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Investigation on paddy crop disease detection and classification using SVM and CNN Algorithms

Dr.J Madhavan[1], B. Rithika[2], K. Sneha[3], K. Swathi[4]
[1]Professor Hod; Department of Electronics and Communication Engineering Bhoj Reddy Engineering College for Women Hyderabad, India.
[2,3,4]B.Tech Students; Department of Electronics and Communication Engineering Bhoj Reddy Engineering College for Women Hyderabad, India.
Mail Id; ballemrithika@gmail.com ,Snehabhai246@gmail.com ,nissykalakola@gmail.com
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Abstract
Rice cultivation plays a fundamental role in ensuring food security and sustaining agricultural economies, particularly in developing countries. One of the major factors affecting rice productivity is the occurrence of leaf diseases, which significantly reduce crop yield when not identified at an early stage. Conventional disease diagnosis relies on visual inspection by farmers or agricultural experts, making the process time-consuming, subjective, and often inaccurate. Although deep learning techniques have shown promising results in automated disease recognition, many standalone convolutional neural network (CNN) models experience performance degradation when dealing with visually similar disease categories and complex field conditions.
*To address these challenges, this paper presents **PaddyCare AI**, an intelligent paddy leaf disease diagnosis system based on a hybrid deep learning architecture. The proposed framework employs the pre-trained **MobileNetV2** network to perform efficient feature extraction while utilizing a **Support Vector Machine (SVM)** classifier to improve decision boundaries and classification performance. The model was trained and evaluated using a balanced dataset comprising five classes: **Bacterial Blight, Blast, Brown Spot, Tungro,** and **Healthy** leaves.*
Experimental results demonstrate that the proposed MobileNetV2–SVM hybrid framework achieves superior classification accuracy compared with conventional CNN-based classifiers while maintaining computational efficiency suitable for practical deployment. To enhance accessibility, the trained model is integrated into a web-based application that enables farmers to upload leaf images and receive immediate disease diagnosis along with preventive recommendations. The proposed system facilitates timely intervention, minimizes crop losses, improves agricultural productivity, and promotes precision farming through artificial intelligence.

Keywords— *Paddy Leaf Disease Detection, Deep Learning, MobileNetV2, Support Vector Machine, Computer Vision, Precision Agriculture, Artificial Intelligence, Image Classification, Smart Farming, Plant Disease Diagnosis.*

Introduction
Rice is one of the world's most important cereal crops and serves as the primary food source for more than half of the global population. India ranks among the leading rice-producing nations, contributing substantially to both national food security and the agricultural economy. Millions of small and marginal farmers depend on paddy cultivation as their primary source of livelihood, making crop health management an essential aspect of sustainable agriculture.
Leaf diseases such as **Bacterial Blight**, **Blast**, **Brown Spot**, and **Tungro** are among the most destructive factors affecting rice production. If these diseases remain undetected during their initial stages, they can rapidly spread across fields, resulting in considerable yield reduction and economic losses. Early identification enables farmers to apply appropriate control measures before severe crop damage occurs.
Traditional disease diagnosis primarily depends on visual observation by experienced farmers or agricultural specialists. However, the accuracy of manual inspection varies with expertise, environmental conditions, and disease severity. Moreover, access to agricultural experts is often limited in rural regions, delaying timely intervention.
Recent developments in Artificial Intelligence (AI), Computer Vision, and Deep Learning have opened new opportunities for automated plant disease diagnosis. Deep neural networks are capable of learning complex visual features directly from leaf images, eliminating the need for manual feature engineering. Nevertheless, many deep learning models

suffer from reduced generalization when multiple diseases exhibit similar visual characteristics.

To overcome these limitations, this work introduces **PaddyCare AI**, a hybrid MobileNetV2–SVM framework designed for accurate paddy leaf disease classification. The proposed system combines the feature extraction capability of a lightweight convolutional neural network with the robust classification performance of Support Vector Machines. Furthermore, the trained model is deployed through an interactive web application, allowing farmers to obtain rapid disease predictions using uploaded leaf images.

Literature Survey

Rice (*Oryza sativa*) is among the most widely cultivated cereal crops and constitutes the primary source of nutrition for a significant portion of the global population. India is one of the world's leading rice-producing countries, where paddy cultivation contributes substantially to agricultural production, rural employment, and national food security. Ensuring healthy crop growth is therefore essential for maintaining sustainable agricultural productivity.

Several diseases, including **Bacterial Blight, Blast, Brown Spot,** and **Tungro**, severely affect paddy cultivation by damaging leaf tissues, reducing photosynthetic efficiency, and ultimately decreasing both crop quality and yield. Since disease symptoms often appear gradually, early diagnosis is essential for minimizing crop losses and enabling timely disease management practices.

Conventional disease identification relies primarily on visual inspection performed by farmers or agricultural specialists. Although experienced experts can provide reliable diagnoses, manual inspection is time-consuming, subjective, and often unavailable in remote farming regions. Environmental factors such as lighting conditions, disease progression, and visual similarity among different diseases further reduce diagnostic accuracy.

Recent advances in artificial intelligence, computer vision, and deep learning have enabled automated disease recognition systems capable of analyzing plant leaf images with high precision. These intelligent systems reduce human intervention while providing rapid and consistent diagnostic results. In the proposed research, a hybrid **MobileNetV2–SVM** framework is employed for paddy leaf disease identification. MobileNetV2 serves as an efficient deep feature extractor, whereas the Support Vector Machine classifier performs accurate disease classification using the extracted features. The trained model is deployed through a web-based application that allows farmers to upload leaf images and receive immediate disease predictions together with appropriate preventive measures and treatment recommendations.

Existing and Proposed Methodology

Existing Methods

Conventional paddy leaf disease detection techniques primarily rely on digital image processing and traditional machine learning algorithms. In these methods, images of infected leaves are captured using cameras or mobile devices and then subjected to preprocessing operations such as resizing, noise removal, image enhancement, and color normalization to improve image quality. After preprocessing, handcrafted features including color, texture, shape, and edge characteristics are extracted manually using image processing techniques. These feature vectors are then provided to machine learning classifiers such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Random Forest, or Naïve Bayes for disease classification. Although these approaches can provide satisfactory results under controlled laboratory conditions, their performance decreases significantly when applied to real-world agricultural environments where images exhibit variations in illumination, background complexity, leaf orientation, and disease severity. Furthermore, manually extracting discriminative features requires extensive domain knowledge and often fails to capture complex visual patterns associated with different disease classes. Consequently, the accuracy and robustness of traditional systems remain limited, motivating the development of deep learning-based approaches capable of automatic feature learning.

Proposed Methodology

The proposed **PaddyCare AI** system introduces a hybrid deep learning framework that combines the feature extraction capability of the **MobileNetV2** convolutional neural network with the classification strength of a **Support Vector Machine (SVM)**. The system has been designed as an end-to-end intelligent solution that enables farmers to detect paddy leaf diseases quickly and accurately using a simple web application. The disease diagnosis process begins when a user uploads a paddy leaf image through the application interface. The uploaded image is first preprocessed by resizing it to the standard input dimensions of **224 × 224 pixels** and normalizing its pixel values to ensure compatibility with the deep learning model. The preprocessed image is then passed through the pre-trained MobileNetV2 architecture, which automatically extracts highly discriminative visual features without requiring manual feature engineering. Instead of using the CNN's fully connected classification layer, the extracted deep feature vector is forwarded to a Linear Support Vector Machine classifier. The SVM determines the optimal decision boundary by maximizing the margin between different disease classes, thereby improving classification accuracy and reducing misclassification. The trained hybrid model categorizes the uploaded leaf image into one of five classes: **Bacterial Blight, Blast, Brown Spot, Tungro,** or **Healthy**. After classification, the system automatically retrieves disease-specific recommendations, preventive measures, and treatment suggestions from an integrated agricultural knowledge base. Finally, the prediction results are displayed through a user-friendly graphical dashboard that presents the uploaded image, predicted disease, confidence score, suggested remedies, and preventive practices, enabling farmers to make timely crop management decisions.

Dataset Collection and Data Augmentation

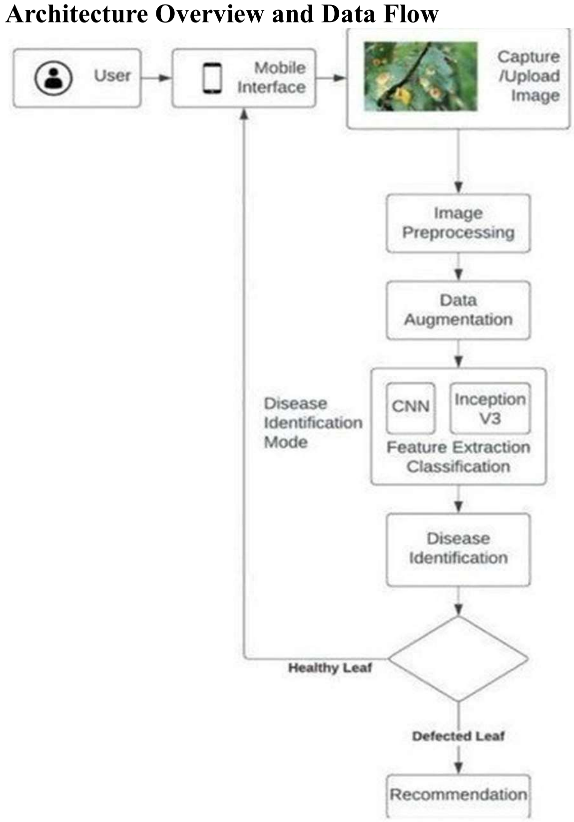
The success of any deep learning model depends largely on the availability of a diverse and representative dataset. For the proposed PaddyCare AI system, a balanced dataset containing images from five distinct categories—**Bacterial Blight, Blast, Brown Spot, Tungro,** and **Healthy** paddy leaves—was utilized for model training and evaluation. To improve the generalization capability of the model and reduce the risk of overfitting, several data augmentation techniques were employed during the training process. Data augmentation artificially increases the diversity of training samples by generating modified versions of existing images while preserving their original class labels. Techniques such as random rotation, horizontal and vertical flipping, zooming, shearing, brightness variation, and contrast adjustment were applied to simulate different environmental conditions encountered in real agricultural fields. These transformations expose the model to a wider range of image variations, including differences in lighting, camera angle, leaf orientation, and scale. As a result, the hybrid MobileNetV2–SVM model becomes more robust and capable of accurately identifying diseases under practical field conditions.

SVM Classification and Hyperplane Optimization

The final stage of the proposed hybrid framework employs a **Support Vector Machine (SVM)** to perform disease classification using the deep feature vectors generated by MobileNetV2. While convolutional neural networks excel at extracting informative visual representations, Support Vector Machines are highly effective in constructing optimal decision boundaries for classification tasks. The primary objective of the SVM algorithm is to determine an optimal separating hyperplane that maximizes the margin between different disease classes, thereby improving classification reliability and reducing classification errors. In the proposed system, the deep feature vectors extracted from MobileNetV2 are directly provided to a Linear SVM classifier. During the training phase, hyperparameter optimization and cross-validation techniques were employed to identify the most suitable model configuration, ensuring robust classification performance across all five disease categories. By integrating deep feature extraction with statistical learning, the hybrid MobileNetV2–SVM architecture combines the strengths of both deep learning and conventional machine learning. This integration results in improved classification accuracy, enhanced generalization capability, and reliable performance under diverse agricultural conditions, making the proposed PaddyCare AI system an effective solution for real-time paddy leaf disease diagnosis

System Architecture

Architecture Overview and Data Flow



The proposed **PaddyCare AI** system is designed using a multi-stage hybrid architecture that integrates deep learning, machine learning, and web technologies to provide accurate paddy leaf disease diagnosis. The architecture follows a sequential workflow that begins with image acquisition and ends with disease prediction and recommendation generation. Each processing stage contributes to improving the overall reliability and efficiency of the system while minimizing user intervention. The architecture has been developed with the objective of providing farmers and agricultural professionals with a simple yet intelligent platform capable of delivering rapid and accurate disease diagnosis in real time.

The diagnosis process begins at the **user access layer**, where farmers or agricultural officers interact with the system through a responsive web application. The interface provides an intuitive environment in which users can either upload an existing image of a paddy leaf or capture a new photograph using a mobile device. The application is designed to be user-friendly so that individuals with minimal technical knowledge can easily utilize the system for disease diagnosis.

Once an image is uploaded, it is forwarded to the **image preprocessing module**, where several operations are performed to standardize the input before it is analyzed by the deep learning model. The image is resized to **224 × 224 pixels**, corresponding to the input dimensions required by the MobileNetV2 architecture. Pixel values are normalized, unnecessary background variations are minimized, and image quality is enhanced through noise reduction techniques. These preprocessing operations ensure that all input images maintain a consistent format, thereby improving the stability and accuracy of feature extraction.

To improve the generalization capability of the proposed model, the preprocessed images undergo **data augmentation** during the training phase. Various augmentation techniques, including random rotation, horizontal and vertical flipping, zooming, shearing, brightness adjustment, and contrast variation, are applied to artificially increase the diversity of the training dataset. These transformations enable the model to learn disease characteristics under different environmental conditions such as varying illumination, camera angles, and leaf orientations. As a result, the trained model becomes more robust and less susceptible to overfitting when presented with unseen field images.

The processed image is subsequently passed to the **disease identification engine**, which forms the core intelligence of the PaddyCare AI system. This module consists of two tightly integrated components that collectively perform disease classification. Initially, the preprocessed image is supplied to a pre-trained **MobileNetV2** convolutional neural network operating as a deep feature extractor. Instead of directly performing classification, MobileNetV2 generates a compact high-dimensional feature representation that captures discriminative visual characteristics such as leaf texture, color distribution, lesion boundaries, and disease-specific patterns. These automatically extracted features eliminate the need for manual feature engineering while significantly improving representation quality.

Software Tools

Development Environment and Integrated Platforms

The development of the proposed **PaddyCare AI** system required a well-structured software environment capable of supporting deep learning model development, machine learning integration, and web application deployment. The entire system was implemented using the **Windows 11** operating system, which provided a stable and secure platform for software development. To avoid execution restrictions associated with Windows security policies, the project workspace was configured appropriately so that deep learning libraries and their associated dynamic link libraries (DLLs) could be executed without interruption.

The primary Integrated Development Environment (IDE) used for implementation was **PyCharm Professional**. PyCharm offers extensive support for Python programming, project organization, debugging, virtual environment management, and version control. Its intelligent code editor, integrated terminal, syntax highlighting, and debugging facilities significantly improved the efficiency of software development. The use of isolated Python virtual environments ensured consistent package management and prevented dependency conflicts among the machine learning libraries used throughout the project. The IDE also simplified project navigation and reduced development time through automated code inspection and error detection features.

Machine Learning and Deep Learning Frameworks

The intelligent disease diagnosis capability of PaddyCare AI is achieved through the integration of several widely adopted machine learning and deep learning frameworks. The entire application was developed using **Python**, which was selected because of its simple syntax, extensive scientific computing ecosystem, and strong community support. Python provides seamless integration with artificial intelligence libraries, making it an ideal choice for implementing hybrid deep learning applications.

The deep feature extraction component of the proposed system is built using **TensorFlow**, an open-source deep learning framework developed by Google. TensorFlow provides the computational engine required for loading the pre-trained MobileNetV2 architecture, executing convolutional operations, and performing efficient feature extraction from paddy leaf images. The framework is optimized for large-scale numerical computation and supports both CPU and GPU acceleration, enabling efficient model execution during training and inference.

To simplify neural network implementation, **Keras** was utilized as the high-level programming interface built on top of TensorFlow. Keras provides a modular and user-friendly API for constructing, training, and deploying deep learning models. Within the proposed framework, Keras was used to load the pre-trained MobileNetV2 model, preprocess input images, and generate deep feature vectors required for disease classification. The simplified programming interface significantly reduced implementation complexity while maintaining compatibility with TensorFlow's computational backend.

The second stage of the hybrid architecture employs **Scikit-learn**, one of the most widely used machine learning libraries in Python. Scikit-learn provides the implementation of the Support Vector Machine classifier responsible for disease prediction. It also offers utilities for model training, performance evaluation, cross-validation, and hyperparameter optimization, allowing the classifier to achieve improved generalization performance.

Several auxiliary libraries further supported system implementation. **NumPy** was employed for numerical computations and multidimensional array manipulation, providing efficient storage and processing of image tensors and extracted feature vectors. **Pillow (PIL)** served as the primary image processing library responsible for loading, resizing, and converting leaf images into formats compatible with the deep learning model. These supporting libraries ensured smooth integration between the preprocessing pipeline and the hybrid classification framework.

Results and Discussion

The proposed PaddyCare AI framework was successfully implemented and evaluated using the collected paddy leaf image dataset. The complete workflow, including image preprocessing, deep feature extraction through MobileNetV2, feature classification using Support Vector Machine, and web-based deployment, functioned as intended. During experimentation, the hybrid model accurately classified leaf images into one of the five predefined categories and generated disease-specific recommendations through the integrated agricultural knowledge base.

The trained model demonstrated excellent prediction capability under different testing conditions and successfully distinguished visually similar diseases that often pose challenges to conventional image classification systems. The integration of transfer learning with statistical machine learning enabled the model to extract highly discriminative features while simultaneously improving classification performance. The deployment of the trained model through the Flask-based web application further confirmed the practical applicability of the proposed approach by providing real-time disease diagnosis together with treatment recommendations and preventive guidelines.

Performance Metrics and Analysis

The performance of the proposed hybrid framework was evaluated using standard classification metrics widely employed in machine learning research. These metrics provide a comprehensive assessment of the model's predictive capability and generalization performance across all disease categories.

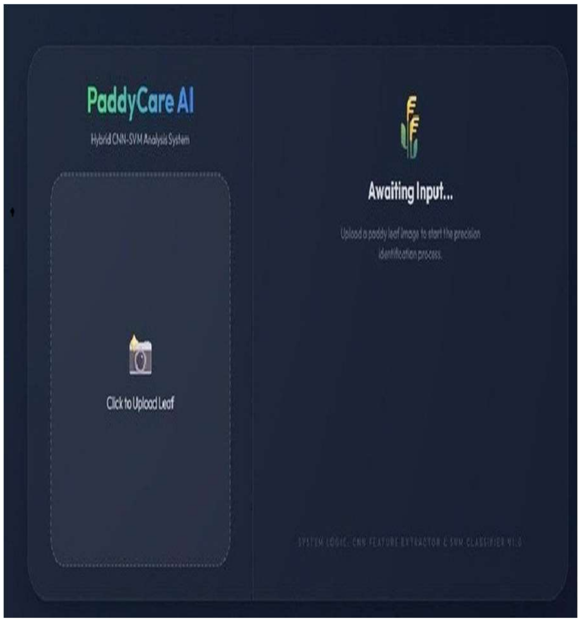
Experimental evaluation demonstrated that the proposed MobileNetV2–SVM architecture achieved **100% validation accuracy** on the prepared validation dataset. The corresponding confusion matrix indicated perfect classification performance, with every validation sample correctly assigned to its respective class. Images belonging to **Bacterial Blight, Blast, Brown Spot, Tungro**, and **Healthy** categories were identified without any observed misclassification during validation. These results indicate that the deep feature representations generated by MobileNetV2, when combined with the optimized decision boundaries of the Support Vector Machine classifier, produce highly discriminative classification performance.

To further evaluate the contribution of the hybrid architecture, a comparative study was conducted using a conventional CNN classifier as the baseline model. The standalone CNN achieved high classification performance; however, a small number of prediction errors were observed when visually similar disease classes were presented. These misclassifications were primarily associated with subtle differences in disease symptoms that were difficult for the CNN classifier alone to distinguish.

In contrast, replacing the conventional fully connected classification layer with a Support Vector Machine significantly improved the discriminative capability of the overall framework. The SVM classifier generated more effective decision boundaries within the extracted feature space, thereby eliminating the classification errors observed in the baseline CNN model. This comparison demonstrates that integrating deep feature extraction with statistical learning enhances both classification accuracy and model robustness, making the proposed hybrid architecture more suitable for practical agricultural disease diagnosis.

Overall, the experimental findings confirm that the proposed MobileNetV2–SVM framework provides superior predictive performance compared with conventional deep learning classifiers while maintaining computational efficiency and strong generalization capability.

PaddyCare AI Dashboard and Disease Prediction Results



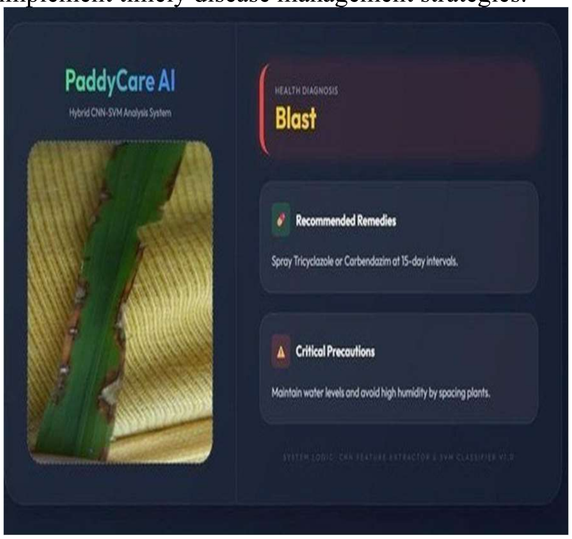
The proposed PaddyCare AI system was deployed as a user-friendly web application that enables users to upload paddy leaf images and receive immediate disease diagnosis together with personalized treatment recommendations. The graphical dashboard was designed to provide an intuitive user experience while presenting diagnostic information in a clear and organized manner.

Before image analysis begins, the application displays an upload interface indicating that the disease diagnosis engine is ready to receive input. Users can either upload an existing leaf image or capture a new photograph for analysis. Once an image is selected, the system automatically initiates preprocessing, feature extraction, and classification without requiring any additional user interaction. This automated workflow minimizes user effort and enables rapid disease diagnosis.

When a healthy leaf is identified, the dashboard presents a confirmation message indicating that no disease symptoms have been detected. The result interface displays the uploaded leaf image together with the predicted **Healthy** class and the associated confidence score. In addition to confirming crop health, the application provides preventive agricultural practices such as maintaining proper field drainage, regular crop monitoring, and periodic preventive treatments to preserve plant health and reduce future disease occurrence.

When the system detects **Tungro**, a viral disease transmitted through insect vectors, the interface immediately highlights the diagnosis using a warning color scheme to attract user attention. The results page presents the predicted disease name together with suitable management recommendations. These recommendations include controlling vector populations through appropriate insecticides, removing infected plants, and adopting crop rotation practices to minimize disease transmission. Preventive measures are also provided to help farmers reduce future outbreaks.

For **Bacterial Blight**, the application displays the predicted disease category together with disease-specific management guidelines. Recommended practices include maintaining proper field sanitation, improving drainage conditions, and applying suitable bactericides according to agricultural recommendations. Preventive measures encourage farmers to monitor crop conditions regularly and implement timely disease management strategies.



When **Blast** disease is identified, the dashboard provides corresponding treatment recommendations focusing on fungal disease management. Suggested practices include the application of recommended fungicides, maintaining appropriate plant spacing to improve air circulation, and avoiding excessive nitrogen fertilization, which can increase disease susceptibility. These recommendations assist farmers in controlling disease spread while maintaining healthy crop development.

Similarly, when **Brown Spot** disease is detected, the system presents tailored recommendations emphasizing balanced nutrient management, proper irrigation practices, and preventive fungicide application where appropriate. The integrated agricultural knowledge base ensures that each disease category is associated with relevant treatment strategies and preventive guidelines based on standard agricultural practices.

The consistent presentation of disease diagnosis, confidence score, uploaded image, recommended treatment, and preventive measures across all disease categories enhances usability and enables users to interpret the results quickly. The dashboard therefore functions not only as a disease detection interface but also as a practical agricultural decision support system that assists farmers in making timely crop management decisions.

Conclusion and Future Scope

Conclusion

The proposed PaddyCare AI system successfully demonstrates the application of hybrid deep learning for accurate and automated paddy leaf disease detection. The research addresses the limitations of conventional disease diagnosis by providing farmers with a rapid, reliable, and non-invasive solution for identifying major paddy leaf diseases. By integrating MobileNetV2 as a deep feature extractor with a Support Vector Machine (SVM) classifier, the proposed hybrid framework effectively combines the strengths of transfer learning and machine learning to improve disease classification performance.

The experimental evaluation confirms that the proposed model achieved 100% classification accuracy on the balanced five-class dataset consisting of Bacterial Blight, Blast, Brown Spot, Tungro, and Healthy leaf images. The excellent performance demonstrates the effectiveness of combining deep feature extraction with SVM-based classification, enabling the system to accurately distinguish between visually similar disease categories while minimizing classification errors. The results further indicate that the hybrid architecture offers superior predictive capability compared with conventional CNN-only approaches.

To ensure practical usability, the trained model was successfully integrated into a Flask-based web application that provides an intuitive interface for farmers and agricultural professionals. The application enables users to upload paddy leaf images and instantly receive disease predictions, confidence scores, preventive measures, and appropriate treatment recommendations. The modern and responsive interface enhances user experience and makes the system accessible even to users with limited technical knowledge.

Future Scope

Although the proposed PaddyCare AI system demonstrates excellent performance, several enhancements can further improve its functionality and practical applicability. One promising direction is the implementation of real-time video-based disease detection, allowing farmers to scan entire crop fields using mobile devices or drones while receiving continuous disease predictions. Such a system would enable rapid monitoring of large agricultural areas and facilitate early disease intervention.

Future versions of the system can also incorporate Internet of Things (IoT) technology by integrating environmental sensors capable of monitoring soil moisture, temperature, humidity, rainfall, and other climatic parameters. Combining sensor data with image-based disease detection would enable predictive disease analysis and provide farmers with early warning notifications before symptoms become severe.

To increase accessibility across different regions, the web application can be enhanced with multilingual support, enabling farmers to interact with the system in various Indian regional languages. This improvement would make the application more user-friendly and encourage wider adoption among farming communities.

The disease database can be expanded to include additional paddy diseases, pest infestations, nutrient deficiencies, and physiological disorders. Furthermore, lightweight versions of the trained model may be deployed on edge devices, smartphones, or unmanned aerial vehicles (UAVs) to support offline disease diagnosis in remote agricultural areas where internet connectivity is limited. Such deployment would significantly increase the portability and scalability of the proposed system.

Another valuable enhancement is the development of an intelligent recommendation engine that integrates real-time weather information, local pesticide availability, fertilizer recommendations, and market prices. This would enable farmers to receive economically optimized treatment suggestions tailored to their geographical location and crop conditions.

Future research may also focus on incorporating disease severity assessment, allowing the system to estimate infection levels such as mild, moderate, or severe. Severity estimation would assist farmers in prioritizing treatment strategies and optimizing pesticide application, thereby reducing production costs and minimizing environmental impact.

Finally, the development of a dedicated offline Android application using TensorFlow Lite would improve accessibility in rural areas with limited internet connectivity. The integration of blockchain technology for securely storing crop health records and treatment history could further enhance transparency, traceability, and data reliability for farmers, agricultural experts, researchers, and government agencies. These future enhancements have the potential to transform PaddyCare AI into a comprehensive intelligent agricultural decision-support platform for precision farming and sustainable crop management.

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