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Python-Based Detection of Paddy Leaf Diseases: A Computational Approach

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ABSTRACT
With paddy being an essential crop in Bangladesh's agricultural landscape, Bangladesh and India stand out as two of the most important nations in the world when it comes to developing paddy agriculture. On the other hand, despite the fact that paddy is an important economic crop, farmers in Bangladesh frequently experience significant losses as a result of the many diseases that afflict the crop. Out of the more than thirty paddy leaf diseases that are known to exist, roughly seven to eight of them are endemic in Bangladesh. These diseases include Brown Spot Disease, Blast Disease, and Bacterial Leaf Blight.

There is a large reduction in paddy plant growth and production as a result of these diseases, which results in severe losses to both the environment and the economy. In order to minimise crop damage and reduce losses for farmers, it is essential to diagnose these diseases as early as possible and with as much precision as possible. Through the utilisation of deep learning convolutional neural network (CNN) models, the primary objective of this research is to identify four prevalent paddy leaf diseases as well as one healthy leaf state through the application of automated detection techniques.

The key goal that we have set for ourselves is to obtain superior outcomes in paddy leaf disease identification in comparison to traditional manual approaches, which frequently suffer from low accuracy and time inefficiency. The results of our evaluation of four CNN models, namely VGG-19, Inception-ResNet-V2, ResNet-101, and Xception, indicate that Inception-ResNet- V2 surpasses the other models with an astounding accuracy of 92.68%. This research prepares the path for disease management measures in paddy farming that are more effective and efficient, which will be of benefit to farmers and will strengthen the sustainability of agriculture.

Keywords — Paddy disease, Brown Spot Disease, Blast Disease, Bacterial Leaf Blight, Crop disease

I. INTRODUCTION

As we move into the 21st century, rice, which is a type of Oryza sativa, continues to hold its preeminent position as the principal grain in the food systems of the world. It is the primary source of both energy and protein for approximately three billion people [1]. Approximately ninety percent of the world's rice production is attributed to the Asia-Pacific Region, which is widely recognised as the epicentre of paddy agriculture [2]. It is estimated that around 75% of the cultivable land in Bangladesh is dedicated to the cultivation of paddy, while more than 80% of the irrigated regions are utilised for rice production. Paddy thus holds the distinction of being the primary staple food in Bangladesh. Therefore, paddy cultivation is an essential component in the process of ensuring that the people of Bangladesh are able to maintain their standard of living [3].

It is important to note that the process of paddy farming in Bangladesh is not without its share of obstacles. Farmers are constantly confronted with a wide variety of challenges, which include and are not limited to the degradation of land, population pressures, climate fluctuation, and the infestation of pests and diseases. A decrease in interest among farmers in paddy cultivation has occurred in recent times as a result of these issues, which have contributed to the situation. In recognition of the fact that pest and disease control are essential components of rice production, this paper goes specifically into the arena of pest and disease management. The bacterial leaf blight, brown spot, leaf blast, leaf smut, and panicle blight are some of the subcategories that fall under the umbrella of the bacterial, fungal, and miscellaneous diseases that are found in paddy. These diseases pose serious hazards to paddy crops. One thing that should be brought to your attention is the alarming increase in the occurrence of these diseases, which can be related, at least in part, to the negative effects of climate change, notably the rising temperatures [5]. With bacterial leaf blight (BLB) and brown spot emerging as strong enemies in rice production, studies estimate that 4-14% of rice yields in Bangladesh are lost annually due to pest and disease pressures. Brown spot and BLB are two of the most severe diseases that can affect rice. In spite of the progress that has been made, improvements in the management of diseases and pests continue to be rather limited [5].

The traditional technique of illness detection is mostly dependent on the manual identification of diseases by specialists. This is a procedure that is not only timeconsuming but also resource- intensive, and it frequently results in errors in disease diagnosis [6]. Consequently, as a result of insufficient disease management techniques, paddy output has experienced a decline in the most recent years [8]. In order to get around this obstacle, there is an immediate requirement for disease detection methods that are both quick and accurate in order to diagnose paddy leaf illnesses as soon as possible. Brown Spot, Healthy Leaf, Leaf Blast, Bacterial Blight, and Leaf Smut are the five paddy leaf diseases that are most frequent, and this study focuses primarily on understanding them.

A new era of innovation in agriculture has been ushered in by the introduction of technologies that utilise artificial intelligence (AI), which have provided answers to problems that have persisted for a long time. When it comes to the detection of diseases in plants, including paddy, artificial intelligence-powered systems that make use of machine learning and deep learning algorithms have significant opportunities. AI-driven disease detection has demonstrated extraordinary effectiveness, enabling farmers to independently diagnose paddy diseases and so revolutionising agricultural techniques. This is despite the fact that there are certain limits associated with the technology. As we look to the future, technological improvements are quite likely to be the catalyst for further revolutions in the agricultural industry, which will ultimately lead to sustainable growth and resilience.

II. RELATED WORK

Over the course of previous research, numerous illnesses that influence rice agriculture have been thoroughly investigated. Research projects that are now being conducted are centred on gaining a deeper understanding of rice illnesses and developing novel approaches to their management. For instance, Kawcher Ahmed et al. [10] utilised machine learning techniques in order to identify three prominent paddy leaf diseases. In order to improve the accuracy of their findings, they utilised four different machine learning models using tenfold cross-validation procedures. For the purpose of illness prediction, Milon Biswas and colleagues [11] focused their attention on three paddy diseases and utilised picture preprocessing techniques in conjunction with an SVM classifier. Using Internet of Things and Artificial Intelligence technology for real-time analysis of non-image data from agricultural sensors, Wen-Liang Chen et al. [12] highlighted bacterial leaf blight as a serious paddy disease. This allowed for efficient disease diagnosis, which was a significant contribution to the field.

An Optimised Deep Neural Network with the Jaya algorithm was created by S. Ramesh and colleagues [13] for the purpose of recognising and classifying four diseases that affect paddy leaf structures. The research conducted by Eusebio L. Mique, Jr. and colleagues [14] focused on the application of Convolutional Neural Network (CNN) and image processing techniques for the purpose of facilitating the diagnosis and control of a variety of paddy diseases. The researchers utilised data obtained from web sources as well as manual capture. A comparison was made between process-based and machine learning-based models for the detection of rice blast disease by David F. Nettleton and colleagues [15]. The authors emphasised the significance of early warnings in order to reduce the impact of the disease.

A survey-based investigation on contemporary image processing and machine learning techniques for the identification and classification of paddy illnesses was carried out by Jay Prakash Singh and colleagues [16]. The study consisted of four stages: image preprocessing, segmentation, feature extraction, and classification. For the purpose of reducing the amount of pesticides used and the amount of pollution that is released into the environment, Prabira Kumar Sethy and colleagues [17] developed a model that makes use of fuzzy logic and machine learning segmentation approaches to predict the severity of diseases that affect rice crops.

KNN and ANN algorithms were used to develop a feature for the identification of rice blast leaf disease, which was proposed by S. Ramesh and colleagues [18]. This feature achieved a high level of accuracy in the early diagnosis of disease. Through the utilisation of a pre-trained deep CNN model (AlexNet) and an SVM classifier, Vimal K. Shrivastava and colleagues [19] were able to achieve a level of accuracy that was remarkable in their efforts to improve conventional plant disease detection systems. A tool for the real-time video-based identification of rice leaf diseases was presented by Dengshan Li et al. [20]. This tool makes use of deep learning techniques and employs models such as faster-RCNN and other CNN architectures.

In order to address two of the most significant issues in rice disease management, Gittaly Dhingra and colleagues [21] carried out an exhaustive investigation on the detection and classification of paddy diseases by the application of image processing techniques. For the purpose of identifying five diseases that can affect paddy leaf, Junde Chen and colleagues [34] utilised a deep learning strategy that included transfer learning. They were able to achieve a high level of accuracy by utilising Dense-Net and Inception modules. These many research endeavours highlight the significance of providing early and accurate disease detection in order to guarantee the protection of crops and the sustainability of agricultural practices.

Many different perspectives on paddy disease research were presented in Table I. Within the scope of this study, there are five classifications, four diseases, and one leaf that is healthy.

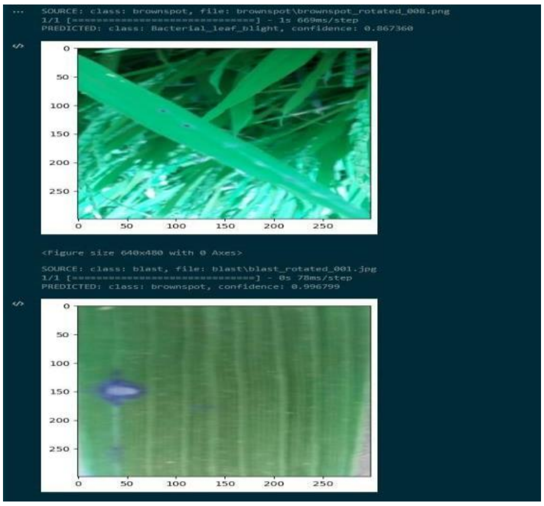
Table 1: Limitations in Previous work

Author Information	Limitations	Future Directions

Author Information	Limitations	Future Directions
Kawcher Ahmed, et al. [10]	The authors aim to utilize high-quality datasets in future research endeavors and explore advanced models to achieve superior accuracy.	The authors plan to focus on enhancing the quality of datasets and implementing more advanced algorithms to improve accuracy further.
Milon Biswas et al. [11]	Despite limited data availability (only 30 images), the authors relied on assumptions for performance measurement due to small dataset size.	The authors intend to address data scarcity issues by expanding the dataset size for more reliable performance evaluation.
Prabira Kumar Sethy et al. [17]	The study focused solely on four types of paddy diseases; future research will encompass a broader range of paddy diseases.	Future research endeavors will involve the exploration of additional paddy diseases to provide a comprehensive understanding of disease dynamics in rice cultivation.
S. Ramesh et al. [18]	Limited to studying one rice leaf disease (leaf blast), the authors express intentions to explore other rice leaf diseases and potentially extend research to other crops.	The authors plan to expand their research scope to include a wider array of rice leaf diseases and explore applications in other crop species for a more comprehensive agricultural impact.
Wen-Liang Chen, et al. [12]	The study focused exclusively on one rice leaf disease, indicating potential future explorations into additional diseases or aspects of rice cultivation.	Future research may involve the investigation of multiple rice leaf diseases or the exploration of other facets of rice
		cultivation to provide a more holistic understanding of disease management.
Vimal K. Shrivastava et al. [19]	The authors suggest that enlarging the dataset could enhance the performance of their proposed model.	Future research will focus on expanding the dataset to improve model performance and explore advanced techniques for more accurate disease detection and classification.
Gittaly Dhingra et al. [21]	While the proposed model exhibits potential, the authors suggest customizing it for identifying and classifying two diseases together for improved accuracy. Additionally, they propose developing mobile-based applications for instant solutions.	Future endeavors will involve refining the proposed model to identify and classify multiple diseases simultaneously for enhanced accuracy. The authors also aim to develop mobile applications for instant disease diagnosis and management.
Dengshan Li et al. [20]	The authors highlight the applicability of their system to other rice diseases and pests, suggesting potential extensions to broader disease management systems.	Future research will explore the integration of the proposed system into comprehensive disease management platforms, potentially extending its applicability to various crop diseases beyond rice.

Author Information	Limitations	Future Directions
S. Ramesh et al. [18]	To improve disease detection and classification accuracy, the authors aim to employ various improvement methods to reduce false predictions.	Future research directions involve the implementation of advanced techniques to enhance accuracy and reliability, ultimately optimizing disease management strategies for rice cultivation.

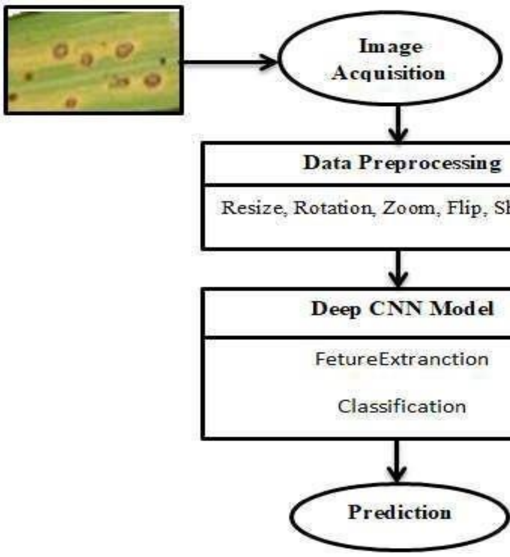
Research that is now being conducted in the field of rice cultivation and disease management highlights the tremendous significance of early diagnosis and the implementation of appropriate mitigation techniques. A number of writers have recently conducted research that investigates the utilisation of cutting-edge technologies, including as machine learning and deep learning, in order to properly detect and categorise illnesses that affect paddy leaf production. On the other hand, these research are not devoid of any specific drawbacks. In the course of their work, numerous researchers have encountered obstacles such as limited dataset sizes, concentrating on only a fraction of crop diseases, or deploying models that have space for improvement in terms of accuracy. The authors have indicated some possible future directions for their research, despite the limitations that have been mentioned. Expanding datasets, investigating more complex algorithms, and developing mobile applications for real- time disease diagnosis are some of the things that fall under this category. The goal of the researchers is to revolutionise disease management procedures in rice production by resolving these restrictions and exploring future research routes. This will ensure that agricultural communities have sustainable crop yields and food security.



III. PROPOSED SYSTEM

In the past, a substantial amount of research has been carried out on the identification of paddy illnesses through the utilisation of machine learning and deep learning approaches across a variety of technological platforms. This research makes use of a standardised methodology, implementing a bespoke deep learning model that is depicted in the flowchart that is included in the accompanying document (Fig. 1). Immediately after the photos of infected paddy leaf have been obtained, the preprocessing phase will begin. At this stage, the captured images are subjected to a number of preprocessing procedures, which may include rotation, zooming, flipping, shuffling, and resizing. A deep convolutional neural network (CNN) is then used to process the images that have been preprocessed that have been obtained. The convolutional blocks that are a part of the CNN architecture are responsible for extracting important information from the input images. After then, the deep neural network (DNN) model makes use of these features, and the weights of each node are initialised depending on the features that were retrieved from the data. The final dense layer of the model is made up of five neural nodes, and the softmax activation function gives the model the ability to make predictions about the class of the data that is provided. Three deep convolutional neural network (CNN) models—namely, VGG-19, ResNet-101, Inception-ResNetV2, and Xception—are utilised in this research project, with the primary emphasis being placed on feature extraction and classification.

IV. SYSTEM OPERATION



This study is an example of quantitative applied research that is based on the concepts of deep learning. The approaches that were utilised throughout the course of this inquiry are discussed in depth in this section.

Utilising CNN for the Purpose of Feature Extraction and Segmentation

Convolutional neural networks, often known as CNNs, are an example of a feed-forward artificial neural network design [22]. They are principally responsible for the extraction of features [23]. Convolutional layers are the components of these networks, and they are

responsible for the effective processing of digital images. When working with smaller visual datasets, it is necessary to use a reduced number of neural nodes; hence, fully linked layer blocks are utilised. On the other hand, larger image collections require a greater number of parameters for processing within an artificial neural network [25]. Convolutional neural networks (CNNs) are made up of neural nodes that are connected to one another and are associated with neighbouring neurons in the convolutional layer. This allows for a localised comparison of visual input segments that are referred to as "feature maps" [24].

Initially, the convolutional layer is responsible for aligning the features of the input image and performing pixel-wise multiplication when comparing the input pixels to the feature pixels. For the purpose of populating the feature map, the generated pixel values are first subjected to a summation process, after which they are divided by the total number of pixels contained inside the feature map. Throughout the entirety of the image, this procedure is repeated, resulting in the production of many different feature maps. For the purpose of removing negative values and introducing non-linearity within the feature maps, activation functions such as Rectified Linear Unit (ReLU) are utilised. In addition, pooling layers, and in particular the Max pooling layer, minimise the dimensions of the input image by preserving the highest possible feature values. The end result of these operations is the generation of feature representations that are acceptable for following classification challenges.

Learning That Can Be Transferred

When it comes to machine learning, transfer learning is a notion that refers to the process of transferring knowledge learned from one model to another model in order to solve issues that are connected to each other [27]. Application training for deep convolutional neural networks (CNN) within Keras often involves the use of the ImageNet dataset, which is a comprehensive visual database specifically designed for object recognition research. During the training process, these models are exposed to millions of photos that cover thousands of different categories [26]. Deep learning applications built with Keras are made up of a number of convolutional, pooling, and dense layers that are arranged in discrete architectural blocks. These architectural designs make use of weights that have been pre-trained, which makes it easier to solve problems that are related to various jobs. In most cases, the final layers of these models consist of dense layers that are optimised for classification tasks. These layers often contain thousands of nodes that are capable of classifying a wide variety of categories. When fully connected layers are customised, it is possible to perform targeted categorization within datasets that contain a small number of data points [28].

V. PADDY DISEASE TYPE AND DATASET DESCRIPTIONS

Insects and diseases are responsible for the loss of a great number of food grains, which has prompted research activities all over the world to tackle agricultural diseases that affect rice. In Bangladesh, a research conducted between 1979 and 1981 found that there were twenty prevalent rice disorders, despite the fact that there were over thirty diseases that were recorded [9]. All three seasons (Boro, Aus, and Aman) are characterised by the presence of thirteen diseases, which include bacterial blight, bacterial leaf streak, sheath blight, leaf blast, brown spot, grain discoloration, stem rot, and leaf scorch. These diseases are widespread throughout the entire year. On the other hand, conditions such as Tungro, Bakanae, Cercospora leaf spot, and zinc deficiency are seen as very minor concerns. Only a brief discussion of the disorders that were investigated in this study is included in this section.

The Descriptions of the Datasets

It was decided to select one healthy paddy leaf in addition to four paddy leaf illnesses, which included brown spot, leaf blast, leaf scorch, and leaf smut, for the purpose of this study. The dataset is comprised of 984 photos that were obtained from a variety of online sources, such as the Kaggle and the UCI Machine Learning Repository. A comprehensive breakdown of the dataset is presented in Table II. This breakdown includes the number of data points that have been designated for training, validation, and testing processes. Figures 4 and 5 offer a graphical representation of the classes that are contained inside the dataset.

1) Brown spot: This frequent paddy leaf disease, which is caused by fungi, initially appears as small circular lesions that range in colour from dark brown to purple-brown (see Fig. 2(a)). These lesions get larger over time, eventually covering the entire leaf in their destructive path.

2) Leaf blast: This disease is caused by the fungus Magnaporthe oryzae, and it is characterised by spindle-shaped spots that range in colour from white to gray-green and have borders that are dark reddish to brownish (see Fig. 2(b)).

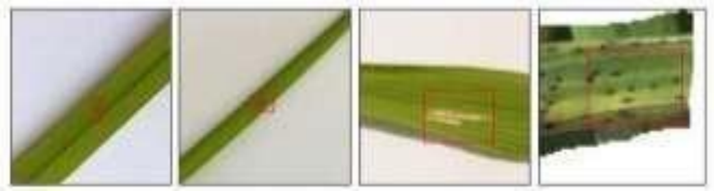
The third type of leaf scorch is caused by a type of bacteria called Xanthomonas oryzae. Infected leaves turn a grayish-green colour, which is then followed by yellowing, straw coloration, and ultimately the death of the leaf (as shown in Figure 2(c)).

The Preprocessing of Data (C)

The Keras ImageDataGenerator function was utilised in order to carry out the tasks of data preprocessing. Nine hundred and eighty-four photos with three colour channels and various pixel values are included in the dataset. Each and every image was decreased in size to a 256- by-256-pixel resolution. In addition, in order to provide a variety of viewpoints, the training images were rotated at random within a range of 15 degrees. The zoom and shear ranges, as well as the width and height shifts, were all set to 0.1. Both the training dataset and the testing dataset were subjected to the same preprocessing approach, which was the rescaling of images. The batch size for the training dataset was set to eight, whereas the batch size for the test set was set to one.

Table 2: Distribution of Train and Test Images for Paddy Leaf Disease Classes

Paddy Leaf Disease Class Name	Number of Images	Number of Images Used for Train and Validation	Number of Images Used for Test
Brown Spot	166	138	28
Leaf Blast	159	131	28
Leaf Blight	216	188	28



(a) (b) (c) (d)

Fig. 2. Paddy Leaf Disease (a) Brown Spot, (b) Leaf Blast, (c) Leaf Blight, and (d) Leaf Smut.

VI. MODEL DESCRIPTIONS

1) Deep Convolutional Neural Network (CNN): Deep CNN models are a subclass of feed- forward neural networks that have been specifically built to optimise network parameters, with the end goal of minimising the cost function. Some of the areas in which these models have made substantial progress include visual imagery analysis, picture and video categorization, object recognition, and natural language processing. These models have been widely utilised in a variety of environments.

The term "precision" refers to the proportion of successfully predicted positive values in comparison to the total number of positive values that were predicted [33]. In order to determine it, Equation (5) is utilised. Deep convolutional neural network (CNN) models are distinguished from ordinary CNN models by the presence of multiple layers. These layers include convolutional layers, activation layers, pooling layers, flatten layers, dropout layers, batch normalisation layers, and dense layers.

3) Recall: The ratio of correctly predicted positive values to the actual positive class instances in the confusion matrix is what is measured by recall. Equation (6) contains the formula, which is used to calculate it. In order to prevent the network from overfitting, dropout methods have been added, and activation functions such as ReLu and Softmax have been implemented to improve the network's capacity to recognise intricate input patterns. As shown in Table V, a number of different deep CNN models exhibit higher performance in classification and detection tasks. These models were chosen on the basis of architectural variety and network depth, as shown in Table III.

Four, the F1 Score: The F1 Score is the weighted mean of Precision and Recall, and it provides a thorough evaluation of the performance of the model by taking into consideration both false positives and false negatives [33]. In comparison to accuracy measures, the formula that it represents, which is illustrated in Equation (7), offers a more nuanced evaluation.

A description of CNN models that are based on deep learning and use Keras [31] A number of different deep CNN models are described in the Keras-based Deep Learning CNN Models Description. This description offers insights into the architectural composition and performance metrics of these models. Using the robustness and flexibility of deep learning frameworks, these models are meant to address a variety of issues that are associated with picture categorization and detection tasks.

In order to achieve optimal performance metrics like accuracy, precision, recall, and F1 score, the architectural design of each model is customised to meet specific requirements. The capacity of these models to extract relevant features from complex data is improved with the use of sophisticated features such as dropout layers, activation functions, and batch normalisation.

In addition, the Top 5 accuracy measure, which is evaluated against the ImageNet validation dataset, provides a benchmark for evaluating the classification skills of the models. Furthermore, the depth of each network, which is described in Table III, offers vital insights on the complexity of the model as well as its ability to deal with difficult datasets.
In general, the Keras-based Deep Learning CNN Models Description is a thorough guide that can be utilised by researchers and practitioners that are interested in utilising deep learning techniques for the purpose of performing image analysis and classification jobs effectively.
Here, TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

Model Name	Top 5 Accuracy	Parameters	Depth
VGG-19	0.9	14,36,67,240	26
ResNet-101	0.928	4,47,07,176	101
Xception	0.945	2,29,10,480	126
Inception-ResNet-V2 [32]	0.953	5,58,73,736	572

VII. RESULT ANALYSIS

A. Analysis of the Results

After analysing the outcomes, it was discovered that the Inception-ResNet-V2 model exhibited the highest level of accuracy when compared to the other three models. For this particular algorithm, a performance table was created, which included information on the precision, recall, and F1 score for each single class that was included in the dataset. The results presented in Table IV demonstrate that the precision scores for Brown Spot, Leaf Blast, Leaf Blight, and Leaf Smut were greater than 0.90, whereas the scores for healthy leaf pictures were 0.78. Leaf Blast received a score of 0.71 for recall, while other classes had scores that were higher than 0.90.

Table IV provides an overview of the four CNN deep learning Keras pre-trained algorithms that were utilised in this study for the purpose of illness categorization and detection in leaf tissue. The Inception-ResNet-V2 method achieved the highest precision of 0.9286, surpassing the other algorithms in terms of precision, recall, and F1 score. It was the algorithm that achieved the highest precision. A level of accuracy of 0.9152 was attained by ResNet-101 when Inception-ResNet-V2 was implemented. A level of accuracy of 0.8942 was achieved by the Xception model, while the VGG-19 model displayed the lowest level of accuracy, which was 0.8143.

Table III also includes a complete examination of these models, which is presented in addition to the accuracy, precision, recall, and F1 Score that are shown, respectively. The following parameters are used to define these evaluation metrics [18]:

1) Accuracy: Accuracy is a core performance indicator that is calculated from the Confusion

Matrix. It represents the proportion of predicted data points that are correct in relation to the overall dataset. An illustration of the formula for accuracy may be seen in Equation 4, where higher numbers indicate a more accurate performance of the model. It is important to note that the precision score for Leaf Blast was the lowest, coming in at 0.82, while the precision, recall, and F1 score for the Leaf Smut class all hit 1.0.

Referring to Table V, which provides full data as well as further insights into the evaluation measures of the models, will provide you with a more in-depth picture.

Table 4. Statistical Analysis Of Different Pre-Trained Keras Model

Models	Accuracy	Precision	Recall	F1 Score
VGG19	0.8143	0.8176	0.8035	0.8041
ResNet-101	0.9152	0.9215	0.9056	0.9056
Inception - ResNet-V2	0.9286	0.9371	0.9262	0.9286
Xception	0.8942	0.8963	0.8865	0.8823

Table 5. The Performance Score For Each Class Of Inception- Resnet-V2 Model

Classes	Brown Spot	Healthy Leaf	Leaf Blast	Leaf Blight	Leaf Smut
Precision	1.00	0.78	0.95	0.91	1.00
Recall	0.93	1.00	0.71	1.00	1.00
F1 Score	0.96	0.88	0.82	0.98	1

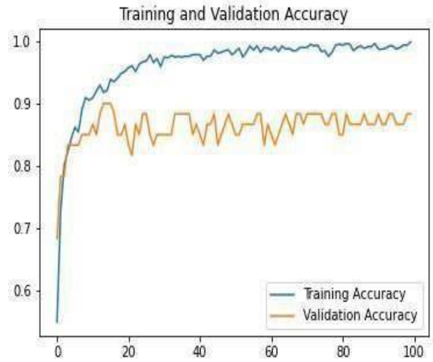


Fig. 6. Training and Validation Accuracy Graph.

An illustration of the model's accuracy throughout training and validation can be found in Figure 6. A high level of accuracy was achieved during the training process, as seen by the blue line, which depicts the training accuracy. The blue line is getting closer and closer to 1.0.

Meanwhile, the validation accuracy, indicated by the orange line, swings within the range of around 0.80 to 0.90, suggesting a somewhat reduced but still acceptable level of accuracy during validation.

Analysis of Errors and Limitations of the Study

Although technological advancements have made the identification of diseases substantially easier, these advancements are not without their drawbacks. Despite the progress that has been made, there are still times when robots have difficulty accurately detecting infections. Even if the ideal model is chosen, there is still a possibility that some errors will occur, albeit at a low frequency.

VIII. COMPARATIVE ANALYSIS

The purpose of this section is to investigate the many approaches that may be utilised to identify and classify paddy diseases and the leaves that they affect. For the purpose of doing rice analysis in a variety of different ways, these methods make use of a variety of machine learning and deep learning tools and technology. In the past, a significant amount of study has been carried out in this field, and it is still being carried out now. Here are some comparisons of earlier research endeavours, which are presented in Table VI.

Previous research has concentrated on one, two, three, or four distinct types of paddy diseases by employing machine learning algorithms, deep learning models, or concepts of computer intelligence.

In this particular work, advanced transfer learning-based deep CNN models were utilised to particularly handle four unique illnesses, namely leaf smut, leaf blast, bacterial leaf blight, and brown spot, in addition to one healthy leaf.

TABLE 6. Comparison Of Previous Research On Paddy Diseases

Models	Accuracy	Precision	Recall	F1 Score
Kawcher Ahmed, et al [10]	Leaf smut, bacterial blight, brown spot	KNN, J48, Naive Bayes, Logistic Regression, Decision Tree, 10-fold cross-validation	97%	Kawcher Ahmed, et al [10]
Wen-Liang Chen, et al. [12]	Leaf blast	CNN, IoT, spore germination	89.4%	Wen-Liang Chen, et al. [12]
Vimal K. Shrivastava et al. [19]	Rice blast, bacterial leaf blast, sheath blight	Deep CNN, SVM, transfer learning, MatConvNet toolbox, AlexNet, NVIDIA GeForce 940M GPU	91.37%	Vimal K. Shrivastava et al. [19]
Dengshan Li et al. [20]	Rice sheath blight, rice stem borer, brown spot	deep CNN, faster-RNN, confusion matrix, VGG16, ResNet-50, ResNet-101, YOLOv3, custom DCNN	The better result from custom DCNN	Dengshan Li et al. [20]
S. Ramesh et al. [18]	Leaf blast	KNN, ANN	99%	S. Ramesh et al. [18]
Prabira Kumar Sethy et al. [17]	Brown spot, bacterial blight, leaf scald, leaf blast	Fuzzy logic, computational intelligence, SVM, K-means	86.35%	Prabira Kumar Sethy et al. [17]

IX. CONCLUSION

This study was carried out with the purpose of evaluating and completely analysing the performance of four different benchmark deep learning network topologies. Various statistical metrics were utilised in this process. The Inception-ResNet-V2 network architecture was found to have the highest attained test accuracy, which was 92.68%. This was determined by analysing the precision, accuracy, recall, and F1 score of the algorithms. There were a variety of web sources and local paddy companies that contributed to the collection of the dataset that was used for training and testing the model. It is composed of five classes, with four classes portraying paddy leaf diseases that are prevalent with paddy leaf infections and one class displaying images of healthy paddy leaf. The Inception-ResNet-V2 has a distinctive design that consists of stem, reduction, and inception-resnet blocks. Together, these blocks have a depth of 571 layers, which is greater than the depth of other networks that can handle the dataset. During the testing process, the ResNet-101 network earned the second-highest accuracy, which was 91.52%. The use of transfer learning strategies was implemented in order to get a more accurate forecast of illnesses that affect rice leaf growth. The application of transfer learning resulted in an increase in accuracy and a reduction in the complexity of the model training process.

X. FUTURE WORK

In order to make this research more sophisticated, it is possible to incorporate a larger variety of paddy leaf diseases and to refine CNN models in order to obtain more accuracy and faster identification. It is vital to conduct a study that is both exhaustive and exhaustive in order to gain an understanding of the parameters that influence the detection of plant diseases. These factors include dataset classes, size, learning rate, and lighting conditions etc. The nature of paddy plant diseases might change over time or depending on the background of the photos, including those that have colour problems. As a result, convolutional neural network models need to be modified in order to enable them to recognise and categorise diseases in situations that are difficult or complex. It is vital to broaden the scope of this study to include other forms of paddy leaf diseases, using larger datasets, and comparing the results with a variety of CNN models. In the future, we will work to overcome these limitations and make use of this research as a basis for identifying other plant leaf diseases with a higher degree of precision. Additionally, the high accuracy that was attained by Inception-ResNet-V2 is highly encouraging, which motivates us to further investigate this model and compare it with other CNN models.

XI. REFERENCES

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