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EFFICIENT PLANT DISEASE DETECTION AND IMAGE CLASSIFICATION USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Amidst changing climatic circumstances and the proliferation of plant diseases, the agricultural industry confronts formidable obstacles in guaranteeing food security. For crop management and production optimisation, early and precise diagnosis of plant diseases is essential. There is a need for more effective solutions since traditional illness detection techniques are frequently labour and time intensive. Deep learning methods have become effective instruments in this field, providing automatic and precise illness identification from pictures. The benefits and drawbacks of deep learning techniques used in plant disease detection are discussed in this paper's review of the field. Along with methods for gathering datasets, augmenting them, and optimising models, it covers a variety of topologies, including convolutional neural networks (CNNs) and its variations. It also looks at how to improve the scalability and efficiency of disease detection systems by integrating cutting edge technology like transfer learning with respective to smartphones along with like Internet of Things (IoT) gadgets and drones. The study highlights the significance of interdisciplinary collaboration across the domains of agriculture, computer science, and data analytics for sustainable agricultural practices. It also discusses future possibilities for research and possible applications.

Keywords: *Plant disease, deep learning, CNN, transfer learning, smartphones resolution, IoT.*

I.INTRODUCTION

One of the main issues facing farmers nowadays is the identification of plant diseases. Plant leaf disease detection has benefited greatly from the introduction of several new approaches, such as Deep Learning, which allows for a deeper level of analysis and computing. Around the world, farmers are detecting and classifying the illness with the use of mobile applications that have deep learning models built in. To identify the illness in plant leaves, it uses a variety of methods such as CNN and ANN. It identifies and diagnoses the kinds of illnesses that are present in leaves using important aspects of the photos.

Agriculture provides the nation with food; crop loss occurs when plant diseases are not detected in a

timely manner. The lackluster agricultural yields in certain Indian states and some African nations are

the cause of famine. Implementing sophisticated technology in the agriculture industry is necessary to combat this kind of societal evil. Recently, there has been evidence that deep learning and machine learning can be useful in early illness detection. It was simpler to recognize prominent traits and categories items based on them thanks to deep learning's mathematical perception. Pre-trained deep learning models are being developed and advanced in a variety of fields through incubation in the real world. Deep learning is a popular method for making predictions and classifying data since neural networks and mathematical computation go well together.

CNN has gained prominence in deep learning as the most popular deep learning algorithm for feature extraction and data dimensionality reduction. Prior to utilising a multi-layer perceptron for predictions, pooling layers lower the dimension without using learnable parameters, and convolutional processes employing filters extract prominent characteristics from the input. CNN differs from ANN in image classification through feature extraction and dimensionality reduction. In the past, classifications and predictions were made using statistical models and analysis; performance was adequate to a certain extent. In terms of computational capacity, deep learning models are more dependable and well-suited than statistical models. In order to diagnose plant leaf diseases using deep learning, a large and diverse amount of data must be cleaned of noise and pictures must be segmented for categorization.

II.RELATED WORK

Convolutional neural networks have proven to be the most effective in a variety of computer vision applications, including picture classification. Plant disease identification is a significant field in deep learning that has seen a lot of recent advancements in techniques. Optimising these solutions for portable devices with limited resources, like smartphones, is crucial. Because deep learning models require a lot of resources, this is a difficult task. This research suggests an effective way to use convolutional neural networks to systematically categorize symptoms of plant diseases. These networks have a low memory footprint, and when combined with the suggested training configuration, they shorten training durations, allowing for the quick creation of industrial applications. A straightforward statistical technique is used to handle the class imbalance problem, which is another serious issue brought on by the incorrect distribution of samples among classes. Transfer learning is a well-known method for training small datasets by moving pre-trained weights acquired from a larger dataset to the smaller dataset. Negative transfer learning, however, is a frequent issue during transfer learning. Consequently, a step-by-step method for transfer learning is suggested, which can aid in quick convergence and minimize overfitting and negative transfer learning when information is transferred between domains.

Although over one third of all food is wasted due to plant illnesses or disorders, the Food and Agriculture Organization of the United Nations recommends raising the food supply by 72% in order to feed the world's population by 2050. In order to assist farmers, prevent output decreases by detecting crop illnesses as soon as feasible, researchers have developed a number of deep learning models.

The diagnosis of plant illnesses is made on the basis of their outward manifestations, which often affect the pulp, leaves, and stems of the plant. To accurately diagnose disease types, however, requires specialized expertise. It is challenging to reach rural areas, particularly in developing nations where smallholder farmers produce the majority of the crop. A diagnostic at the expert level can be obtained with the help of cutting-edge technologies.

For example, cellphones are now widely accessible at reasonable rates; this, together with the broad internet connectivity, can provide a good foundation for a smartphone-based illness detection service. Crop illnesses may be identified and labelled by a mobile disease detection system by taking a picture of the affected plant portion. This is because crop diseases are diagnosed based on visual symptoms that might manifest at different areas of the plant. This can save crop losses by cutting down on the phases in the typical diagnostic process, which calls for an expert to visit the field. Additionally, the suggested system's functionality may be expanded beyond accurately identifying plant diseases to include advertising from different suppliers of agricultural products and recommendations for potential cures.

The subject of plant disease identification has previously been approached using a variety of machine learning and sophisticated deep learning approaches. Plant disease identification is the subject of some research [5], which is addressed in [6] and [7]. These studies utilise a series of sequential image processing techniques, including picture capture, image pre-processing, image segmentation, feature extraction, and classification.

The majority of these approaches made use of traditional machine learning methods combined with hand-crafted features. Discriminant information is extracted from pictures using hand-crafted features like SIFT, HoG, colour, and shape-based feature extraction. This information is then input into a classifier. The classifier is then taught a complicated distribution that can distinguish between several classes in order to learn the discriminant characteristics. K-Means clustering was employed by Sannakki et al. [8] to extract colour characteristics for the purpose of diagnosing illness in pomegranate leaves. Shape- and color-based characteristics were retrieved by Patil and Szambre [9], and Support Vector Machine (SVM) was used for classification. When compared to more sophisticated deep learning techniques, conventional methods can need significant picture preprocessing, which comes with a cost. These preprocessing techniques include scaling the picture, using a Gaussian or other smoothing filter to reduce noise, and more. The illness detection pipeline experiences an overhead as a result of these preprocessing procedures.

Figure 1: Samples from various classes in the PlantDoc Dataset show the gap between lab-controlled and real-life images

When characteristics are well-defined and the data is sparser, conventional approaches are still applicable. However, because Convolutional Neural Networks (CNN) are able to extract the most discriminant characteristics from the pictures, sophisticated deep learning approaches often outperform traditional hand-crafted feature methods if data availability is not an issue. CNNs can extract many degrees of information from picture pixels, ranging from fundamental colour and shape information to very sophisticated information including texture, object forms, curves, etc. Moreover, it is not necessary to do preprocessing processes like noise reduction. The challenge of disease detection has been aided by the recent development of deep learning [10], and sophisticated deep learning-based solutions [11], [12], and [13] have been put forth in the field of plant disease detection.

Several studies, including [14] have demonstrated strong results on both public and private datasets. The authors of [17] classified illness on leaf pictures using two well-known CNN architectures, GoogleNet [18] and AlexNet [19], and reported their findings on a publicly accessible PlantVillage [20] dataset. Using apple leaf photos from the PlantVillage dataset, the authors of [21] were able to classify healthy leaves with 90.4% accuracy and black rot with 90.4% accuracy. Using an early version of the PlantVillage dataset, the authors tested in [16] and obtained an accuracy of 99.53%.

Figure 2. Examples of different phenotypes of tomato plants. A) Healthy leaf B) Early Blight (Alternaria solani) C) Late Blight (Phytophthora Infestans) D) Septoria Leaf Spot (Septoria lycopersici) E) Yellow Leaf Curl Virus (Family Geminiviridae genus Begomovirus) F) Bacterial Spot (Xanthomonas campestris pv. vesicatoria) G) Target Spot (Corynespora cassiicola) H) Spider Mite (Tetranychus urticae) Damage.

No.	Ref.	Task	Dataset	Method	Acc.	Pros and Cons
1	[12]	Plant disease detection	Pepper dataset PlantVillage	MobileNetV2	99% 99.69%	High accuracies were reached but lab images used for training
2	[18]	Classify beans leaf disease	1296 field images from iBean	MobileNetV2	97%	Dataset images are individual leaves cut from the plant and held in the hand
3	[20]	Detection and classification of 6 rice leaf diseases	6,330 field-collected images	YOLOv3 Mask RCNN Faster R-CNN RetinaNet	79.19% 75.92% 70.96% 36.11%	Low performance achieved
4	[22]	Plant disease detection	213 images from PlantVillage and Citrus datasets	2-layers CNN	94.55%	High accuracy on a small dataset Lab images used for training, the model will have low performance with field images
5	[23]	Detection of 5 citrus fruits and leaves diseases	1724 Cardamom field leaves	U^2-Net EfficientNetV2	98.26%	U^2-Net is used for background removal to keep a single leaf on the image which is suitable for classification
6	[25]	Corn leaf disease classification	PlantVillage	EfficientNetB0 DenseNet121 Features concatenation	98.56%	More complex features captured by fusion; Lab images used for training, low performance expected on field images
7	[26]	Plant disease classification	PlantVillage Rice Cassava	CNN based on inception layer, residual connection and depth-wise separable convolution	99.39% 99.66% 76.59%	High accuracies achieved Lab images used for training, low performance expected on field images
8	[27]	Tomato leaf disease identification	13.185 images from Tomato dataset	Hybrid CNN	95%	Requires less computation to achieve high performance Lab images used for training, low performance expected on field images
9	[13]	Plant classification Disease classification	PlantDoc	Dual-stream hierarchical bilinear pooling model	84.71% 75.06%	Identify field plants and diseases Low accuracy

Table 1. Summary of plant disease detection models.

REFERENCE PAPER	DATASET	DISEASES	MODEL	ACCURACY
[1]	Random Plants	Random Disease	SVM, K-Means	96% 85%
[2]	Plant Village Dataset	Diseases on 38 crops	AlexNet, GoogleN et	99%
[3]	Cotton	Bacterial light Fungal Spots	ANN	MSE = 6.105e-10
[4]	RandomPlants	Anthracnose(A) BlackSpot(B) RedLeaf (RB)	Fuzzy c-means ANN	A = 89% B = 59% RB = 82%
[5]	Ladies Finger	Healthy, Unhealthy	CNN	96%
[6]	Spinach	Leaf Spot White Rust	ANN	98.7%
[7]	Soya Bean	BacterialSpot Spider mite	ResNet GoogleNet	RN =94.29% GN=93.43%
[8]	Soya Bean	Anthracnos Bacterial	SoyNet K-means	98.24%
[9]	Tomato	Leaf spot Leaf Blight	AlexNet SqeezNet	=95.65% =94.3%
[10]	Potato	EarlyBlight LateBlight	VGG19+ J. R	97.8%
[12]	Apple	AppleScab AppleRust	Similar To LeNet5	98.42%
[14]	Maize	Leafblight LeafSpot BrownSpot	GoogleN -et Cifar10	98.9% 98.9%
[15]	Millet	Mildew	VGG16+ CNN	95%
[16]	Corn	Rust LeafBlight	Deep-CNN	98.4%
[17]	Olea europaea or Wild	Leaf scorch	Self designed-NN	98.6%
[18]	Spinach	Cercospora	ResNet -50	98.94%

Table 2. Summary of the existed works.

Thus, it is necessary to design a system that can handle real-world issues including dim illumination, background noise, unequal class distribution, and difficulties brought on by the hardware constraints of portable electronics. Furthermore, using data augmentation techniques is necessary to make up for the absence of sufficient training data. Because of the enormous influence of these technologies, governments and major businesses will be able to scale farming at a greater level with fewer specialists and at a cheaper cost of human resources, in addition to helping small farms raise their total production. This study addresses the aforementioned difficulties with the following contributions:

1. A CNN-based plant disease detection technique that is effective in identifying plant diseases in uncontrolled environments is suggested.
2. The class frequencies in an unbalanced dataset can be balanced using a statistical class-balancing procedure that is suggested.
3. By facilitating the quick creation of industrial applications, the stepwise transfer learning approach is utilised to train CNNs on tiny datasets efficiently.
4. A solution based on MobileNet is suggested, which can be implemented on handheld devices since it requires less hardware resources because it doesn't have a thick layer appropriate for handheld devices.
5. To speed up any CNN architecture's convergence process, a stepwise transfer learning technique is suggested.
Both overting and negative transfer learning have been found to be lessened by it.
6. Lastly, the precision of the suggested model is on par with cutting-edge techniques while using less resources.

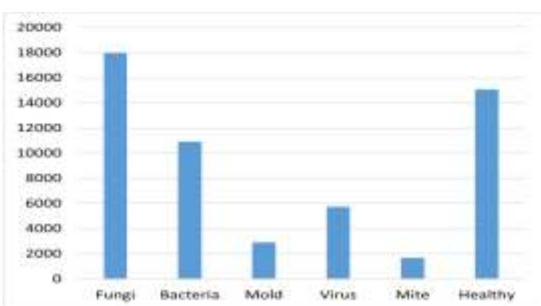
The remainder of the document is arranged as follows. In part II, we describe our suggested procedure; in section III, we present the results of our experiments. In part V, we wrap up the work with important findings and possible paths for further research after discussing the suggested methodologies in section IV.

III.PROPOSED WORK

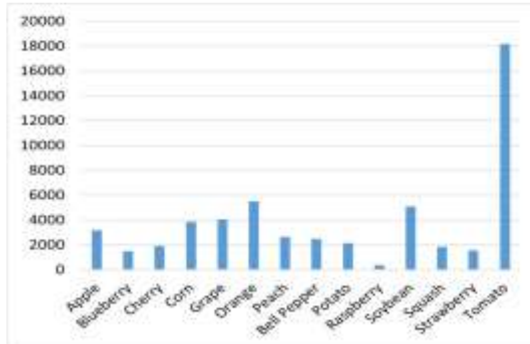
The work's goal is to enable computer vision technologies to assist in resolving typical issues with plant disease symptom classification. The methods suggested have broad use, not only in the identification of plant diseases but also in the majority of industrial settings where quick development of machine learning algorithms is needed.

When sufficient data is available for training, sophisticated convolutional neural networks have demonstrated strong performance on certain tasks in the past. Huge picture collections for a particular crop disease combination aren't usually achievable, though. Using data augmentation approaches, which enable CNNs to learn representative properties of illness classes, these problems of class imbalance and data scarcity are solved.

Furthermore, there is a chance that misclassifications will occur due to a variety of deficiencies in the data gathered in the field, such as poor illumination, poor image quality, and unclear symptoms. Additionally, because of their greater computational costs, huge model sizes, and longer running times, traditional CNNs are not well suited for hand-held devices with limited resources. In order to examine the impact of these circumstances and attempt to address these difficulties in our suggested approach, we meticulously planned the experimental setting in this work. A CNN without a thick layer is utilised to lower the model size, which results in a quick and compact model size by removing a lot of add-multiplication operations. The datasets, their difficult qualities, and the methods we used to improve the performance of our suggested system will be covered in more detail in later parts.



(a)



(b)

Figure 3. (a) Sample frequencies in PlantVillage dataset per disease category. (b) Sample frequencies in Plant Village dataset by plant classes.

IV.DATA PREPROSSING

This dataset was created to support the training process for the diseases' visual signs that are known to be harmful to pepper plants. It has 99,507 photos in total, all of which are accurately labelled and correspond to 24 kinds of disorders. The National Institute of Horticultural and Herbal Science, Republic of Korea, has also contributed support. Given that the programme is intended for general users and mobile devices, standard digital cameras are used to take the pictures in various daylight settings. The collection includes illnesses on many plant sections, such as the pulp, leaves, and stems, providing a more thorough coverage of the range of plant diseases. Of the 24 categories, 6 illnesses are associated with the pulp, 6 with the stem, 9 with the leaf, 2 with larvae, and 1 with pictures of healthy plants from all three sections—the leaf, pulp, and stem. Figure 2 displays a few representative photos from the aforementioned dataset.

V.IMAGE CLSSIFICATION

A development in machine learning, deep learning is motivated by the nervous system computing of the human brain. The word "deep" refers to deep layers, vector operations, and statistical techniques of computing and interpretation. The data is stored in the nodes that make up the internal workflow of deep learning models, and the arrow on the data denotes numerical operations.Feed forward artificial neural networks are those that use the back propagation technique to do both forward and backward propagation. Feature extraction and convolutional neural networks gave CNN more compatibility than ANN.

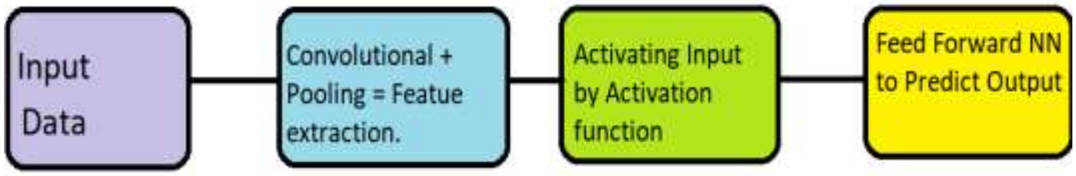


Figure 4. CNN Workflow

When employing deep hidden layers for deep computing, ANNs do not extract features. Similar to a filter being applied to the data, convolutional layers are filters that carry out convolutional operations on input data to extract high-level features. Low level features are attempted to be recovered from high level features collected by convolutional layers using a pooling layer that employs max pooling or mean pooling.

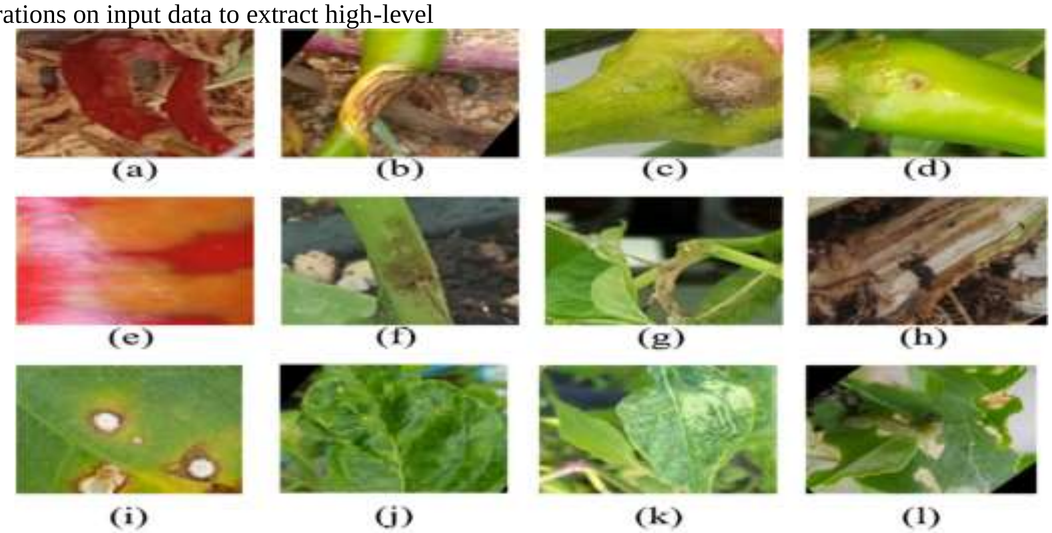


Figure 5. Some sample images from our pepper dataset. (a) Phytophthora blight (pulp), (b) Biter rot (pulp), (c) Gray mold (pulp), (d) Moth damage (pulp), (e) Tomato spotted wilt virus (pulp), (f) Tomato spotted wilt virus (stem), (g) Gray mold (stem), (h) Bacterial wilt (stem), (i) Bacterial leaf spot, (j) Damping off (leaf), (k) Tomato spotted wilt virus (leaf), (l) Gray mold (leaf).

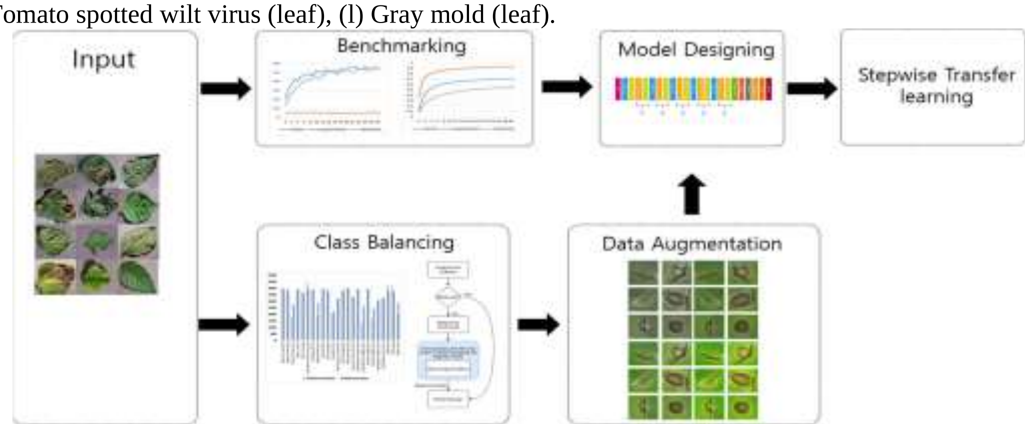


Figure 6. Workflow of the methodldogy.

Data Preparation: For the pepper dataset, which is rather large as seen in Figure 8(a), the original image resolution was 1600 x 1200.

In order to concentrate primarily on the sick region and exclude the background, the photos were first cropped, as seen in Figure 8(b). Following that, three sections of these crops were randomly selected for testing, validation, and training. In order to expand the dataset's sample size, data augmentation is the last step. As seen in Figure 8(c), the augmentation techniques included rotation, cropping, lighting, dipping, and saturation fluctuation. To ensure that any skewness resulting from data preparation stages like augmentation is eliminated, it should be mentioned that the final findings were additionally assessed using 5-fold cross-validation.

Class Balancing: We require certain methods for creating images when oversampling is used for underrepresented classes. There are two methods for oversampling the data: the Synthetic Minority Oversampling Technique [25], which includes under sampling the majority class and oversampling the minority class in order to get the best results, and the Adaptive Synthetic Sampling Approach for Unbalanced Learning [24]. Generative Adversarial Networks (GAN) for data augmentation are another method that may be utilised to balance the data [26]. For a basic classification assignment, a more conventional approach was adopted because GAN-based augmentation is an overhead. In order to improve the total amount of training data, we finally combine the findings and do further data augmentation. This balanced data is then utilised for the model construction step, as seen in Figure 8.

Data Augmentation: To improve the amount of samples and resilience towards unknown data, certain simple augmentation approaches were applied to all classes in addition to applying more sophisticated techniques for data augmentation. To include the symptoms in varying resolutions, images were scaled. As seen in Figure 8(c), other augmentation processes include dipping, rotating, translating, adding noise, and altering the lighting.

Model Selection: In the current era of extremely sophisticated deep learning technology, which is supported by an enormous number of potent architectures, choosing the right model that best fits the dataset and intended application may be quite challenging. The majority of sophisticated deep learning models require a lot of resources since they are made to take use of the enormous processing power of contemporary hardware.
Due to the limited processing power and storage capacity of handheld devices and other embedded systems in Internet of Things contexts, it is imperative to do preliminary benchmarking on mobile versions of deep learning models in addition to massive deep learning architectures. Using a variety of models trained with varying configurations and varying computational complexity, initial benchmarking was conducted on the input dataset. The configurations include of ne-tuning, transfer learning, training from scratch, transfer learning with frozen layers, and transfer learning for feature extraction. The conducted tests are displayed in Table 1.

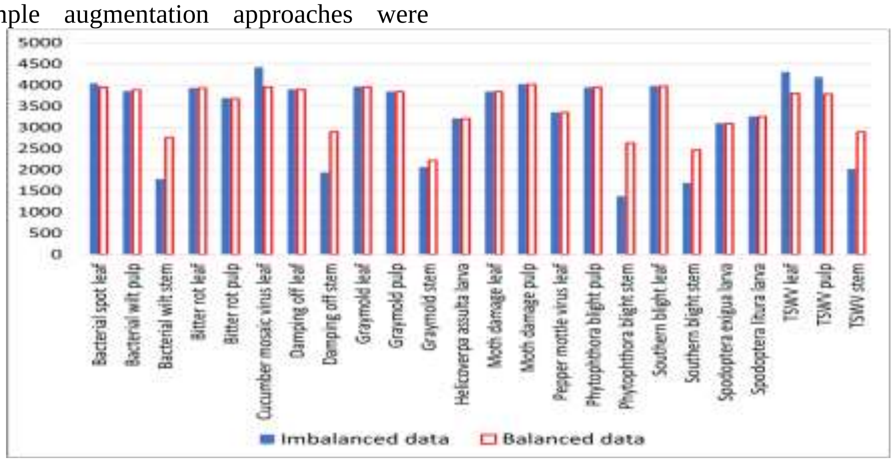


Figure 7. The number of images per class in the Pepper dataset before and after class balancing.

Model	ImageNet Accuracy	Million Multi-Adds	Million Parameters
VGG-16	71.5 %	15,300	138
Inception-V3	**81.2 %**	5,000	23.2
MobileNet_V1	70.6 %	569	4.2
MobileNet V2	72.8 %	300	3.4
MobileNet V3 Large	73.3 %	155	**7.5**
MobileNet V3 Small	58.0 %	**21**	**1.56**

Table 3**.** Comparison of selected benchmarked models on ImageNet dataset.

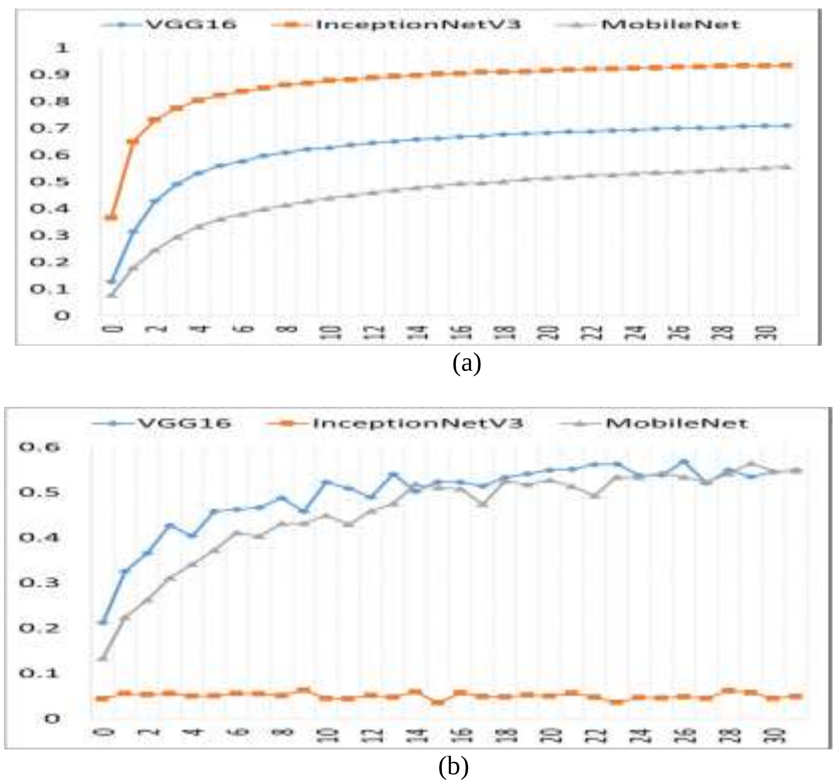


Figure 8. Benchmark comparison of (a) training and (b) validation accuracies using different models on Pepper disease recognition dataset.

Similar to VGG-19's validation accuracy, but with 27 times more multiplication and addition operations and 33 times more parameters, it is equivalent. We create a model based on MobileNet_V3_Large in order to preserve a balance between the complexity of the model and the dataset, taking into account the benchmarking results displayed in Figure 11. Figure 12 shows the MobileNet architecture. With a limited number of trainable parameters, the model's deep architecture and unique structure enable it to effectively learn the features in our data and produce good classification results. Reducing the number of parameters in a model reduces the likelihood of overfitting, an important consideration when learning representations on small-scale datasets.

Pre-trained weights can be moved from a source domain to a target domain using the transfer learning approach [29].

A sizable dataset is often utilised as the source domain while the model is first being trained. The dataset that is intended to be used with that model is known as the target domain. Transfer learning is based on the logical assumption that, if the data type is consistent across domains, the fundamental characteristics that are retrieved from data are comparable even across domains. The fundamental low-level traits collected in the first layers are largely the same, regardless of the diversity of photos from other fields. Moreover, a high-complexity model is likely to overfit the training data since there are typically insufficient samples available to train the model from start.

There are three primary research questions in transfer learning:

1) Transferring information: What to transmit, 2) Transferring information: How to transfer, and 3) Transferring information when to transfer [29]. The degree of similarity between the source and destination domains determines how best to handle these problems.

Replace the classification head with the number of classes corresponding to the target domain if the domain and target classes are extremely similar. This will transfer the whole model. Less layers can be successfully transmitted, though, if the domains are not too similar.

Thus, the most important determinant of when and how to transfer is similarity between domains. There is relatively little visual resemblance in high-level characteristics when moving from the ImageNet to the Plant Disease dataset. Section II.B.4 of the benchmark experimentation shows the outcomes of only altering the classifier. Finding the best transfer learning approach is essential in light of these findings.

VI.RESULTS AND DISCUSSION

The experimental design, dataset statistics, and assessment metrics utilised in this study are all covered in depth in this part, which is followed by a number of experiments and the findings of those experiments. Lastly, a thorough comparison with alternative approaches is provided.

This section provides an explanation of the training conditions used for the experiments carried out in this study. Pre-trained weights are loaded, layers are frozen, learning rate is scheduled, stepwise transfer learning method is used, and finally, validation on unobserved data is performed as part of the training strategy.

You may utilise the pre-trained weights in different configurations to get different outcomes. For example, by eliminating the requirement to learn all the fundamental characteristics from scratch, these weights may be utilised to accelerate the training process. These weights may also be used to extract features, therefore they can be utilised as a feature extractor. These features can then be used as the basis for additional sophisticated applications, such as object identification, semantic segmentation, and instance segmentation, or they can be used as the input for a classifier.

For comparison's sake, we employed the pre-trained weights in two different scenarios. First, the baseline findings were produced by using the weights as a feature extractor. These outcomes were utilised to assess the performance improvements brought about by using various training optimisation techniques, including freezeout and our suggested stepwise transfer learning approach.

These outcomes demonstrate the dataset's outstanding performance.

These measures, however, are lacking in insight, hence comprehensive findings are also supplied, with each illness class's metrics included in table 5. The ability to analyse each class performance can aid in improving the model's performance. It is especially beneficial when there is an issue with class imbalance.

To assess our approach on a publicly available dataset, the same tests were carried out on the PlantVillage dataset. Figure 15 displays the comparative training accuracies (a). The trend and the pepper disease dataset are nearly comparable.

Figure 15(b) displays the validation accuracy. Analysis is also given according to class, as seen in table 8. Table 6 offers a comparison of a few assessment indicators. This demonstrates that, for the PlantVillage dataset, the suggested solution has outperformed the earlier approaches. There aren't enough public datasets accessible to test on, however more tests might be conducted on additional datasets that are available.

Data source	Training data	Validation data	Testing data	Total classes
PlantVillage	43448	5430	5430	15
Pepper dataset	79621	9943	9943	24

Table 4. Statistics of training and testing data used in this study.

Methods	Cross-validation accuracy	Recall	F1-score
VGG-16 with TL	79 %	58 %	83 %
1.0-MobileNet w/o TL	77 %	66 %	66 %
MobileNet_V1 with TL	97 %	84 %	83 %
MobileNet_V1 with stepwise transfer learning	99 %	98 %	98 %
MobileNet_V3_Large with stepwise transfer learning	**99%**	**99%**	**99%**

Table 5. Comparison of our method with previous methods on the

pepper disease dataset.

Methods	Cross-validation accuracy	Recall	F1-score
AlexNet [17]	97.86 %	97.82 %	97.82 %
GoogleNet [17]	98.39 %	98.37 %	98.37 %
VGG-16 with TL	71.40 %	56.10 %	82.43 %
MobileNet_V3_Large w/o TL	73.10 %	62.05 %	63.59 %
MobileNe_V3_Large with TL	98.50 %	98.37 %	97.12 %
MobileNet_V3_Large with stepwise transfer learning	**99.69 %**	**99.40 %**	**99.62 %**

Table 6. Comparison of our method with previous methods on PlantVillage dataset.

The trade-off between accuracy and memory efficiency is what led us to choose this approach over other deep CNN recognition implementations, but our ultimate objective is to make it feasible to use on portable devices. For example, huge model capacities are often overridden by limited datasets in architectures like VGG and Inception-V3.

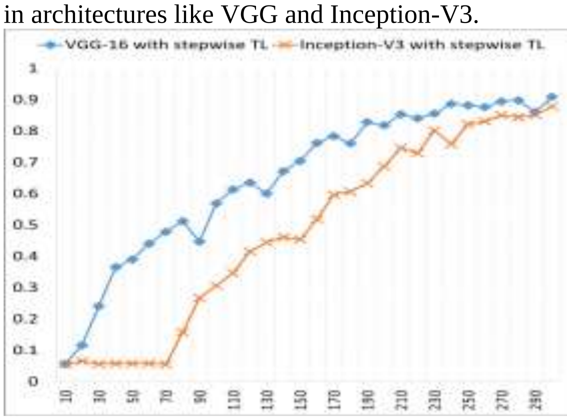


Figure 9. (a) Training and (b) Validation accuracies of benchmark models not selected for the next stage. However, when trained with stepwise transfer learning, they have achieved improved validation accuracy and overfitting is reduced to significantly.

In order to empower the average farmer and contribute to an improvement in crop output, the chosen model aims to make this system capable of operating well in contexts with limited resources, such as hand-held devices.

To further examine the effectiveness of the suggested stepwise transfer learning (TL) approach, experiments were carried out. We employed VGG-16 and Inception-V3, the two models from the benchmarking phase. Extreme overfitting was seen during the straightforward training of Inception-V3 on our dataset; however, the model was trained in stepwise TL configuration. During the first few epochs, the model tends to overfit, but if we train for a long enough period of time, the first layers unfreeze and the model begins to learn. For both VGG-16 and Inception-V3 trained using stepwise transfer learning, training and validation accuracy are given in Figure 16. Table 9 provides more comparisons between various transfer learning methodologies. As seen in Table 9, all three approaches—Simple Transfer Learning, FreezeOut, and Stepwise Transfer Learning—are also assessed on a held-out test set. Furthermore, it is critical to give an explanation for the model's functionality. While models may be trained on repeating background characteristics, for instance, in some situations, their accuracy may be adequate despite the presence of irrelevant features. Consequently, Grad-cam [31] is used to provide the activation visualisation in Figure 17, demonstrating that the models are focused on the appropriate places. The target category is indicated on the horizontal axis, and it is this category that the model is trained to predict. As a consequence, areas are engaged for that particular target group.

VI.CONCLUSION

An effective deep learning-based method for categorising plant diseases in an uncontrolled setting is described in this research. Class imbalances are the first thing to be examined in the dataset since they are known to prevent accurate classification outcomes. The class-balancing method's ability to improve system performance has been greatly aided by a thorough examination of the dataset. The stepwise transfer learning has aided in decreasing the CNNs' convergence time. In addition to the suggested model, two other models that were trained using a stepwise transfer learning configuration also shown notable improvement.

Stepwise transfer learning has been shown to have aided in both decreasing negative learning and accelerating convergence. The problems unique to the plant disease detection problem are taken into consideration while proposing a plant disease classification system. In particular, the viability of implementing the classifier on handheld devices is taken into consideration as a practical solution. Since these devices do not yet have high-end hardware, it is critical to create efficient designs. PlantVillage, a publicly accessible resource, and the Pepper crop dataset are used to assess the suggested classification scheme.

More sophisticated deep learning approaches may be used for real-world applications, and this work can be expanded to include additional crops and illnesses. In terms of high accuracy, CNN-based computer vision tasks have undoubtedly reached a significant milestone; yet, in order for industry and consumers to profit from state-of-the-art research, attention must be paid to workable solutions. If implemented correctly, this approach can eventually contribute significantly to raising agricultural productivity while also helping to reduce losses for small farms. Lastly, there are a number of industrial uses for this method where it is desirable to construct machine learning algorithms quickly.

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