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AN EFFICIENT APPROACH FOR RICE DISEASE DETECTION USING AN ENSEMBLE OF DEEP CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT
For most developing countries technically capable farmers, the identification of rice disease is still in its early stages. The current method for identifying rice infections is manual visual inspection, depending only on the skilled observers' unaided vision. When the illness diagnostic process is carried out manually, it takes a lot of time, and the pathologist's expertise is crucial to the diagnosis' correctness. Computer-aided diagnostic systems are therefore a good fit for this issue. There is a need for a model that can perform successful classification without the need for pre-processing, as opposed to depending on conventional machine learning techniques that necessitate perfect manual feature extraction to get good results. In order to identify plant illnesses, this project suggests using a convolutional neural network (CNN). It uses a database that has nine common rice illnesses in it. Four deep learning architectures DenseNet201, MobileNetv2, Vgg19 and AlexNet based on convolutional neural networks (CNNs) are used to study these disorders. Through transfer learning, four different pre-trained models are used for the study. This work uses an Ensemble model which consists of Densenet201, MobileNetV2, and Vgg19m in addition to individual models. The accuracy, precision, recall rate and F1-Score, among other performance indicators, are used to assess the effectiveness of the suggested methodology.

KEYWORDS:
Deep Learning, Convolutional Neural Networks (CNNs), Transfer Learning, Rice disease detection.

INTRODUCTION
Convolutional neural networks (CNNs) have shown to be a successful solution for rice disease detection and localization based on the rice plant's leaves. Following the trajectory, current CNN research indicates that the detection and segmentation of rice leaf disease has increased with the application of CNN. A sick rice leaf typically has spots, colors, and malformed shapes all over it. Therefore, a diseased leaf that differs from a healthy rice leaf in terms of color, texture, and dimension offers a chance to do image analysis using a CNN network and gather data on pixel-by-pixel inconsistencies throughout the leaf. It is anticipated that every pixel in a leaf will be identical in terms of all possible properties and characteristics, including texture, color, and intensity. On the other hand, when a small subset of pixels deviates from the rest, it tells us about an object's consistency or the existence of additional objects. Despite this, a small number of studies have been conducted to identify rice diseases using CNN, yet, there are still gaps in the knowledge regarding CNN-based rice leaf disease detection. First of all, as rice diseases vary from nation to nation, a thorough investigation into the majority of the epidemic diseases in a particular nation should be carried out. Instead of focusing on a small number of important classes, there should be a greater variety of rice diseases.

Second, a study is done investigating, if transfer learning, ensemble approaches, or novel CNN architectures may improve the accuracy of rice leaf disease detection. As a result, the purpose of this work is to evaluate how well-suited early cutting-edge CNN architectures such as DenseNet201, MobileNetV2, AlexNet, and Vgg19 for classifying rice plant disease detection. The final objective of this research is to identify the model with the best accuracy rate for rice leaf disease classification. Additionally, the transfer learning of MobileNetV2, DenseNet201, AlexNet, and Vgg19 networks, as well as the ensemble learning of Densenet201, MobileNetV2, and Vgg19 networks, are the objectives of this study. The fact that rice disease detection among farmers in the majority of developing nations with technological laggards is still in its early stages is another reason why this research is being done.

Using qualified specialists unaided eyes to visually evaluate rice crops is still a typical approach of diagnosing rice disease. To achieve this, a sizable team of specialists and ongoing observation are needed. For impoverished farmers, this is expensive and time-consuming when their farm is huge. However, in some nations, farmers lack the necessary tools or are unaware that they can seek advice from specialists. Plant disease detection by hand is a more time-consuming process that is only possible in certain locations and is prone to human mistake. As a result, the need for automatic detection approaches has grown. The following are this paper's primary contributions: First, utilizing a dataset of the 3 most common rice diseases. This research compares four original CNN architectures: DenseNet201, AlexNet, MobileNetV2, and Vgg19. Secondly, applied transfer learning approach on DenseNet201, MobileNetV2, AlexNet, and Vgg19 to determine whether transfer learning is capable of increasing accuracy. Thirdly, an ensembled model based on Densenet201, MobileNetV2, and Vgg19 networks was applied to draw a comparison between original, transfer learning, and ensemble techniques.

LITERATURE SURVEY

One of the most important cereal crops is rice, which is the primary food source for a significant portion of the world's population. However, the high incidence of many diseases that affect the crop at every stage of growth presents major challenges to the sustainable cultivation of rice. These diseases, which can be brought through a wide range of pathogens such as nematodes, fungi, viruses, and bacteria, can seriously reduce yields and endanger food security, especially in areas where rice production is a major industry. Now, it is critical to develop efficient methods for detecting and controlling diseases in order to maintain the productivity of rice farming systems. The quick and accurate diagnosis and implementation of suitable control measures is crucial to minimize crop losses caused by rice diseases.

To reduce crop losses brought on by rice diseases, prompt and accurate diagnosis and the application of appropriate control measures are essential. Visual inspection has long been the method employed by plant pathologists or agronomists to identify diseases, which can be laborious, imprecise, and prone to mistakes. But with the speed at which technology is developing, particularly in the fields of computer vision and machine learning, there has been a paradigm shift in the detection of rice disease away from human techniques and toward automated, data-driven approaches.

Research has recently focused a great deal of interest on using deep learning techniques, namely convolutional neural networks (CNNs), to automatically identify and categorize rice diseases from pictures of leaves, stems, and other plant parts. In contrast to conventional techniques, deep learning-based methods provide several benefits, including the ability to train discriminative features straight from unprocessed image data, scalability to enormous datasets, and the possibility of real-time field deployment.

The purpose of this survey is to present a comprehensive analysis of the current state of the art in deep learning-based diagnosis of rice illness.

The awareness of deep learning approaches for image processing and pattern identification has increased recently. The 39 classes of plant leaf photos in the Plant Village dataset were categorized in this study using the EfficientNet deep learning architecture. Modern deep learning architectures that have been used in research to detect plant leaf diseases required to be compared to the success rate of the suggested design. Both the original and enhanced experiments were conducted using the Plant Village dataset. The average accuracy and average precision measures on the original and enhanced datasets demonstrated that the B4 and B5 models outperformed previous CNN designs.

The literature survey encompasses a diverse range of studies leveraging deep learning methodologies for plant disease classification and identification. Atila et al. (2019) proposed a novel approach utilizing the EfficientNet deep learning model for plant leaf disease classification, demonstrating its superior performance. Geetharamani and Pandian (2019) conducted research on plant leaf disease identification using a nine-layer deep convolutional neural network, showcasing the effectiveness of deep learning in this domain. KC et al. (2019) introduced depthwise separable convolution architectures tailored for plant disease classification, emphasizing computational efficiency without compromising accuracy. Furthermore, Chen et al. (2020) explored the integration of deep transfer learning and lightweight network architectures for plant disease identification, focusing on efficiency and performance. Khan et al. (2018) developed an automatic system for fruit crop disease recognition, combining correlation coefficient analysis and deep CNN features. Sibiya and Sumbwanyambe (2019) proposed a computational procedure for maize leaf disease recognition using convolutional neural networks. Mokhtar et al. (2015) investigated the use of Support Vector Machine algorithms for identifying tomato leaf viruses, providing valuable insights into disease management in tomato cultivation. Mark et al. (2018) introduced MobileNetV2 architecture characterized by inverted residuals and linear bottlenecks, offering efficient yet powerful CNN models for various computer vision tasks. Acharya et al. (2020) proposed an ensemble of CNNs for paddy crop disease detection, highlighting the significance of leveraging multiple models for improved accuracy in agricultural disease diagnosis. These studies collectively underscore the importance of deep learning techniques in revolutionizing plant pathology, offering promising avenues for more efficient disease diagnosis and management in agriculture.

PRE-TRAINED MODELS

Transfer learning has emerged as a powerful technique in deep learning for adapting pre-trained models to new tasks with limited labeled data. Convolutional neural networks (CNNs) trained on large-scale datasets such as ImageNet have learned rich feature representations that can be transferred to related tasks, accelerating training and improving performance. In this paper, we conduct a comparative study of transfer learning using four popular CNN architectures: AlexNet, VGG19, MobileNet, and DenseNet. We investigate their effectiveness, computational efficiency, and transferability of learned features across different image classification tasks, providing insights for practitioners and researchers in selecting and optimizing CNN architectures for transfer learning applications.

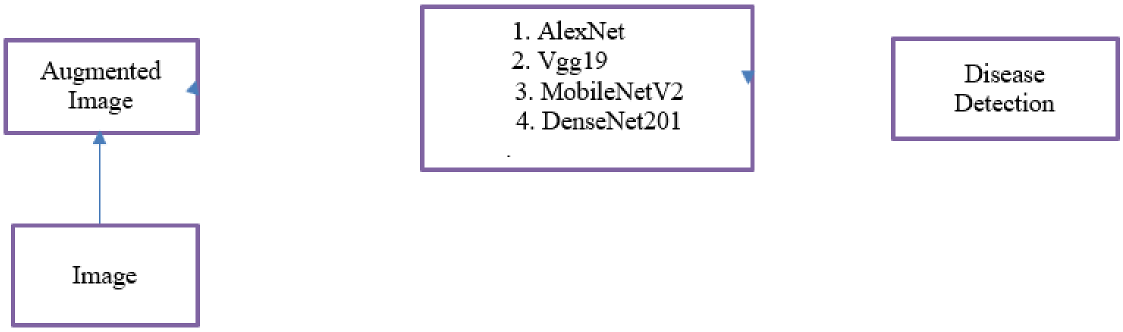

Fig 1: Block diagram

There are four pretrained models are being used in this approach., they are:
1. AlexNet
2. Vgg19
3. MobileNetV2
4. DenseNet201

AlexNet

AlexNet comprises a deep architecture with eight layers, including five convolutional layers followed by three fully connected layers. One of the first convolutional neural networks (CNNs) to be utilized for image identification and classification applications is AlexNet. It incorporates ReLU activation functions, which mitigate the vanishing gradient problem and accelerate convergence during training. Max-pooling layers are employed to downsample feature maps, reducing spatial dimensions and extracting dominant features. Additionally, AlexNet incorporates dropout regularization, randomly dropping neurons during training to prevent overfitting and improve generalization performance. Although the input size is stated as 224x224x3 in most places, it actually comes out to be 227x227x3 because of some padding. There are more than 60 million parameters in AlexNet. Images may be classified by the pretrained network into 1000 different object categories.

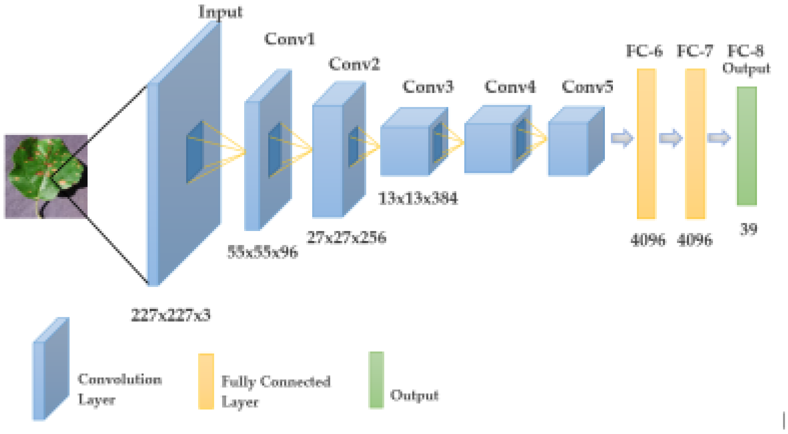

Fig 2: Schematic Representation of Alexnet

VGG19

VGG stands for Visual Geometry Group.VGG19 consists of 19 layers, including 16 convolutional layers and 3 fully connected layers. The architecture follows a uniform pattern, with small 3x3 convolutional filters and max-pooling layers applied throughout the network. There are 16 convolution layers in VGG-19, organized into 5 blocks. Following each block is a Maxpool layer which reduces the input picture size by 2 and raises the convolution layer's number of filters by 2. This uniform design facilitates model understanding, implementation, and experimentation. VGG19's deep architecture enables it to extract hierarchical features from input images, capturing both low-level features like edges and textures, and high-level semantic features relevant to the task of image classification. With 144 million parameters, VGG-19 is a remarkably huge model. Images may be classified by the pretrained network into 1000 different object categories.

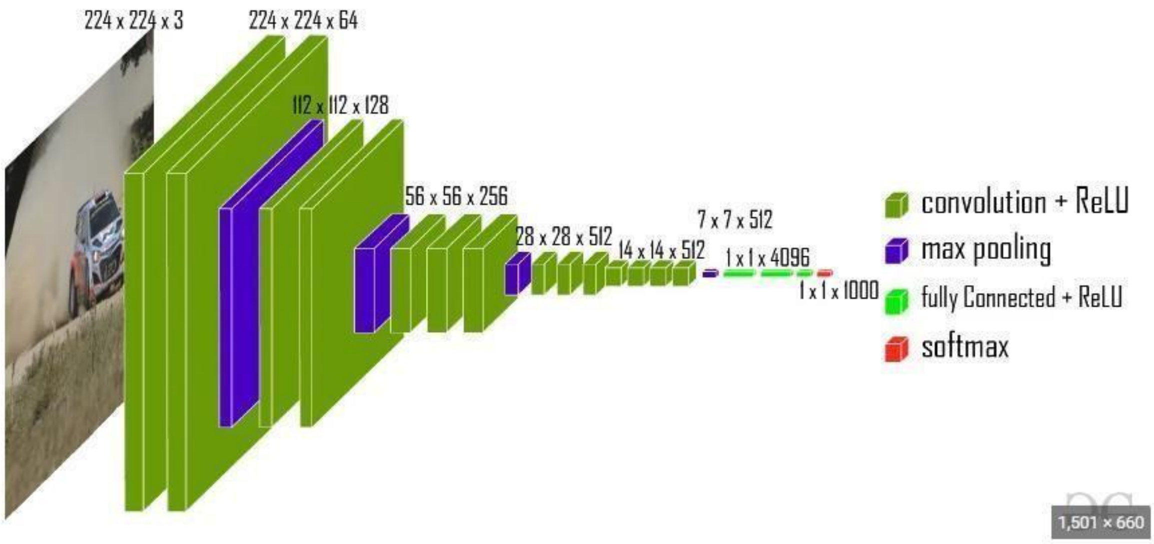

Fig 3: Schematic Representation of Vgg19

MobilenetV2

MobileNetV2 employs a novel architecture characterized by inverted residuals and linear bottlenecks. It utilizes depth-wise separable convolutions to reduce computational complexity while preserving representational capacity. The introduction of linear bottlenecks further enhances model efficiency by reducing the number of parameters and computations. By reducing the number of channels before applying depthwise separable convolutions, the bottleneck design in MobileNetV2 considerably lowers the computational cost. This design decision aids in preserving a sensible ratio between accuracy and model size.Additionally, MobileNetV2 incorporates inverted residuals, which leverage

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expansion layers followed by depth-wise convolutions to capture and propagate information more effectively through the network. The main network (width multiplier 1, 224×224) typically employs 3.4 million parameters and 300 million multiply-adds in computing. Images may be classified by the pretrained network into 1000 different object categories.

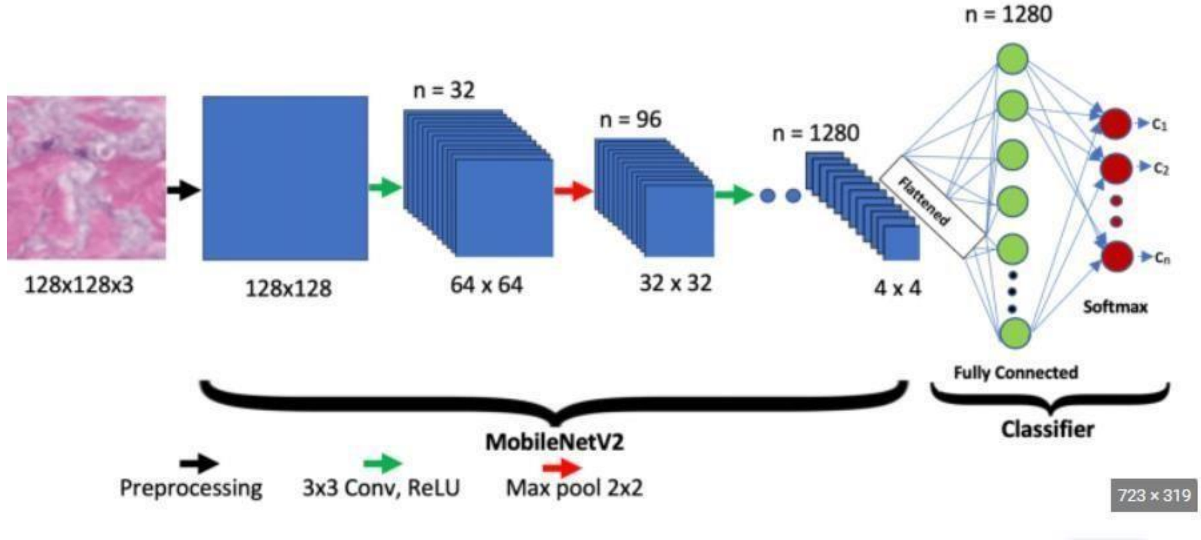

Fig 4: Schematic Representation of MobilenetV2

DenseNet201

DenseNet employs a dense connectivity pattern wherein each layer is connected to every other layer in a feed-forward fashion. DenseNet-201 employs neural networks with 201 layers and 20,242,984 parameters. The network has learned rich feature representations for a wide range of images, with an image input size of 224 × 224.This dense connectivity facilitates feature reuse and enables each layer to directly access the gradients from the subsequent layers, thereby alleviating the vanishing gradient problem. DenseNet comprises dense blocks, each containing multiple layers with direct connections between them. Additionally, DenseNet incorporates bottleneck layers and transition layers to reduce computational complexity and control feature map sizes throughout the network. The vanishing-gradient issue being resolved, enhanced feature propagation, feature reuse, and a notable decrease in the amount of parameters. Images may be classified by the pretrained network into 1000 different object categories.

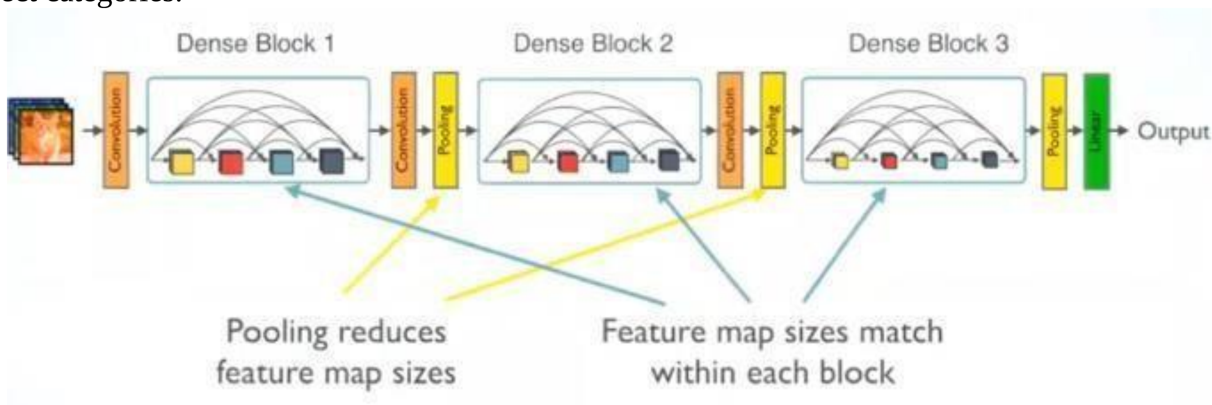

Fig 5: Schematic Representation of Densenet201

ENSEMBLE METHOD

There is a decrease in performance metrics using pretrained models such as Vgg19, AlexNet, DenseNet201, and MobileNetV2. Implementation of Ensemble methods appears as a purposeful, and intentional step toward improving the overall forecast accuracy. By utilizing the complementing qualities present in several models, ensemble learning provides a systemic solution to these problems. It provides versatility in the addition and composition of models, enabling experimentation and optimization to tackle particular machine learning problems. Ensemble approaches are regarded as the most advanced. These techniques improve the predictive performance of a single model by training many models and combining their predictions. Ensemble learning algorithms work by running a "base learning algorithm" and formulating a hypothesis in response to the output. Processes for validation and fine-tuning must be carefully considered during the training and assessment of ensemble models. Predictive accuracy and generalization capabilities can be improved iteratively by fine-tuning ensemble topologies, aggregation techniques, or individual model parameters based on validation performance.

The predictions of several different models are integrated to create a final prediction in ensemble learning, a potent machine learning technique. It is predicated on the essential idea of diversity. Ensemble approach seek to reduce the shortcomings of individual models and generate more reliable and accurate predictions by integrating many models that are trained on various subsets of data or with various algorithms. This strategy is justified by the possibility that multiple models would represent different facets of the underlying data distribution or show varying degrees of sensitivity to distinct patterns or features. Ensemble approaches can effectively harness the strengths of individual models while limiting their weaknesses by combining the predictions of various models.

The key advantage of ensemble learning is its ability to improve generalization performance. Generalization refers to the ability of a model to accurately predict unseen data points beyond the training set. Traditional machine learning models, such as decision trees, support vector machines, or neural networks, may suffer from overfitting, where they memorize noise or idiosyncrasies in the training data rather than capturing the underlying patterns. Ensemble method can help alleviate overfitting by combining multiple models that generalize well to different parts of the data distribution. It offers a versatile framework that can accommodate wide range of model types and learning algorithms.

THE DESIGN STRUCTURE OF ENSEMBLE MODEL

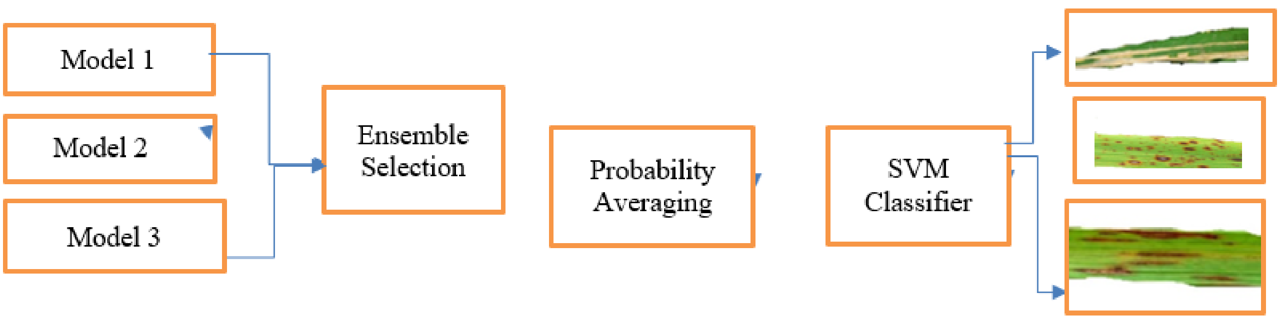

Fig.: Block Diagram of Ensemble Model

The description of the above block diagram is as follows:

1. Model 1: The probability scores of the pre-trained model, MobileNetV2 after training are considered.
2. Model 2: The probability scores of the pre-trained model, Densenet201 after training are considered.
3. Model 3: The probability scores of the pre-trained model, Vgg19 after training are considered.
4. Ensemble Selection: It is a technique within the ensemble learning that involves evaluating the performance of individual models on a validation set and selecting a subset of models that collectively achieve the best predictive performance.
5. Probability Averaging: Probability averaging in ensemble learning involves averaging the class probabilities predicted by individual models instead of the final predictions. This provides a more enhanced approach to decision-making, potentially improving overall accuracy.
6. Disease Detection: The final step is disease detection. Disease detection refers to the process of identifying or classifying whether an input image or data sample corresponds to a particular disease.

Ensemble learning offers several advantages that contribute to its popularity in machine learning. Firstly, it enhances predictive performance by combining multiple models, thereby reducing the risk of overfitting and improving generalization. Secondly, it can handle complex relationships in data by leveraging diverse base learners, such as decision trees, support vector machines, or neural networks. Additionally, ensemble methods are robust to noisy data and outliers, as errors in individual models can be mitigated through aggregation. Furthermore, they provide insights into feature importance, aiding in feature selection and model interpretability. Overall, ensemble learning stands out for its ability to boost predictive accuracy, handle diverse datasets, and provide robust solutions to various machine learning problems.

RESULT ANALYSIS

In this work, the four pre trained CNN models and an Ensemble model which is a combination of MobileNetV2, DenseNet201 and Vgg19 networks are presented. Firstly, the observation is focused on how the models were getting trained in the training stage. The accuracy curve and loss curve are used to identify the error during training period of a model. It is observed that training and validation losses are slowly reduced during the training process. For each individual models, the training and validation accuracy increases as there is an increase in the number of epochs. Secondly, the confusion matrix is used to evaluate each individual modified pre trained model and the proposed Ensemble model. The confusion matrix visualizes and summarizes the model's performance. The following figures represent the confusion matrix for the four modified pre-trained CNN models and proposed Ensemble model.

In the work, the number of test images is 24, which is 8 each for the three classes namely Bacterial leaf blight, Brown spot and Leaf smut. Out of all the pre-trained models the DenseNet201 is classifying the images better when compared to the other three networks, but not up to mark of prediction. Finally, the confusion matrix of the proposed Ensemble model has the highest prediction accuracy and it just misclassifies only one sample of the Bacterial leaf blight disease. From these quantitative analysis by calculating accuracy, precision, recall and F1-Score.

Considering the values in the confusion matrix obtained in such classifications, the metrics given between are calculated using indices such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). Here, TP is the number of correctly classified diseased images in each category, while TN, on the other hand, represents the sum of the correctly classified images in all other categories except for the relevant category. FN gives the number of misclassified images from the relevant category. FP gives the number of misclassified images in all other categories except for the relevant category. The performances of Ensemble and other state-of-the-art CNN models discussed in this paper are measured using different metrics such as Accuracy, Recall, Precision and F1-score.Recall is the ratio of correctly predicted positives out of all true positives. On the other hand, accuracy indicates the rate of correctly classified samples out of all samples. Precision is the proportion of correctly predicted positives out of all positive identifications. F1-score indicates the harmonic mean of precision and recall. It provides a balance between precision and recall and is particularly useful when there is an uneven class distribution.

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

$$\text{Precision} = \frac{TP}{TP+FP}$$

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

$$\text{F1-Score} = \frac{2TP}{2TP+FN+FP}$$

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Fig.1.1. Simulation Result of AlexNet

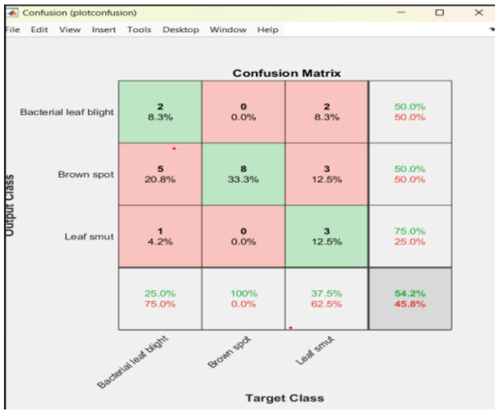

Fig.1.2. Simulation Result of Vgg19

Fig 1.3 Simulation Result of MobileNetV2

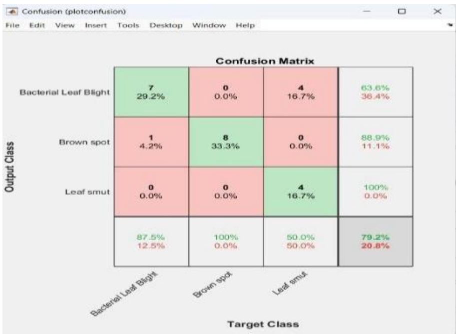

Fig.1.4. Simulation Result of DenseNet201

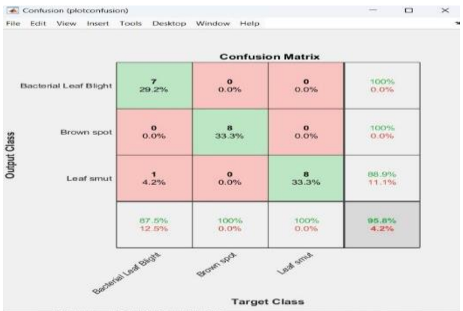

Fig.1.5. Simulation Result of Ensemble Method

COMPARITIVE ANALYSIS

PRE-TRAINED MODELS	ACCURACY		PRECISION	F1-SCORE	RECALL
Alexnet	Without augmentation	27.5	42.3	42.3	42.3
	With augmentation	42.5	48.3	48.3	48.3
MobilenetV2	Without augmentation	39.2	45.4	45.4	45.4
	With augmentation	95	97	97	97
Vgg19	Without augmentation	36	53	53	53
	With augmentation	95	97	97	97
Densenet201	Without augmentation	67.6	73.4	73.4	73.4

	With augmentation	97.3	98.2	98.2	98.2

Table 1.1: Analysis of the Networks with and without augmentation

COMPARITIVE ANALYSIS OF THE NETWORKS

SL.No	Networks	Accuracy	Precision	Recall	F1-Score
1.	AlexNet	20	0.33	0.33	0.33
2.	Vgg19	37	0.54	0.54	0.54
3.	MobileNetV2	50	0.66	0.66	0.66
4.	DenseNet201	66	0.79	0.79	0.79
5.	Ensemble Method (Proposed Method)	92	0.95	0.95	0.95

Table 1.2: Comparison of existing and proposed Networks

CONCLUSION

In conclusion, compared to individual networks like Vgg19, DenseNet201, AlexNet, and MobileNetV2, ensemble learning stands out as a potent strategy for enhancing model performance and robustness. Across a variety of tasks and datasets, ensemble approaches improve accuracy, resilience, and generalization by utilizing the combined knowledge of multiple sources. Ensemble learning is a flexible and successful technique for handling difficult machine learning problems in real-world applications because of its adaptability, flexibility, and tolerance to overfitting.

REFERENCES

1. U. Atila, M. Ucar , K. Akyol, et al., Plant leaf disease classification using EfficientNet deep learning model, Ecological Informatics (2019), https://doi.org/10.1016/j.ecoinf.2020.101182
2. Geetharamani, G., Pandian, A., 2019. Identification of plant leaf diseases using a nine-layer deep convolutional neural network (CNN). Computer Electronics Enineering. 76, 323–338. https://doi.org/10.1016/J.COMPELECENG.2019.04.011
3. KC, K., Yin, Z., Wu, M., Wu, Z., 2019. Depth-wise separable convolution architectures for plant disease classification. Computer Electronics Agriculture. 165, 104948. https://doi.org/10.1016/J.COMPAG.2019.104948
4. Chen, J., Zhang, D., Nanehkaran, Y.A., 2020b. Identifying plant diseases using deep transfer learning and enhanced lightweight network. Multimedia. Tools Applications. 1–19. https://doi.org/10.1007/s11042-020-09669-w
5. Khan, M.A., Akram, T., Sharif, M., Awais, M., Javed, K., Ali, H., Saba, T., 2018. CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features. Computer Electronics Agriculture 155, 220–236. https://doi.org/10.1016/j.compag.2018.10.013
6. Sibiya, M., Sumbwanyambe, M., 2019. A Computational Procedure for the Recognition and Classification of Maize Leaf Diseases Out of Healthy Leaves Using Convolutional Neural Networks (CNN). Agriculture Engineering 1, 119–131. https://doi.org/10.3390/agriengineering1010009
7. Mokhtar, U., Ali, M.A.S., Hassanien, A.E., Hefny, H., 2015. Identifying Two of Tomatoes Leaf Viruses Using Support Vector Machine. Springer, New Delhi, pp. 771–782. https://doi.org/10.1007/978-81-322-2250-7_77
8. Mark, S., Andrew, H., Menglong, Z., Andrey, Z., Liang-Chieh, C., 2018. Mobilenetv2: Inverted residuals and linear bottlenecks, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 4510–4520.
9. Acharya, A., et al., 2020, November. Plant disease detection for paddy crop using ensemble of CNNs. 2020 IEEE International Conference for Innovation in Technology (INOCON). IEEE, pp. 1–6