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Deep Learning-Based Classification of Rice Leaf Diseases Using Hybrid Ensemble Models

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Abstract

This research aimed to identify the possibility of applying deep learning to rice leaf diseases diagnostic procedures. The study applied different data preprocessing techniques that were the key to getting the data ready for the analysis process to a set of commonly used rice leaf images. The first process implemented was training different kinds of deep learning models, such as ResNet and DenseNet architectures, on the preprocessed data. To ensure the best possible performance, the top single models from each set were then combined into all the ensemble methods in a way that made them the most potent. The pre-trained models used were ResNet152V2, DenseNet121, InceptionResNetV2, MobilityNetv2, and all models were trained on the preprocessed data. The algorithms' success in classification was assessed based on the measures of accuracy, precision, recall, and F1 score. The most successful classifiers were combined into hybrid ensembles using the Ensemble method. The holistic approach to this matter brought the desired result that is a 98% accuracy in the classification of rice leaf diseases, which is truly a remarkable result that no single model can bring.

Keyword: Rice leaf disease detection, deep learning, computer vision, Convolutional neural networks, transfer learning.

INTRODUCTION

In almost half of the world, crop of rice is a one of the main grains of sustenance. Nearly everywhere in the globe cultivates it. About ten percent of all agricultural area is used for rice production. Production of rice has a major economic impact on India. Exported rice makes up a sizable share of the world's overall rice production. The agricultural industry accounts for 20.2% of GDP in our nation as well [1], and the world's population is growing at an exponential rate, which in turn is driving up demand for rice. Pressure to increase output inevitably builds up in the agriculture sector as a result. Foreign nations import and export a wide range of agricultural products. Nearly fifty percent of the globe's population depends on rice, which is a major crop globally [2]. Rice output should be increased by reducing yield losses because there is a limited amount of agricultural land. Agriculture has always presented a number of enduring problems to farmers and planting specialists.

Rice cultivation is highly dependent on environmental factors such as humidity, rain, soil, and weather. The amount of water required for rice cultivation is high, creating an ideal environment for the growth of microorganisms such as bacteria and fungi. This increases the likelihood of rice crops becoming infected with a variety of diseases. Currently, rice infections are on the rise, wreaking havoc on rice cultivation. The losses due to infections are the most affecting factor out of these. Loss due to various plant infections is about 20% to 100% [3]. Rice causes parasitic and non-parasitic disorders. Diseases might be minor, moderate, or severe.

Rice is an essential meal for many people worldwide due to its flexibility. It is grown mostly in water-rich Africa, Asia, and America. It contains vitamins, minerals, and fiber. It symbolizes plenty and fortune in many civilizations. Rice's value as a staple crop extends beyond nutrition and economics. It may be prepared in many ways, from boiled or steamed to fried or sweet rice. This has far-reaching geopolitical, environmental and security consequences. The production and distribution of rice should be done in a manner that is sustainable and fair in order to promote peace and stability in the world. Because it is a staple food for a large part of the world, rice is a key determinant to food security and hence, security of a nation.

This research aims to build and test machine learning models which can consistently identify and classify rice leaf diseases utilizing large and diverse datasets. Data collection, preprocessing, model training, & ensembles modelling comprise this multi-step process. To maximize each model's merits and minimize its drawbacks, an ensemble (model) strategy using many methodologies is created. The ensemble approach combines several predictions to enhance sickness detection performance by providing more reliable findings.

This study improves agricultural output, resource utilization, and sustainability by increasing rice leaf disease diagnosis. This study may help decision-makers, farmers, and various other stakeholders manage illnesses, reduce risks, and create policies

RELATED WORK

[4] The author of the research paper underscores the critical importance of rice leaf disease detection for the agricultural sector, given that nearly half of the world's population relies on rice as a staple food. The author notes that numerous researchers have addressed this issue, achieving varying results depending on the techniques employed. In this study, the author specifically applied the AlexNet technique to detect three prevalent rice leaf diseases: bacterial blight, brown spot, and leaf smut. This paper highlights that the use of AlexNet, a specialized classification technique in deep learning, yielded remarkable outcomes compared to previous works. The paper reports an impressive accuracy of over 99%, attributing this success to the implementation of an efficient methodology and effective image augmentation strategies. Through this research, the author emphasizes the potential of deep learning techniques like AlexNet in significantly enhancing the detection of rice leaf diseases, thereby contributing to improved agricultural practices and food security.

[5] In this research paper, the author emphasizes the significant negative impact of rice diseases on crop yield, highlighting that accurate diagnosis is crucial for mitigating these effects. The author draws attention to the fact that current techniques for identifying rice infections are frequently ineffective and imprecise, and they frequently call for specific tools. The study offers an automated diagnosis technique created and put into use using a smartphone application in order to solve these issues. Based on deep learning methods, the system makes use of a vast dataset of 33,026 pictures that depict six distinct types of rice diseases: brown spot, bacteria stripes disease, sheath blight, fake smut, neck blast, and leaf blast. The basis of this method is the Ensembles model, which integrates several sub models to increase diagnostic precision. The author validated the Ensembles Model using a new set of pictures, and the top 3 sub models, according to metrics which includes learning rate, recall, precision, and sickness detection accuracy, were SE-ResNet-50, ResNeSt-50, and DenseNet-121.

[6] The need of recognizing rice illnesses of leaf in agriculture is emphasized by the author of this research in order to preserve the health and production of rice crops. According to the research, traditional methods of identifying illnesses are flawed since they often require a lot of time and depend on human judgement, which may lead to delay in medical treatment and diagnosis. To address this issue, the author suggests using convolutional neural network to identify and categories brown spot, leaf smut, and bacterial leaf blight—three common diseases that affect rice leaves. The research compares the efficacy of the proposed CNN model against other CNN variations and offers the model's outcomes. Notably, batch normalization and dropout methods were not required for the model to achieve an accuracy score of 87% with an error rate (loss) of 0.75 percent. The author comes to the conclusion that this CNN-based method presents a viable means of promptly identifying and categorizing rice leaf diseases, which might enhance crop management and reduce yield losses in rice cultivation.

[7] The author of the research article emphasizes how essential rice is to India as a major crop and how diseases affecting rice leaves may significantly reduce crop yield and quality. Because diseases like Brown Spot, Hispa, and Leaf Blast directly affect food safety and economic stability, it is imperative to recognize them. To solve this, the author looks

at a variety of machine learning and deep learning techniques which have been used to diagnose various diseases in rice leaves, evaluating the models based on performance metrics including precision, recall, and accuracy. The author continues by stating that deep learning models have shown superior performance in comparison to traditional machine learning techniques. In particular, the research discovered that a 5-layers convolutional model outperformed models like as VGG16, which attained a lesser accuracy of 58.4%, to provide the best accuracy of 78.2%. These findings imply that deep learning techniques provide more precise rice leaf disease identification, which may help farmers maintain healthy crop yields and minimize financial loss.

[8] In this research paper, the author emphasizes the critical role of rice in Bangladesh's economy, highlighting the necessity of timely disease detection for optimal plant growth. The author suggests an automatic rice leaf disease diagnosis system that makes use of machine learning methods in recognition of the labor-intensive process of manual disease identification. The three prevalent rice diseases that are the subject of this research are brown spot, leaf bacterial blight, and leaf smut. The author feeds the detecting algorithm with crisp pictures of the afflicted rice leaves on a white backdrop. Several machine learning techniques, such as Logistic Regression, K-Nearest Neighbor's, J48 (Decision Tree), Naive Bayes, were used for training after the necessary pre-processing. After ten-fold cross-validations on the test dataset, the Decision Tree algorithm's accuracy exceeded 97%, according to the findings, proving the value of machine learning in improving the detection of diseases in rice farming.

CNN ARCHITECTURES

DenseNet121: This particular design, known as DenseNet121, was chosen due to its dense inter connections, which allow for enhanced feature reuse and efficient gradient movement. photographs of rice leaves, which are necessary for disease classification, capture complex patterns and minute details. These photographs are vital for disease classification. All of the layers in the Dense-Net are interconnected and use feed-forward processing to exchange data. It creates "Dense Blocks" for this reason, which connect each layer directly. Dense blocks have many convolutional layers. The following is the equation for a dense block: batch norm -> conv 3 x 3 -> ReLu Give up. The initial convolutional layer receives the input features, transforms them into extra features, and then passes the resultant information to the 2nd convolution layer of dense block 1. Only when all of the map features have the same size can they be concatenated. The transition layer is utilized to provide uniformity in the feature map. A second dense block receives the result of a transition layer of the second dense block as well as the output of the first dense block. The following functions comprise the transition layer: Batch norm, ReLu, convolution 1x1, dropout, and pool 2x2. In a typical 16 L-layer convolutional network, there is one link between each layer. The layers that are above them utilize the feature maps generated by the layers given below them as inputs, and vice versa. DenseNet reduces the number of parameters while improving feature propagation and resolving the vanishing-gradient problem.

ResNet152V2: ResNet is well-known for its residue connections, specifically its ability to assist in the resolution of the vanishing gradient issue that occurs in deep neural networks. The ResNet152V2 model is an extremely deep model that is capable of capturing complicated and high-level information such as photos of rice leaves. This enables it to distinguish between illnesses that are similar to one another more effectively. ResNet152V2, a sophisticated deep learning architecture, diagnoses rice leaf diseases for picture categorization. Batch normalization & residual connections improve ResNet, enabling deep networks without gradient disappearance. This design is great at extracting detailed patterns and attributes from rice leaf pictures, making it appropriate for many disease diagnoses. Skip connections preserve important model properties while decreasing overfitting, promoting learning. Due to its high cross-dataset generalization, ResNet152V2 can identify rice leaf diseases more accurately, improving crop management.

METHODOLOGY

The methodology has been illustrated in Figure 1

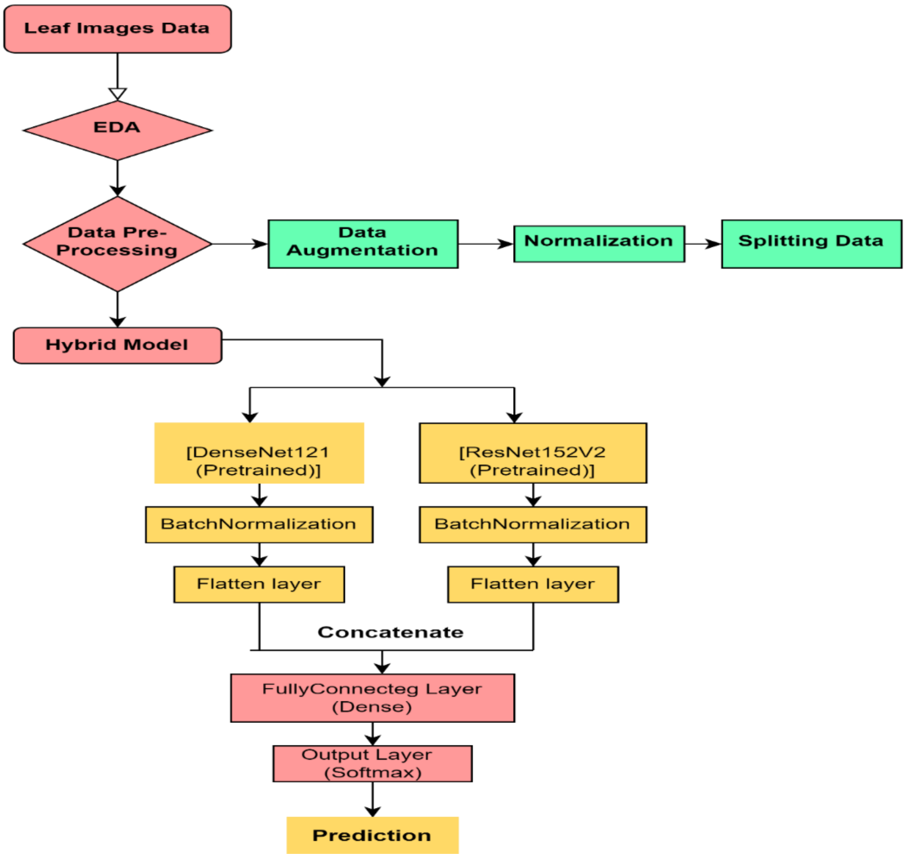

Figure 1 Flow of Methodology

A. Dataset

The data was collected from kaggle.com, a popular platform for data science and machine learning competitions. On Kaggle, a large number of datasets are available for public use. Individuals and teams may compete to solve a variety of data-related challenges on the well-known platform Kaggle, which also hosts datasets and data science contests. Datasets, instruments, and tools for machine learning, data analysis, and artificial intelligence (AI) development are made available to a group of data analysts and hobbyists via Kaggle. This data is meant to be used for the identification and classification of nine distinct rice leaf diseases: Narrow brown spot, Hispa, Neck Blast, Brown Spot, Leaf Blast and Leaf Scaled as show in fig 2. Each classification represents a unique pathogen that affects rice plants. In order to facilitate the process of training and evaluating deep learning models designed to automatically identify certain diseases, the dataset provides annotated images. Researchers investigating diseases of plants and agricultural technology, both experts and amateurs, may utilize this knowledge to develop effective solutions for early rice crop health diagnosis and management.

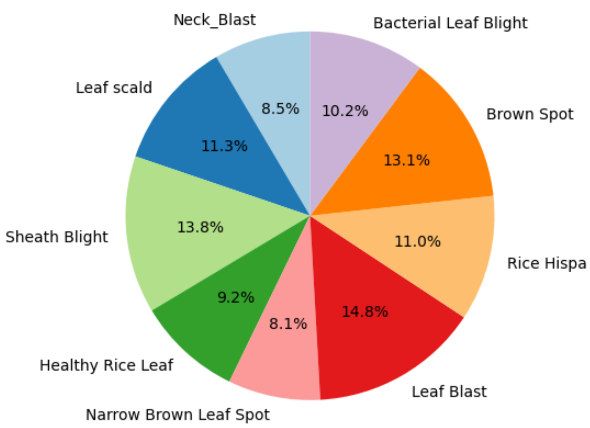

Figure 2 Dataset Sample

Overall, the data collection process in this research involved careful selection and cleaning of the data to ensure that it was of high quality and suitable for the research question at hand.

B. Image Pre-Processing

To get the desired outcome, pre-processing of data includes scaling, cropping, and noise removal from the original picture. Improving some picture properties that are necessary for a later step is the primary goal of the preprocessing stage. In this step, certain unwanted aspects from the supplied picture must be removed. The second step in the preprocessing procedure divides the picture into clusters. Some of the picture's unnecessary elements, such the backdrop and unimportant sections, are eliminated to speed up image processing.

The identification of diseases is greatly aided by image enhancement. It describes the process of enhancing an image's quality, interpretability, and clarity to make it simpler for medical experts to identify and diagnose illnesses. To sum up, image enhancement plays a critical role in the identification of rice leaf disease since it improves the identification of disease signs, helps distinguish sick leaves from healthy leaves, lowers noise, standardizes pictures, makes quantitative analysis easier, and allows for automation. Image improvement helps promote sustainable agriculture, increased crop yields, and efficient disease control by enhancing the accuracy and interpretation of rice leaf pictures.

Resizing: In the first pre-processing step, known as resizing, have changed the size of each picture to a fixed 256 × 256 pixel size. In order for algorithms using deep learning to function, this step standardizes the input photos through making them the same size. Inappropriate resizing might result in the original image being warped or losing information.

Decoding: Using an image function from the TensorFlow library, and decoded the pictures in this next pre-processing stage. After a photograph is saved in the original format (such as JPEG or PNG), it must be decoded so that algorithms for machine learning may use it as a matrix of pixels. The images are now prepared for feature extraction and classification. However, in the event that the dataset contains a large number of images, decoding may take some time.

Rescaling: The next stage of pre-processing is rescaling, where utilize the libraries of Keras to normalize the pixel values of each picture within a range of from 0 to 1. Divided the pixel values of each image by the maximum of 255 pixels that may be included in an 8-bit picture. Various machine learning algorithms perform better after this stage because they often function better with normalized input data. But if done carelessly, rescaling also cause the original picture to become distorted or lose information.

Data Splitting: To quickly evaluate the performance of our deep learning models, separated the data set into test 20%, validation 10%, and training sets 70%. The testing sets and validation functioned as a separate dataset for assessing model performance, whilst the training set, which included the bulk of the data, was utilized to train the models and assured that the models have been trained and assessed on separate subsets of data by dividing the dataset in this way, which allowed for accurate estimate of the model's performance and generalization to previously unknown data.

C. Training

For the purpose of multi-class picture categorization, this is a novel kind of deep-learning algorithm which includes two convolutional neural networks (CNNs), namely DenseNet121 and ResNet152V2. The following paragraphs will present a comprehensive description of each part of this model.

1. Pre-Trained Model: DenseNet121

The first architecture component utilizes the pre-trained DenseNet121, which is a convolutional neural network inherited from ImageNet. The DenseNet architecture is a so-called "dense" architecture with entwined connections, in which all layers are feed-forward linked to all other layers. The dense connection thus causes better gradient flow and propagation of the observation characteristics. When used the argument include_top=False, we remove the classification layer from the original DenseNet121, and thus obtain the network as a feature extractor only.

Subsequently, the trainable=False command ensures that during training the pre-trained weights remain fixed, allowing the model to use already learned features while not updating them. The input to the model is an image of size (256, 256, 3) that is a regular RGB image. After the input picture has passed through DenseNet121's convolution layers, batch normalization is used to normalize the output, which is then flattened into a one-dimensional vector of features. This procedure also ensures that the extracted features are ready for further processing.

2. Pre-Trained Model: ResNet152V2

The third architecture component is the ResNet152V2, which is a CNN that has its weights pre-trained on the dataset called ImageNet. The ResNet network makes use of "residual" connections, which serve to avoid the vanishing gradient problem by enabling the flow of gradients more seamlessly throughout deeper layers. ResNet152V2 is also affixed feature extractor with frozen weights by using the trainable=False argument, like the DenseNet121 model. The include_top=False command removes the top classification layer, and the network is built only from the convolutional layers without the top architecture piece being added. This model also processes the input image, and the feature maps are normalized using batch normalization and then flattened which is akin to the way DenseNet121 is employed. This dual feature extraction process gives the architecture access to the best sides of both the DenseNet and ResNet models.

3. Input Layer and Feature Extraction

The architecture uses a single input layer of shape (256, 256, 3), which represents the input RGB image. This input is fed into both DenseNet121 and ResNet152V2 models. The model takes use of the complimentary extraction of features capabilities of both ResNet's residuals learning framework and DenseNet's densely linked layers by using two distinct architectures at the same time.

4. Concatenation of Extracted Features

Two different ResNet152V2 and DenseNet121 output feature vectors are combined into one feature vector. The concatenation step incorporates each network's high-level properties to enrich the output image. The differing feature extraction methods for both network for data is used to improve the model's capacity to detect increasingly complex data structures.

5. Fully Connected Layers

Following the combination of the characteristics of the two networks, the design reveals a succession of layers that are closely linked to one another. These layers provide additional processing to prepare the composite feature vector for classification. Batch normalization is used following the 512 units of the first entirely connected layers with ReLU activation in order to provide steady and rapid convergence during training. Next is batch normalization, followed by an activation of ReLU and a second completely connected layer with 256 units.

6. Output Layer

The dense layer of the final output layer is composed of nine units, which match the nine possible classes in the classification task. This layer generates a probability distribution across the nine classes using Soft Max function of activation. The model's prediction is based on the group with the greatest chance.

7. Compilation and Training

The hybrid model is built using the Adam optimizer, which is well-liked in deep learning because to its flexible learning rate capabilities. The category crossentropy loss function is chosen as it is a popular loss function for multi-class classification problems. The model's accuracy provides a straightforward means of evaluating categorization performance.

8. Model assessment

To ensure disease classification accuracy and reliability, this research must analyze deep learning models. For model evaluation, we focus on accuracy and F1-score. These metrics give crucial information about the model's classification skills and a good platform for comparing models and hybrids' rice leaf disease classification abilities.

RESULTS AND DISCUSSION

Based on evaluation criteria, the model classified rice leaf diseases successfully. The model achieves 98% for recall, precision, accuracy, and F1 Score. These findings show how well the model categorizes rice leaf diseases. To calculate precision, divide the total number of true and false positives by the total number of true positives. It evaluates how well the model finds good examples. The model's 98% precision rating shows its accuracy in recognizing positive events. For the purpose of computing the recall metric, the number of false negatives and true positives is divided by the total number of true positives. It acts as a gauge to determine whether or not the model is capable of identifying each and every outstanding case. The fact that the model has a recall score of 98% demonstrates that it has a very high level of memories for positive instances.

During process of computing F1 Score, which represents a weighted measurement of the accuracy of the model, recall and accuracy are taken into account. The recall and accuracy essential methods are used in the computation of this value. The F1 Score of the model is 98%, which indicates that it was able to strike an optimal balance between the accuracy & recall.

Below is the summary of the results in tabular form:

Table 1 Model Comparison without Image Augmentation

Metric	Value
Precision	98%
Recall	98%
F1 Score	98%
Accuracy	98%

Here are visual results of proposed mode –

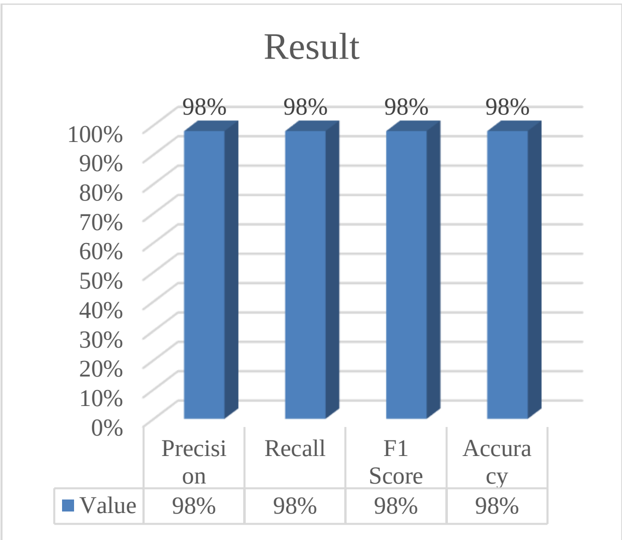

Figure 3 Result Comparison

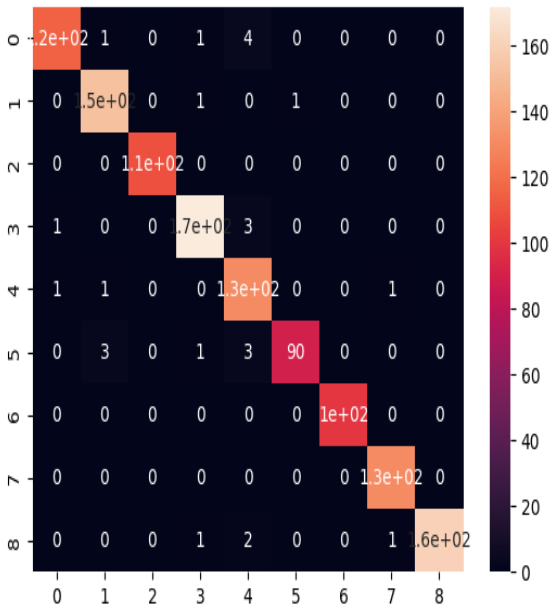

Figure 4 Confusion Matrix of proposed model on test data

Our suggested approach to rice leaf disease detection is a major improvement over current practices, especially with regard to scalability, accuracy, and resilience. By comparing our approach with the existing work, and highlight the improvements and novelty of our research. Prior research used the VGG19 model and convolutional neural network to categories rice leaf diseases. Using 10-fold cross validation, performance measures indicated accuracy values ranging from 95% for several rice leaf diseases. Dataset used in the existing work contained only 320 images, limiting the model's capacity to capture the complexity rice leaf disease patterns.

Table 2 Comparing the Proposed method with Existing Work

Model	Accuracy
Convolutional neural network (Exiting work) [9]	95%
Hybrid Ensemble Model (Proposed Work)	98%

Unlike the existing work, which was limited to a dataset containing only a small number of images, our research leverages a significantly larger dataset comprising 11790 images. This larger dataset improves the robustness and generalization abilities of our models in identifying different rice leaf illnesses and enables a more thorough examination of rice leaf disease categorization. Particularly for rice leaf diseases classification, suggest employing hybrid ensemble models, which combine the predictions of many base models via the application of the hybrid Ensemble approach. When compared to single models or basic ensembles, this method improves classification accuracy and resilience by using the complimentary characteristics of several algorithms for deep learning and ensemble approaches to detect a range of rice leaf diseases. When it comes to model performance and classification accuracy for rice leaf disease detection, our study outperforms previous studies. Our models perform better than those described in the previous literature and provide a better balance between recall and precision in the diagnosis of rice leaf diseases, overall values for accuracy ranging from 0.95 percent to 0.98 percent and F-1 scores range 0.98

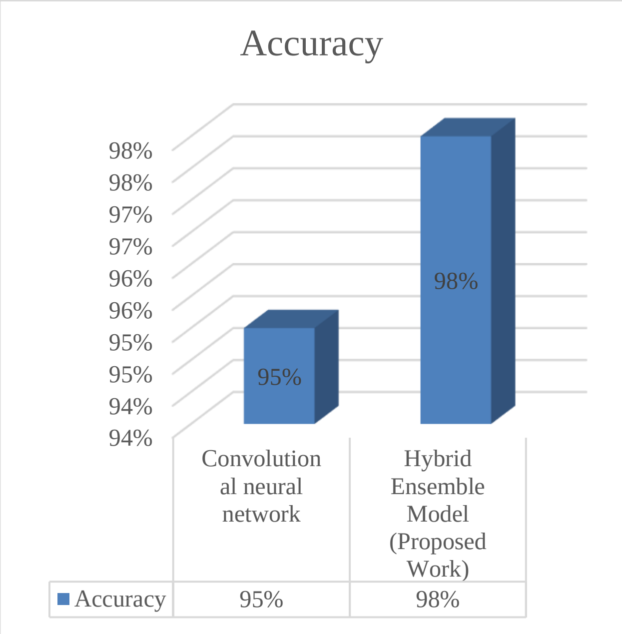

Figure 5 Graph of Comparing the Proposed method with Existing Work

CONCLUSION

In summary, examined transfer learning image classification for rice leaf disease diagnosis in this thesis. Also utilized the disease of rice leaves dataset and several pre-processing methods to prepare the photos for classification. Pre-processing includes rescaling, resizing, and decoding the photos to ensure homogeneity and improve the model's rice leaf disease recognition. Based on the findings and limitations of this study, there are several potential future directions for research in rice leaf diseases detection.

First, different deep learning approaches might be investigated for greater performance, even though transfers learning has been shown to be an efficient methodology for diagnosing rice leaf diseases. Autonomous learning and Deep reinforcement, for example, employed to improve the model's ability to learn and generalize to new and unidentified sickness patterns.

Secondly, although the categorization diseases of rice leaf are the only topic of this thesis, deep learning has several more potential benefits in the control of agricultural diseases. Future work could explore other applications such as disease progression tracking, automated disease detection or severity diseases detection.

REFERENCE

[1] “India GDP sector-wise 2021 - StatisticsTimes.com.” https://statisticstimes.com/economy/country/india-gdp-sectorwise.php (accessed Sep. 28, 2022).

[2] “•World rice acreage 2020 | Statista.” https://www.statista.com/statistics/271969/world-rice-acreage-since-2008/ (accessed Feb. 16, 2022).

[3] S. Savary, A. Ficke, J. N. Aubertot, and C. Hollier, “Crop losses due to diseases and their implications for global food production losses and food security,” Food Secur., vol. 4, no. 4, pp. 519–537, Dec. 2012, doi: 10.1007/S12571-012-0200-5.

[4] Matin, Md Mafiul Hasan, et al. "An efficient disease detection technique of rice leaf using AlexNet." Journal of Computer and Communications 8.12 (2020): 49-57.

[5] Deng, Ruoling, et al. "Automatic diagnosis of rice diseases using deep learning." Frontiers in plant science 12 (2021): 701038.

[6] Amith, K. R., et al. "Comparative Study of Various Optimizers and Transfer Learning Methods of Rice Leaf Disease Detection Using CNN." 2023 International Conference on Recent Advances in Science and Engineering Technology (ICRASET). IEEE, 2023.

[7] Pallapothala, Tejaswini. "Rice leaf disease classification using CNN." *IOP Conference Series: Earth and Environmental Science*. Vol. 1032. No. 1. 2022.

[8] Ahmed, Kawcher, et al. "Rice leaf disease detection using machine learning techniques." 2019 International Conference on Sustainable Technologies for Industry 4.0 (STI). IEEE, 2019.

[9] Kulkarni, Priyanka, and Swaroopa Shastri. "Rice leaf diseases detection using machine learning." *Journal of Scientific Research and Technology* (2024): 17-22.