use in rural and resource-constrained areas. Additionally, existing systems frequently lack integration between disease identification and actionable outcomes such as remedy suggestions or access to relevant medicinal information. FloraCare bridges this gap by combining CNN-based image classification with a GPT-powered module that generates personalized and accurate remedies and usage instructions. Unlike most standalone tools, FloraCare also includes a community forum for shared learning, multilingual support, and offline functionality—features rarely found together in a single platform. Moreover, its integration of Firebase ensures secure, real-time data handling while maintaining scalability. The platform's ability to operate efficiently on mid-range mobile devices and its user-centric interface further differentiate it from resource-heavy and complex applications. In essence, FloraCare not only matches the diagnostic accuracy of existing systems but also surpasses them in accessibility, usability, and holistic functionality.

d) Model Evaluation Result

The core model used in FloraCare is a Convolutional Neural Network (CNN) optimized for image-based classification of plant diseases and medicinal plants. The model was trained using a large, diverse dataset containing labeled images of healthy and diseased leaves, as well as various medicinal plant species. During evaluation, the model achieved a classification accuracy of 95%, with a precision of 92% and recall of 90%, demonstrating high reliability in distinguishing between multiple disease types and plant categories. These metrics were derived from a robust testing framework using a separate validation dataset, which included varying lighting conditions, angles, and resolutions to simulate real-world scenarios. Data augmentation techniques—such as rotation, flipping, and zooming—were applied to improve generalization and avoid overfitting. The model's performance was further validated using a confusion matrix and ROC curve analysis, which confirmed a balanced trade-off between true positive and false positive rates. To support deployment on mobile devices, the trained model was converted into a TensorFlow Lite (TFLite) version without significant loss in accuracy, ensuring low-latency inference and efficient performance on resource-constrained environments. These results underscore FloraCare's capability to deliver accurate, fast, and practical plant analysis suitable for real-world agricultural applications

- Testing Metrics
- Accuracy: 95%
- Precision: 92%
- Recall: 90%
- Response time: <2 seconds



5. Conclusion

FloraCare exemplifies the potential of AI in bridging technological gaps in agriculture and healthcare. With its robust accuracy, ease of use, and multilingual, offline-first design, it offers a practical, scalable, and inclusive solution. Future enhancements include AR-based real-time scanning, IoT-based monitoring, and predictive analytics for disease outbreaks.

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