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Detection of diseases in rice leaf using convolutional neural network with transfer learning based on ResNeXt

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ABSTRACT

Rice is the most cultivated crop in the agricultural field and is a major food source for more than 60% of the population in India. The occurrence of disease in rice leaves, majorly affects the rice quality, production and also the farmers' income. Nowadays, new variety of diseases in rice leaves are identified and detected periodically throughout the world. Manual monitoring and detection of plant diseases proves to be time consuming for the farmer and also a costly affair for using chemicals in the disease treatment. In this paper, a deep learning method of convolutional neural networks (CNN) with a transfer learning technique is proposed for the detection of a variety of diseases in rice leaves. This method uses the ResNeXt network model for classifying the images of disease-affected plants. The proposed model's performance is evaluated using accuracy, precision, recall, F1-score and specificity. The experimental results of ResNeXt model measured for accuracy, precision, recall, F1-score, and specificity, are respectively 99.22%, 92.87%, 91.97%, 90.95%, and 99.05%, which proves greater accuracy improvement than the existing methods of SG2-ADA, YOLOV5, InceptionResNetV2 and Raspberry Pi.

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1. INTRODUCTION

Agriculture is the most significant thing in the development of the Indian economy as the food demand keeps increasing day by day due to the ever-growing population in the country. The sector of agriculture needs improvement to attend to the problem of food scarcity [1]. The rice plant (Oryza sativa L.) is the most substantially available and the second largest produced food crop, which provides the most significant economic contribution if used as an export product. In the Indian economy, rice production is the primary income source and provides food for the world's population [2]. The rice crop fields are majorly affected by climate change, especially global warming. Due to such environmental and climatic changes, the biological and abiotic stresses which hinder the normal growth of crops, are becoming increasingly frequent [3]. Crop diseases tend to spread very quickly, posing a threat to healthy crops. Farmers face challenges when it comes to finding and diagnosing diseases in rice. It is not an easy task and requires a lot of time and attention [4]. Rice plants are affected by pests, and insects as well as most importantly affected by various diseases before the cultivation and early growing period. So, the advanced treatment and detection of rice plant diseases are crucial to ensure high quality and quantity of rice [5]. Accurate and early detection of rice leaf diseases has permits timely action that also decreases the disease impact. Therefore, an automatic monitoring system for the detection of diseases is a necessity, to allow for effective detection of rice leaf diseases [6]. Frequently used pesticides namely bactericides, nematicides, and fungicides, negatively impact the rice fields causing or increasing risk of diseases in them. Some examples of diseases include sheath blight and bacterial blight with symptoms affecting the rice color, form, and blast, which are characteristics of a sudden infection [7]. Bacterial leaf streak (BLS) is the most dangerous disease, and it occurs in the early stage of rice growth, spreads quickly and causes dreadful damage to the rice plant. The early monitoring and detection of BLS is of utmost importance to maintain the production of rice [8].

Convolutional neural networks (CNN) is a method of deep learning, that is commonly used to analyze disease imagery [9]–[11]. CNN has three layers consisting of the input, hidden, and output layers [12], [13]. It processes transfer learning more accurately and is capable of being trained with the convolutional layers. Its parameters are tuned and retained for extraction and classification [14], [15]. In computer vision and object detection research fields, the presence of multiple extremely small sized objects in the image poses to be a highly challenging problem for correct object identification. There are several object detection techniques that address this problem, such as pre-post processing techniques (data augmentation, network input size, image tiling), pre-trained model, and network architecture solutions (multi-scale feature map, multi-scale region proposal network (RPN), feature pyramid network (FPN), anchor boxes and loss function). These techniques serve various useful purposes, all aimed at improvement of object detection accuracy. However, in this research, the inclusion of any additional mechanism for performance enhancement inevitably complicates the process in some ways, such as memory consumption, inference time, or computation cost.

Haruna *et al.* [16] implemented the augmentation of the data pipeline by using the style-generative adversarial network adaptive discriminator augmentation (SG2-ADA). This method was used to improve single shot detector (SSD) and faster-region-based convolutional neural network (faster-RCNN) models, for detecting major diseases in rice leaves. In detecting rice leaf diseases, the SSD and faster-RCNN models performed augmentation on images. The proposed system achieved efficiency in detecting rice leaf disease and required fewer training datasets to create high-quality images. The limitations of this method were high time consumption and costly assurance of standard data augmentation quality. Jiang *et al.* [17] implemented the CNN to identify diseases in rice leaves by using the image features and the particular disease could be classified and predicted by utilizing the support vector machine (SVM). Optimal parameters were acquired for the SVM model through the 10-fold cross-validation method using two different parameters, c and g. This proposed model achieved higher accuracy and high convergence speed by using the SVM and deep learning model, but training the model needed a greater number of images. Jiang *et al.* [18] introduced a multi-task transfer learning model by using the visual geometry group network-16 (VGG16) model. This method is used ImageNet for initial training in transfer and alternating training, that recognizes the diseases in the leaf of the rice and wheat. This model is based on the alternate and fine-tuning learning method in multi-tasking and transfer learning. This proposed model achieves higher accuracy in recognizing the diseases in both rice and wheat and but, the amount of images required to train the model.

Azim *et al.* [19] introduced an approach for the classification and detection of diseases in the rice leaf. This model can detect the three different types of diseases in rice leaves as leaf smut, brown spot and bacterial leaf blight. In this method, using the saturation threshold, the backgrounds of the images are removed, and the areas of disease-affected portions were segmented. The characteristic features of shape, texture domain and color were taken out from the images. This model achieves higher accuracy in classification and reduced the model complexity but requires some disease images to classify the model and time complexity. Haque *et al.* [20] introduced a classification and detection of diseases in rice leaves based on the deep learning method of the YOLOv5 model by using the CNN. Using the YOLOv5 algorithm, the number of images of the rice leaf diseases was identified. This model used the collection of around 1,500 datasets for the classification and detection of diseases. The advantage of this proposed model was providing higher accuracy even when using a greater number of datasets. However, detection of new and unshaped images to be difficult for this model. Krishnamoorthy *et al.* [21] introduced a CNN algorithm, specifically the InceptionResNetV2 method that performed the transfer learning technique for rice leaf disease detection. For detection, this model observed the three major diseases spotted in rice leaves, leaf blast, brown spot, and bacterial blast. By using different parameters, the CNN model was fine-tuned for high accuracy. Hence, during the classification, the implemented method achieved the best accuracy, but it had problems in transfer learning and showed time complexity while training. Rumy *et al.* [22] introduced a system for detection of rice leaf diseases by using artificial intelligence (AI) techniques with edge devices. With a white background, this edge device used Raspberry Pi for the classification of disease images, and then the model was made to execute machine learning (ML). This proposed system considers three diseases in rice leaf, which are leaf blast, hispa and brown spot, and were most commonly seen occurring in Bangladesh. The advantages of this proposed model were that it was less time-consuming, highly accurate, and comprised of low-cost devices. The limitation of this proposed model was that it required more time to train the model.

From the overall analysis, it is inferred that the existing methods had limitations of higher time consumption to train the process, negative problem in the transfer learning, costly assurance of standard data augmentation quality, use of a wider range of images for efficient classification, and difficulty in detecting unshaped images. To address these complications, this research proposed a CNN with transfer learning approach, based on the ResNeXt architecture, to efficiently detect the diseases in the rice leaf. ResNeXt is used for classifying images into different classes and it also helps to decrease the error rate. Fine-tuning is used to change the original architecture and optimize memory storage. The proposed method achieves better results than the existing methods by utilizing the identity mapping as the residual function, which makes the training process easier by learning the residual mapping rather the actual mapping.

The major contributions of this proposed paper are detailed as follows:

– The development of the deep learning (DL) model is utilized for the detection of diseases in rice leaves.
– Transfer learning technique with CNN is established to achieve the most accurate classification and detection of plant diseases.
– ResNeXt is used for classification of images into different classes and it helps to decrease the error rate. Fine-tuning is used to change the original architecture and optimize memory storage.

The structure of the paper is organized as follows. Section 2 describes the proposed method. Section 3 explains the CNN classification model. Section 4 describes the result and comparisons. Finally, section 5 describes the conclusion.

2. PROPOSED METHOD

In this work, the developed model's purpose is detection of a variety of rice leaf diseases. In this section, various processes are explained that as data acquisition, data pre-processing and augmentation, feature extraction using a pre-trained model, fine-tuning, testing dataset, classification, and finally the results and analyses. Figure 1 shows the proposed diagram of rice leaf disease detection.

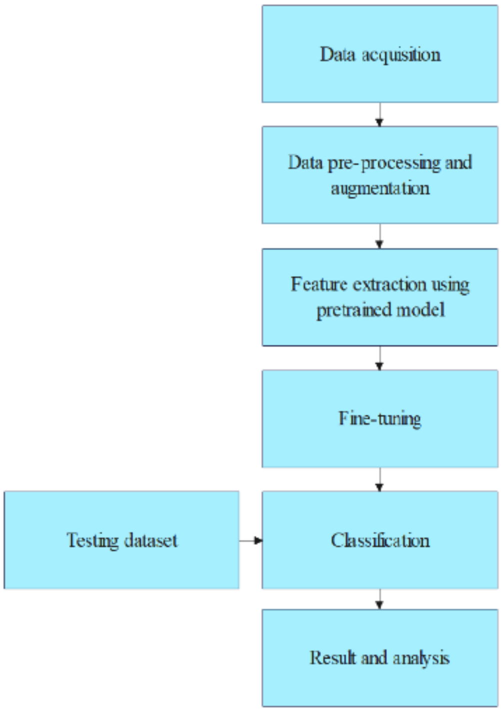

Figure 1. Effects of selecting different switching under dynamic condition

2.1. Data acquisition

The first stage of the proposed method is the dataset collection. In this method, various images depicting rice leaf diseases, taken at rice cultivation fields, are collected. The data collection consists of three classes of diseases namely leaf blast, bacterial blight, and brown spot. The class of healthy leaves is collected from 5,200 images. The symptoms of bacterial blight consist of a lesion, that normally initializes in the rice leaf tip, then spreads throughout the plant [23]. This is a very dangerous disease that affects rice production. The brown spot is a type of fungal disease. The symptoms of this disease have big spots on the leaf and it affects an entire leaf. In the early phase of this disease, circular, dark brown lesions are seen on the leaf. The symptoms of leaf blast disease have circular spots of greyish-green color with dark green border on the rice leaves. This is one of the most dangerous diseases in rice plants in various countries. The ResNeXt is used to implement the classification function. ResNeXt is a ResNet improved version and it processes the generation of transformation with the same topology. The ResNeXt is a uniform neural network, that reduces the number of hyperparameters required by the conventional ResNet. In image classification, the ResNeXt is a simple network having greatly componentized architecture. The collected rice leaf diseased images are then provided to the pre-processing step for improving the accuracy and reliability of the classifier.

2.2. Data pre-processing and augmentation

After the collection of data, the next stage is pre-processing of the images, which is a needed task for developing the input data to a normal state, that which is suitable for the establishment and training of the deep learning model. This improvement process in the data quality leads to the efficient, accurate, and meaningful extraction of features from the data. In the dataset collection, all images have red, green, and blue (RGB) coefficients in the range of 0-255 and different ($h \times w$). These images undergo the process of resizing and rescaling. In the pre-processing stage, every image pixel value is rescaled in the range of 0-1 and the whole image is resized into $224 \times 224 \times 3$ pixels shape. Augmentation of data is an easy process for applying minimum modifications to the original images to produce the new images. The image augmentation technique is used to increase the volume of original images in the dataset, for the purpose of training. In the real-time process of augmentation, horizontal and vertical image flipping, rotation, shearing, and random zooming are some of the applied image-altering techniques [24]. These image processing operations are employed by the image data generator class, which is prepared by the deep learning algorithm.

Some pre-processing techniques such as thresholding, is one of the simplest techniques for image pre-processing, which is majorly divided into local, global, and adaptive. It has the ability to create binary images of all pixels between 0 and 1. By utilizing this approach, the disease in the affected leaf is identified at an early stage, hence it reduces the data complexity and makes detection and classification, a simpler process. The (1) demonstrates this technique.

$$dst(x,y) = \begin{cases} maxval \ if \ src\ (x,y) \ > \ thresh \\ 0 \qquad otherwise \end{cases} \tag{1}$$

where the image pixel value is symbolized by x and y. The resultant pre-processed images are then provided to the feature extraction process.

2.3. Feature extraction using a pre-trained model

The feature extraction process utilizes the pre-processed image output as the input. The feature extraction helps to reduce the amount of redundant data from the dataset. In the end, the reduction of the data helps to build the model effortlessly and also increases the speed of learning and generalization steps in the machine learning process. The feature extraction method is an effective tool to extract the important informative features for the reduction of dimension. It is used to reduce the amount of required sources to describe a large amount of data. A large number of image categories are provided for feature extraction. An output of high-level data such as shape, color, texture, are identified in the process of feature extraction. The CNN [25] model extracts the input image features at the time of query by having pooling and convolutional layers that were prepared with various sets of filter sizes. In feature extraction and reduction of data for spectra analysis, the DL model is introduced due to the ability of its powerful representation by using transfer learning. Using the split function of the train test, 70% of collected data is used for training, and the remaining 30% of data is used for testing and validation. As in the DL framework, the autoencoder network learns abstract features from the hidden layer, which makes it a popular choice for the extraction of features. Data reduction is achieved with the hidden layers in the neural network through effective maintenance of data information [26].

A pre-trained model is used for training the model using a large image dataset. The required training time for deep learning is largely reduced. In ImageNet, the VGG-16 pre-trained model is used, which is fixed by a human-stipulated recognition system. ImageNet is a larger dataset with 1,000 categories. The pre-trained model is employed with parameters of 13 convolutional layers and a fully connected layer.

2.3.1. ResNeXt

The ResNeXt is a development of the deep residual network [27]. It is a simple network for image classification and it is made up of repeated blocks of the layers. Image classification is the process of classifying the images, and is the task of assigning a label to the image from a pre-defined set of categories. It is used to solve the problem of increasing error rate in the classification model. ResNeXt uses the similar blocks in the layers, for a multiple number of times that aggregates the set of transformation with the same topology.

The architecture of ResNeXt is homogeneous and it reduces the number of hyperparameters. This architecture is very simple and similar to the ResNet, but only the difference is another dimension is presented, called as the Cardinality dimension. The split-transform-merge strategy initially splits the input image into a 1×1 convolutional layer in low dimensions and then transforms the image into a 3×3 or 5×5 filter and finally, these are combined by using the summation operation. The transformations are collected in the same topology, for easier implementation [28]. ResNeXt is mainly used to control the large input and improve accuracy. Figure 2 shows the ResNeXt architecture. The resultant extracted features are then forwarded to the classification process to effectively classify the rice leaf diseases.

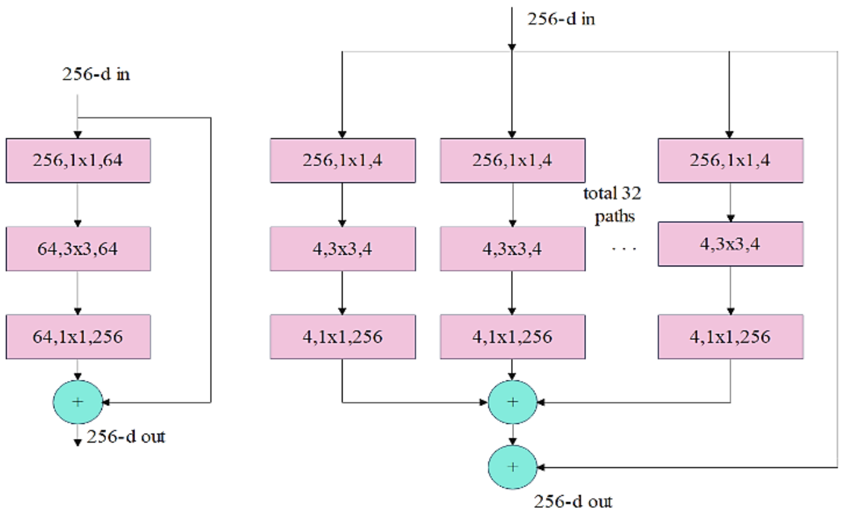

Figure 1. ResNeXt architecture

3. CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

The classification process utilizes the extracted image features as the input. In this classification method, a variety of rice leaf diseases are classified using CNN. A novel methodology is proposed for the detection of rice leaf diseases by using images of three rice leaf diseases, leaf blast, bacterial blight, and brown spot, collected from rice cultivation fields. CNN is a deep learning model, which is specially used for identifying patterns in image recognition and classification problems. The main idea of CNN is to develop a deeper network with a small number of parameters. CNN provides optimistic results when used in various fields. It contains multiple layers known as input layer, convolutional layer, pooling layer, fully connected layer, and output layer, and these are connected by learned weights and biases. These layers execute important functions in CNN by using the kernels such as size, padding and number. CNN is based on neurons organized in layers, starting with input layer and ending with the final output layer, connected by learned biases and weights. In between, the hidden layers transform the feature space of the input to match the output with one convolutional layer as hidden layer, which is needed in a CNN to form patterns. In this work, the ResNeXt model that is trained by the pre-trained model, works as a classifier to classify the variety of disease images of rice leaves. CNN passes the sample labelled image to the network layer, which generates the output at the final class. The convolutional operation is expressed in (2) as,

$$G[i,j] = \Sigma_{u=-k}^{k} \sum_{u=-k}^{k} H[u,v]F[i-u,j-v] \quad (2)$$

where H and F are symbols of the kernel, i and j are the indices of row and column.

Max-pooling is a hidden layer, which serves to combine and it greatly reduced the number of calculations. The classified images are then forwarded to the fine-tuning process. Figure 3 shows the CNN architecture.

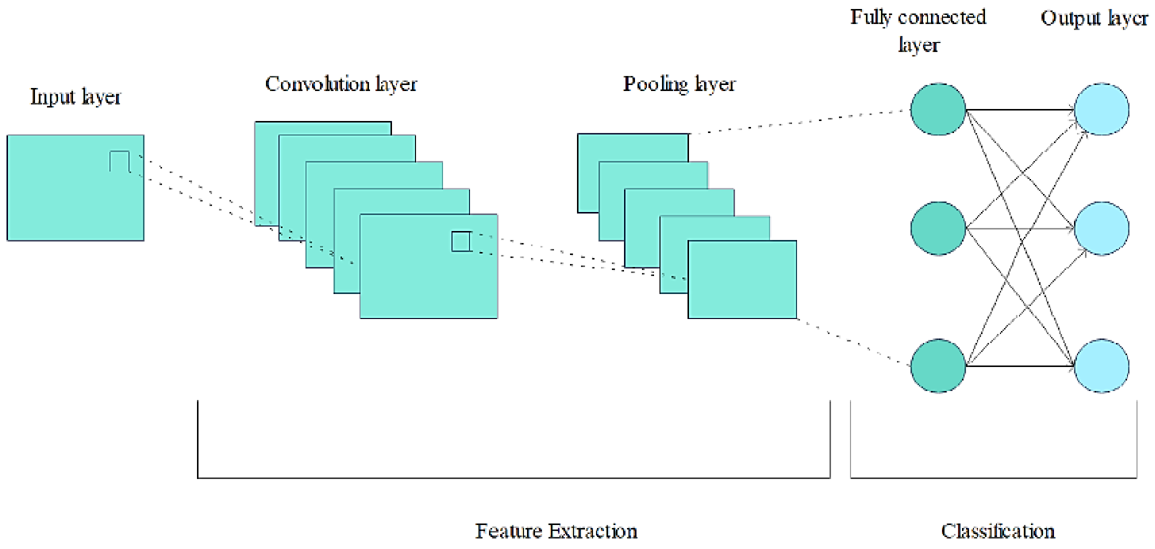

Figure 2. Convolutional neural network architecture

3.1. Fine-tuning

The classified images are then fine-tuned to obtain from pre-trained CNNs. Fine-tuning [29] is used to modify the raw data and optimize the data in the memory storage. The fine-tuning technique of the transfer learning-based approach is a helpful method for adjusting the resources' usage by performing feature extraction process utilizing "network surgery". Validating and generating the CNN model by selecting the most appropriate parameters using trial-and-error methods to determine the number of layers, learning rate, number of nodes and so on is indeed a difficult task. The various methods of fine-tuning the CNN include, updating the architecture, and re-training the model [30]. Generally, fine-tuning process consists of four important steps:

- The CNN model is pretrained.
- The final output layer is truncated and the parameters and designs of the entire model are copied to generate the new CNN.
- The head of the CNN is replaced with a set of fully connected layers. Then the model parameters are initialized randomly.
- The output layer is trained from scratch, with all parameters fine-tuned based on the initial model.

ResNeXt is an architecture of deep CNN. It consists of multiple convolutional layers. To increase the network depth, small convolutional filters are used to construct the architecture of the model. It takes the 224×224 image size with the three color channels as input. Then the input image with the 3×3 size of a small receptive field is passed to the convolutional layer and max-pooling layer. In this network, the activation function of ReLU reduces the set of ResNeXt training times. The ReLU feature is used to speed up the learning process, reduce the network size, avoid overfitting, improve generalization, and apply the max-pooling layer rather than the average model. A max-pooling layer follows the convolutional layer sets with 2 pixels to maintain the occupied resolution. The ResNeXt network has 16 convolution layers with the ReLU activation function between the input layer and max-pooling layers. After the convolutions, the linear classifier is made up of a fully connected layer between the first and second fully connected layers.

3.2. Testing dataset and classification

This research utilizes 70% of the data for training the model, and the balance 30% of the data for testing it, thereby partitioning the dataset into training dataset and testing dataset. After the developed model substantially learns from the training dataset, its implementation performance is validated by feeding it with data from the testing dataset. A thorough evaluation of the proposed method is done to achieve the desirable simplicity, accuracy, efficacy, and robustness. Hence, a large number of parameters are used to evaluate the classified data by the model. 500 image samples of disease affected rice leaves are given as input features, to the proposed CNN classifier for the identification and classification of the variety diseases in rice leaves. From this, 350 images are used for training the classifier and 150 images for testing the classifier, after which the image data is classified by the CNN classifier. Finally, the CNN classifier proficiently detects the various types of diseases, and appropriately classifies them into the correct disease classes.

4. RESULTS AND DISCUSSION

In this section, the proposed ResNeXt model's experimental results are discussed, and the comparison is done with existing methods, namely, VGG16, ResNet50, DenseNet201 and Inception V4. In this paper, the proposed model is simulated by using Python environment with the system configuration of 16 GB RAM, Intel core i7 pre-processor and Operating System of Windows 10 (64 bit). The statistical parameters of accuracy, precision, recall, F1-score, and specificity are used for evaluating the model's performance. The parameters are calculated from the disease detection executed by the proposed model on all the images of rice plants. The mathematical representations of these parameters are as:

– Accuracy: The ratio of all correct classifications to the total number of classifications.

$$Accuracy = \frac{True\ Positive\ \ + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative} \tag{3}$$

– Precision: the ratio of true positives over the classifications of all positives.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{4}$$

– Recall: proportion of original positives that were correctly classified.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{5}$$

– F1-score: combines precision and recall and gives average value of weight.

$$F1 - score = \frac{2x\ Precision\ x\ Recall}{Precision + recall} \tag{6}$$

– Specificity: proportion of original negatives that were correctly classified.

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ positive} \tag{7}$$

4.1. Performance analysis

This section shows the performance analysis of the CNN model with transfer learning in terms of achievable sum rate. The performances of the proposed CNN model are analyzed along with those of VGG16, ResNet 50, DenseNet201, and Inception V4 models. Table 1 shows these experimental results in light of the evaluating parameters which are accuracy, precision, recall, F1-score, and specificity. The likewise performance measures achieved by the various aforesaid network models are statistically shown in Figure 4.

Table 1. Performance analysis of various network models

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)
VGG16	88.71	85.81	81.85	82.85	85.87
ResNet 50	89. 81	87.83	83.86	83.87	91.88
DenseNet201	89.86	90.85	85.88	86.85	97.85
Inception V4	99.19	91.87	89.89	87.88	97.89
ResNeXt	99.22	92.87	91.97	90.95	98.88

The accuracy, precision, recall, F1-score and specificity of VGG16, ResNet 50, DenseNet201 and Inception V4, are measured and compared with those of the proposed ResNeXt model. The comparison proves the desirable improvement of the proposed ResNeXt model over the other models, as it achieves accuracy of 99.22%, precision of 92.87%, recall of 91.97%, F1-score of 90.95% and specificity of 98.88% respectively. Table 2 represents the comparison of the CNN model without transfer learning. The performance measure of CNN without transfer learning is shown in Table 2 and Figure 5.

The existing methods such as recurrent neural network (RNN), long short-term memory (LSTM), gated recurrent unit (GRU), deep neural network (DNN) are compared with the proposed method. The proposed CNN achieves accuracy of 84.0%, precision of 83.70%, recall of 82.40, F1-score of 84.78% and specificity of 83.09%. The performance measure of CNN with transfer learning is shown in Table 3 and Figure 6. The existing methods such as RNN, LSTM, GRU, DNN are compared with the proposed method.

The proposed CNN achieves accuracy of 99.22%, precision of 92.87%, recall of 91.97%, F1-score of 99.05% and specificity of 98.88% respectively.

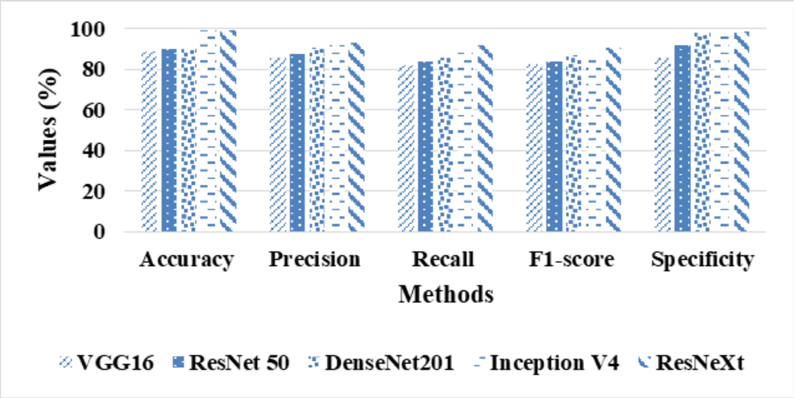

Figure 4. Performance analysis of various network models

Table 2. The comparison of the CNN model without transfer learning

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)
RNN	73.85	71.37	71.29	72.90	63.85
LSTM	75.29	75.21	75.19	75.87	71.29
GRU	79.87	78.89	78.26	78.98	74.87
DNN	82.39	80.56	79.37	80.23	83.97
CNN	84.0	83.70	82.40	84.78	83.09

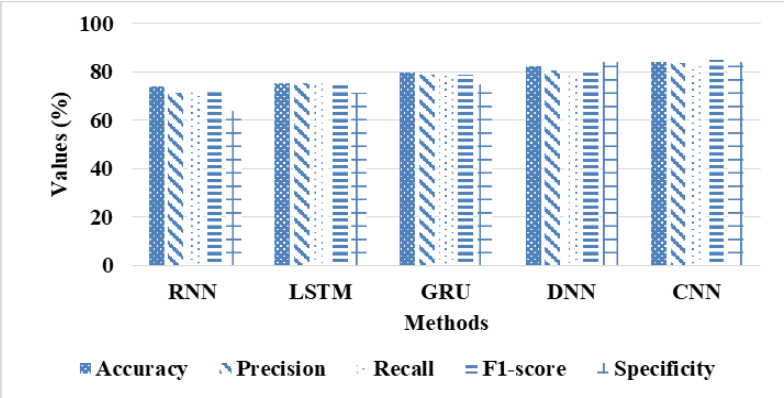

Figure 5. The comparison of CNN model without transfer learning

Table 3. The comparison of CNN with transfer learning

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)
RNN	82.24	81.37	80.24	81.30	83.05
LSTM	88.87	84.81	83.38	84.58	83.29
GRU	92.47	89.39	85.68	86.55	88.47
DNN	95.27	92.56	89.33	87.22	91.26
CNN	99.22	92.87	91.97	99.05	98.88

4.2. Comparative analysis

This section talks about the comparative analysis of the proposed CNN classifier in terms of accuracy, precision, and recall are shown in Table 4. Existing researches of [16], [20]–[22] are used to evaluate the effectivity of this classifier. The proposed model is trained, tested, and fine-tuned with the transfer learning approach.

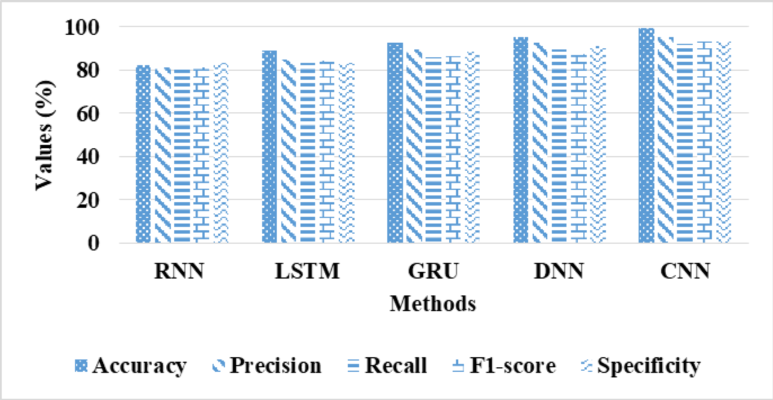

Figure 6. The comparison of CNN with transfer learning

Table 4. Comparative analysis of the existing models with the proposed model

Author	Method	Accuracy (%)	Precision	Recall	F1-score
Haruna *et al.* [16]	SG2- ADA	91.83	0.49	0.14	N/A
Haque *et al.* [20]	YOLOV5	96.5	N/A	N/A	N/A
Krishnamoorthy *et al.* [21]	InceptionResNetV2	95.67	0.91	0.90	0.98
Rumy *et al.* [22]	Raspberry Pi	97.50	0.98	0.97	0.98
Proposed-CNN with transfer learning	ResNeXt	99.22	0.92	0.91	0.99

4.3. Discussion

This section provides the discussion about the result comparisons of the proposed method. The SG2-ADA [16] had the limitation of high time-consumption and the assurance of standard data augmentation quality was costly. The limitation in the existing model YOLOV5 [20] was that it was difficult to effectively detect the rice leaf of new and unshaped images. In the computer vision research field of object detection, the wide variance in the object sizes, presence of multiple objects or extremely small sized objects in the image were challenging problems. Therefore, several object detection techniques are developed to address such problems, for example: pre-post processing techniques (data augmentation, network input size, image tiling), pre-trained model, and network architecture solutions (multi-scale feature map, multi-scale RPN, FPN, anchor boxes and loss function). All these techniques were created for various purposes, but the common aim was improvement of object detection accuracy. However, any additional performance enhancements in these researches would always land up complicating the system even more, especially in terms of memory consumption, inference time, and computation cost. To address these complications, this paper proposed a CNN with transfer learning approach based on the ResNeXt architecture to proficiently detect diseases in the rice leaf. The ResNeXt successfully classifies the images correctly into their respective class of disease, namely, leaf blast, bacterial blight, and brown spot. It also aided in decreasing the error rate. The ResNeXt's original architecture was then fine-tuned, and the memory storage was optimized. The computed results of the various performance metrics show that the proposed method achieved enhanced results in all of these parameters. The accuracy was measured at 99.22%, precision at 0.92 and recall at 0.91, which are comparatively much better performance achievements than the existing methods of YOLOV5, that achieved accuracy as 99.06%, precision as 0.90 and recall as 0.67.

5. CONCLUSION

In this research, the effective classification and detection of rice leaf diseases are carried out by the proposed CNN classifier model. The model comprises of CNN-based ResNeXt architecture and is pre-trained using fine-tuning approach. The evaluation of this CNN using the transfer learning technique, is done by measuring the proposed model's execution efficacy with respect to multiple parameters. From the resultant parametric measures estimated from the ResNeXt model's implementation, it is inferred that the ResNeXt has indeed proven to be highly suitable for appropriate identification and detection of disease occurrence in rice leaf and that it also reduces the time complexity. This paper used 70% of the data for training the proposed model and 30% for testing the process of image classification conducted by the proposed model. It achieves a classification accuracy of 99.22%, precision of 92.87%, recall of 91.97%, F1-score of 99.05% and specificity of 98.88% respectively.

This proposed method also has certain limitations, for instance, more samples are required to make full use of CNN, it is fully dependent on the transfer learning, it will be unsuitable for a wider range of other applications, as it is built only based on the plant image database. The future scope for the research is to utilize the hyperparameter optimization techniques for the detection of plant diseases. Moreover, these techniques may be extended to cover many other rice diseases wherein symptoms may appear in other parts of the plant, so that the efficiency of the proposed system is further improved.

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