Integrated Application for Paddy Disease Detection and Remedy Suggestion

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Abstract - In India, agriculture is the backbone of rural communities, with the majority of villagers relying on it as their primary livelihood. However, challenges such as disease management, soil quality assessment, and weed control often limit productivity. While Kisan call centers provide essential support, their effectiveness is constrained by communication barriers and the limitations of verbal explanations. This paper proposes an innovative solution through a machine learning-based mobile application designed specifically for farmers. The app enables users to upload images of paddy disease symptoms, soil test results, and weeds for analysis. Leveraging advanced algorithms, it provides automated, data-driven recommendations for disease control, crop management, and soil improvement. The app also offers local language interfaces, making it accessible to less educated farmers. By continuously refining its decision-making capabilities through user feedback, the app evolves to meet the specific needs of different regions and farming practices. This approach not only enhances efficiency and productivity but also empowers farmers with immediate, reliable expert advice, bridging the gap between traditional practices and modern technology. Ultimately, the application aims to significantly improve agricultural outcomes, contributing to the sustainability and growth of the farming sector in India.

***Key Words*:** Paddy crop disease, Integrated, Application, suggestion, soil, weeds, resolution etc.

1.INTRODUCTION

Agriculture remains a cornerstone of the Indian economy, employing nearly half of the country's workforce. India is globally recognized as a leading producer of pulses, rice, wheat, spices, and their by-products. The economic success of farmers hinges on the quality of their produce, which is heavily influenced by plant growth and yield. Identifying diseases that affect plants is crucial for optimizing farming practices, as these diseases not only harm crop health but also disrupt the ecological balance, leading to financial difficulties for farmers. Traditional farming practices often involve labor-intensive methods for disease detection and soil testing. Most farmers lack access to efficient diagnostic tools, leading to suboptimal crop management. For example, soil testing, essential for understanding nutrient content and determining appropriate crops or fertilization techniques, is frequently neglected. This results in lower yields as farmers often rely on outdated cultivation methods. Additionally, weed management remains a persistent challenge, requiring effective solutions to ensure healthy crop growth. Machine learning, particularly in computer vision, offers a promising solution by automating the identification of crop diseases. By analyzing large datasets of images, machine learning models can distinguish between healthy plants and those affected by diseases through visual patterns and cues. This technology has the potential to revolutionize crop disease management by providing rapid, accurate, and accessible diagnostic tools. The integration of weed identification and soil testing into a single user-friendly application can further enhance farming practices, offering comprehensive solutions to the challenges faced by cultivators. By embracing these advancements, farmers can improve crop yields, maintain ecological balance, and secure their livelihoods in a competitive agricultural market..

2. LITERATURE REVIEW

The influence of atmospheric conditions on users' moods was analyzed in [2] to identify suitable crops for farming. The weather data collected from this study has since been widely utilized to recommend crops based on soil and climate variables. Pudumalar et al. in [3] discussed the challenges farmers face due to inadequate crop selection knowledge and developed an algorithmic recommendation system employing models such as Random Forest, Naive Bayes, the CHAID model, and K-Nearest Neighbors. In [4], the authors explored various applications of Artificial Neural Networks (ANN), Machine Learning (ML) technologies, and IoT advancements aimed at enhancing agricultural practices. These technologies enable precision farming techniques, including weed detection, crop prediction, and yield estimation, all powered by machine learning.

In the seed dataset collection process outlined in [5], temperature regulation proved essential, with humidity levels being critical to maintaining sufficient moisture content for most plants. The DHT11 sensor was used throughout the experimentation phase, successfully recommending ideal plant

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options based on location, temperature, and humidity indexing. The study employed models like the Naive Bayes Classifier, which consistently demonstrated successful outcomes, reflecting the growing importance of digital tools and AI frameworks in modern agriculture.
Finally, [6] focused on predicting late blight diseases in potatoes using Extreme Learning Machines, achieving an accuracy of 91.5%. Similarly, Sharma et al. proposed using Backpropagation Neural Networks to predict potato Late Blight Diseases, as detailed in [7].

3. METHODOLOGY

The proposed system aims to develop an integrated paddy disease application that leverages deep learning to detect plant diseases, suggest crops based on soil analysis, and identify weeds, while also offering relevant remedies. This application provides farmers with automatic pesticide recommendations corresponding to the detected diseases. Upon opening the app, users are presented with a language selection menu followed by four options: disease detection, soil testing, weed detection, and smart help. Selecting any of the first three options activates a camera interface, allowing users to capture photos that are analyzed by trained deep learning models to provide crop suggestions or remedy recommendations specific to the chosen option. The Smart Help option allows farmers to submit problem details through a form, with the option to attach images. These submissions are then analyzed by agricultural experts through a secure back-end system, accessible only after authentication, ensuring expert advice is provided to address the issues raised by farmers.

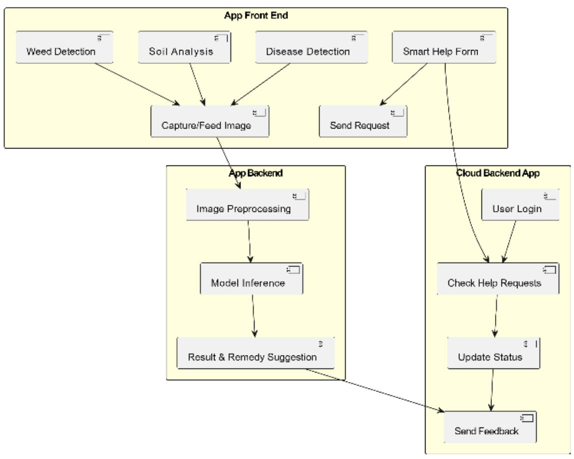

Fig -1: Block Diagram of the System

The implemented methodology is given below.

1. Image Dataset Collection: Gather images of plant diseases, soil samples, and weeds.
2. Preprocessing Techniques: Clean and standardize the dataset for model training.
3. Model Training: Train deep learning models to recognize diseases, soil types, and weeds.
4. Mobile Application Development: Develop an Android app for image analysis and result display.
5. Remedy Suggestion System: Suggest remedies and provide analysis results in the app.
6. Crop Recommendation System: Recommend suitable crops based on soil analysis.
7. Multilingual Support: Implement the app in multiple languages.
8. Text-to-Speech System: Convert text output to audio for illiterate users.
9. Cloud-Based Backend: Develop a cloud backend with CRUD functions and a smart help form.

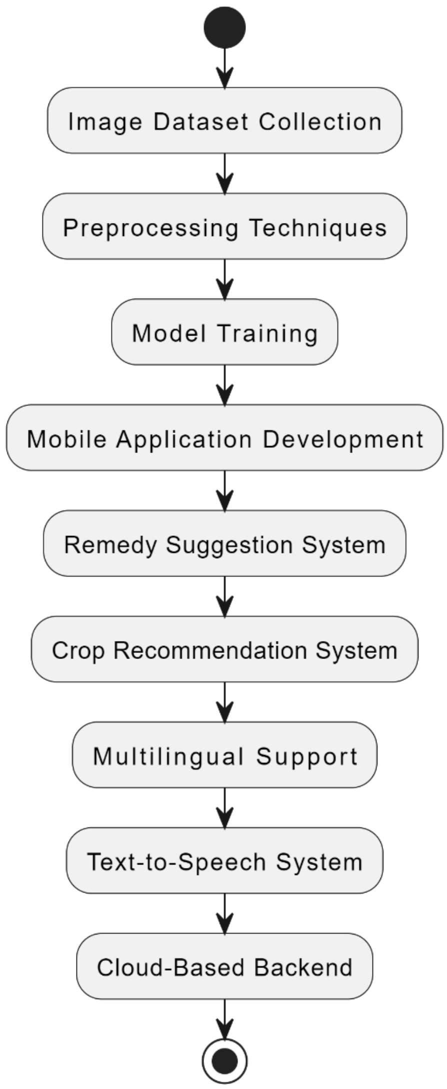

Fig -2: Process Flow diagram

4. IMPLEMENTATION

Based on the Methodology decided the implementation was carried out . The project involves the development of three machine learning models for paddy disease detection, soil analysis, and weed detection, each trained using a comprehensive dataset. The dataset for disease detection includes images classified into five categories: leaf smut, tungro, blight, blast, and healthy. The training set of 3,314 images is used to train the model to distinguish between these categories, while a validation set of 436 images helps finetune the model to prevent overfitting. The testing set of 432 images provides a final evaluation, ensuring the model's accuracy and generalization capabilities. Preprocessing steps, including resizing and normalization, prepare the images for effective training. The model is implemented using a Convolutional Neural Network (CNN) with layers that progressively learn hierarchical features, leading to high classification accuracy.

Fig -3:Sample of dataset Collected

For soil analysis, the dataset includes images representing different soil types, which are processed and normalized similarly to the disease detection model. The model is trained to classify soil samples and suggest suitable crops based on the detected soil type. The training process follows the same pattern, with training, validation, and testing phases to ensure the model's reliability. The final model is integrated into an Android application, allowing farmers to capture or upload images of their soil, which the model then analyzes to provide crop recommendations.

The weed detection model is trained using a dataset that includes images of various weed types, such as crabgrass, nutsedge, goosegrass, and carpet weeds. The training process mirrors that of the other models, with preprocessing, model training, and validation steps to achieve accurate classification. Once trained, this model is also incorporated into the Android application, where it assists farmers in identifying weeds and provides suggestions for their removal.

The final implementation involves exporting all three models to the TensorFlow Lite (tflite) format for deployment on the Android application developed in Android Studio. This app enables farmers to diagnose paddy diseases, analyze soil, and detect weeds directly from their smartphones, providing them with timely and actionable insights to improve their agricultural practices.

The Android application developed in Android Studio integrates various functionalities to assist farmers by capturing images of crops and weeds, converting text recommendations into audio, and analyzing soil and weed data using pre-trained machine learning models. Images are processed by resizing, normalizing, and converting them into tensors for model analysis, which then outputs confidence scores to predict diseases. The app's interface, designed with XML files, separates the visual layout from the backend logic managed by Java/Kotlin files, ensuring a modular and maintainable structure. This approach allows for seamless user interaction, providing timely and actionable insights to improve agricultural practices.

5. RESULTS AND DISCUSSION

The model performance is evaluated and the results are plotted.

The confusion matrix for the Disease detection system is given below.

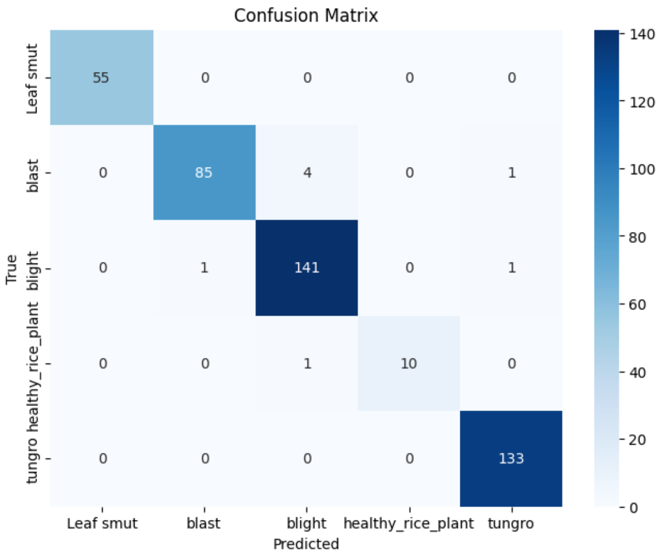

Fig -4. Confusion Matrix- Paddy Disease detection

Also the confusion Matrix for the Soil Analysis system is given below.
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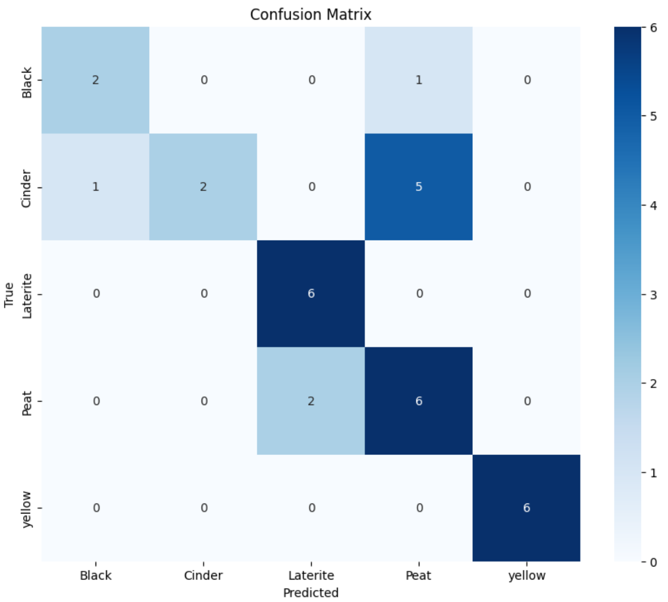

Fig -5. Confusion Matrix- Soil detection

Similarly The confusion matrix for the weed detection system is given below.

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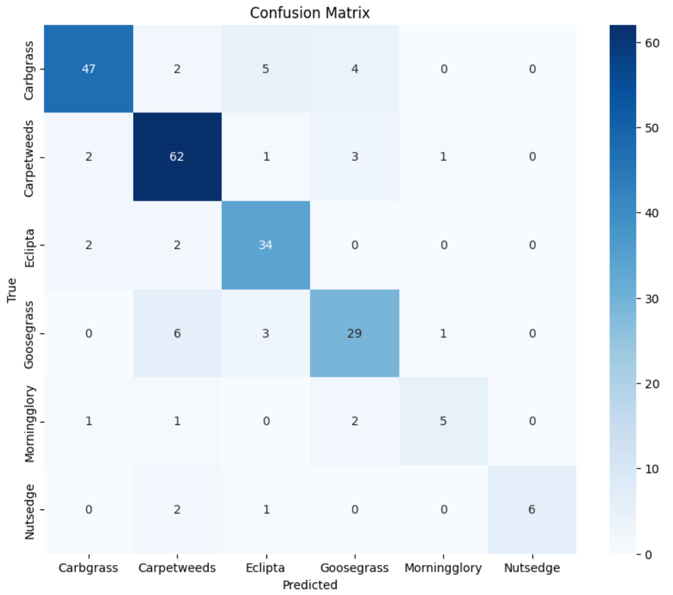

Fig -6. Confusion Matrix- Weed detection

The project results are evaluated through the performance of three distinct models: disease detection, soil detection, and weed detection. The disease detection model demonstrates exceptional accuracy, achieving 98% overall, with perfect classification for classes like Leaf smut and Tungro. However, minor misclassifications occur between Blast and Blight, indicating some confusion between these two classes. The slightly lower recall for the Healthy rice plant class is attributed to its smaller dataset size, which may have affected the model's learning.

The soil detection model, which classifies five soil types, achieves a balanced performance with an overall accuracy of 71%. While the model performs exceptionally well in identifying Laterite and Yellow soils with perfect precision and recall, it struggles with Cinder, which is often misclassified as Peat. This suggests the need for further refinement, particularly in distinguishing visually similar soil types.

The weed detection model shows strong performance with an overall accuracy of 82%, excelling in the classification of Carpetweeds and Nutsedge. However, there are notable challenges in distinguishing Crabgrass, Goosegrass, and Morningglory, where frequent misclassifications occur. This highlights the need for improved feature extraction and model training to better differentiate between these weed types.

In summary, while the models exhibit high accuracy and reliability in most classes, areas for improvement have been identified, particularly in reducing misclassifications and enhancing recall for underperforming classes. These insights will guide future refinements, aiming to improve the effectiveness of the models in practical agricultural applications.

The table of the comparative analysis is as shown below.

Table -1: Comparative analysis

Model	**Accuracy**	**High Performance Classes**	**Low Performance Classes**
Disease Detection	98%	Leaf smut, Tungro	Healthy rice plant
Soil Detection	71%	Laterite, Yellow	Cinder, Peat
Weed Detection	82%	Carpetweeds, Nutsedge	Crabgrass, Goosegrass, Morningglory

The graph illustrating the performance analysis of the three models: Disease Detection, Soil Detection, and Weed Detection. The bar plot represents the accuracy of each model, while the line plots show the number of high and low-performance classes for each model. This visual representation helps in understanding how well each model performs overall and highlights areas where improvements can be made.

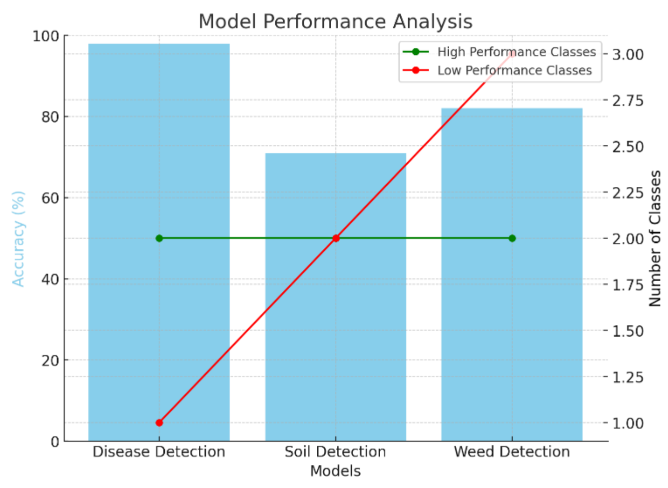

Fig -7. Graph of Performace Analysis

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Finally the deployed android application and the results of the same are as shown below. The app can be used for effectively determination of the paddy disease, soil analysis and also for the detection and remedy suggestion on weeds and diseases.

Fig -8. App Welcome Screen

Fig -10. App Language change

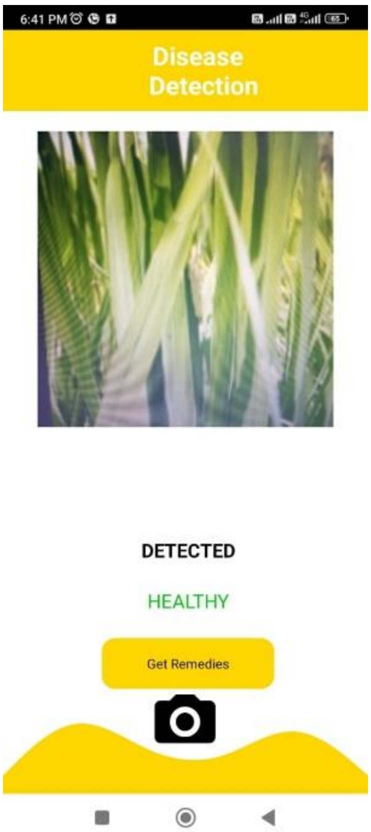

Fig -9. App Disease Detection

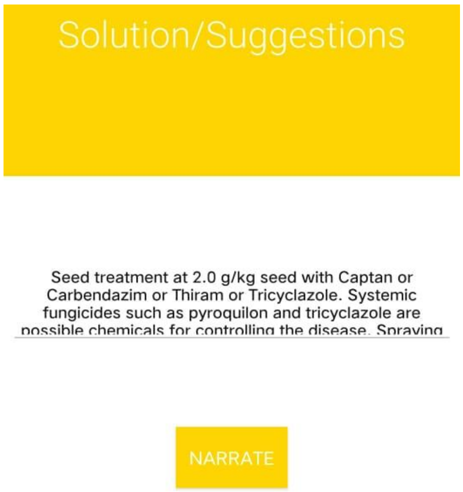

Fig -11. App Remedy Suggestion

The farmer help and assist portal developed is as shown below.

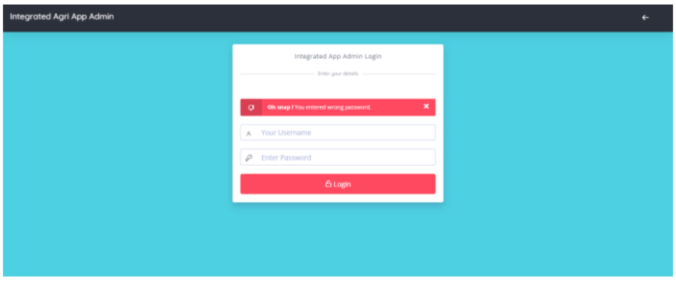

Fig -12. Farmer Support system

The Admin panel to assist farmers requests are as shown below.

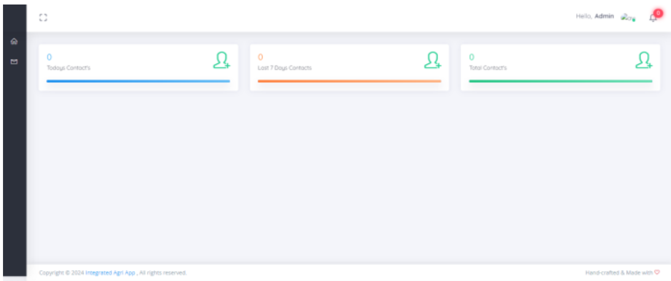

Fig -12. Farmer Support system- Admin Panel

6. CONCLUSIONS

The system implemented and the analysis done can lead to conclusion that , this project successfully developed and evaluated machine learning models for the classification of paddy diseases, soil types, and weeds, and integrated these models into a user-friendly Android application. The models demonstrated high accuracy, particularly in the classification of diseases and weeds, with overall accuracies of 98% and 82%, respectively. The soil detection model, while slightly less accurate at 71%, still provided valuable insights into soil health. Despite these strong performances, the project identified areas for improvement, particularly in reducing misclassifications and enhancing recall for certain classes. The insights gained from confusion matrices and classification reports will guide future refinements, ensuring the models become even more reliable and effective tools for practical agricultural applications. The resulting application empowers farmers by providing timely, accurate, and actionable insights, ultimately contributing to improved crop management and agricultural productivity.

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