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Implementation of Deep CNN Model for the Detection of Plant Leaf Disease

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Abstract— The potato is the most important tuber crop in the world, and it is grown in about 125 different nations. Potato is the crop that is most commonly consumed by a billion people worldwide, virtually every day, behind rice and wheat. However, a number of bacterial and fungal diseases are causing the potato crop's quality and yield to decline. Potato Leaf diseases must be promptly identified and prevented to increase production. Various researchers look for solutions to protect plants instead of traditional processes which take more time. Recent technological developments have thrown up many alternates to traditional methods which are labour intensive. The application of AlexNet model Deep Convolutional Neural Network(CNN) to recognise diseases in potato plants avoids the disadvantages of selecting disease spot features artificially and makes more objective the plant disease feature extraction. It improves research efficiency and speeds up technology transformation. Accuracies ranging from 85% - to 95% were obtained using AlexNet model Deep.

Keywords- Deep Convolutional Neural Network, Leaf disease Detection, Alex Net, Mobilenet.

I. INTRODUCTION

Global food security is threatened by plant diseases, causing severe consequences for small farmers whose lifestyle is based on healthy crops. Smallholder farmers contribute over 80% of the agricultural output, yet 50% to 60% of the yield is wasted due to pests and diseases [1]. Agricultural organisations and institutions consult with many domain experts to prevent/reduce crop loss. On the other hand, due to a lack of facilities in many nations, farmers may not know to contact professionals in rural areas [2]. Early diagnosis of plant illnesses (before symptoms appear) can be a useful source of information for putting efficient disease control measures in place to stop the spread of plant diseases.

To identify and categorize different plant diseases using the current model, human intervention is necessary due to several factors, including a lengthy training period, high storage costs, and high computational costs. [3]. Experts examine plants continuously over a long period of time in order to manually observe any infections that may be present. Hence, these approaches of disease identifications are time-consuming [4]. It is difficult to accurately locate high informative disease regions using Le-Net architecture and this often reflects on the classification [5]. Recent developments in agriculture include the use of numerous computer vision-based deep learning systems for tasks like predicting pest infections, detection of diseases in plant, management of water resources, etc [6]. An automated system like this one can assist farmers and

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agronomists in making timely judgments and minimising considerable financial loss [7].

Deep neural networks have transformed plant pathology by producing remarkable outcomes without the requirement for time-consuming feature engineering [8]. Deep neural networks have improved picture categorization accuracy dramatically.This offers researchers use of different techniques to identify diseases in plants. AlexNet was used by Ali Fauzi et al. [9] to teach classifying newly discovered plant diseases. During testing, model accuracy was significantly decreased.The 3 stage Convolutional Neural Network training method. It discovers the existence of lesions in the first stage, and in the second stage[10]. To detect infection, it creates a heat map. Last but not the least, heat maps are used to classify features observed in earlier stages [11-12]. The efficiency of different Convolutional Neural Network techniques in identifying plant leaf disease depends on various factors: only a few annotated images are available, and the disease symptoms, capturing conditions, and image background are all poorly represe [13].

In the proposed work, Deep Convolutional Neural Networks (DCNs) offer a more scalable method for classifying images and recognising objects, drawing on the ideas of matrix multiplication to find patterns in images [14]. The breakthrough use of graphics processing units (GPUs) to improve the performance of convolutional networks was pioneered by the AlexNet model. AlexNet's architecture consists of 5 convolutional layers, 3 max pooling layers, 2 fully connected layers, 2 normalization layers, and 1 SoftMax layer. AlexNet introduced the concept of multi-GPU training by distributing parts of the neural model to different GPUs, enabling efficient parallel processing [15].This concludes that less time is spent to training the larger model. A Convolutional Neural Network requires lessor pre-processing time then other classification algorithms.The following is the summary of this paper's major contributions:(i)A cutting-edge interactive deep learning system for locating the infected regions of damaged plant leaves.(ii)Under adverse situations that are difficult to detect, such as substantial inter and intra class fluctuations and incredibly small patches of diseased leaves, the proposed model achieves a greater accuracy [16].(iii)Empirical data have been used to examine the suggested framework. These outcomes were also contrasted with other cutting-edge multistage object detection methods [17]. It has been found that the suggested framework produces meaningful results using lower computational resources and parameters [18].

II. CONVOLUTIONAL NEURAL NETWORK

Neural networks are used in Deep Learning to understand representations of features directly from the data. Neural networks, which are modeled after biological nerve systems, incorporate several nonlinear processing layers utilizing straightforward components that operate in paralle[19]l. Deep learning models can classify objects with state-of-the-art accuracy, sometimes outperforming human ability. Models that have been made utilizing a substantial amount of labeled data and complex neural network topologies, frequently with some convolutional layers[20]. These models require a lot of intensive computational training and can typically speed up training by using a powerful GPU. Image files, sometimes millions of them, are used by many deep learning systems. MATLAB offers the image Data store function to rapidly access several picture files for deep learning[21].

The figure 1 shows theblock diagram of proposed method. Here we input the collected datasets from the system.Pre-processing seeks to enhance the picture data by removing undesirable distortions or improving specific image characteristics crucial for further processing and analysis tasks.A digital image is split up into multiple subgroups known as Image Segments. It help further streamline processing and analysis by bringing down the complexity of the image. The term for this is image segmentation[22]. The Pooling layers are placed after the initial convolutional layer, and the fully connected layer is lastly placed. With each layer, the Convolutional Neural Network's complexity gradually rises, allowing it to recognise greater portions of the image [23]. In the first layers, fundamental components like colours and borders are highlighted

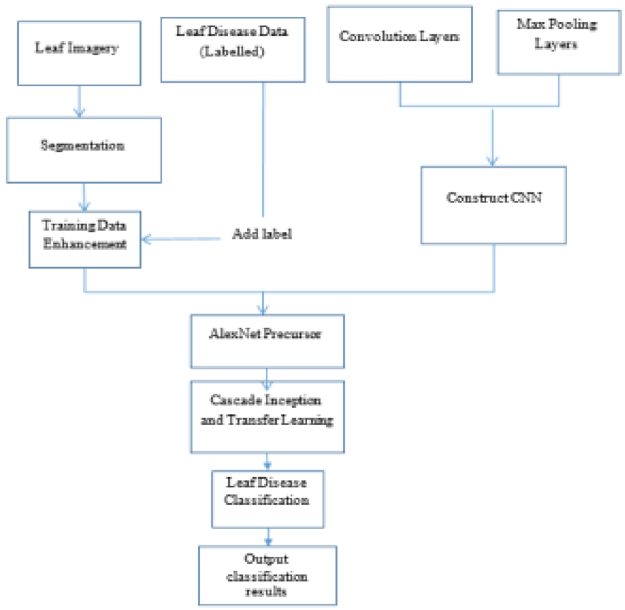

Figure 1. Block Diagram of Proposed method

As the visual data moves though the Convolutional Neural Network, larger features or shapes of the object are recognized progressively until the whole of the intended object[24]. Classification algorithms try to identify the category of a fresh observation from among several categories based on

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a tagged training set. Depending on anatomical anatomy, characteristics, and tissue preparation, classification accuracy varies[25].

Plants typically develop diseases when their normal structure, growth, function, or other activities are repeatedly disrupted by some causal agent, leading to an abnormal physiological process. This disruption of crucial physiological or biochemical processes in a plant causes specific illnesses or symptoms. The principal agents causing plant leaf diseases can be categorised roughly into either infectious or non-infectious. Infectious plant diseases are carried out by pathogenic organisms, like fungi, bacteria, myco-plasma, viruses, viroids, nematodes, or parasites.

An infection has the capacity to multiply both within and outside of its host and proliferate to additional hosts that are susceptible to it. Unfavorable growing conditions, such as excessive temperatures, unfavorable oxygen and moisture ratios, harmful elements in the environment or soil, and an oversupply or deficiency of a necessary mineral, are the main causes of non-infectious plant illnesses. Since non-infectious causal agents are not living organisms that can multiply inside of a host, they cannot be transmitted. In nature, multiple infections may affect plants at the same time.Plants are often more vulnerable to infections by any pathogens when they must deal with nutritional deprivation or an imbalance between oxygen and soil moisture and a plant that has already been ill is frequently vulnerable to further infections. The disease complex is made up of all the factors that cause illness in a plant.

Understanding typical development patterns, varietal features, and natural variability within a plant species – relative to the environmental conditions under which plants grow - is necessary for the capacity to recognise a disease.Thus, to identify these diseases we have used the Convolutional Neural Network technique. Convolutional Neural Network coding in MATLAB software is provided to train the model to identify normal or diseased one. Here we have specified two common leaf diseases such as early blight and late blight and the output is described below.

2.1 Evalution Metrics:

In feature extraction since it is based on leaf image , the image features are extracted and used for training classifiers. Accuracy is the metric derived from confusion matrix, the evaluation of the proposed models is made by comparing it with existing models. Table shows the different metrics used in the evaluation Process

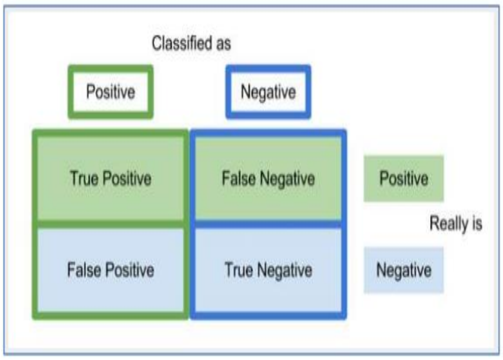

Fig 2 Confusion Matrix

The displayed figure shows a confusion matrix with key measurements such as true positives (TP), true negatives (TN),false positives (FP) and false negatives (FN). These measures are used to evaluate the performance and accuracy of classification models.

Table 1. Confusion Matrix

Metric	Mathematical Equation	Range of Values	Optimal Value
F1-Score	((p*r))*2/(p+r)	[0;1]	1
Precision(p)	TP/(FP+TP)	[0;1]	1
Accuracy	(TN+TP)/(FP+FNTP+TN)	[0;1]	1
Recall(r)	TP/(FN+TP)	[0;1]	1

From the table precision refers tp positive predictive value while recall refers to true positive rate. The F1 score metric is made up to both precision and recall as a harmonic mean of them. It is measure without imbalance while an accuracy measure may show imbalance.

Different framework associated with CNN based frameworks are as follows

- Rate of Learning:0.0001
- Optimizer: Adam
- Loss function: Categorical_crossentopy

III. RESULTS AND DISCUSSION

Recent advances in deep learning algorithms have provided significant advances in the early detection and identification of plant diseases. Unlike conventional methods that rely heavily on various variables such as feature extraction, disease region segmentation, and image enhancement, our approach centers around the use of deep learning-based transfer learning strategies for disease identification. is. Our method employed depth-wise separable convolution in the starting block. This effectively reduces the number of parameters compared to traditional convolution, resulting in more efficient and streamlined processing.

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Experiments are made with the proposed deep learning framework. Then the results are compared with Different deep learning models like MobileNet, ResNet-20, VGGNet-16,GoogLeNet and AlexNet. The observations are made in terms of leaf disease prediction accuracy, Batch size, time and space complexity analysis.

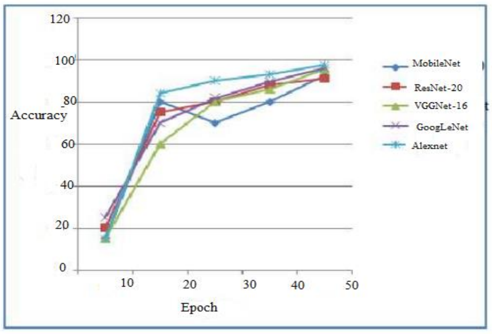

Fig 3 Model Accuracy at Different Epoches

As shown in Figure 3, the horizontal axis contains the epoch details, while the vertical axis has the accuracy (%). As the number of epochs is increased, the accuracy of all prediction models improves noticeably. When the number of epochs reached 50 (convergence), the proposed deep learning model known as Alexnet demonstrated the best accuracy of 90.71%, whereas mobileNet demonstrated the lowest performance of 88.52% .

Table 2. Trained model using different DeepCNN Models

.Deep CNN Models	Validation Accuracy(%)	Batch Size	Training Time	Memory Used (GB)
MobileNet	88.52	18	5 min 14 sec	12
ResNet-20	89.63	128	4min 57sec	3.3
VGGNet-16	79.28	32	2min 42 sec	3.1
GoogLeNet	88.51	32	2min 48 sec	4.3
Alexnet	90.71	128	2min 37 sec	2.84

Table 1shows the comparison of different Deep CNN models. The validation accuracy of Mobile net is 88.52%, and computation time is 5 min 14 sec. But for ResNet-20, the validation accuracy is 89.63%, and computation time is 4 min 57 sec. The validation accuracy of VGGNet-16 is 79.28%, and computation time is 2min 42 sec. The validation accuracy of GoogLeNet is 88.51%, and computation time is 2min 48 sec.Figure 5 Shows Accuracy, Batch size,time and Memory used for Various Deep CNN models.

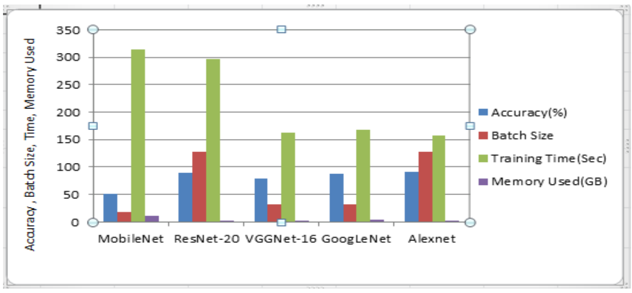

Figure 5 Shows Accuracy, Batch size,time and Memory used for Various Deep CNN models.

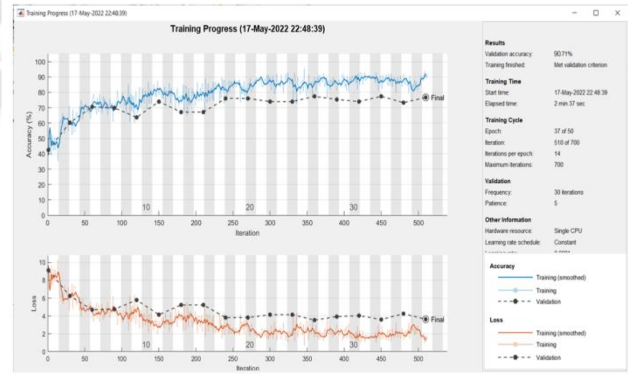

Figure 6. Trained model using AlexNetDeep CNN

Fig 4 shows the Trained model using AlexNet Deep Convolutional Neural Network. We have trained the model using AlexNet (deep Convolutional Neural Network) method for testing the samples and we have a reached a accuracy higher than 90.71% the epochs is 50 and the loss is very less compared to other methods and also the time taken for testing is 2min 37sec. From the above discussion it very clear the Alexnet Deep CNN model yields better result when compared with other models. The Alexnet Deep CNN Algorithm is applied to detect different disease for PotatoLeaf.

IV. SAMPLES DISCUSSION

4.1 Early Blight Samples:

Alexnet Deep CNN Algorithm is used in determine the potato leaf disease.Figure 7 showcases a sample image of Early Blight, a plant disease caused by fungal species. The disease primarily affects older leaves, leading to the development of circular dark brown rings or lesions. Over time, these lesions expand and may spread to stems and other leaves. It is worth noting that Early Blight typically causes relatively minor damage to the overall plant.To train our model effectively, we utilized a dataset containing similar sample images of Early Blight. By exposing the model to these images during the training process, it learns to recognize the characteristic circular dark brown rings or lesions associated with this disease.Once trained, we tested the model's performance using a separate set of testing images. This evaluation allowed us to assess the model's ability to accurately

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identify and classify Early Blight in unseen images. The model's effectiveness in correctly identifying the disease contributes to timely intervention and targeted management strategies, minimizing the impact of Early Blight on plant health and overall crop yield.

By employing our trained model, farmers and agricultural professionals can swiftly identify Early Blight-affected leaves and implement appropriate measures such as targeted fungicide applications, adjusting irrigation practices, or removing infected plant parts. This aids in preserving crop health, reducing yield losses, and ultimately promoting better agricultural outcomes.

Figure 7. Early blight sample

4.2 Late Blight Samples

Figure 8 shows the Late blight sample. A distant relative of fungus called oomycetes is the disease-causing agent in late blight. On the leaves, petioles, and stems, there are irregular-shaped lesions. The potato tubers begin to rot, and the entire plant has a whitish cottony fungus growth. The plants are severely affected and damaged. We train the model for late blight with these set of training images and when tested we obtain a perfect result.

Figure 8. Late blight sample

4.3 Testing Model

Figure 9and 10 shows the simulation output for Early Blight. Image is given and due to circular dark brown rings and as Early blight will develop circular to angular dark brown lesions and roughly circular brown spots appear on leaves and stems. with concentric rings that form a “bull’s eye” pattern it is identified as Early Blight. Concentric rings form as these spots grow in size, giving the areas a target-like look. Often spots have a yellow circular affected area. So it is detected as Early Blight.

Figure 9Early blight

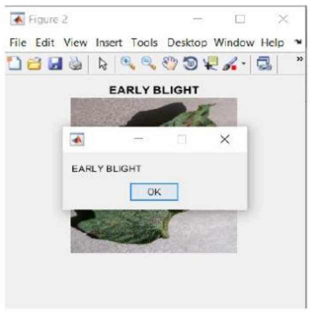

Figure 10 Simulation Output

In Figure 11 and 12 the simulation output depicts the visual representation of a leaf affected by Late Blight. The input image provided exhibits characteristic symptoms associated with this plant disease.One prominent symptom of Late Blight is the presence of dots or lesions on the underside of the leaves, which may be surrounded by ring-shaped structures responsible for spore production. Additionally, grayish-white mycelium can be observed in the affected areas. The disease progression typically starts at the edges of the leaves and gradually extends towards the center and the stem, resulting in black, damaged plant tissue. This pattern of symptom development serves as a key diagnostic feature for Late Blight.By accurately identifying these specific symptoms in the input image, our model successfully classifies it as Late Blight. This capability of the model allows for early disease detection, enabling farmers and agricultural professionals to take timely action, such as implementing appropriate fungicide treatments or adjusting cultivation practices, to mitigate the impact of the disease on the

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crop.The utilization of the model's automated identification and classification system contributes to the improvement of agricultural practices. It aids in minimizing crop losses, facilitating targeted disease management, and promoting better overall agricultural development.

Figure 11 Light blight

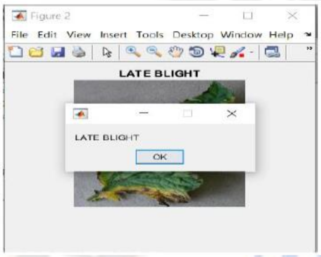

Figure 12 Simulation Output

In Figure 13 and 14, the simulation output for a normal leaf is depicted. The input image provided represents a healthy leaf without any visible lesions, spots, fungal infections, or grayish-white patches. Consequently, the leaf is accurately identified as a normal leaf. Through thorough testing, the model successfully achieved correct results in identifying diseased leaves, including cases of early blight and late blight, as well as normal leaves. Early blight is characterized by the development of circular to angular dark brown lesions on both leaves and stems. As the disease progresses, roughly circular brown spots can also be observed.The model's ability to accurately detect and differentiate between diseased and normal leaves, as well as its capability to identify specific disease symptoms such as the circular to angular dark brown lesions in early blight, contributes to its effectiveness in plant disease diagnosis. This aids in facilitating timely interventions and appropriate management strategies to mitigate the impact of diseases on crops, ultimately leading to better agricultural outcomes.

Figure13 Normal Leaf

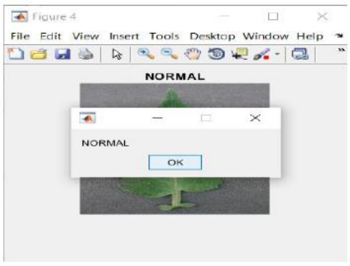

Figure 14 Simulation Output

One characteristic symptom observed in certain plant diseases is the formation of concentric rings as the spots on leaves or stems increase in size, resulting in a distinctive target-like appearance. Additionally, these spots often exhibit a yellow circular affected area, further aiding in their identification.In the case of late blight, a destructive plant disease, it initially manifests as small, wet spots that rapidly enlarge and transform into purple-brown, oily-looking patches. These symptoms are highly indicative of late blight and can serve as crucial diagnostic markers for plant pathologists and farmers.The utilization of our model in identifying and classifying these plant diseases contributes to the advancement of agricultural development. By training the model on a comprehensive dataset of plant disease images, it learns to recognize and accurately classify specific disease symptoms, such as the target-like appearance with concentric rings and the presence of yellow circular affected areas. Furthermore, the model can reliably detect the progression of late blight, identifying the small wet spots that evolve into distinctive purple-brown, oily-looking patches.

By providing a reliable and automated method for identifying plant diseases, our model offers valuable support for farmers and agricultural professionals. Timely and accurate disease identification enables swift intervention measures, such as targeted treatments, adjustments in crop management practices, and implementation of disease prevention strategies. Ultimately, this aids in minimizing crop losses, optimizing resource allocation, and enhancing overall agricultural productivity, contributing to better agricultural development.

V. CONCLUSION

In the proposed work, the researchers were compared with Different deep learning models like MobileNet, ResNet-20, VGGNet-16, GoogLeNet and AlexNetdeep CNN models for classifying plant diseases, specifically focusing on detecting potato plant diseases. The evaluation results indicated that the accuracy achieved by the AlexNet model was significantly higher at 90.71%, compared to other model. Moreover, the researchers observed that the AlexNet model outperformed other model in terms of reducing losses, Mewmory space, Batch Size and elapsed time. This implies that the AlexNet model not only provided superior accuracy but also demonstrated improved efficiency in terms of computational resources and training time. Based on these findings, the researchers concluded that the DeepCNN algorithm, specifically the AlexNet model, is more effective in detecting plant diseases compared to the other Model. The utilization of the AlexNet model resulted in higher accuracy rates and better overall outputs.

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