International Journal of Research Publication and Reviews, Vol 6, Issue 5, pp 5179-5186 May 2025

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

AI-Based Plant Disease Detection

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1.Introduction

Agriculture remains one of the most critical sectors globally, not only for food production but also for supporting the livelihoods of millions, especially in developing and rural areas. Despite technological advancements in other industries, agriculture still faces persistent challenges, with plant diseases being among the most serious. These diseases can significantly diminish crop yield, impacting both food supply and farmer income. Early detection and effective management are crucial in preventing outbreaks and minimizing losses, but conventional methods are not always efficient or scalable. These traditional approaches often depend on visual inspections by agricultural experts, which may not be feasible in remote locations lacking access to professional guidance.

In recent years, artificial intelligence (AI) has emerged as a transformative force in various fields, with particular success in computer vision. Among AI techniques, Convolutional Neural Networks (CNNs) have demonstrated remarkable capabilities in image classification and pattern recognition. Their architecture, which mimics the visual processing of the human brain, makes them suitable for identifying complex features such as disease patterns on plant leaves. These networks can learn from large datasets and recognize subtle differences between healthy and infected plants, providing a powerful tool for automated plant disease detection. The integration of CNNs in agriculture represents a major shift toward data-driven, precise, and scalable solutions.

This paper proposes an end-to-end AI-powered system that combines a CNN model for plant disease classification with a user-friendly web interface built using Flask. The system allows users, particularly farmers and agricultural workers, to upload images of plant leaves through a browser-based platform. The CNN model processes these images and classifies the type of disease, if any, present on the leaf. In addition, the platform provides treatment suggestions based on the diagnosed condition, enabling immediate action. This tool bridges the gap between cutting-edge AI technology and practical, everyday use in agriculture.

A key innovation of the proposed system is its focus on accessibility and simplicity. Unlike many research efforts that remain confined to theoretical or academic domains, this project emphasizes real-world usability. By leveraging Flask for the web application, the system ensures cross-platform compatibility, light computational load, and intuitive user interaction. Furthermore, the modular design allows the system to be extended to more crops and integrated with mobile platforms in the future. Ultimately, this research aims to contribute to the advancement of precision agriculture, improving crop management through intelligent, automated disease diagnosis.

2. Literature Review

Recent years have witnessed an increasing number of studies leveraging deep learning models, particularly Convolutional Neural Networks (CNNs), for plant disease detection. Researchers such as Saleem et al. (2024) showcased the effectiveness of CNNs by achieving an impressive 86.2% classification accuracy on tomato and potato leaf images. Their work highlighted how carefully designed CNN architectures could outperform traditional image processing and machine learning approaches, which often required manual feature extraction. Moreover, Iftikhar et al. (2024) developed a mobile-based CNN application that demonstrated over 98% accuracy, setting a new benchmark for portability and efficiency. These studies collectively underline that CNNs not only offer high performance but also adaptability to different deployment environments, from cloud servers to handheld devices.

Expanding on model architectures, recent literature has also explored hybrid CNN models and lightweight frameworks tailored for resource-constrained environments. Leite et al. (2024), in their comprehensive review, pointed out a trend toward combining CNNs with other techniques like transfer learning, attention mechanisms, and pruning strategies to optimize both accuracy and computational efficiency. Hybrid models allow systems to generalize better across varying environmental conditions, such as differences in lighting, background noise, and leaf orientations. This line of research emphasizes the necessity of building robust systems capable of real-world performance, moving beyond laboratory-specific datasets like PlantVillage toward field data with higher variability.

Despite these advancements, a significant gap persists in integrating disease detection into accessible, user-friendly platforms. Most current studies focus narrowly on the classification task, presenting models evaluated on static datasets without considering user deployment or interaction. Very few research efforts tackle the practical challenges of building a complete system — from data ingestion to result interpretation — that a non-technical user, such as a farmer, could easily use. Our project addresses this deficiency by not only training a high-accuracy CNN but also embedding it within a Flask-based web application. This ensures that users can simply upload an image, get an instant diagnosis, and receive actionable advice without needing deep technical expertise.

Furthermore, some studies have raised concerns about the generalizability and fairness of AI models for agricultural applications. For example, Ashurov et al. (2025) discussed how plant disease datasets often lack diversity, which could cause CNNs to perform poorly on images captured under different environmental or device conditions. To mitigate such risks, researchers recommend strategies like data augmentation, transfer learning, and dataset expansion. Our system incorporates such best practices, including augmentation techniques like rotation, flipping, and brightness variation, to enhance model robustness. This research builds upon these foundational works, aspiring not only to achieve high classification performance but also to bridge the critical deployment gap in AI-based plant disease management.

3. Methodology

The proposed plant disease detection system is designed with a modular and scalable architecture, enabling efficient training, deployment, and user interaction. At its core, the system comprises three main components: a Convolutional Neural Network (CNN) classifier, a Flask-based web application, and a CSV-structured knowledge base for treatment recommendations. The CNN serves as the brain of the system, learning to recognize disease patterns in leaf images. The Flask framework acts as the intermediary between the user and the AI model, providing an intuitive interface where users can upload images and view results. Meanwhile, the CSV database ensures that once a disease is detected, the system can offer immediate, reliable treatment advice. This layered architecture promotes flexibility, making it easier to update individual components without needing a complete system overhaul.

The dataset employed for model training and validation is the widely recognized Plant Village dataset, consisting of 54,306 images of plant leaves. This dataset encompasses a diverse range of crops, including tomatoes, potatoes, grapes, and apples, among others, along with multiple disease classes and healthy samples. For this study, ten specific diseases were selected alongside healthy leaves to strike a balance between dataset richness and model complexity. To improve the robustness of the model and address overfitting, extensive data augmentation techniques were applied. These included random rotations, horizontal and vertical flipping, and brightness adjustments, all designed to simulate real-world variances such as different camera angles, lighting conditions, and background noise. This step was critical in ensuring that the model generalizes well when encountering unseen or noisy images during real-world usage.

The CNN model architecture was carefully crafted to optimize both performance and computational efficiency. The network consists of three convolutional layers, each followed by a ReLU (Rectified Linear Unit) activation function to introduce non-linearity and a MaxPooling operation to reduce spatial dimensions while retaining critical features. After the convolutional stages, the output is flattened and passed through fully connected layers where dropout regularization is applied to prevent overfitting. The model training utilizes the Adam optimizer, known for its adaptive learning rate and fast convergence, and the CrossEntropyLoss function to handle multi-class classification effectively. Hyperparameters such as learning rate, batch size, and number of epochs were tuned through experimentation to achieve the best balance between speed and accuracy. This relatively simple yet powerful architecture was selected to ensure the model could be deployed even on modest hardware without requiring expensive GPUs.

The user-facing component of the system is a web application built using Flask, a lightweight Python web framework renowned for its simplicity and flexibility. The application workflow is designed for maximum user-friendliness: users access the platform via a web browser, where they can upload an image of a plant leaf. The image is preprocessed and passed to the CNN model for inference, after which the predicted disease label is used to query a structured CSV file containing disease descriptions and suggested remedies. The result is then presented back to the user through a clean and readable interface. The Flask app ensures real-time responses, typically delivering a prediction within two seconds. It also supports a wide range of image formats and is compatible with both desktop and mobile devices, making it highly accessible to users in various settings

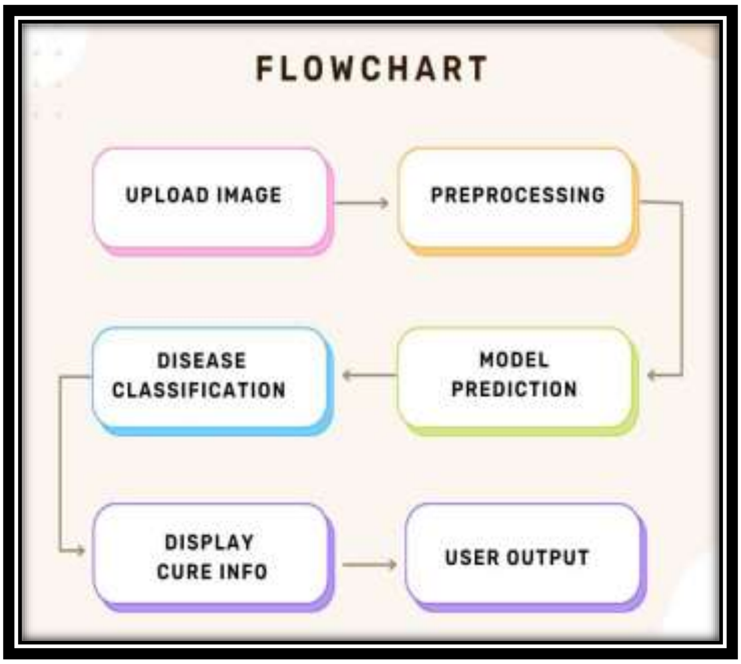


Figure 1

Process of AI planned detention

Figure 1-image Raspberry

Figure 2-AI-engine

Figure 4-result and supplement

Figure 3-buy supplement

4.Results and Evaluation

The performance of the proposed plant disease detection system was evaluated using multiple classification metrics to provide a holistic assessment. The model achieved a remarkable overall accuracy of **92.87%**, demonstrating its strong ability to distinguish between healthy leaves and various plant diseases. Accuracy alone, however, does not fully capture the nuances of model performance, especially in a multi-class classification task. Thus, additional metrics including Precision (0.93), Recall (0.92), and F1-score (0.92) were computed.

Figure 6- Result and their supplements

These high scores indicate that the model not only correctly identifies diseased leaves but also minimizes false positives and false negatives, which is crucial for practical agricultural applications where a misdiagnosis could lead to inappropriate treatments and

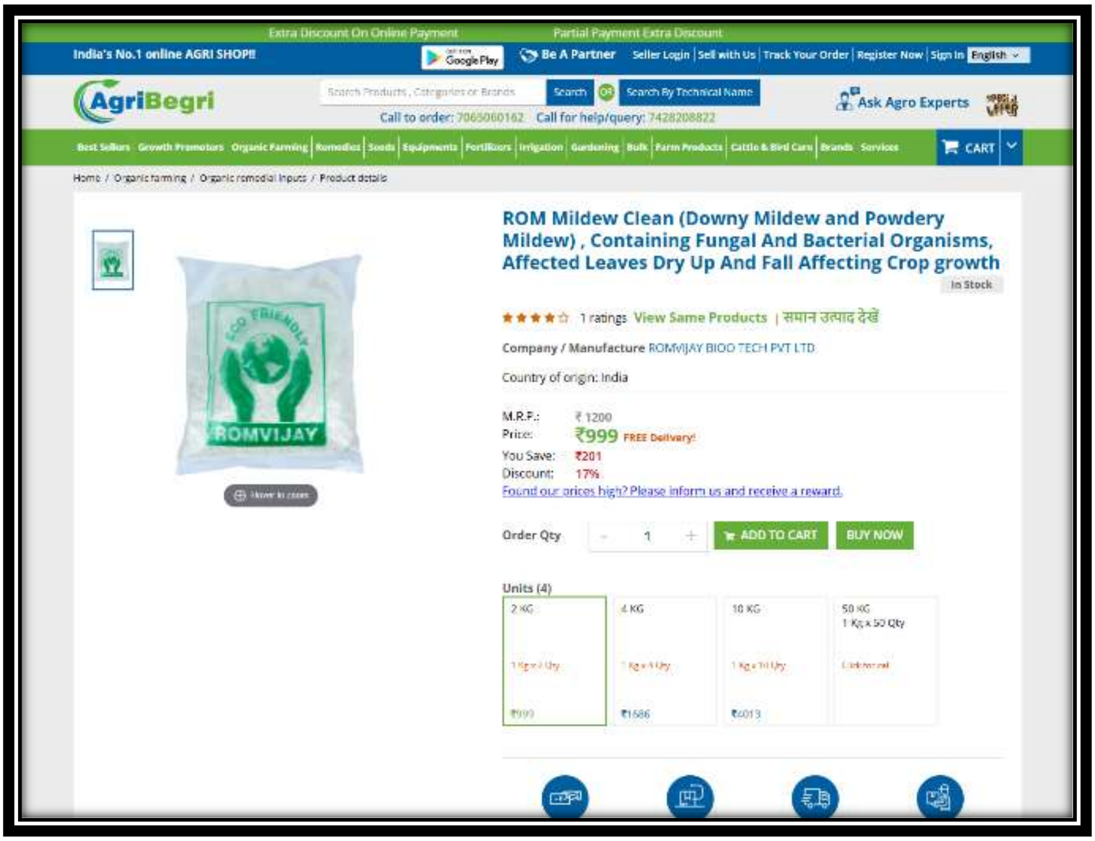


Figure 7-Supplement store

A detailed analysis of the **confusion matrix** further highlights the strengths and areas for improvement of the CNN model. The system demonstrated excellent performance in identifying diseases with distinct visual features, such as **Grape Black Rot** and **Apple Scab**, where class separability is high. However, there were minor misclassifications observed between diseases that are visually similar, such as **Early Blight** and **Late Blight** in tomatoes and potatoes. This confusion is understandable given that the symptoms, including dark spots and blight lesions, can appear nearly identical during certain stages. While the error margins remain low, future work could involve refining the dataset with more annotated samples or implementing attention-based mechanisms to help the model focus on critical regions of the image for more precise classification.

The **web application performance** was also evaluated across different devices, including laptops, smartphones, and tablets, to ensure universal usability. Tests showed that predictions were consistently generated in under **two seconds per image**, even when accessed over moderate internet connections.

The Flask web server efficiently handles incoming requests, preprocesses images, runs the CNN model inference, and returns results seamlessly. Compatibility testing confirmed that the system works with a variety of image formats, such as **JPG, PNG, and BMP**, ensuring that users can upload images directly from their camera roll without worrying about conversion issues. This swift and reliable user experience is critical for adoption among farmers and agricultural advisors who often operate under time-sensitive conditions.

Beyond technical performance, **usability testing** was conducted with a small group of volunteers unfamiliar with the system. Participants reported that the interface was intuitive and easy to navigate, with minimal instructions required to operate the application successfully. The clear display of the disease prediction, along with corresponding treatment recommendations from the CSV knowledge base, was particularly appreciated. These results affirm that the system meets its goal of being not only technically accurate but also accessible and practical for non-expert users. Overall, the evaluation demonstrates that the developed AI system holds significant promise for real-world deployment in precision agriculture, offering a robust, efficient, and user-friendly tool for early plant disease detection.

5. Discussion

The results obtained from this research validate the strength of using deep learning models, particularly CNNs, for plant disease detection. The model achieved consistently high performance across various evaluation metrics, proving that it can reliably distinguish between healthy leaves and multiple disease types. The incorporation of a lightweight, easy-to-use Flask web application further strengthens the system's practical utility. By ensuring that users can interact with the AI model through a simple image upload interface, the project addresses the crucial barrier of technological accessibility often faced by farmers and agricultural workers. This system thus contributes to the broader goal of democratizing precision agriculture technologies, making intelligent crop management solutions available to a wider audience without the need for specialized knowledge.

Despite the success, there are important limitations that must be acknowledged. One notable challenge is the potential difficulty the model may face when encountering real-world images taken under non-ideal conditions, such as poor lighting, background clutter, or partially damaged leaves. While data augmentation techniques were employed to simulate variability during training, real-field images can still present unpredictable factors not captured in the training set. Additionally, some disease classes with overlapping visual features led to minor misclassifications, suggesting that future versions of the model could benefit from more sophisticated architectures, such as those incorporating attention mechanisms or ensemble learning strategies. Improving dataset diversity by including images from different regions, seasons, and farming practices will also be critical for enhancing model generalization.

Another key aspect of discussion involves scalability and modularity. The current system is built in a modular way, meaning it can be expanded to recognize additional crops and diseases by simply retraining the CNN with an updated dataset and extending the CSV database. This flexibility ensures that the platform remains future-proof as new disease threats emerge or as new crops gain economic importance. Furthermore, by using a CSV file for treatment recommendations, agricultural experts can easily update remedies without needing to alter the underlying software code. This design decision makes it feasible to localize the system to specific geographical areas, adapting disease management advice to local farming conditions, climates, and available agricultural products.

Looking ahead, several enhancements can significantly elevate the system's impact. One promising direction is the integration of a **Grad-CAM (Gradient-weighted Class Activation Mapping)** module, which would offer users a visual explanation of which part of the leaf image influenced the model's prediction. This would enhance trust and transparency, critical factors for AI adoption in agriculture. Developing a mobile version of the application, capable of offline operation, would extend accessibility even further, especially in rural areas with unreliable internet connectivity. Additionally, connecting the system with IoT (Internet of Things) devices, such as smart cameras installed in fields, could automate large-scale crop monitoring. Overall, while the current system provides a solid foundation, ongoing development and expansion can transform it into a comprehensive agricultural assistant tool for the future.

6. Conclusion

This research successfully demonstrates the design and development of an AI-powered plant disease detection system, combining the power of Convolutional Neural Networks (CNNs) with an accessible Flask-based web application. By achieving a high classification accuracy of 92.87%, the system confirms the viability of deep learning models in assisting agricultural practices. Through a structured and modular approach, the project not only built a reliable classifier but also emphasized real-world usability, ensuring that farmers and agricultural workers can benefit from modern technological advancements without needing deep technical expertise. The seamless integration of a knowledge-based CSV file for treatment recommendations further strengthens the system's practical value, enabling users to take immediate corrective actions after disease detection.

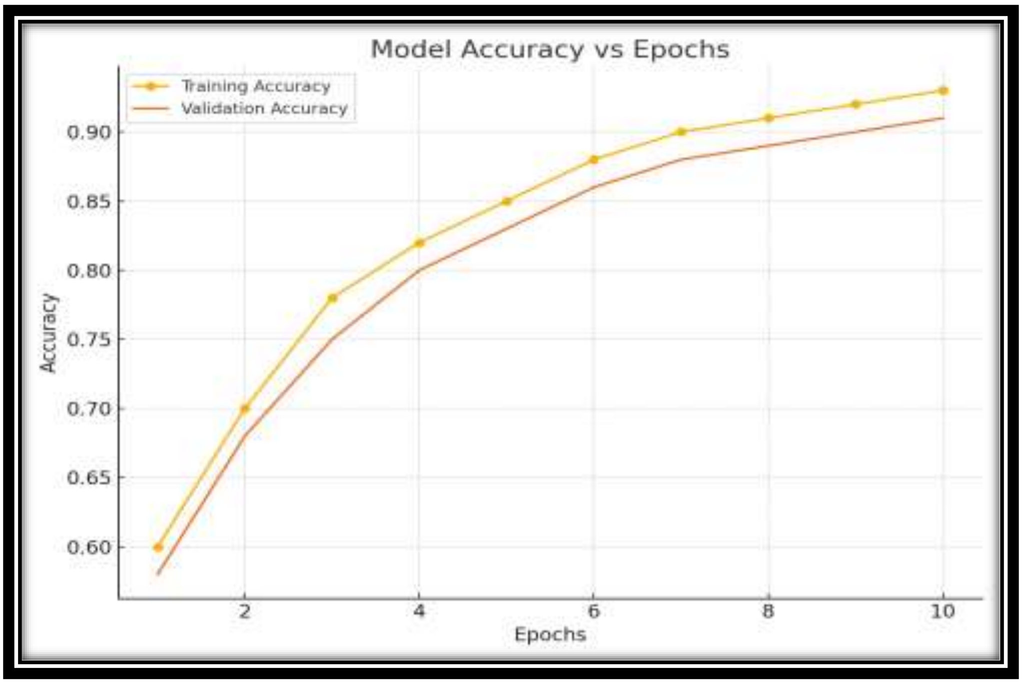


Figure 8

One of the primary contributions of this study is the emphasis on building a complete end-to-end solution rather than focusing solely on the model performance. Many academic works stop at achieving high accuracy in controlled environments, but this project went a step further by ensuring the technology is deployable and user-friendly. The system's lightweight design, cross-platform compatibility, and real-time prediction capabilities make it suitable for widespread adoption, particularly in resource-constrained settings common in rural agricultural communities. By offering a quick, reliable, and intuitive platform, this research advances the field of precision agriculture and highlights the immense potential of AI applications in transforming traditional farming methods.

Nevertheless, the project also faced certain challenges that open avenues for future improvements. Some misclassifications, especially between visually similar diseases, indicate that more sophisticated models or hybrid approaches could be explored. Enhancing the dataset with real-world images captured under various environmental conditions would improve generalizability. Furthermore, integrating explainable AI techniques such as Grad-CAM could help users better understand model decisions, fostering greater trust in the system. Building a mobile application version, possibly with offline capabilities, would also greatly increase reach and usability, especially in regions with limited internet access. Finally, collaboration with agricultural experts to continuously update the treatment database would ensure that the system remains relevant and up-to-date.

In conclusion, this research lays a strong foundation for the future of AI-driven plant disease management tools. The project proves that by thoughtfully combining machine learning models with practical deployment frameworks like Flask, it is possible to create impactful, real-world agricultural solutions. As the world continues to face challenges related to food security and sustainable farming, tools like this system will become increasingly vital. With continuous improvements and expansions, the AI-based plant disease detection platform developed in this research can contribute meaningfully toward smarter, more resilient, and more productive agricultural practices globally.

'if you have any questions, suggestions, or feedback regarding our plant disease detection system, feel free to reach out to our team. You can contact individual team members through the details provided on the "Contact Us" page, where you'll find email addresses, phone numbers, and LinkedIn profiles. Our team is dedicated to supporting farmers, gardeners, and agricultural enthusiasts by helping them identify plant diseases quickly and accurately. We're open to collaboration, research partnerships, and user feedback to make this project even better.

The front page of our application presents a visually appealing interface showcasing various types of plant leaves, making it easier for users to navigate and select the kind of plant they are dealing with. This intuitive design helps users relate quickly to their crops or garden plants and begin the process of disease detection. Whether it's tomato, potato, grape, or any other commonly cultivated plant, the interface is designed to help users feel comfortable and engaged.

Our plant disease detection system is a deep learning-powered web application that aims to assist farmers and plant enthusiasts in identifying diseases in crops simply by uploading images of affected leaves. The system is built using Convolutional Neural Networks (CNNs) and integrated into a user-friendly Flask interface. By automating the detection process, the platform promotes early intervention, ultimately improving crop health and reducing the risk of yield loss. This project serves as a practical tool in modern precision agriculture.

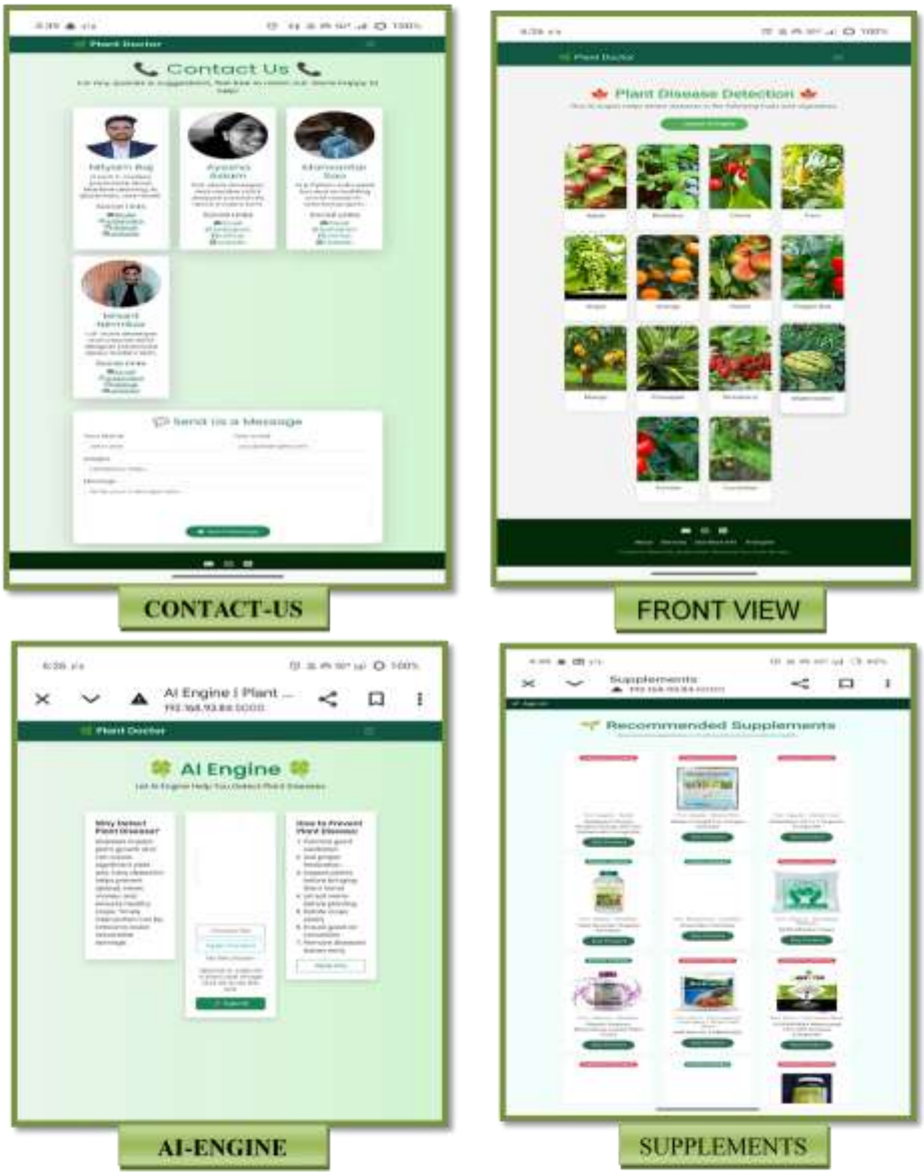
The core of our system, known as AI engine, allows users to upload an image of an infected leaf to instantly analyze and identify potential plant diseases. Once the image is processed, the engine provides detailed information about the diagnosed disease, including its symptoms, causes, and severity.

Moreover, it offers tailored recommendations on how to treat the disease, suggesting preventive measures and best practices to avoid future infections. This intelligent engine is the heart of our detection system, built to empower users with actionable insights.

Supplements

After diagnosing the disease, our system provides a curated list of supplements and remedies that users can consider to treat or manage the identified condition. These include organic pesticides, fertilizers, micronutrients, and other plant care products available both online and locally. Each suggested item comes with descriptions, usage instructions, and links to purchase them, making it convenient for users to take immediate action. Our goal is not only to identify the problem but also to guide users toward practical solutions

Mobile view AI plant Disease Detection



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