RESEARCH PAPER

Automated Plant Leaf Disease Diagnosis using Deep Learning

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ABSTRACT

Plant varieties are essential for the survival of human beings and animals, as they act as an alternative source of food, fiber, fodder, and other raw materials for domestic needs and industries in any society. Early identification of plant leaf diseases is very important for keeping the health of crops intact. Crops being infected can affect the overall yield of crops, which may be detrimental to the earnings of farmers. With the emergence of artificial intelligence technology, it has become possible to deploy systems for quicker identification of illnesses. This work has been carried out for the prediction of plant diseases based on visual phenotypic manifestations, such as images of leaves. For this purpose, the dataset has been created after retrieving data from the PlantVillage dataset. The clinical reliability of different deep learning models of various representational capacities has been tested while using ImageNet pre-trained parameters. The experimental results show that MobileNetV2 achieves the highest accuracy of 96.15%, outperforming deep CNN (76.92%) and medium CNN (61.54%). The test accuracy and class-wise F1-scores for the CNN are observed to be substantially very high. The generalization ability and result of DCNN and MCNN are moderate and poor, respectively, as observed. Additionally, the proposed CNN only uses the disease-affected areas on the leaf, thus making the result more interpretable.

Keywords: Deep learning, MobileNetV2, Vegetable leaf, Leaf disease, Agriculture.

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Introduction

Agriculture is an essential economic activity around the globe that con-tributes substantially to national GDPs, providing employment for billions of people around the globe. According to the annual report of 2024-25 published by the Ministry of Agriculture and Farmers Welfare, 54.6% of the total work- force is involved in agriculture-related activities. The environmental impacts of agriculture include effects on land use, water usage, greenhouse production, and biodiversity, which demand a green revolution and techniques that can reduce these impacts considerably. Preserving genetic variation is essential for growing a hardy plant that can endure current temperatures, new disease organisms, and pests, thus assuring food supplies into an uncertain future [1]. This can be achieved through selective plant variety, ground preparation, planting, irrigation, nutrition, and protection against weeds and plant dis- eases that can harm plant growth and affect its production. Plant diseases due to fungi, bacteria, and viruses appear as observable signs and symp- toms, consisting of changes in color, necrotic spots, texture, and shape on the surface of leaves. While biological attributes such as chlorophyll, water stress, nutrient stress, plant aging, and pathogens themselves are not quanti- tatively measurable, their impacts are naturally linked and exhibited on the surface of plant leaves [2]. For example, chlorophyll degradation manifests as yellowing or chlorosis, while fungal infections produce necrotic lesions and irregular textures. Bacterial diseases lead to water-soaked spots, and viral infections cause mosaic or mottling patterns. To tackle this issue, a range of image processing and deep learning techniques have been preferred for plant disease recognition due to their superior performance [3]. The CNN models implicitly learn these symptom-level visual cues, enabling effective disease discrimination without requiring specialized sensors or biochemical measure- ments. This image-based approach offers a non-invasive, cost-effective, and scalable alternative for field-level plant disease diagnosis.

In this study, a deep learning based framework is presented for the iden-
tification of plant leaf disease using image-based analysis. The proposed methodology will utilize the transfer learning technique to effectively cope with the scarcity of labeled datasets available in the field of agriculture. With the proposed technique, the model can be trained quickly. Generally, the pro- posed model will utilize the pre-trained, powerful model MobileNet-V2 for the experiment. Moreover, different depth-related CNN models have also been developed to effectively compare the learning capability of the models.

The models have been trained on the benchmarked disease detection dataset of the three different disease categories: Common rust disease, Early blight disease, and Bacterial spot disease.

The following points summarize the contributions of this paper:

- To analyze the performance of CNN models with varying depth for plant leaf disease classification using image-based data.
- To examine disease-affected regions of the leaf through qualitative in-terpretability analysis.
- To identify a computationally efficient model suitable for automated plant disease diagnosis.

1. Related Work

This is due to the rapid development of AI applications, making the us- age of smart imaging tools highly prevalent in the field. This has made it possible to create automated systems to identify diseases quickly and pre- cisely. Researchers have already started applying deep learning approaches, such as CNN, for image classification tasks. This differs from the traditional image classification approaches, where the model needs several features to perform tasks effectively. However, CNN does not require several features to perform effectively. Instead, the CNN has several filters, enabling the re- quired features to be extracted from images for effective classification. The availability of powerful GPUs, CPUs, and their high speeds enabled the devel- opment of deep learning approaches, particularly due to the introduction of powerful techniques to handle real data without the necessity of any hand- crafted attributes. In this article, the author has discussed a comparative analysis where they have applied various machine learning and deep learning approaches on a publicly available dataset. They have concluded that the deep learning approach performs better compared to machine learning ap-proaches. Table. 1 describes the summary of various recent works involved in plant disease detection, where a variety of approaches ranging from CNN to hybrid models are used.

Transfer learning is a method that helps a model developed for a source task to be adapted and applied to a target task. The knowledge transfer between CNNs involves applying the feature representations learned from a large-scale dataset in one domain and then fine-tuning the model on a small-scale dataset in another domain. [7] Extracts features from image dataset using pretrained models such as DensetNet-201, Inception-ResNet- V2 & NasNet-Mobile. [8] Use ResNet50 & DenseNet121 to classify tomato disease. [9] proposed model based on MobileNetV2 architecture for reducing the memory usage & computational expenses. The said architecture replaces the classification layer with five different layers to improve accuracy.

Table. 2 highlights the characteristics of benchmark datasets commonly used in plant disease classification research. Large-scale datasets such as PlantVillage
ovide a diverse set of leaf images from various crop species

		ns
6	Village Paddy Classi-fication	eal-time ation
	se tion Dataset	mber of
tex	Plant Leaf Fresh- and Disease Detectio angladesh); L2: Village Dataset	sease cla images
V2	it Dataset	increase s ime

and diseases, which are useful for developing generalizable deep learning models. Unlike other studies that focus on single-crop species or small self-collected datasets with small sample sizes, this study examines representative disease categories across three prominent crop species. These crops are chosen based on their agricultural significance, diversity in leaf images of various diseases, and the availability of expert-labeled samples. The inclusion of diseases from various plant species in the proposed dataset configuration allows for a bal- anced assessment of model generalization and class discrimination.

able 1: Recent work on Plant Disease Detection

2. Dataset & Experimental Setup

The models were implemented using Google Colab for Python. The PlantVillage dataset is a large set of 38 different classes of plant species and their respective diseases. In the proposed research study, as the crop

Table 2: Descriptions of widely used plant disease datasets

ef		ea	tegor	ecie	asse	age
10]	ge Dataset	016	sificati	14	38	,036
11]	antDoc	020	sificati	13	30	,569
6]	ase Classi-f	025	sificati	1	10	,407

selection is focused only on the top three major crops, which are tomato (2127 samples of leaves), potato (1000 samples of leaves), and corn (1192 samples of leaves), classes other than these are not taken into account within the research study. The crop leaves, along with the details of the crop, are provided in the following Table. 3. In the experimental analysis of the pro- posed research study, a multi-class classification approach is implemented, where every single type of leaf is assigned to a predefined disease class, such as Corn Maize in the common Rust disease, potato leaves in the Early Blight disease, and Tomato leaves in the Bacterial spot disease. While implement- ing the proposed plant disease detection system, the quality assurance of the collected data plays a vital role in the detection of plant diseases. Any sort of inaccuracies in the collected dataset during the training of the real-time detection systems might lead to a negative impact on the performance of the detection systems. The experiment is conducted using a single plant disease dataset, which is split into the training, validation, and test sets to avoid biased performance evaluation. Before training, all images are resized to 224×224×3 and normalized to identify consistent visual patterns while reducing illumination and scale variations. The detailed framework steps are discussed in Fig. 1. This preprocessing step facilitates effective feature learning across models of varying complexity. Model training is performed using standard optimization techniques with categorical cross-entropy loss. Performance evaluation is conducted using accuracy, precision, recall, and F1-score, along with confusion matrices to analyze class-wise prediction be- havior. Additionally, training and validation accuracy–loss curves are exam- ined to identify trends of underfitting or overfitting. Test-set performance is treated as the primary indicator of real-world applicability. Computational efficiency is further assessed using parameter count and inference time, en- abling deployment-oriented comparison among the evaluated models.

Table 3: Description of Selected Dataset

		nber of Imag
	ust	1,192
	ıt	1,000
	pot	2,127

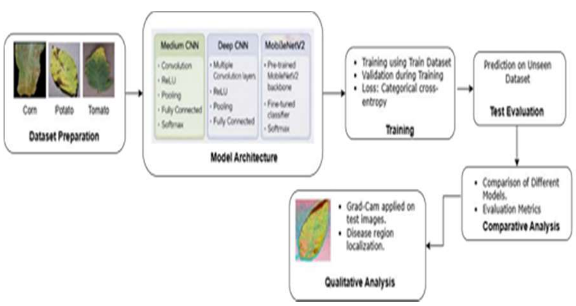

Figure 1: Plant Disease Identification Framework

3. Model Architecture

The proposed framework employs disease classification based on phe-notypic characteristics, which are visually extracted from images of leaves. Though various factors such as chlorophyll, water stress, nutrient deficien- cies, and aging affect plant diseases, they all cause symptoms such as leaf color, lesions, texture, and shape changes. The CNN model uses an implicit learning mechanism without using any measurements based on symptoms. Three types of CNN are considered, which are classified based on various levels of complexity, i.e., medium CNN (MCNN), deep CNN (DCNN), and a transfer learning-based model using MobileNetV2 (MNet) to study the ef- fectiveness of shallow and deep-level CNN for disease classification. Table. 4 highlights the architectural configuration details of the proposed models.

3.1. *Medium CNN*

The MCNN model has been developed to learn the basic visual elements from the leaf images, which can include different shades of colors, edges, and other texture features that may reflect the symptoms of any disease. There- fore, the model is composed of multiple convolutional layers, followed by different kinds of pooling, which help reduce the dimensions while learning useful features. Then, the model consists of fully connected layers for the classification of different classes. This model has been implemented with an appropriate number of learning parameters, which helps achieve convergence in a quick manner. However, the model, being shallow, is unable to learn all the disease-related features, which can be considered necessary for under- standing the irregular shapes and texture variations that reflect symptoms of disease. In the context of the present research work, the MCNN is used for analyzing the underfitting phenomenon.

3.2. *Deep CNN*

The DCNN framework uses a considerably larger number of trainable parameters. By using a larger number of convolutional layers, the model can learn hierarchical representations of features. This covers a range of features from low-level visual features such as edges and color contrasts to disease- specific representations such as lesion shape, texture, and spatial distribution. The use of pooling layers is an effort to reduce the resolution while using the convolutional layers to detect salient features of the image to identify specific diseases efficiently in plants. This makes the model highly sensitive to the visual representations of different diseases affecting plants on the one hand and makes it highly prone to overfitting on the other.

3.3. *MobileNetV2*

Due to the use of depth-wise separable convolutions and inverted residual blocks, the performance of MobileNetV2 is improved with reduced numbers of parameters and computational cost, and better feature extraction capability [12]. The MNet architecture uses pre-trained weight values on the dataset, which allows the use of pre-trained generic visual features learned from a variety of images in the wild [13]. Pre-trained features represent the basic features of image contents, such as texture

	CNN	MCNN	DCNN	
	6 × 256 × 3	6 × 256 × 3	256 × 256 × 3	56 × 256 × 3
n Layers	2	3	6	53
	2 → 64	→ 64 → 128	→ 64 → 128 (× per block)	Fixed
	Max	Max	Max	erage
ected Lay-	128	256	512	256
	–	0.4	0.5	0.4
Weights	–	–	–	mageNet
ion Ability	Poor	Limited	Moderate	High

orientation, color gradients, and spatial hierarchies, which are easily transferred to leaf disease images. Fine- tuning of the network on the plant disease dataset adjusts the models for the use of domain-specific visual characteristics.

4. Results & Discussion

The performance of the evaluated models is assessed using an independent test dataset to provide an unbiased estimate of their generalization capabil- ity. Unlike training and validation metrics, which primarily reflect learning

Table 4: Network Structure Configuration

behavior, test-set evaluation serves as the primary basis for performance comparison and scientific claims in this study.

4.1. *Training & Evaluation Metrics*

To measure the effectiveness of plant disease classification models, various metrics are implemented. The metrics given in Table. 5 measure the correct- ness and discrimination ability of each model, which is vital for an accurate diagnosis system. The MCNN model indicates a low class-wise discrimina- tive ability, showing zero precision, recall, and F1-score for Corn Common rust and Potato Early blight disease classes. Though a very high value for the recall is shown, it only shows the biased nature, i.e., selecting a single class always, which does not indicate learning anything from feature repre- sentations. Thus, the low macro F1-value indicates that the model is unable to learn and generalize across various classes of diseases. The DCNN model exhibits a better performance in terms of class-wise discriminative ability, which shows a perfect value for Corn Common rust and Potato Early blight diseases. However, precision is also variable, especially for Potato Early blight disease, showing a mixture of confused classes, i.e., disease patterns, which look somewhat similar. Though a rapid increase is shown for overall accuracy, which surpasses that of MCNN, a significant change between macro and weighted values indicates the effect of class imbalance and overfitting. In contrast, the MNet transfer learning model has high precision, recall, and F1-scores across all classes, indicating a high level of transferability. The high level of balance evidenced by the close relationship observed between the macro-averaged and the weighted values is an indication of the high level of generalization exhibited. The improved performance observed in the case

of the MobileNetV2 model is an indication of the viability of the transfer learning mechanism in plant disease identification scenarios.

Table 5: Models Classification Report of Different Models Trained on the Plant Leaf Disease Dataset

		ecision	ecall	-Score
NN		0.00	0.00	0.00
		0.00	0.00	0.00
		0.62	1.00	0.76
		0.75	1.00	0.86
		0.58	1.00	0.74
		1.00	0.63	0.77
V2		0.75	1.00	0.86
		1.00	1.00	1.00
		1.00	0.94	0.97

4.2. *Training & Validation Performance*

The training and validation performance of the suggested models is ex- amined based on accuracy and loss curves over a given number of epochs. When it comes to MCNN as shown in Fig. 2, the training accuracy increases sharply, almost reaching perfect scores within a few initial epochs, while val- idation accuracy remains low and stagnant throughout all epochs. During this period, training losses become negligible, as they approach zero, while validation losses rise steadily over each epoch. This observation indicates significant overfitting, and this CNN tends to memorize instances without understanding any key feature of the disease that could help it classify accu- rately, thus failing on test instances.

The learning curve in Fig. 3 shows a smoother learning trend than that in MCNN. For DCNN, the accuracy in both training and validation data generally tends to increase. The validation accuracy is high during the early stages of the training process. The corresponding values in the loss curve decrease steadily in both the training and validation data. There is a minor fluctuation in the validation data, along with a difference in the accuracy

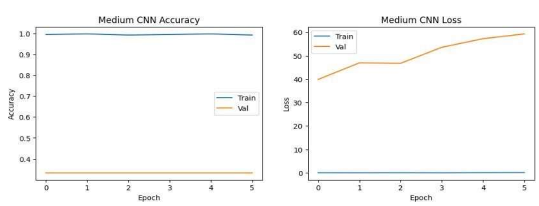

Figure 2: MCNN Accuracy vs Loss Curve

in both the training and validation data, which indicates that overfitting is occurring during the training process.

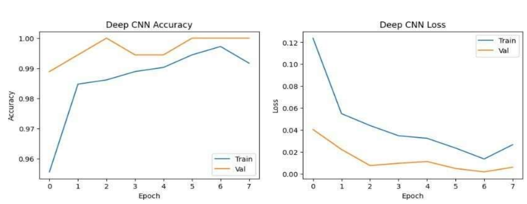

Figure 3: DCNN Accuracy vs Loss Curve

The learning stability and balance of the MNet model on both the train- ing and validation sets can be observed. In Fig. 4, the MNet model has an increased validation accuracy from the beginning, reflecting the training accuracy throughout the learning process. In addition, the gap between the training and validation accuracy indicates that the MNet model has a high level of learning generalization and the transfer of features learned during the training process. The loss curves for both the training and validation sets confirm the competence of the MNet model,
where the loss curves decrease and converge throughout the learning process. This can be attributed to the

application of pre-trained weights and DW separable convolutions, which fa- cilitate the learning of features and the avoidance of excessive parameters.

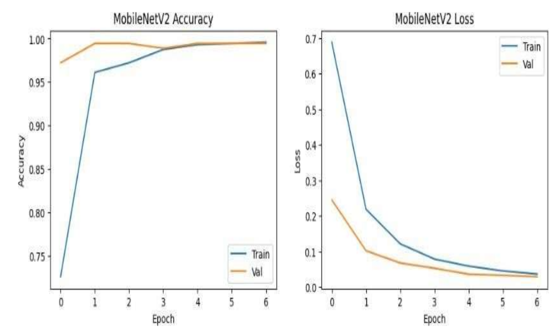

Figure 4: MNet Accuracy vs Loss Curve

4.3. *Test Dataset Evaluation*

For the MCNN as shown in Fig. 5, all the test classes are dominated and classified as Tomato Bacterial spot. There are no instances where any of the classes, i.e., Corn Common rust or Potato Early blight, are correctly classified. This implies that the model did not learn discriminative features for all classes, giving rise to its failure in classifying test classes. On the other hand, the D-CNN model clearly outperforms the M-CNN, where all test classes of Corn Common rust and Potato Early blight are correctly classified. It can be inferred that the feature extraction capability of the model has improved, possibly due to its deeper layers. However, classes from Tomato Bacterial spot are misclassified as classes of Potato Early blight and Corn Common rust. The MNet model has its confusion matrix perfectly classified. There is a single misclassification in the class of Tomato Bacterial spot, and all other classes are classified very accurately. This can be due to the pre-trained features being used in the model, which can learn better feature representations for the images.

4.4. *Comparative Analysis*

This section is concerned with selecting the best approach for practical implementation in the diagnosis of phytopathogenic diseases. As indicated

n Table. 6, MCNN has the lowest accuracy in the test phase despite good training accuracy. Although MCNN has a very good inference timing, it is not good at differentiating classes of diseases with distinctive external appearances, as was confirmed in the analysis of the confusion matrix. As can be seen in Fig. 6, the DCNN improves the accuracy in the test phase, but it does so at a cost in the number of parameters and the inference timing. The difference in accuracy in the validation and test phases is a good indication of overfitting. The inference timing is speedier in the DCNN. The performance of the transfer learning approach is good in all aspects as compared to the other CNN models. MNet has the highest test accuracy paired with the fewest parameters and shortest inference timing.

Table 6: Comparative Results of Different Models

							Time (
	9917	333	154	2540	4689	,785 283	527.53
	9917	000	692	7877	7707	,669 283	,632.36
	9960	944	9615	9416	9637	586, 91	0,625.57

4.5. *Qualitative Analysis using GradCAM*

The test dataset is exclusively utilized for the final performance evaluation of the models and the post hoc interpretability analysis of the classifier out- puts, employing Gradient-weighted Class Activation Mapping (Grad-CAM). The Grad-CAM images indicate the leaf surface areas that are responsible for the classification of disease type [14][15]. The Grad-CAM images of the proposed models, constructed employing the test dataset images, are illus- trated in Fig. 7. As per the Grad-CAM images of the MCNN classifier, the

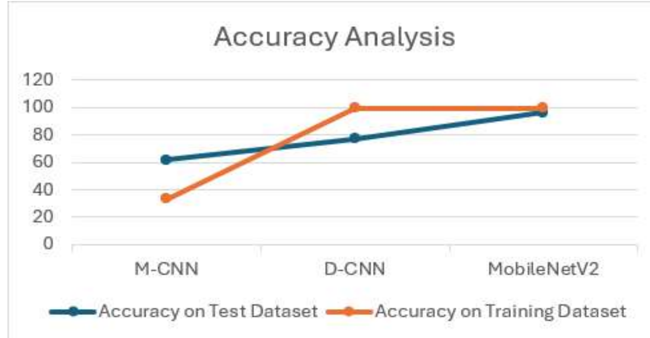

Figure 6: Accuracy of Different Models on Test Dataset vs Training Dataset

activation patterns are relatively weaker, indicating the stronger influence of areas other than the disease-affected regions of the leaf. The activated regions of the Grad-CAM images are less correlated with disease-affected re- gions of the test image. On the other hand, the disease classification is more acceptable based on the Grad-CAM images of the DCNN classifier, which cover a greater surface area of the leaf. The DCNN classifier is able to iden- tify disease-affected areas of the leaf, including those having discoloration or texture changes. However, the activation patterns of the DCNN Grad-CAM images are relatively lower, considering the possible influence of background or contextual characteristics. The MNet classifier has the highest discrim- inative Grad-CAM images for disease classification. The activation maps are concentrated primarily on visually prominent disease-affected regions, such as lesion clusters and discolored areas, while largely suppressing irrel- evant background information. This indicates that MNet effectively learns transferable and disease-specific visual representations, resulting in improved robustness and generalization.

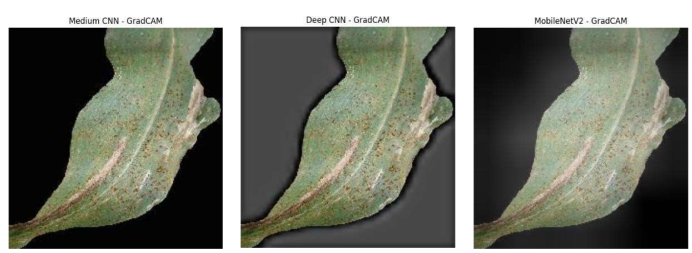

Figure 7: GradCAM Image of Test Data Using Different

Models

6. Discussion

The experimental results make it explicit that, in this work, the model learns to predict plant diseases based on discriminative visual phenotypic pat- terns rather than explicit physiologic and biochemical parameters. This com- parative analysis shows that there are notable differences in generalization behavior across architectures tested, model complexity and feature represen- tation, along with transfer learning, play an important role in image-based agricultural diagnosis. Most diseases tend to show subtle changes in lesion texture and color gradient, along with spatial arrangements on the surface of a leaf. Shallow or moderately deep networks cannot model such complex patterns, resulting in unstable learning and susceptibility to perturbations in lighting conditions, view angle, and background. By contrast, a DCNN with increased depth and hierarchical feature extraction has substantially im- proved learning capability. This model effectively captures low-level features like edges and color contrasts, mid-level features such as lesion boundaries and spot morphology, and high-level disease-specific spatial arrangements. However, the noticeable drop in test accuracy compared to validation accu- racy does indicate overfitting. Its superior performance can be explained by the substantial leverage of pre-trained visual representations learned from large-scale natural image datasets. These representations embody generic yet very transferable attributes such as texture orientation, color transitions, and spatial hierarchies, which can be used directly for leaf disease symptoms. MNet therefore, demonstrates enhanced robustness to inter-class similarity and intra-class variation, while achieving better generalization performance for unseen test data.

Furthermore, the addition of computational metrics like the number of parameters and time to infer demonstrates the applicability of the model in the deployment process. Even if deep models achieve higher accuracy, their computational cost acts as a deterrent in certain situations. The accuracy of the result demonstrates that the transfer-based lightweight machine learning models not only perform well in classification, but they also decrease the time of the inference, making it more applicable to mobile-based applications in agriculture. Moreover, the Grad-CAM result on the test image demonstrates that the focus is on the disease area and not random artifacts.

7. Conclusion & Future Work

Most of the prominent contributions are based on RGB images only, not using physiological parameters explicitly. In the present work, the focus is on image-based identification of diseases, considering the effect of physiolog- ical and environmental changes, which are embedded using visible changes observed on the leaf surface. In the present work, the comparative analysis of convolutional neural network-based models for the purpose of image-based leaf disease identification is proposed. Such models were considered for anal- ysis to understand the effect of architectural depth and representation abil- ity on the effectiveness of the models for the intended purpose. From the results, it could be observed that the performance of the models increases with the representation ability, but only up to a certain limit. For instance, the shallow models were found to perform with limited generalization ability and clear class bias during testing image analysis. In contrast, the transfer learning model performed with the highest accuracy among all the models during test image analysis. In the qualitative analysis, the effectiveness of the models was also validated, where the strongest model was found to focus only on the disease-affected regions, unlike the others, where diffuse atten-tion was observed. This interpretability not only increases the reliability of the classification, but also assures that the predictions are based on biolog- ically relevant visual features and not on backgrounds. In the future, the framework could be further generalized to other crop plants and categories of diseases, and the predictions made could be based on multimodal features to increase the reliability of diagnosis.

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