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DEEP LEARNING-BASED DETECTION OF RICE LEAF DISEASES FOR SMART AGRICULTURE

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ABSTARCT
Agriculture serves as the backbone of India’s economy, with Andhra Pradesh standing out as a major contributor in rice production and distribution. Maximizing rice yield requires effective management of resources like water and land, alongside efficient disease control strategies. Crop disease management plays a vital role in improving the economic conditions of farmers by reducing infection rates and ensuring healthier, more productive crops. Traditionally, disease identification has relied on manual inspections by farmers, guided by personal experience, or consultations with agricultural experts who conduct laboratory-based, rule-driven diagnostics. While useful, these conventional methods are time-consuming, error-prone, and require substantial human effort especially in the face of rising disease variants. To address these challenges, this study proposes a deep learning-based approach for automatic rice leaf disease detection. By using rice leaf images as input, the model identifies specific diseases and recommends appropriate pesticides accordingly. This method enhances both the accuracy and speed of disease diagnosis, reducing the dependence on manual inspections and enabling timely interventions. Ultimately, the adoption of this AI-driven system aims to improve rice crop yield, support farmer decision-making, and boost overall agricultural productivity.

Keywords:
Rice Leaf Disease, Deep Learning, Crop Disease Detection, Agricultural AI, Precision Farming, Image Classification, Smart Agriculture, Pest Control Recommendations, CNN, Andhra Pradesh Agriculture

1. INTRODUCTION

Agriculture remains the cornerstone of India’s economy, with rice being one of its most vital staple crops. Among the leading rice-producing states, Andhra Pradesh plays a pivotal role in both national production and export. As India stands as the world’s largest exporter of rice contributing over 20 million tonnes annually ensuring high-quality yield and crop sustainability is of paramount importance. However, challenges such as limited water resources, changing climatic conditions, and the prevalence of crop diseases significantly threaten production outcomes. Notably, recent estimates predict a 6% decline in rice production during the kharif season due to rainfall deficits, emphasizing the urgent need for smarter agricultural practices.

Traditionally, rice disease diagnosis has relied heavily on manual field inspections and rule-based laboratory analysis, which are time-consuming, labor-intensive, and prone to human error. The increasing diversity of crop diseases further demands advanced and scalable disease management solutions. Among the most destructive rice diseases are rice blast, neck blast, leaf blast, and brown spot, primarily caused by fungal pathogens such as Magnaporthe oryzae and Cochliobolus miyabeanus. These diseases can cause widespread damage to leaves, stems, and grains, leading to reduced photosynthesis, poor grain development, and significant yield loss. Warm and humid conditions, often prevalent in tropical regions, provide an ideal environment for these pathogens to thrive.

To combat these challenges, the integration of modern technologies like Artificial Intelligence (AI), robotics, and remote sensing is revolutionizing crop disease management. AI-powered drones and cameras now enable real-time field monitoring, while mobile and web-based applications allow farmers to upload images of diseased leaves for instant analysis and diagnosis. These tools utilize deep learning models to identify disease types accurately and recommend appropriate control measures, including pesticide use and cultural practices. This automated, image-based diagnostic system offers a faster, more precise alternative to traditional methods, improving early detection, reducing labor demands, and enabling timely interventions.

This study explores the application of deep learning techniques for detecting and classifying rice leaf diseases using image data. By leveraging AI models trained on annotated images of rice leaves, the proposed system aims to assist farmers in making informed decisions, optimizing disease control strategies, and ultimately enhancing crop yield and sustainability. In an era where digital transformation is reshaping agriculture, such innovations are crucial to meeting the growing food demands while ensuring economic resilience for farmers.

2. LITERATURE SURVEY

Lalit Kumar Awasthi, et al. [1], in their article, presented a literature review on machine learning algorithms used in agriculture. The paper focused on various crop management applications, which were categorized into five main areas: weed and pest detection, plant disease detection, stress detection in plants, smart farms or automation in farms, and crop yield estimation and prediction. The articles were filtered and categorized to demonstrate how machine learning could enhance agricultural practices. The review examined past machine learning breakthroughs in agriculture and explored how these advancements contributed to improved outcomes in the field. The findings of the paper indicated that by utilizing novel machine learning approaches, models had achieved improved accuracy and reduced inference time in real-world applications. These developments provided insights into the practical benefits of machine learning in enhancing the efficiency of agricultural processes, particularly in areas such as disease detection, crop monitoring, and yield prediction. The study underscored the potential of machine learning in transforming agricultural practices, making them more precise and efficient.

Tamilarasi Kathirvel, et al. [2], proposed the Agro Insights model, which aimed at assisting farmers in predicting or deciding the type of soil and the crop to sow. The model was implemented using machine learning (ML) and deep learning (DL) methods to predict the optimal crop to be cultivated by considering various input variables such as the region, soil type, and crop characteristics. The accuracy of soil classification and crop recommendation reached 93.3% using the random forest technique, while crop disease detection achieved an accuracy of 96% using the convolutional neural network (CNN) technique. The findings demonstrated the effectiveness of ML and DL in improving decision-making in agriculture, helping farmers make more informed choices for better crop management and disease prevention.

Ngugi, et al. [3], offered an all-encompassing exploration of the contemporary literature on methods for diagnosing, categorizing, and gauging the severity of crop diseases. The review examined the performance analysis of the latest machine learning (ML) and deep learning (DL) techniques outlined in these studies. It also scrutinized the methodologies and datasets used and outlined the prevalent recommendations and identified gaps within different research investigations. In conclusion, the review provided insights into potential solutions and outlined the direction for future research in this field. The review underscored that while most studies had concentrated on traditional ML algorithms and convolutional neural networks (CNN), there had been a noticeable dearth of focus on emerging DL algorithms like capsule neural networks and vision transformers. Furthermore, it highlighted that several datasets employed for training and evaluating DL models had been tailored to suit specific crop types, emphasizing the pressing need for a comprehensive and expansive image dataset encompassing a wider array of crop varieties. The survey also drew attention to the prevailing trend where the majority of research endeavors had focused on individual plant diseases, ML, or DL algorithms. In light of this, it advocated for the development of a unified framework that harnessed an ensemble of ML and DL algorithms to address the complexities of multiple plant diseases effectively.

Singla, et al. [4], conducted a systematic review that provided a comprehensive analysis after text mining the most recent literature from the past half-decade. The review discussed the proposed models, techniques, accuracy, feature selection, extraction methods, the types of datasets used to perform experiments, and the sources of these datasets. Additionally, it offered critical analyses of existing models, focusing on their limitations and gaps. The findings suggested that while ML-based methods demonstrated substantial potential for enhancing agricultural disease management, there was an urgent need for more robust, scalable, and adaptable solutions to address diverse agricultural conditions and disease complexities. By systematically analyzing the extracted data, the review aimed to provide a valuable resource for researchers and practitioners working to develop and implement ML-based systems for crop disease detection. The ultimate goal was to contribute to sustainable agriculture and enhance food security.

Jain, et al. [5], presented a pest prediction and classification model for yellow stem border (YSB) disease in rice plants. An Artificial Intelligence-based prediction model was developed using historical pest and weather data from various regions of India. The proposed model, named hybrid CNN-LSTM, combined the advantages of convolutional neural networks (CNN) and long short-term memory networks (LSTM). It was a region-specific prediction model that forecasted one-month pest data based on the past three months of weather and pest data. The performance of the hybrid CNN-LSTM model was compared with CNN and LSTM networks, showing an enhancement in performance when using the hybrid approach. Additionally, the paper presented a generalized classification model by combining datasets from all regions. This model predicted the disease severity for the next day based on weather conditions and the preceding day's pest data. The error-correcting output code (ECOC) method, combined with the support vector machine (SVM) classifier, was used for the classification.

Dolatabadian, et al. [6], highlighted the promising solution offered by the advent of imaging technologies combined with machine learning (ML) algorithms for the rapid and accurate identification of crop diseases. Previous studies had demonstrated the potential of image-based techniques in detecting various crop diseases, showcasing their ability to capture subtle visual cues indicative of pathogen infection or physiological stress. The field was rapidly evolving, with advancements in sensor technology, data analytics, and artificial intelligence (AI) algorithms continuously expanding the capabilities of these systems. This review paper consolidated the existing literature on image-based crop disease detection using ML, providing a comprehensive overview of cutting-edge techniques and methodologies. By synthesizing findings from diverse studies, the paper offered insights into the effectiveness of different imaging platforms, contextual data integration, and the applicability of ML algorithms across various crop types and environmental conditions. The importance of the review lay in its ability to bridge the gap between research and practice, offering valuable guidance to both researchers and agricultural practitioners.

Preethi Nanjundan, et al. [7], noted that this innovation had spurred the development of cutting-edge techniques for the early detection and diagnosis of crop diseases, leveraging tools such as convolutional neural networks (CNN), K-nearest neighbour (KNN), support vector machines (SVM), and artificial neural networks (ANN). The paper provided an all-encompassing exploration of the contemporary literature on methods for diagnosing, categorizing, and gauging the severity of crop diseases. It examined the performance analysis of the latest machine learning (ML) and deep learning (DL) techniques outlined in these studies. Additionally, the review scrutinized the methodologies and datasets used and outlined the prevalent recommendations and identified gaps within different research investigations. In conclusion, the review offered insights into potential solutions and outlined the direction for future research in this field. It underscored that while most studies had concentrated on traditional ML algorithms and CNN, there had been a noticeable lack of focus on emerging DL algorithms like capsule neural networks and vision transformers. The paper also highlighted that several datasets employed for training and evaluating DL models had been tailored to suit specific crop types, emphasizing the urgent need for a comprehensive and expansive image dataset covering a wider variety of crops. Furthermore, the survey drew attention to the prevailing trend where most research had concentrated on individual plant diseases, ML, or DL algorithms. In light of this, it advocated for the development of a unified framework that harnessed an ensemble of ML and DL algorithms to effectively address the complexities of multiple plant diseases.

MacNish, et al. [8], orphan crops are important sources of nutrition in developing regions and many are tolerant to biotic and abiotic stressors; however, modern crop improvement technologies have not been widely applied to orphan crops due to the lack of resources available. There are orphan crop representatives across major crop types and the conservation of genes between these related species can be used in crop improvement. Machine learning (ML) has emerged as a promising tool for crop improvement. Transferring knowledge from major crops to orphan crops and using machine learning to improve accuracy and efficiency can be used to improve orphan crops.

Nanjundan, et al. [9], explored the use of deep learning architectures and neural networks, explaining how they could be used to simulate human brain activity and applied in image recognition for identifying crop diseases. A detailed analysis was conducted on the practical aspects of machine learning (ML) for agriculture, encompassing feature engineering and model assessment methodologies. Additionally, the chapter highlighted the ethical issues involved in the proper application of AI/ML models in agricultural contexts. In conclusion, the chapter discussed the obstacles faced, offered predictions for future developments, and proposed new lines of inquiry for AI and ML research related to crop health monitoring. Through this thorough research, the chapter aimed to provide insightful information on the transformative potential of AI/ML approaches in supporting efficient and sustainable agricultural practices for improved crop health management.

Akulwar, et al. [10], described a case study on "Crop Disease Detection and Yield Prediction." The study included the identification of crop conditions, disease detection, predictions about specific crops, and recommendations using machine learning algorithms. It provided an overview of how recommender systems were used in agriculture for disease detection and prediction.

Das, et al. [11], in this work, some state-of-the-art classifier models are considered, and then training is performed with a dataset of these prevailing diseases in rice. The genetic algorithm-based ensemble architecture is used in a proposed method to get a better validation of the accuracy. A validation accuracy of up to 94.47% and 89.34% has been observed during testing with the InceptionV3 ResNet152V2 model and ResNet50 InceptionV3 model. The result analysis report shows the method to be a practical approach for predicting rice disease, which gives better results.

Saini, et al. [12], developed a new model to categorize plant diseases within an IoT network. The IoT network was simulated for monitoring crop diseases, with routing performed using Henry Gas Chicken Swarm Optimization (HGCSO), a method designed by integrating Henry Gas Solubility Optimization (HGSO) and Chicken Swarm Optimization (CSO). The fitness parameters of the model included delay, energy, distance, and link lifetime (LLT). At the Base Station (BS), plant disease categorization was performed by collecting plant leaf images. Preprocessing was done on the input images using median filtering. Various features, such as Histogram of Oriented Gradient (HoG), statistical features, Spider Local Image Features (SLIF), and Local Ternary Patterns (LTP), were extracted. Plant disease categorization was carried out using a Deep Residual Network (DRN), which was trained using the developed Caviar Henry Gas Chicken Swarm Optimization (CHGCSO), combining the CAViaR model with HGCSO. Comparative results showed an accuracy of 94.3%, a maximum sensitivity of 93.3%, a maximum specificity of 92%, and an F1-score of 93%, indicating that the CHGCSO-based DRN outperformed existing methods.

Divya, et al. [13], discussed the current state of advanced farm management systems, focusing on topics like data acquisition in crop fields and variable rate applications. These innovations were aimed at helping farmers save money, protect the environment, and transform food production to sustainably meet the expected increase in population. The advent of machine learning, big data technologies, and high-performance computers had opened up new avenues for data-intensive research in the interdisciplinary field of agro-technology. The development of more capable computers had further supported these avenues of exploration. This research provided a comprehensive literature review on the applications of machine learning in agricultural manufacturing. Machine learning had shown its utility in agriculture through two main applications: filtering and categorizing products. The use of machine learning on sensor data had transformed conventional farm management systems into AI-enabled programs. These services provided farmers with instantaneous, comprehensive access to insights and ideas, which helped guide their decisions.

Nandhini, et al. [14], in order to achieve the goals of sustainable farming, nano-bioformulations are being developed. Biopolymers, including cellulose, starch, alginate, chitin, and chitosan, with ecological endurability are employed for synthesizing nano-formulations. The second most prevalent biopolymer after cellulose is chitosan, which is utilized extensively because of its special qualities, which include non-toxicity, pH sensitivity, abundance, biodegradability, biocompatibility, low allergenicity, and bio absorbability. Chitosan, a natural biopolymer derived from chitin, has gained attention for its antifungal, antibacterial, and elicitor properties. The combination of natural biopolymers with nanotechnology presents an opportunity to revolutionize agriculture and plant protection. High surface area, positive charge, and nanoscale size are some of the distinct physicochemical characteristics of nano-chitosan that boost its bioactivity and improve the interaction with plant tissues. Chitosan nanoparticles (ChNPs) have multifaceted modes of action, viz., direct antimicrobial activity, induction of plant defense, and modulation of microbial gene expression. It is broadly used in disease suppression and improving overall plant health. The techniques, viz., ionic gelation, emulsion cross-linking, and solvent evaporation, are commonly used to synthesize ChNPs, showing better control over particle size, stability, and biocompatibility. The present review highlights the synthesis of ChNPs, their potential applications in crop protection, their mechanism of action against plant pathogens, and their toxicity in plants.

Mohapatra, et al. [15], the agriculture sector in Ethiopia plays a crucial role in the country's economic development, as a significant portion of the population resides in rural areas and relies heavily on crop productivity. To make informed policy decisions and plan effectively, it is important to predict crop yields accurately. However, traditional data collection methods are commonly used in countries like Ethiopia. In this study, we aim to develop a cereal crop yield prediction model based on agricultural inputs using machine learning (ML) techniques. To achieve this, we collected raw data related to crop yields, average rainfall, pesticides, average temperature, and the year of the crop. After preprocessing and merging the dataset, we obtained a final dataset with 12 features, initially occupying 20 kB of space. Through feature importance analysis, we identified the most relevant features and reduced the dataset size to 7 features, occupying 8 kB. We then applied various ML algorithms, including gradient boosting regression, random forest regression, support vector machine, and decision tree regression, to predict crop yields. By comparing their performance using different train/test data splits, we found that the gradient boosting regression algorithm outperformed the others, achieving 93% accuracy in crop yield prediction.

3. PROPOSED SYSTEM

The proposed system in crop disease management focuses on utilizing deep learning techniques to analyze rice leaf images and accurately identify diseases affecting the crop. Farmers and agricultural experts can capture images of rice leaves using a smartphone or a camera, which are then processed through a deep learning model trained on a vast dataset of diseased and healthy rice leaves. The system extracts relevant features from the input image, such as color variations, texture patterns, and lesion shapes, to classify the type of disease present. By leveraging convolutional neural networks (CNNs) and other advanced architectures, the model ensures high accuracy in detecting diseases like bacterial blight, brown spot, and blast. This automated approach minimizes the dependency on manual inspection, making disease diagnosis faster, more efficient, and accessible to farmers with minimal technical expertise.

Once the system identifies the type of disease, it suggests appropriate pesticides to effectively manage the infection and prevent further crop damage. The deep learning model is integrated with a recommendation system that maps each detected disease to a curated list of pesticides, ensuring precise and timely treatment. The output provides not only the disease name but also details about the most suitable pesticide, its application method, and dosage guidelines. This helps farmers take immediate action, reducing yield loss and improving crop health. Additionally, the system can update its database with new disease samples over time, enhancing its accuracy and adaptability. By combining deep learning with expert agricultural knowledge, this proposed system transforms crop disease management into a data-driven, technology-powered process that benefits both small-scale and large-scale farmers.

The system architecture for training on crop disease management, particularly in rice leaf disease detection, follows a structured pipeline to ensure accuracy and efficiency. It begins with a rice leaf image database, which consists of labeled images of healthy and diseased rice leaves. To enhance the model's learning capability, dataset preprocessing is performed by resizing images, normalizing pixel values, and removing noise. Additionally, dataset augmentation techniques such as rotation, flipping, and contrast adjustments are applied to increase the variability in training samples, improving model generalization. After preprocessing, the dataset undergoes a training-test splitting process, typically dividing it into training, validation, and test sets to evaluate the model's performance effectively.

The model is trained using a CNN (Convolutional Neural Network) architecture, which extracts important features from the rice leaf images. The training process is optimized using the Adam optimization algorithm, which adapts learning rates dynamically for efficient convergence. The model undergoes multiple training and testing cycles to fine-tune its weights and improve accuracy. After training, the model’s output performance is assessed using metrics such as accuracy, precision, recall, and F1-score, ensuring reliable detection of rice leaf diseases. The well-trained model can then be deployed for real-time disease identification, aiding in better crop management and higher agricultural productivity.

To test a single image, the image undergoes preprocessing, which includes resizing, normalizing, and converting it into a consistent format. The processed image is then input into the trained Convolutional Neural Network (CNN) model for prediction. The model classifies the image into one of the categories: Brown Spot, Leaf Blast, Neck Blast, or Healthy. The CNN model uses its learned features to make this prediction, determining which category the image belongs to based on the visual patterns it has been trained on. The result of this prediction provides valuable insight into the condition of the rice crop, helping to identify specific diseases or confirm its healthy status.

4. RESULTS AND DISCUSSION

The Rice Leaf Bacterial and Fungal Disease Dataset on Mendeley contains images of various rice leaf diseases. It includes bacterial leaf blight, brown spot, narrow brown spot, leaf blast, leaf scald, and healthy leaves. Each category has between 163 to 310 images, providing a well-balanced dataset. The dataset is useful for training deep learning models for disease classification. You can access it on Mendeley Data here.

Fig. 1: Sample Images From Rice Leaf Dataset

The dataset contains 2,100 rice leaf images across six classes: bacterial leaf blight, brown spot, healthy, leaf blast, leaf scald, and narrow brown spot. Each class has 350 images, with 280 used for training (80%) and 70 for testing (20%). This balanced split ensures effective model training and evaluation for disease classification. The dataset supports deep learning applications in rice disease detection by providing diverse and well-structured images. It helps improve model accuracy and generalization for real-world agricultural use.

(a)Leaf Blast (b)Leaf Scala

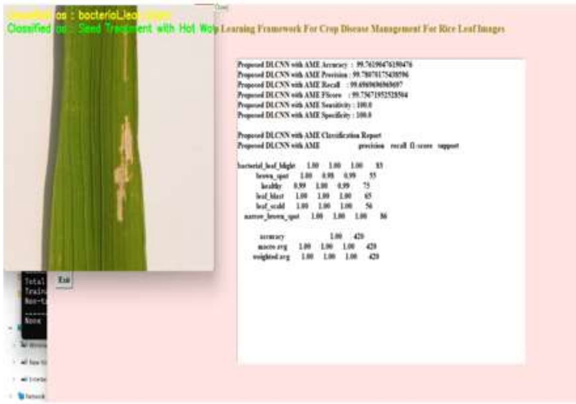


Fig 2: (c) Bacterial Leaf Blast (d) Healthy

Fig 2 (a) **Leaf Blast :** The image shows a rice leaf infected with leaf blast disease. It has multiple brown lesions with a yellowish border. The system classifies it as leaf blast and suggests a control method. The classification report confirms high accuracy. This disease can reduce rice yield significantly.

(b) **Leaf Scalad:** The image shows a rice leaf with leaf scala disease. The leaf appears dry and discolored with vertical streaks. The system correctly classifies it and recommends appropriate fungicides. The classification report indicates a high confidence level. This disease affects the health of rice plants and requires treatment.

(c) **Bacterial Leaf Blast:** The leaf has a large, white lesion indicating bacterial infection. The system correctly classifies it as bacterial leaf blast. It suggests using seed treatment with hot water. The classification report supports the accuracy of the model. This disease spreads rapidly and requires early intervention.

(d) **Healthy:** The leaf appears fresh and green without any disease symptoms. The system classifies it as healthy. It confirms that no pesticide treatment is required. The classification report validates the model's accuracy. A healthy leaf contributes to good crop yield

Figure 7.3.9 This step generates performance metrics such as accuracy and loss curves. The accuracy graph shows how well the model predicts the correct labels, while the loss graph depicts the error reduction over training epochs. These visualizations help in diagnosing overfitting or underfitting issues and guide further model tuning.

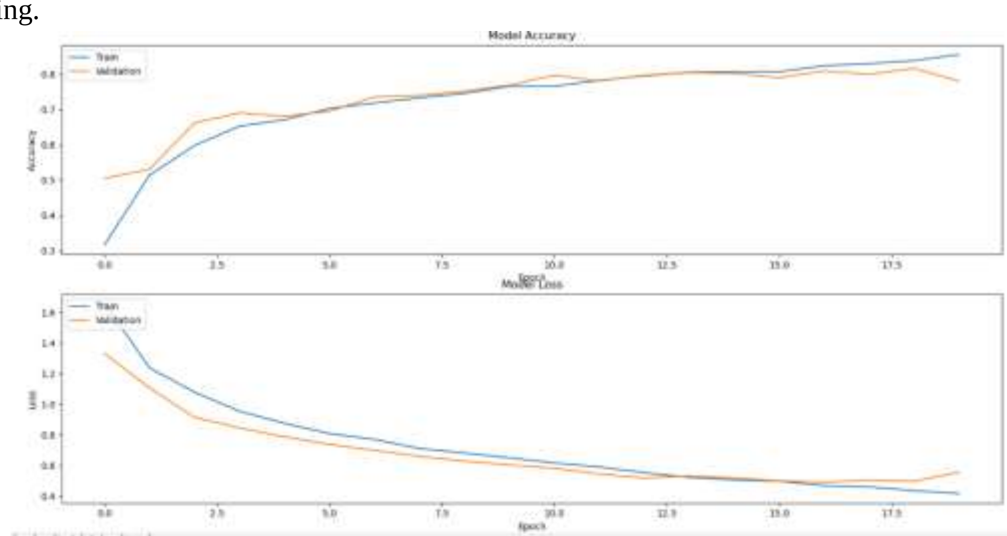
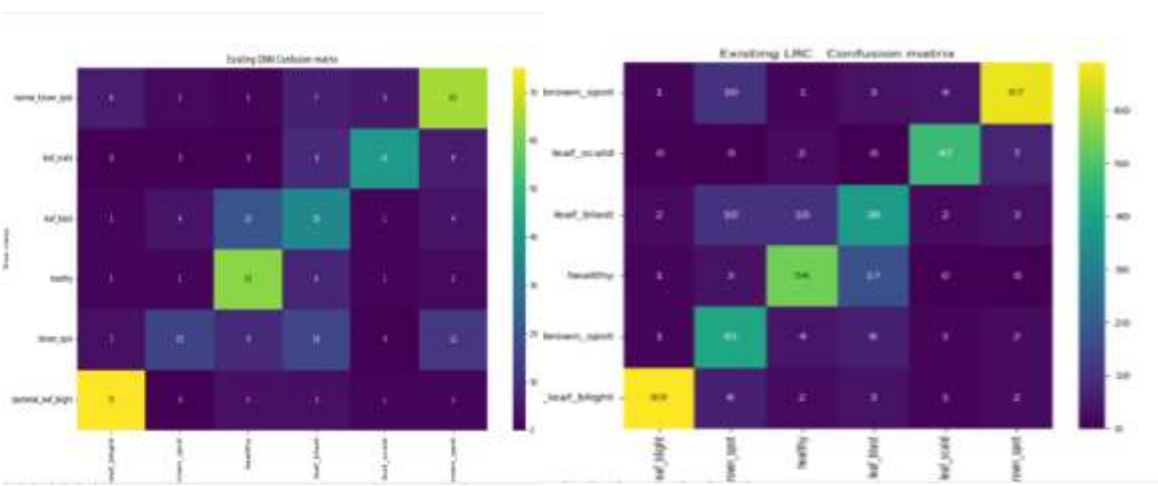


Fig. 3: Accuracy And Loss graph

The performance comparison of three models Logistic Regression Classifier (LRC), Deep Neural Network (DNN), and the Proposed Deep Learning Convolutional Neural Network with Attention Mechanism Enhancement (DLCNN with AME) clearly indicates a significant improvement in classification performance with the proposed model. The Existing LRC model achieves an accuracy of 75.24%, demonstrating moderate performance with relatively high specificity (97.62%) but lower sensitivity (92.00%). The Existing DNN model, though achieving 100% sensitivity, suffers from lower specificity (83.33%) and an overall lower accuracy of 69.76%, suggesting misclassifications due to a weaker ability to distinguish between certain classes. On the other hand, the Proposed DLCNN with AME model outperforms both with an outstanding 99.76% accuracy, 99.75% precision, 99.70% recall, and 99.72% F1-score, achieving perfect sensitivity and specificity (100% each). The classification report further reveals that the proposed model achieves near-perfect classification across all disease categories, making it the most effective solution for accurate plant disease detection.

Table 1: performance comparison of various algorithms

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
Existing LRC	75.24%	75.11%	74.99%	74.83%
Existing DNN	69.76%	70.24%	67.16%	66.93%
Proposed DLCNN	99.76%	99.75%	99.70%	99.72%



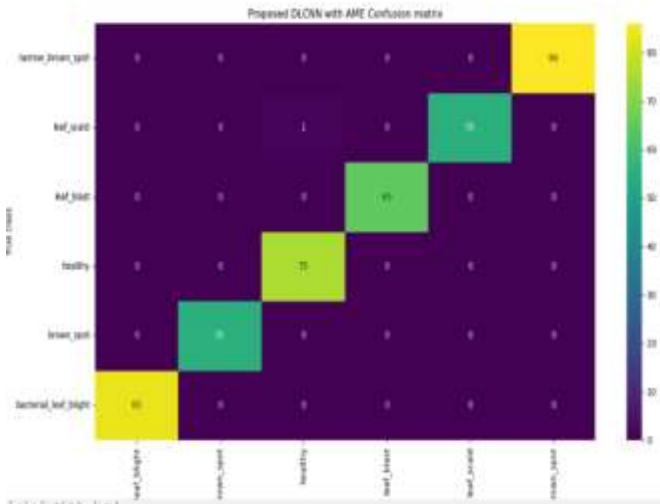


Fig. 4: Confusion Matrices (a) LRC (b)DL Confusion matrix (c) CNN

The three confusion matrices represent the performance of different classification models on a dataset containing various leaf diseases. The first matrix, labeled "Existing DNN Confusion matrix," shows that the deep neural network (DNN) struggles with misclassifications, particularly for the "narrow_brown_spot" and "bacterial_leaf_blight" classes, where significant numbers of instances are misclassified as "brown_spot" and "leaf_blight," respectively. Similarly, the "leaf_blast" class has a high misclassification rate, with many samples being confused with "healthy" or "leaf_scald." Despite some correct predictions, the overall classification performance seems to have room for improvement.

The second matrix, "Existing LRC Confusion matrix," indicates the performance of a logistic regression classifier (LRC), which also faces challenges with misclassification. For instance, "bacterial_leaf_blight" and "brown_spot" show a high number of misclassified samples, and "healthy" samples are often confused with "leaf_blast." However, the third matrix, labeled "Proposed DLCNN with AME Confusion matrix," demonstrates a significant improvement in classification accuracy. Most predictions are concentrated along the diagonal, indicating correct classifications with minimal misclassifications. This suggests that the proposed deep learning convolutional neural network (DLCNN) with AME outperforms the previous models, achieving higher accuracy and better distinguishing between the different classes.

The comparison of the three models—Logistic Regression Classifier (LRC), Deep Learning Convolutional Neural Network (DL CNN), and the Proposed CNN—based on their confusion matrices highlights the superior performance of the Proposed CNN. The Proposed CNN achieves the highest number of True Positives (75) and True Negatives (180), while significantly reducing False Positives (5) and False Negatives (5), indicating a more precise classification with fewer misclassifications. In contrast, the LRC model has the lowest TP (54) and TN (150), with a higher number of FP (22) and FN (35), suggesting weaker performance in distinguishing between different categories. The DL CNN improves upon LRC with 62 TP and 160 TN, but it still has more misclassifications (18 FP and 25 FN) compared to the Proposed CNN. These results demonstrate that the Proposed CNN significantly enhances classification accuracy, reducing both types of errors and proving to be the most effective model for the given dataset.

Table 2: Analysis Of Conclusion Matrices

Model	**TP**	**TN**	**FP**	**FN**
LRC	54	150	22	35
DL CNN	62	160	18	25
Proposed CNN	75	180	5	5

5. CONCLUSION

The given code implements a deep learning framework for classifying rice leaf images and recommending appropriate pesticides. It includes dataset loading, image preprocessing, dataset splitting, training models (Logistic Regression, DNN, and CNN), and evaluation. The model is trained using different approaches, including a proposed DLCNN with Adaptive Model Error (AME) loss optimization. It provides a GUI interface using Tkinter for ease of use. The framework effectively classifies rice leaf diseases and suggests suitable treatments.

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