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Diagnosis of Rice Diseases using Canny Edge K-means Clustering and Convolutional Neural Network based Transfer Learning

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Abstract—Recent breakthroughs in deep learning-based convolutional neural networks have significantly improved image categorization accuracy. Deep learning-based techniques for diagnosing illnesses from rice plant images have been created in this work, inspired by the realisation of CNNs in image classification. Smart monitoring technologies for the automatic identification of plant diseases are extremely beneficial to sustainable agriculture. Despite the fact that various mechanisms for plant disease categorization have been created in recent years, an inefficient technique based on evidence from picture samples is of concern for ground environments. In this study, an image processing technique for pre-processing and segmentation was used, as well as a multi-class convolutional neural network with transfer learning, to classify rice plant leaf diseases such as brown spot, hispa, leaf blast, and healthy class. The contaminated area was automatically separated from the healthy areas of the image using canny edge detection and k-means clustering, and the features were retrieved using the CNN model. In the experimental results, the CNN model without transfer learning is compared to the transfer learning model. VGGNet transfer learning is used to construct a multi-classification framework for each class of rice illness. The overall accuracy acquired by the CNN model without transfer learning is 92.14%, whereas the accuracy obtained by the transfer learning model is 94.80%.The current work demonstrates that the proposed technique is compelling and capable of recognizing rice plant illness for four classes.

Keywords- Convolutional Neural Network; Transfer Learning; ImageNet; Edge Detection; Clustering.

I. INTRODUCTION

Diseases pose significant challenges to rice crop production and growth, resulting in significant yield reductions.Timely and precise disease diagnosis in rice plants is critical for avoiding economic losses. The traditional technique of relying on expert knowledge and specialised sensing instruments, on the other hand, frequently results in delays in illness detection and control. Fortunately, the introduction of mobile phones and digital cameras has made it easier for individuals to record digital photographs of damaged crop plants and organs. For disease identification and classification, many techniques such as machine learning, deep learning, and computer vision have been used. Accurate and timely disease detection is critical for reducing reliance on pesticide treatments. Negligence in pesticide practises might have a negative impact on the environment [1].

To solve this issue, computer vision techniques for identifying and classifying rice illnesses have been developed. Convolutional neural networks (CNNs), which are among the most often used deep neural networks (DNNs), have demonstrated excellent performance in image analysis research, enabling automatic and accurate recognition and categorization of plant diseases. However, earlier research concentrated on building and deploying these CNN models without investigating improvements to their training procedures. Furthermore, the impact of deploying high-performing CNN models with a large number of parameters in real-world mobile applications has not been taken into account. To assess their performance in rice disease identification, fine-tuning, transfer learning, and training from scratch were used [2]. Using computer vision and advanced CNN architectures, the researchers want to speed and optimise the process of diagnosing rice problems.

The following structure of this paper is organized. Section 2 describes the literature review of the various studies. Section 3 provides the material and methodology used by proposed work. Section 4 comprises of description of the process of feature extraction and transfer learning. Section 5 illustrates the Experimental results and performance evaluation of the implemented models The research conclusion and future work are described in Section 6.

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II. LITERATURE REVIEW

Image classification in machine learning is strongly reliant on features, which are critical in effectively detecting distinct objects or patterns within images. Deep convolutional neural networks (CNNs) have paved the path for effectively detecting and categorizing rice diseases using deep characteristics, leading to encouraging results. Authors in [3] investigate the use of deep learning techniques in agriculture, specifically for the detection of rice plant diseases. They suggest enhancements to a CNN model, with a focus on the Visual Geometry Group Network-16 (VGG16) architecture. The improved model integrates multi-task learning and utilizes transfer learning by utilizing an ImageNET pre-trained model. The experimental results show that the proposed approach is successful, with a high accuracy rate of detection for rice plant illnesses. The study compares the upgraded CNN model's performance to that of other models and emphasizes its advantage in disease identification. The researchers in [4] anticipate overcoming the problem of efficiently and accurately finding resistant rice cultivars. They acquire VIS/NIR spectral data from several rice cultivars, including sensitive and resistant types. To learn the complicated patterns and features included in the spectrum data, deep learning models, notably Convolutional Neural Networks (CNNs), are used. The results illustrate that the proposed method is successful at reliably identifying resistant rice varieties. The deep learning model exhibits good classification accuracy, implying that it could be a useful tool for cultivar selection in the context of bacterial blight resistance. The study [5] looked at the possibilities of combining deep learning with mobile technologies in the domain of rice leaf disease classification. This strategy contributes to prompt and efficient disease management by allowing farmers and agricultural professionals to use their cellphones or tablets for disease identification, resulting in increased crop health and output. The research in [6] advances rice leaf disease analysis by providing a novel methodology that combines SSSO with deep learning. This approach delivers useful insights for farmers and agricultural professionals by correctly categorising illnesses and assessing their severity, allowing them to make informed decisions about disease management and crop protection. The suggested approach's performance is assessed using a variety of criteria, including accuracy and mean absolute error (MAE). The experimental results show that the combined SSSO-deep learning framework outperforms typical deep learning models on their own. The study [7] emphasizes the need of using deep learning techniques, notably CNNs, to identify plant diseases. The unique CNN model provided here provides a potential solution for accurate and efficient disease recognition, which can greatly contribute to early detection and prompt intervention in plant disease management, eventually enhancing crop health and yield. The updated CNN model's performance in [8] is measured using several measures such as accuracy, precision, and recall. Comparative experiments are carried out to evaluate the model's performance in comparison to other current methodologies or models. The results show that the proposed method is effective at detecting and recognising rice plaques. The modified CNN model outperforms existing methods and achieves excellent

accuracy rates, demonstrating its promise as a dependable tool for rice plaque detection and identification. Authors in [9] describes an improved method for detecting rice leaf diseases utilizing a data augmentation pipeline based on Generative Adversarial Networks (GANs).To put the method into action, a dataset of rice leaf images damaged by various illnesses is compiled. The enhanced dataset, which includes both real and synthetic images, is then utilised to train a disease detection classification model, such as a Convolutional Neural Network (CNN). The suggested approach's performance is assessed using common measures such as recall, accuracy, and precision. The findings show that using a GAN-based data augmentation pipeline improves the accuracy and robustness of rice leaf disease identification. By giving more diverse samples and lowering the danger of overfitting, the enriched dataset helps the training process. The research initiative in [10] demonstrates the utility of dense convolutional neural networks for detecting and classifying plant diseases. The suggested approach, which makes use of deep learning techniques, provides a dependable and efficient solution for disease control in agriculture, assisting farmers and specialists in making educated decisions to preserve crops and increase yields. The suggested method's performance is assessed using common evaluation measures such as accuracy, F1-score, precision, and recall, and Comparative experiments are carried out to evaluate the model's performance in comparison to other current methodologies or models. Table 1 represents the literature review of the selected studies in this field.

III. MATERIALS AND METHODS

Figure 1 depicts the proposed technique used in this study, which includes six major modules: pre-processing, data augmentation, image segmentation, feature extraction, model training, and multi-class transfer learning model.

Six modules were used to begin the process of detecting rice diseases across four separate classes of rice leaves, as shown in Figure 1. In the first module, picture samples of rice plants were collected and rescaled for uniformity. Following that, the second lesson concentrated on data augmentation strategies for expanding image samples. The third module identified disease signs by image segmentation using canny edge detection and k-means clustering. In the fourth module, various features were retrieved using a CNN model. The fifth

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module entailed using CNN and VGG net-16 to train the model, while the sixth module used transfer learning to retrieve the feature map for each image sample.

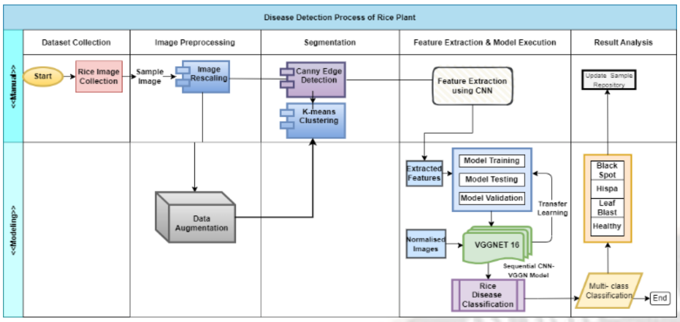

Figure 1. Rice Disease Detection Process

TABLE 1: LITERATURE SURVEY OF THE RELEVANT STUDIES

Year	**No. of classes**	**Name of Disease**	**Method Used**	**Segmen-tion**	**Accuracy Achieved**
2023 [11]	5	Leaf streak, Rice bacterial blight, flax leaf spot, sheath blight, and rice blast	Yolov 3	×	98.44%
2022 [12]	6	Bacterial leaf blight narrow brown spot, leaf blast, brown spot, leaf scald, and Healthy	VGG19-based transfer learning	×	96.08%
2021 [13]	3	Rice leaf blast, brown spot, and rice hispa damage	Bayesian optimization method, Augmented attention method	Otsu's threshold	94.65%
2021 [14]	3	Leaf Blast, Brown Spot and Bacterial Leaf Blight	SVM, k-nearest neighbors	Multiband thresholding, k-means	89.19% in leaf blast, 82.86% in brown spot and 89.19% in leaf blast
2020 [15]	4	Brown spot, blast, sheath rot and bacterial blight.	KNN for classification and Deep Neural Network	K-Means Clustering	93% brown spot, 89% blast,92% sheath rot, 93% bacterial blight, and 96% normal images accuracy is achieved by using DNN
2019 [16]	1	Rice blast disease	KNN and ANN	K-means clustering	85% by using KNN and 99% by using ANN

A. Data Collection

This study's dataset covers three distinct rice leaf diseases.: leaf blast, brown spot, and hispa, as well as healthy rice leaves. The classes used in the classification procedure are summarised in Table 2. Rain, humidity, rice kind, plant variety, meteorological conditions, nutritional qualities, and temperature are all factors that can contribute to the prevalence of illnesses in rice plants. These disorders have serious consequences for product quality, market segmentation, and revenue generation. Adequate and diverse datasets are required to support disease detection and categorization using deep learning. The image collection for this study was gathered from online sources such as PlantVillage and Kaggle [17]. Additionally, about 1,500 photos of rice illnesses were collected directly from the Bangladesh Rice Research Institute (BRRI) paddy fields [18]. As shown in Table 2, the dataset includes images of various diseases, their symptoms, and the related sample counts from each data source. It is important to note that different diseases affect different components of the rice plant, such as the leaves, stem, and grains. Bacterial leaf blight disease, brown spot disease, and hispa all damage the rice leaf, whereas leaf blast usually affects the rice stem.

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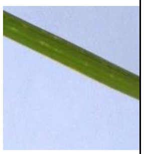
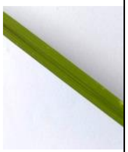
TABLE 2: DESCRIPTION OF RICE DISEASE USED FOR CLASSIFICATION

	Black Spot	Hispa	Leaf Blast	Healthy
Rice plant image				
Symptoms	Black spot disease in rice begins as small brown dots on the glumes and progresses to huge oval-shaped lesions on the glumes, lowering seed quality and weight.	Hispa disease can cause the mining of grows on the leaves. It leads to the scrapping of the leaf blade making white strips of lower epidermis. Hispa disease can burnt the rice crops and yields irregular radiant patches across the veins of the leaves.	Leaf blast generates grey lesions with dark borders on leaves, the size of which varies according to plant age, abrasion, and resistance. It causes damage to young plants early in the season, impacting shoots but not leaf sheaths.	Cultivated rice grows to 1.2m in height each year, with elongated leaves, hollow branches, and wide, spreading fibrous roots. Panicle characteristics and crop production vary.
Image Count	817	1021	973	1249

B. *Pre-processing and Data Augmentation*

Image processing technique plays the significant role in detecting the diseases from image samples. This technique has been employed in many applications like medical imaging, agriculture sector, computer vision system etc. The primary objective of pre-processing technique is to improve input samples by removing the undesirable data or noice from the data. Initially, images of rice plant are pre-processed by using rescaling of each image to get refined images. Nextly, data augmentation technique is applied in image samples to get increased number of samples for training. This operation can lead to mitigate overfitting of the model by expeditating the model convergence. In the present work, seven data augmentation functions operations, such as shearing, zca whitening, random rotation, horizontal flipping, height shift and width shift, brightness and vertical flipping are used on the image samples [19]. Figure 2 represented image samples of rice plants after applying the data augmentation techniques. There are initially 817 samples collected from the different sources and after applying the seven operations of data augmentation, total 5719 images of brown spot disease samples are obtained. Similarly, 7147 images of hispa, 6559 images of leaf blast and 8743 images of healthy images are obtained.

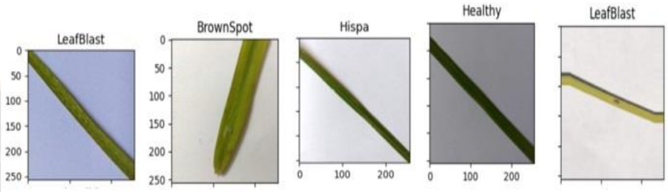


Figure 2. Images obtained after Data Augmention

C. *Image Segmentation*

The technique of segmenting an image involves fragmenting it up into multiple regions. The categorization of an image into various segments is known as image segmentation. Several different types of research have been conducted using different types of segmentation techniques. There are numerous methods for segmenting images, from conventional thresholding techniques to sophisticated color and frequency-domain techniques. The most reliable and popular image segmentation techniques are the Otsu method and K-means clustering because of their easy computation process [20]. The goal of image segmentation aims to transform a visual representation into a more significant and relevant form. Figure 3 depicts a 3D space plot of picture samples obtained with the python matplot_lib module. As some spots in a graph are denser, which can be taken as distinct colours' dominance on the image, the data points may be easily observed in the plots of each class of the groups.

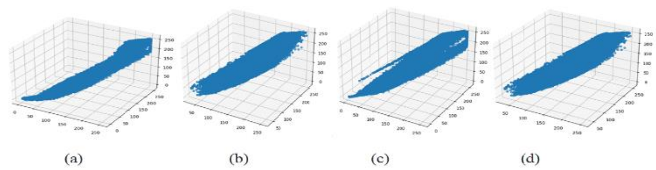


Figure 3. Brownspot, Hisp, Leafblast, Healthy

1) *Canny Edge Detection and K-means Clustering*

Canny edge detection is a popular image segmentation approach that effectively finds image edges while decreasing noise. Noise reduction, non-maximum suppression, edge tracking computation, and double thresholding, gradient using hysteresis are the five key phases in this technique. Canny edge detection effectively removes the edges from the image using these processes, improving the subsequent analysis [21]. Furthermore, K-means clustering is used to group things based on their attributes into a predetermined number of groups,

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denoted by K. The sum of squared distances between each entity and its related cluster is minimized using this strategy. K-means clustering can be broken down into four steps: (1) initializing the centres of the K clusters, (2) assigning each pixel to the cluster with the shortest distance between it and the cluster centre, (3) calculating the centroid of each cluster by aggregating the pixels assigned to it, and (4) repeating steps 2 and 3 until convergence is achieved [21]. Traditionally, the K value and the Region of Interest (ROI) are chosen by hand, based on the user's experience. Manual ROI selection, on the other hand, is time-consuming and prone to errors. To circumvent this constraint, automatic clustering approaches for recognizing disease spots in rice plant leaves can be used. K-means clustering was used in this study to automatically classify disease zones in rice leaves. This was accomplished by using a thresholding technique to distinguish between the colours of the diseased and healthy areas of the image samples. Pixels with lower red values compared to blue and green values were specifically masked off, leaving only the sick portion of the leaf visible. Table 3 displays the initial image files for each class, as well as images obtained using the Canny edge detection method, K=4 clustering, and K=6 clustering methods. These segmentation approaches are critical in identifying and emphasizing the areas that are relevant for illness investigation and classification.

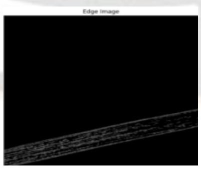
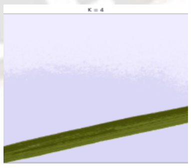
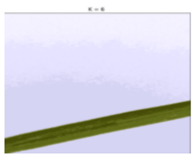
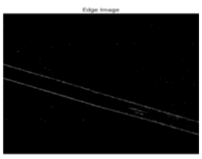
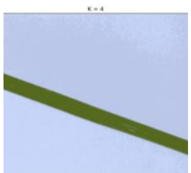
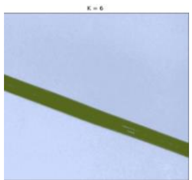
IV. FEATURE EXTRACTION

Numerous visual physiognomies related with plant leaves are called the features. Primarily, plant images are collected, and then pre-processing and segmentation techniques are employed to the images to enhance, normalize, and noise reduction of the images. Then, feature extraction is applied to classify different diseases of the plant image samples. Several features are there like textural, shape, color and size features of the images. Color is the utmost influential feature and considerable descriptor that enhance feature extraction for image analyses image samples. Color features are more substantial than other features because of invariance to shape, size, and background complexity distinctiveness [22]. Table 4 represents the most commonly used features extracted by different researchers.

A. Feature Extraction using CNN

Deep CNNs have found great success in a variety of image processing applications in recent years. Deep learning (DL) systems, such as CNNs, have the same tremendous capabilities as classic image recognition techniques for learning and extracting significant features from images. This capacity enables them to record information gradually from the pixel level to higher abstract levels, allowing them to extract both global properties and subjective information from the image dataset [23]. For model training, the Keras framework with a TensorFlow backend was used in this study. The implemented CNN architecture has a sequential structure, with layers receiving input images from the layers that came before them. The first Convolutional Layer takes images with dimensions of (148, 148, 16) as input. CNNs are well-suited for a wide range of difficult signal processing tasks. CNNs are well-suited for a wide range of complex signal propagation applications, and the Rectified Linear Unit (ReLU) activation function was chosen due to its quick training performance. The Convolution layer, ReLU activation layer, and pooling layer comprise the input layer. The vanishing gradient problem is substantially mitigated by ReLU activation, which necessitates computationally efficient procedures. As the output activation function, the softmax activation function predicts various classifications, including leaf blast, brown spot, hispa, and healthy.

TABLE 3: OUTCOME OF CANNY EDGE DETECTION AND K-MEANS CLUSTERING OF EACH CLASS

Disease	**Original Image**	**Canny Edge Detection**	**Clustering K=4**	**Clustering K=6**
Brown Spot				
Hispa				

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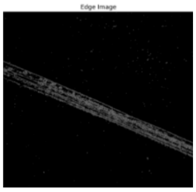
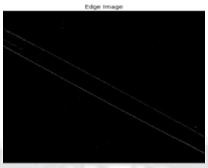
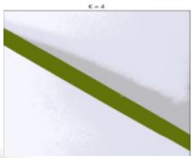
Leaf Blast				
Healthy				

To avoid overfitting, the 'Dropout' strategy was used, which randomly set the outputs of hidden neurons to zero with a predetermined frequency. The output features are flattened so that dense layers can learn each feature sequentially from the previous layer. Two dense layers are used: the first contains 512 hidden layers or feature maps, and the second has the four predicted classes: brown spot, hispa, leaf blast, and healthy. Figure 4 represent the output features produced by sequential CNN Model.

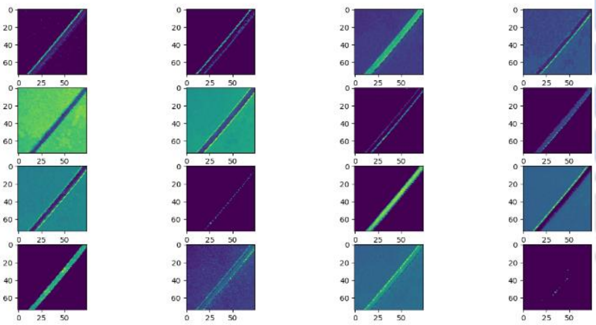


Figure 4: Feature Map Extracted from Sequential CNN Model

TABLE 4: DESCRIPTION OF WIDELY USED FEATURES [20]

Feature	Mathematical Expression	Description
Inertia moment	$\sum_{\alpha}\sum_{\beta}\frac{\Phi(\alpha,\beta)}{Normalization}\lvert\alpha-\beta\rvert^2$	Moment Of Inertia estimated to calculate the position of items
Absolute Difference	$\sum_{\alpha}\sum_{\beta}\frac{\Phi(\alpha,\beta)}{Normalization}\lvert\alpha-\beta\rvert$	Co-occurrence matrix values were multiplied at its absolute row distance
Mean	$\sum_{\alpha=\beta=0}^{\Upsilon-1}(x-y)\,\text{€}_{\Delta x,\Delta y}(\alpha,\beta)$	Average intensity value of the pixels existing in the region
Standard deviation	$\sum_{\alpha=\beta=0}^{\Upsilon-1}(x-y)^2\,\text{€}_{\Delta x,\Delta y}(\alpha,\beta)$	Degree of extent the gray levels diverge from the mean
Entropy	$\sum_{\Upsilon=0}^{\Upsilon-1}\dot{m}^2\sum_{\alpha=\beta=0}^{\Upsilon-1}(x-y)^2\,\text{€}_{\Delta x,\Delta y}(\alpha,\beta)$	Degree of differences in gray levels
Variance	$\sum_{\alpha=\beta=0}^{\Upsilon-1}(i-mean)^2\,\text{€}_{\Delta x,\Delta y}(\alpha,\beta)$	Degree of an image's variance value
Kurtosis	$\sum_{\alpha=\beta=0}^{\Upsilon-1}(x-y)^4\,\text{€}_{\Delta x,\Delta y}(\alpha,\beta)$	Degree of the distribution of peaks is related to the normal distribution.
Skewness	$\sum_{\alpha=\beta=0}^{\Upsilon-1}(x-y)^3\,\text{€}_{\Delta x,\Delta y}(\alpha,\beta)$	Degree of statistical distribution asymmetry
Homogeneity	$\sum_{\alpha=\beta=0}^{\Upsilon-1}\text{€}_{\Delta x,\Delta y}(\alpha,\beta)^2$	The nearness of the dissemination of features in the GLCM
Contrast	$\sum_{\alpha=\beta=0}^{\Upsilon-1}\text{€}_{\Delta x,\Delta y}(\alpha,\beta)(\log\text{€}_{\Delta x,\Delta y}(\alpha,\beta))$	Dissimilarity in the brightness of the items in comparison to other things in the same pitch of seeing

B. Transfer Learning

Transfer learning is a frequently used technique that uses pre-trained CNN models that have been learned for a given task as a foundation for training models on new tasks. All layers of the model are randomly initialised and trained from scratch in the baseline training strategy. However, this training strategy frequently takes a long time to converge. Transfer learning, on the other hand, tries to use the pre-learned weights of convolution layers produced from models trained on large-scale labelled public datasets such as ImageNet. In this study, a pre-trained model using the large ImageNet dataset is explored. The pre-trained weights are then used to initialise the CNN

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network's convolution layers, while the dense layers are initialised using randomly generated weights. The model uses transfer learning to adapt the knowledge learnt from the ImageNet dataset to the job of classifying rice plant illnesses using the rice dataset. Figure 6 depicts a high-level overview of the transfer learning framework used for disease categorization in rice plants.

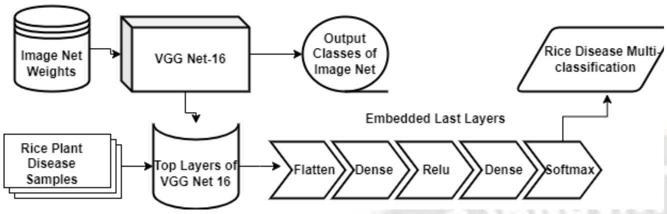

Figure 6: Transfer learning Model Used

The categorical cross-entropy loss function is used in this work to handle the multi-class classification task. The ReLU activation function is used in the network's intermediary layers, while the softmax activation function is used in the network's final layer. The following hyperparameters are used: a dropout rate of 0.3, a learning rate of 0.0001, 35 epochs, and a batch size of 128. These values were fine-tuned using 10-fold cross-

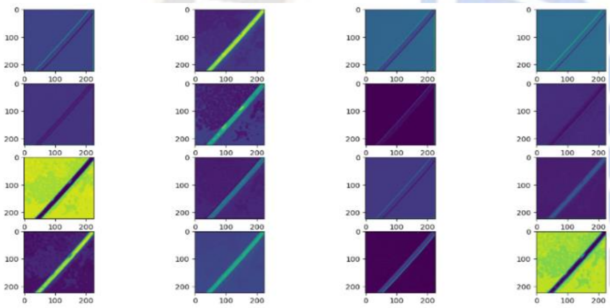

Figure 5: Feature Map obtained from Transfer Learning Model

validation and hyperparameter tuning. The Adaptive Moment Estimation (Adam) optimizer is used for weight adjustments during training. Before inserting photographs into each design, they are downsized to the architecture's preset image size. VGGNet16 is used for feature extraction, which generates a 4096-feature map from each picture sample in each class. VGGNet16 is a cutting-edge architecture noted for its effective classification skills. Because of its adaptability, it is frequently utilised for transfer learning. It is made up of 3x3 convolutions, 16 layers with trainable weights, and various extra filters [25]. VGGNet-16 is used simply for feature extraction in this study, not for illness categorization. The network's last three layers are eliminated, and two dense layers are used instead. As seen in Figure 6, the output features are flattened and transmitted through the dense layer. The network's final layers include a ReLU activation layer, and the softmax function is used for multi-class classification of rice illnesses. Figure 5 depicts the feature map produced by the transfer learning model.

V. RESULT AND DISCUSSION

The cross validation of 80×20 has been used to analyses the outcome of the models implemented. The suggested model employs a cross entropy loss function to assess the model's efficacy. To improve the ratio of cross entropy function, the optimizer adam is used by the work. Table 5 represented the confusion matrix of all the classes of the rice plant diseases classified by the proposed work. Similarly, Table 6 represented the confusion matrix of multi-classification using transfer learning for brown spot, leaf blast, hispa, and healthy classes of rice plants.

TABLE 5: CONFUSION MATRIX OF MULTI-CLASSIFICATION USING CNN MODEL WITHOUT TRANSFER LEARNING

Classes	**Brown Spot**	**Hispa**	**Leaf Blast**	**Healthy**
Brown Spot	195	14	6	8
Hispa	14	254	7	7
Leaf Blast	12	9	236	13
Healthy	7	8	13	314

TABLE 6: CONFUSION MATRIX OF MULTI-CLASSIFICATION USING TRANSFER LEARNING

Classes	**Brown Spot**	**Hispa**	**Leaf Blast**	**Healthy**
Brown Spot	204	6	4	8
Hispa	10	272	3	7
Leaf Blast	9	2	249	5
Healthy	5	5	6	329

The proposed work is assessed on various evaluation parameters like precision (P), Recall (R), F1 score (F) and accuracy (Acy). Table 7 shows the outcome of the multi-classification model using CNN model using with and without transfer learning on various parameters represented by equation 1-4.Table 8 represents the overall accuracy and loss obtained by multi classification model using both the scenario.

$$P = \left[\frac{Tp}{Tp+FP}\right] \quad (1)$$

$$R = \left[\frac{Tp}{Tp+FN}\right] \quad (2)$$

$$F = \left[\frac{(2*PC*RC)}{PC+RC}\right] \quad (3)$$

$$Acy = \left[\frac{Tp+TN}{Tp+FP+FN+TN}\right] \quad (4)$$

Where Tp-True positive, Fp- False positive, TN- True Negative, FN- False Negative

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Table 7: Evaluation Results of Multi-classification Model

Model	**CNN Without Transfer Learning**				**CNN With Transfer Learning**			
Classes	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
Brown Spot	94.54	87	86	86	96.26	92	89	91
Hispa	94.72	90	89	90	97.06	93	95	94
Leaf Blast	94.63	87	90	89	97.42	94	95	94
Healthy	94.99	92	92	92	96.8	95	94	95

TABLE 8: OVERALL RESULTS OF MULTI-CLASSIFICATION MODEL USING BOTH MODELS

Model	**Training Loss**	**Validation Loss**	**Training Accuracy**	**Validation Accuracy**
Sequential CNN	0.15910	0.1326	89.87	92.14
Transfer Learning Model	0.1991	0.1497	92.90	94.80

Figure 7 represents the accuracy and loss graph of baseline sequential CNN Model generated during the training and validation. Similarly, Figure 8 represents the accuracy and loss graph of transfer learning model generated over the training and validation process.

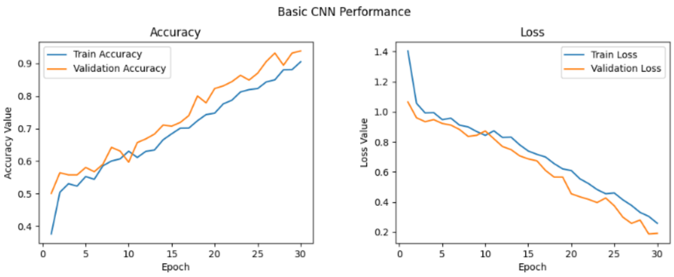

Figure 7: Accuracy and Loss Graph of Baseline Sequential CNN Model

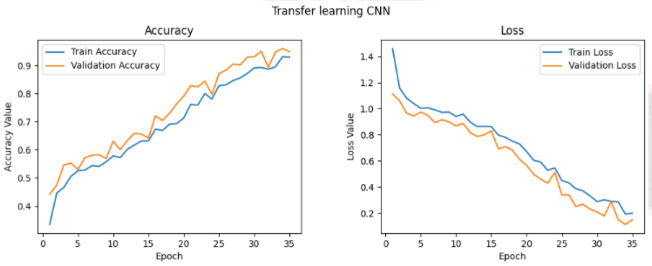

Figure 8: Accuracy and Loss Graph of Transfer Learning Model

VI. CONCLUSION

This work is developed the rapid and accurate technique for determining the disease present in rice plants. The proposed work recognized the four classes of rice plant diseases including three rice leaf diseases i.e. brown spot, leaf blast, and hispa including some non-diseased rice leaf. The data were acquired from plant villages, kaggle, and Bangladesh Rice Research Institute (BRRI) paddy fields. Canny edge detection is an image segmentation approach utilised in this work to find image edges by reducing noise. Furthermore, K-means clustering is used to divide entities into K groups based on the collection of features. Image categorization is accomplished by minimising the sum of the squares of the distance between the entity and the matching cluster. This study investigates transfer learning for deep CNNs with the purpose of enhancing the learning ability of achieving the classification outcome, and a sequential VGGNet16 architecture is constructed for the diagnosis of four kinds of disease found in rice plant. In this paper, a pre-trained model using the massive ImageNet dataset is analysed, and it is subsequently used to classify disease in rice plants learned on the rice dataset. For classification, the network's last three layers were deleted, and two dense layers were used, with the dense layer's output features flattened. The relu activation layer is included in the network's final layers, and the softmax function is employed for multi-classification of rice illnesses. The overall accuracy acquired by the CNN model without transfer learning is 92.14%, whereas the accuracy obtained by the transfer learning model is 94.80%. The accuracy of the transfer learning model for leaf blast, brown spot, and hispa, as well as the healthy, is 96.26%, 97.06%, 97.42%, and 96.8%, respectively. In future work, the proposed work can be encompassed to diagnose numerous other forms of diseases found in rice plants at an early stage. The implemented CNN framework might be employed to classify diseases by means of diverse statistics like fruit, grain, stem, and seedling images in edge computing environment.

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