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Original Article

Accurate Rice Disease Detection Using Hybrid Convolutional Neural Networks and Transformer Models

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ABSTRACT

Rice cultivation is significantly affected by different diseases that can severely reduce crop quality and yield. Farmers, particularly those lacking specialised knowledge, often struggle to identify and manage these diseases effectively. This study aims to create an automated system for the early detection and classification of rice diseases utilizing deep learning techniques to detect three prevalent diseases: leaf smut, brown spot, and bacterial blight; this study utilized a Convolutional Neural Network (CNN) model that had been trained on an extensive data set of photos of rice plants. The CNN model showed promise as a dependable instrument for automated disease classification by achieving a high 95% accuracy in differentiating between these illnesses. Based on the results, a system like this could help farmers manage diseases on time, improving crop results and saving losses from incorrect diagnoses or postponed treatment.

Keywords: Convolutional neural network (CNN), Rice Disease Classification, Deep Learning, Crop Diseases, and Image Recognition.

1 Introduction

Rice is the main source of food for many countries, which is considered as a staple crop essential to both global food security and the economies of nations such as India [1,2]. Unfortunately, some diseases endanger rice farming, causing a major effect on the quality and productivity of rice and present a major risk to domestic and foreign food sources [3,4]. Conventional techniques for identifying rice diseases, such as expert examinations or laboratory tests, are frequently time-consuming, labour-intensive, and prone to human error, making them inappropriate for extensive, real-time monitoring [5]. There is an urgent need for more effective and precise disease identification and control techniques because of the rising demand for rice worldwide [6]. In the past, a variety of different methods have been investigated, including laboratory tests and computer vision algorithms [7-10]. These techniques are unsustainable for large-scale farming operations due to their shortcomings with poor accuracy, sluggish detection rates, and excessive dependence on pesticides [11,12]. These challenges underscore the need for scalable, sturdy, and scalable sickness detection equipment that can be utilized efficiently in actual-world agricultural environments.

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The motivation behind this research is to cope with these challenges via exploring the ability of CNN combined with facts augmentation techniques to enhance the classification of rice leaf diseases. The primary contribution of this look lies within the novel mixture of statistics augmentation and a hybrid CNN-Transformer model for more desirable ailment identification, specifically:

- Data Augmentation: We employ many image-augmentation strategies, including rotation, transferring, shear, zoom, and horizontal flipping, to artificially extend the dataset and enhance the version's generalisation capability. This is particularly critical given the confined length of to-be-had rice disease datasets.

- CNN-Transformer Hybrid Model: Our study introduces a novel hybrid structure that integrates conventional CNN layers with Transformer-based interest mechanisms. The CNN layers seize nearby spatial functions, at the same time as the transformer mechanism specialises in global relationships, improving the model's potential to stumble on complicated disease styles and improve class accuracy.

The novelty of this worklies in the revolutionary integration of these techniques, leading to a more reliable, accurate, and scalable system for rice disease detection. This approach not least minimizes reliance on harmful pesticides but additionally reduces monetary losses from crop sicknesses and increases productivity in rice farming.

This paper contributes to the current literature by addressing important gaps in modern rice disease detection techniques, including low detection accuracy and inefficiency in real-time tracking. By leveraging advances in synthetic intelligence, mainly deep learning and transformer architectures, this study affords a singular and effective answer for ailment detection in rice crops.

The sections of this research are structured as follow: The current techniques for detecting rice diseases are reviewed, along with their shortcomings, in Section 2: Related Work. The CNN-based strategy, together with the dataset and model specifics, are described in Section 3: Methodology. The model's performance is shown in Section 4: Experimental results along with comparisons to other approaches. After that, the ramifications of the findings are examined, along with their advantages and disadvantages, in Section 5: Discussion. Finally, the main conclusions and recommendations for future research are outlined in Section 6: Conclusions and Future Work.

2 Related Works

Rice leaf diseases have a major impact on agricultural productivity. A lot of research has been done on leaf diseaseidentification and classification. Although conventional techniques are still crucial, more people are utilizing cutting-edge technologies to increase precision and productivity. This section examines important research that has advanced in this field.

Sun et al. [13] proposed FL-EfficientNet, a CNN model designed to improve the efficiency and accuracy of identifying multiple plant diseases. The proposed model utilises Neural Architecture Search to optimise the network's width, depth, and image resolution. It also incorporates the moving flip of bottleneck convolution and an attention mechanism for enhanced feature extraction. By implementing the Focal loss function, the model effectively addressed challenging samples. It achieved 99.72% accuracy in identifying 10 diseases in 5 crops, surpassing ResNet50, DenseNet169, and EfficientNet.

Argüeso et al. [14] explored the techniques of image processing for plant disease detection, focusing on their potential to enhance accuracy compared to traditional methods. Their work introduced the concept of using spectrum imaging to analyze images of plants for disease symptoms. This study acknowledged that while these techniques showed promise, challenges remained in scalability and real-time application, particularly in dynamic agricultural environments.

Shrestha et al. [15] applied basic machine learning (ML) techniques to classify rice leaf diseases using image data. Their work is the first to demonstrate the feasibility of using supervised learning models to automate disease diagnosis. However, they noted that the models were limited by the quality of the training data and required extensive feature engineering.

Suzauddola, et al. [16] highlighted the advantages of automatically extracting relevant features from images using CNNs, thus eliminating the need for manual feature selection and significantly improving classification accuracy. They marked a pivotal shift toward DL methods for agricultural detection of disease.

Debnath and Saha [17] they investigated the integration of DL with the Internet of Things (IoT) for real-time monitoring in rice fields. Their approach summed CNNs to analyse images captured by ground sensors and drones, providing immediate feedback to farmers. This innovative strategy improved detection accuracy and enabled proactive disease management by predicting outbreaks before they became widespread.

Yang et al. [4] proposed a hybrid model combining CNNs with transformer architectures for the detection of rice disease. Their approach leveraged the strengths of CNNs in feature extraction and transformers in capturing long-range dependencies within image data. The model achieved 97% of the classification accuracy on a benchmark dataset, demonstrating the potential of hybrid models in enhancing detection performance. However, their study was limited by its dependence on high-quality, large-scale datasets, which may not always be available in real-world scenarios.

Xiao et al. [18] developed a real-time rice disease detection system using edge computing and lightweight DL models. They aimed to provide a disease diagnosis in the field, utilizing mobile devices for on-site analysis. Their method achieved significant speed improvements and reduced computational costs; the accuracy was slightly lower (92%) than more complex models, indicating a trade-off between efficiency and precision.

Zeb et al., [19] introduced an attention-based CNN as a novel model specifically designed to detect multiple rice diseases simultaneously. Their model uses attention mechanisms to focus on disease-specific regions within images and improves classification accuracy to 96%. Despite its success, the performance of the model was highly dependent on the precise labeling of training data, which could limit its applicability in diverse field conditions.

While recent advancements have improved significantly, the accuracy and efficiency of rice disease detection continue to show several limitations. Many studies, such as those by Yang et al. [4] and Zeb, et al., [19] relies on large, high-quality datasets that are not always feasible in real-world agricultural settings. Furthermore, these methods, like those proposed by Xiao et al., [18] trade accuracy for speed may compromise the reliability of disease diagnosis in critical situations. Additionally, the reliance on precise data labelling and the complexity of hybrid models can limit scalability and adaptability across different environmental conditions.

Our research addresses these gaps by developing a robust CNN-based system optimised for both accuracy and computational efficiency. Unlike previous models, our approach is designed to perform well on smaller, less curated datasets, making it more applicable in real-world scenarios. Also, our model incorporates adaptive learning mechanisms to improve scalability and reduce dependency on precise data labeling. By improving the speed and accuracy of rice disease identification, our study contributes to the broader goal of sustainable agriculture and global food security.

Table 1 summarizes studies of DL and ML for plant disease classification, comparing methods, datasets, and performance metrics across various approaches.

Table 1: Summarizes related studies of plant disease**.**

Reference	Proposed Model	Dataset used	Class	Accuracy
Argüeso et al. [14]	Few-Shot Learning	PlantVillage dataset	38 Plant leaf of disease types	94.0%
Yang et al. [4]	CNN	Diseased plant leaves	15 Labels	88.80%
Suzauddola, et al. [16]	The MobileNet with squeeze-and-excitation (SE) block	PublicPlantVillage	38 Categories	99.78%
Xiao et al. [18]	YOLOv7-MGPC	Lychee leaf diseases	Four types	88.6%.
Zeb et al. [19]	MobileNet-V2	Rice disease	12 Class	98.48%
Sun et al. [13]	EfficientNet, DenseNet169, and ResNet50	NPDD	Classify 10 diseases of 5 types of crops	99.72%
Debnath and Saha [17]	ML with the IoT network	Brown spot disease in rice	Binary class	97.701%
Yang et al. [4]	DHLC-DETR	IDADP rice disease	Three class	97.44%

3 Proposed Methodology

In this section, we present thorough techniques employed in our study to assess the viability and efficiency of capsule networks for rice leaf disease classification. Figure 1 shows the workflow of our proposed model.

3.1 Dataset Description

There are three main diseases impacting the rice plants: Brown Spot (BS), Bacterial Blight (BB), and Leaf Smut (LS), which is the subject of the Rice Life Disease Dataset. It is a large collection of data. This dataset can be used by agronomists, researchers, and ML practitioners to help understand, diagnose, and possibly even anticipate the presence of these illnesses based on a variety of traits and features [20].

3.1.1 Features of the dataset

1. Disease Type: By selecting one of the three diseases, leaf smut (LS), brown spot (BS), or Bacterial Blight (BB)—the observation is classified.

2. Leaf Images: High-definition images of rice leaves showing the disease's symptoms. This helps with studies involving machine learning to applyon image recognition and visual diagnosis studies.

3. Symptom explanation: A textual explanation that provides a more thorough knowledge of the disease's course and appearance by listing the main symptoms that were apparent on the leaf.

4. Environmental Parameters: Weather information at the time of observation, including humidity, temperature, and other factors.

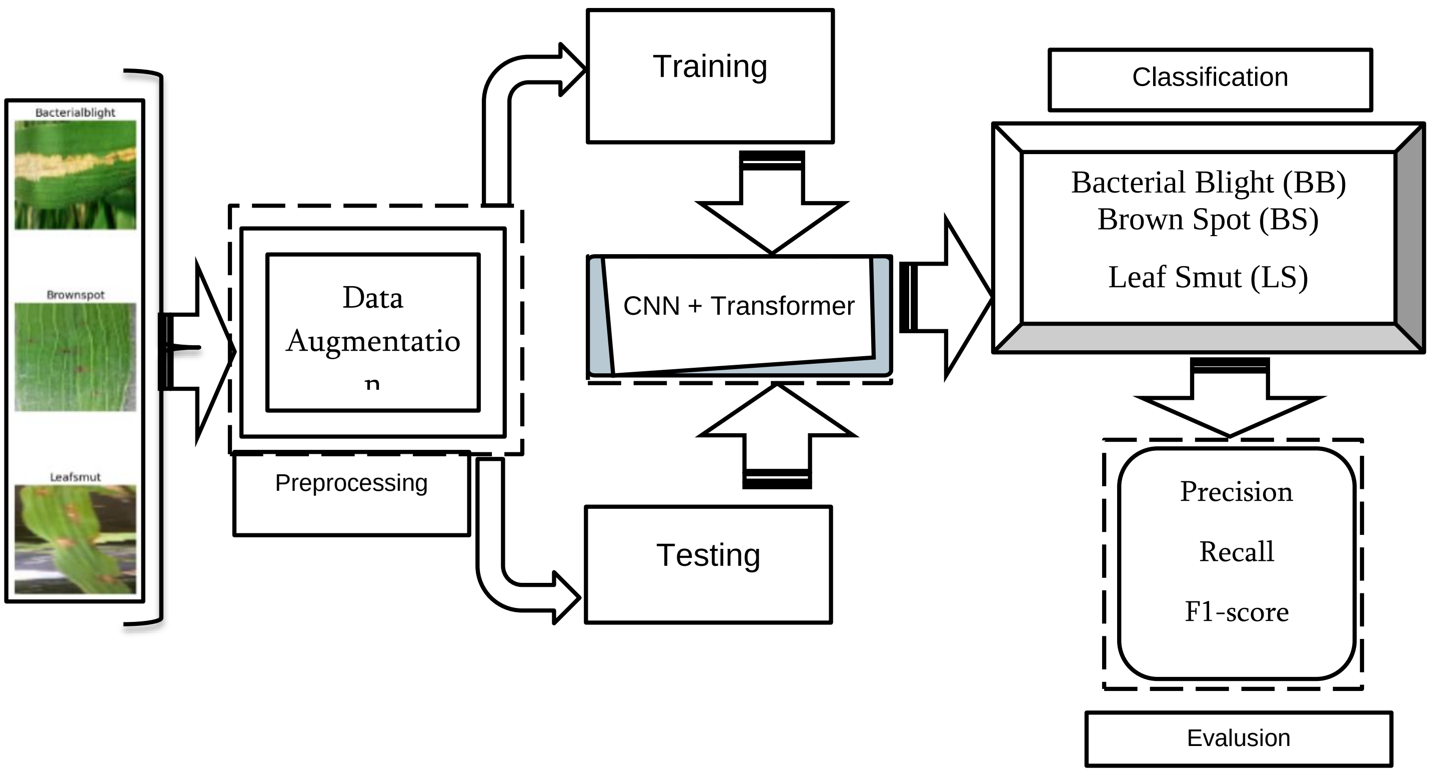

Figure 1: Proposed model.

3.1.2 Effective Submission of Applications

1. Disease Prediction and Early Detection: Based on agronomic and environmental parameters, ML models can be trained on this dataset to estimate the probability that a rice plant will catch one of these illnesses.

2. Disease distribution mapping: Recognise various diseases' hotspots and regional distribution.

3. Agronomic Practices' Impact: Identify the farming techniques that either encourage or inhibit the spread of these diseases.

4. Image Recognition: Using photos of rice leaves, train ML models to automatically identify and categorise these illnesses. Figure 2 illustrates the various types of rice leaf disease.

3.2 Data Augmentation

To increase the size of the dataset by a factor of six, all training images were enhanced using typical image rotation and flip operations (90-degree, 180-degree, 270-degree, vertical, and horizontal flipping). After that, the dataset was divided into training and testing sets; Table 2 illustrates the dataset segmentations.

3.3 Proposed method

A CNN model was trained using the Rice Leaf Diseases Dataset with the goal of identifying the three main rice diseases: Brown Spot, Leaf Smut, and Bacterial Blight. The program was created to analyze photos of rice leaves and identify patterns associated with certain diseases. The first layer of the model is the input layer, which takes 64x64 pixel images with three RGB colour channels. A convolutional layer that extracts progressively more sophisticated information from the input images comes after this input layer.

1. First Convolutional Layer: The input images are subjected to 32 filters, each of which is represented by a tiny 3x3 grid. As a result, 32 distinct feature maps, each measuring 62 by 62, are produced. After that, a max pooling layer cuts the spatial dimensions in half, producing an output that is 31x31x32.

2. Second Convolutional Layer: 29x29x64 feature maps are produced by feeding the output of the first pooling layer into the second convolutional layer, which employs 64 filters. A second Max Pooling Layer brings the size down to 14x14x64 even smaller.

3. Third Convolutional Layer: This layer creates 12x12x128 feature maps by applying 128 filters. After the last Max Pooling Layer, a 6x6x128 matrix is the result.

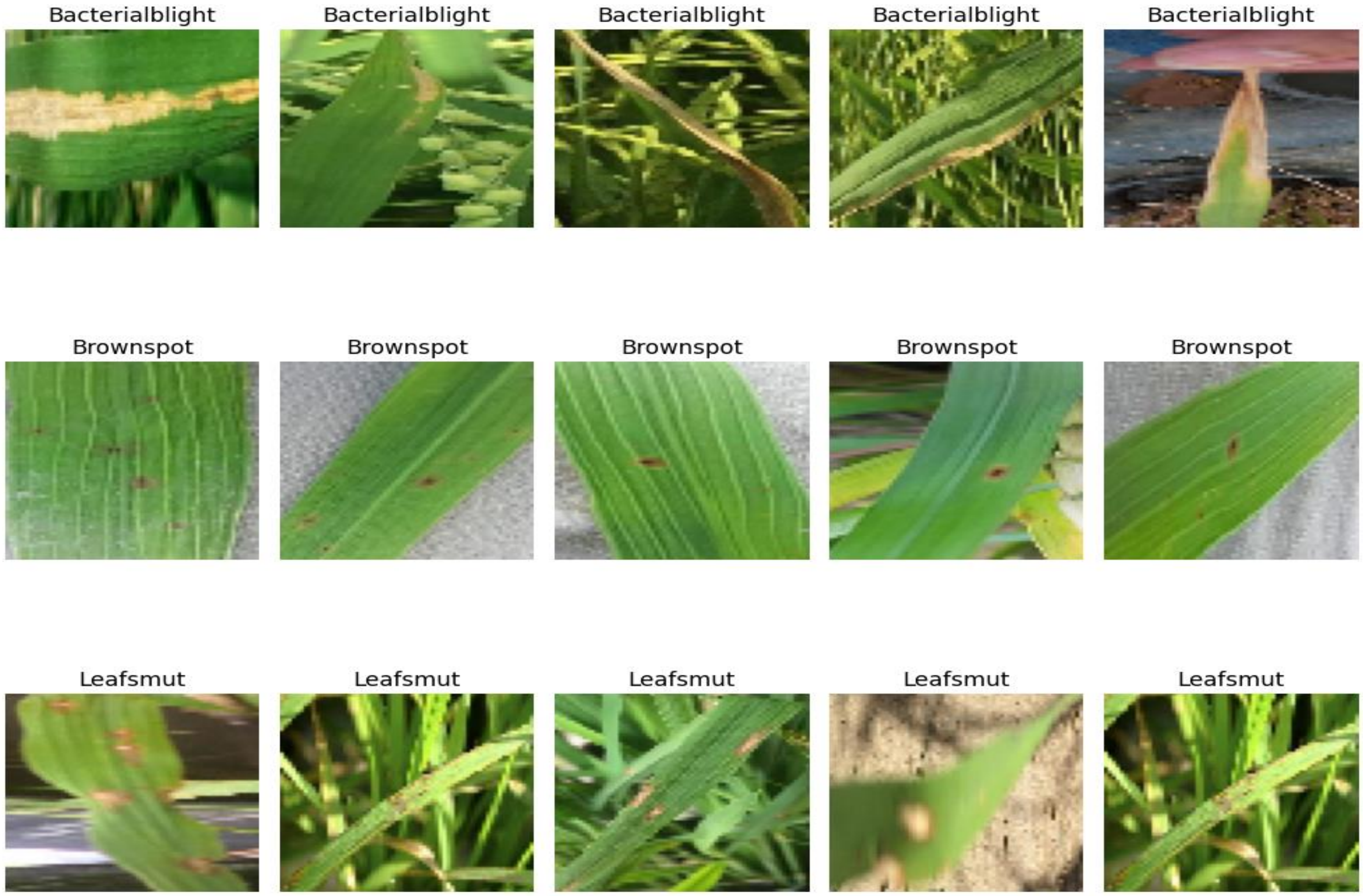

Figure 2: Types of rice leaf disease sample.

The collected features are now flattened into a single 4608-size vector and fed into a dense layer with 128 fully connected neurons. This thick layer learns High-level combinations of the features collected by the convolutional layers. By using a second Multi-Head Attention Layer to focus on many input components at the same time, the model can comprehend the visual features more deeply. After being flattened, the output of this attention mechanism is then routed to a second dense layer containing three neurons, each of which represents one of the three disorders. Figure 3 illustrates the modified steps of the proposed methodology.

Table 2: Data set of rice leaf disease.

Classes	Original Images	Training Set	Augmentation	Testing Set
Bacterial Blight	1200	960	5760	240
Brown Spot	1000	800	4800	200
Leaf Smut	918	734	4404	184
Total	3118	2494	14964	624

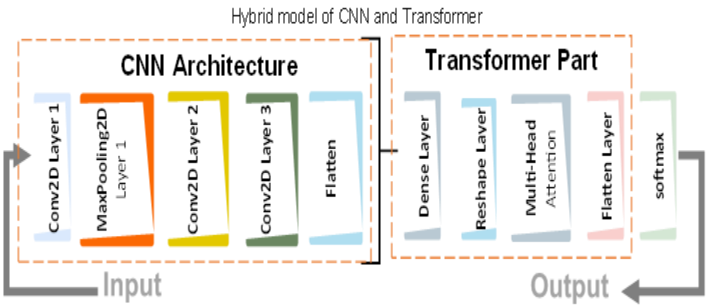

Figure 3: Proposed hybrid model of CNN and transformer model.

3.4 Training and parameters

After implementing different modifications of the image (flips and rotations), 15,588 images make up the augmented dataset on which the model is trained. Table 3 shows a screenshot of the implementation of the training.

The architecture of this model aims to achieve high accuracy in rice leaf disease identification from photos while being lightweight and efficient. By utilising attention mechanisms, the model is better able to identify the diseases by concentrating on the areas of the image that are most relevant.

Table 3: Model Training.

Found 3118 images belonging to 3 classes.

Found 780 images belonging to 3 classes.

Model: "functional_7"

Layer (type)	Output Shape	Param #	Connected to
input_layer_7 (InputLayer)	(None, 64, 64, 3)	0	-
conv2d_20 (Conv2D)	(None, 62, 62, 32)	896	input_layer_7[0][0]
max_pooling2d_20 (MaxPooling2D)	(None, 31, 31, 32)	0	conv2d_20[0][0]
conv2d_21 (Conv2D)	(None, 29, 29, 64)	18,496	max_pooling2d_20[0][0]
max_pooling2d_21 (MaxPooling2D)	(None, 14, 14, 64)	0	conv2d_21[0][0]
conv2d_22 (Conv2D)	(None, 12, 12, 128)	73,856	max_pooling2d_21[0][0]
max_pooling2d_22 (MaxPooling2D)	(None, 6, 6, 128)	0	conv2d_22[0][0]
flatten_13 (Flatten)	(None, 4608)	0	max_pooling2d_22[0][0]
dense_14 (Dense)	(None, 128)	589,952	flatten_13[0][0]
reshape_6 (Reshape)	(None, 1, 128)	0	dense_14[0][0]
multi_head_attention_6 (MultiHeadAttention)	(None, 1, 128)	131,968	reshape_6[0][0], reshape_6[0][0]
flatten_14 (Flatten)	(None, 128)	0	multi_head_attention_…
dense_15 (Dense)	(None, 3)	387	flatten_14[0][0]

Total params: 815,555

Trainable params: 815,555

Non-trainable params: 0

Table 4: Classification Report.

Model	**Classification Report:**				
	Type	**Precision**	**Recall**	**F1-Score**	**Accuracy**
CNN without Transformer and Augmentation	Bacterialblight	53%	78%	93%	65%
	Brownspot	74%	83%	78%	78%
	Leafsmut	75%	0.8%	0.14%	37%
	Macro Avg	67%	56%	52%	58%
	Weighted Avg	67%	63%	58%	63%
After CNN with Transformer and Augmentation	Bacterialblight	100%	89%	94%	95%
	Brownspot	95%	100%	98%	97%
	Leafsmut	91%	97%	94%	94%
	Macro Avg	95%	95%	95%	95%
	Weighted Avg	96%	95%	95%	95%

3.5 Evaluation matrix

In this study, the performance of our CNN proposed model for classifying rice leaf diseases was evaluated utilizing various key metrics: precision, accuracy, F1-score, and recall [21]. These metrics fully recognise the model's efficiency in correctly identifying and classifying diseases. In the following, we define each metric and provide the corresponding equations.

Accuracy, which is the ratio of correctly predicted cases (both true positives and true negatives) to the total number of cases, provides an overall measure of the model's performance in classifying the different categories [22].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where:

TP = number of correctly predicted positive instances.

FP = number of negative instances incorrectly predicted as positive.

TN = number of correctly predicted negative instances.

FN = number of positive instances incorrectly predicted as negative.

Precision, also known as Positive Predictive Value (PPV), measures the ratio of true positive predictions between all positive predictions made through the model [23].

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Recall, named Sensitivity or True Positive Rate, evaluates the proportion of true positive cases correctly identified via the model.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

The F1 score is the harmonic mean of precision and recall and provides a single metric that balances both concerns [24].

$$F - measure = 2 * \frac{(Precision\ *\ Recall)}{Precision + Recall} \tag{4}$$

The F1 score ranges from 0 to 1, with 1 indicating perfect precision and recall.

4 Results and Discussions

The proposed CNN model showed excellent performance in classifying three common diseases in rice plants: Leaf smut, Brown spot, and Bacterial blight. As outlined in Table 4, the hybrid model achieved an overall accuracy of 95%, complemented by a precision of 96%, recall of 95%, and an F1-score of 95%, while the CNN without applied transformer and augmentation achieved an accuracy of 63%. These metrics reflect the model's robustness in distinguishing between the different disease classes, with consistently high macro and weighted average values. However, some misclassifications were noted, indicating potential areas for refinement. In general, these findings underscore the effectiveness in the ultimate task of classifying rice plant disease.

As shown in Figure 4, the ROC curve illustrates the performance in terms of accuracy and validation accuracy, along with the corresponding loss and validation loss metrics. The curve effectively demonstrates the trade-off between the true positive rate and the false positive rate, providing insight into the model's discriminative ability across various thresholds.

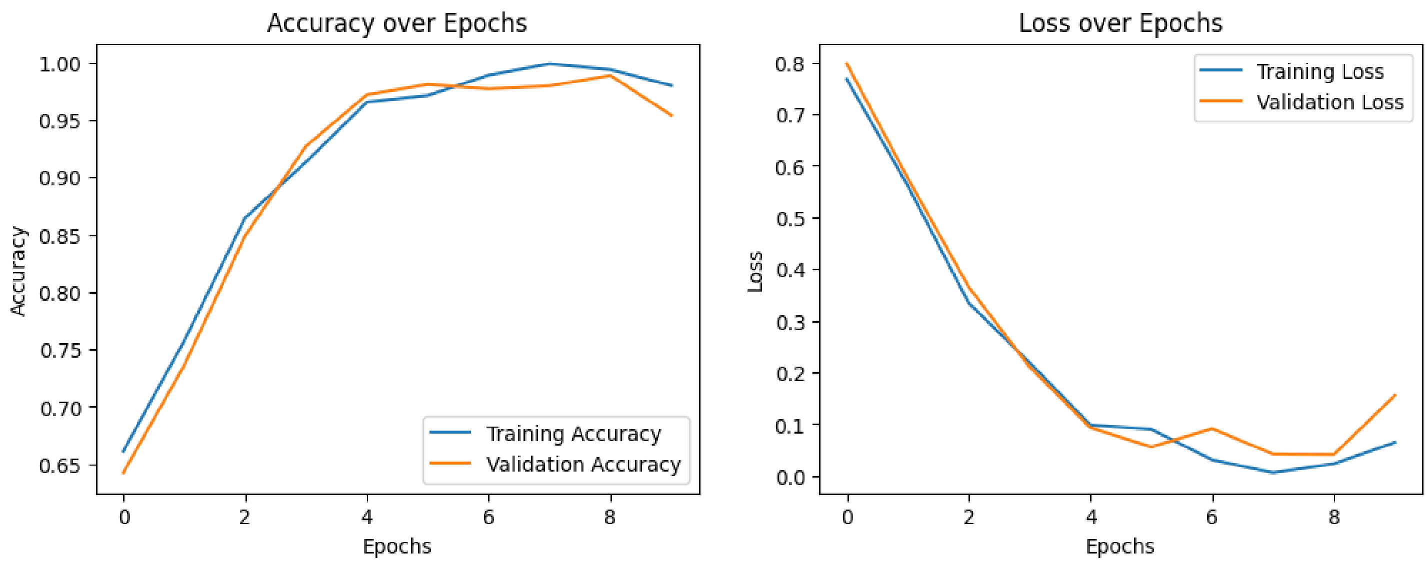

Figure 4: ROC curve of Accuracy and Validation Accuracy with loss and Validation Loss.

The performance in classifying diseases is illustrated in the confusion matrix of Figure 5; Key findings highlight its high recall and precision across the three classes as follows:

- Bacterial blight: 239 out of 269 cases were accurately diagnosed by the model, whereas 19 cases were incorrectly identified as leaf smut. This class had great recall and precision rates, although there was room for growth.
- Brown spot: This class was the best categorised, showing the model's ability to detect Brown spots by accurately identifying all 324 cases.
- Leaf smut: Of the 187 cases, the model correctly identified 181; the other six cases were misclassified as Brown spot or bacterial blight. Although slightly lower, the recall for this class was still acceptable.

In our study, the CNN model effectively classifies three prevalent rice plant diseases—bacterial blight, Brown spot, and Leaf smut—achieving an overall accuracy of 95%, with corresponding precision, recall, and F1-scores also at 95%. This performance level highlights the robustness and reliability in a critical agricultural context.

In this study, we compare the performance of our proposed model, a hybrid CNN + Transformer architecture, to existing state-of-the-art studies based on the metrics of precision and accuracy presented in Table 5.

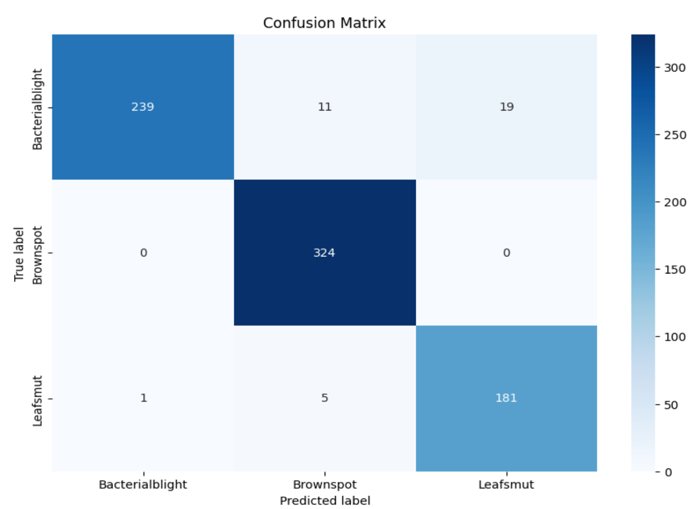

Figure 5: Confusion matrix.

The performance of various models demonstrates notable variations in precision and accuracy. For example, the ADSNN-BO model proposed by Wang et al. [25] achieved a precision of 94.65%, setting a high standard in the domain of DL applications.

Table5: Comparison with state-of-the-art models.

Reference	Year	Model	Accuracy
Wang et al. [25]	2021	ADSNN-BO model	94.65%
Dogra et al. [28]	2023	CNN-VGG19 model	93%
Daniya et al. [26]	2023	RWW-based NN	94%
Aggarwal et al. [27]	2023	Multiple DL	94%
Devi et al. [29]	2024	EfficientNet-U-Net	89.48%
Proposed model	2025	Hybrid CNN+Transformer	95%

The RWW-based neural network developed by Daniya et al. [26] which reported a precision of 94%. This indicates a robust capability for classification tasks, suggesting potential applicability in complex data environments.

However, our proposed model outperforms these previous efforts, achieving a precision of 95%. This slight yet significant improvement highlights the effectiveness of the hybrid CNN + Transformer architecture in enhancing model performance. It indicates our model's superior ability to leverage both convolutional and transformer-based methodologies, which can extract and represent features more effectively across different data types.

When considering accuracy, the multiple DL approach presented by Aggarwal et al. [27] is 94%, while the CNN-VGG19 model by Dogra et al. [28] offers an accuracy of 93%. On the contrary, the EfficientNet-U-Net model by Devi et al. [29] shows a lower accuracy of 89.48%. These findings suggest variability in the effectiveness of model architectures in achieving high accuracy.

The integration of CNN and Transformer factors in our proposed model contributes to enhancements in precision and accuracy. It indicates a promising path for future research in deep getting to know. Our consequences advise that the hybrid method may offer significant advantages over singular version architectures; even as trendy fashions have established magnificent skills in terms of precision and accuracy, our proposed Hybrid CNN+Transformer version virtually distinguishes itself as a superior alternative, showcasing proof of more suitable performance metrics which can result in better sensible packages in the field. This advancement represents a crucial breakthrough in leveraging hybrid model techniques for improved results in deep mastering tasks.

Conclusion

This study proposed a hybrid CNN+Transforme model for the type of three of the most common rice plant diseases: Bacterial blight, Brown spot, and Leaf smut. The proposed method verified a high universal accuracy of 95%, highlighting its sturdy ability as a reliable device for automatically detecting rice disease. The accuracy completed, mixed with the version's performance, underscores the advantages of this technique over conventional techniques, which are regularly labour-intensive, time-consuming, and prone to human blunders. By allowing for an early and correct analysis, this method gives sizable advantages, including decreasing the financial effect of crop diseases and reducing the reliance on dangerous pesticides, thereby contributing to improved food safety. Future paintings must focus on expanding the model to hit upon a broader variety of rice illnesses, integrating it into actual-time monitoring systems, and exploring the mixture of CNNs with different AI strategies like Reinforcement Learning and Transfer Learning to enhance accuracy and scalability. These advancements may result in extra strong, adaptable answers, reworking sickness control practices in agriculture. Ultimately, this study contributes to precision agriculture, helping sustainable farming practices and enhancing crop yields and global food safety.

Authors contribution

W.K.A, E.T.M and A.A.N contributed ideas and the writing of this manuscript.

Conflict of intrestrst

No

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No

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