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Potato Leaf Disease Detection using Deep Learning

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***Abstract*—Potato is a widely consumed staple food that has risen to become the world's fourth most consumed staple food. Furthermore, global demand for potatoes is increasing significantly, owing primarily to the global pandemic coronavirus. However, potato diseases are the leading cause of harvest quality and quantity declines. Various diseases, such as early blight and late blight, have a significant impact on the quality and quantity of potatoes, and manual interpretation of these leaf diseases is time-consuming and inconvenient. Diseases in potato plants, fortunately, can be identified based on leaf conditions. As a result, in this paper, we present a system that uses deep learning to classify two types of diseases in potato plants based on leaf conditions, using the GoogleNet, Resnet50, and the VGG16 convolutional neural network architecture model to create an accurate classification system. This experiment achieved 97% accuracy for the first 40 CNN epochs, indicating the feasibility of the deep neural network approach.**

Keywords—Leaf disease classification, deep learning, vgg16, resnet50, googlenet, potato plant.

1 INTRODUCTION

There are many different types of occupations in the world, but agriculture is the most common. The Indian economy, which is heavily reliant on agriculture, is no exception. Potato is the most versatile crop, accounting for approximately 28.9% of total agricultural crop production in India. After maize, wheat, and rice, potatoes are the world's fourth largest agricultural food crop. India is the world's second-largest producer of potatoes, with 48.5 million tonnes produced each year [1]. According to the Agricultural and Processed Food Products Export Development Authority (APEDA), Uttar Pradesh is India's leading potato producer, accounting for more than 30.33% of total production. In the textile industry, potato starch (farina) is utilized for sizing cotton and worsted. Potatoes are high in potassium, vitamins (especially C and B6), and fibre. It lowers total cholesterol levels in the blood and aids in the treatment of diseases such as high blood pressure, heart disease, and cancer.

Plant and agricultural lands are victimized by diseases. Microorganisms, genetic disorders, and infectious agents such as bacteria, fungi, and viruses are the causal factors of these diseases. Potato leaf diseases are primarily caused by fungi and bacteria. Late and early blight are fungal diseases, whereas soft rot and common scab are bacterial [2]. So, detecting and diagnosing these diseases on such vital vegetation motivates us to devise an automated strategy that could enhance crop yield, increase farmer profit, and make a significant contribution to the country's economy.

Previously, many computer vision and image processing researchers proposed using traditional image processing techniques such as LBP [3], and K-means clustering [4] to detect these leaf diseases. Deep learning models perform better at mapping functions and thus generate better features. So, in this paper, we developed a deep learning model to detect potato leaf diseases that employ several classifiers.

Using the Deep Learning approach, the proposed research methodology focuses on the classification and identification of healthy and disease-infected leaf conditions. The architecture used in this study is VGG16 which is a VGG Network Group of the Convolutional Neural Network architecture models. Also different types of CNN architectures like ResNet50 and GoogleNet are used in this work.

2 LITERATURE REVIEW

In [5], the authors present, review, and recognize the need for developing a rapid, cost-effective, and reliable health-monitoring sensor to aid agricultural advancements. They described the currently used technologies, which include spectroscopic and imaging-based plant disease detection methods, as well as volatile profiling-based plant disease detection methods, with the goal of developing ground-based sensor systems to aid in monitoring plant health and disease under field conditions.

It was decided to use image processing disease recognition approach among other approaches commonly used for plant disease diagnostics, such as double-stranded ribonucleic acid (RNA) analysis, nucleic acid probes, and microscopy, after analysing their work and the analysis presented by the authors of [6-9].

[10] proposes an SVM-based Multiple Classifier System (MCS) for pattern recognition of wheat leaf diseases. [11] describes a software prototype system for rice disease detection based on infected images of various rice plants. Cotton leaf diseases were also identified using an approach [12] that regularizes and extracts eigen features from images as well as developing and decomposing scatter matrix. [13] describes the design and implementation of an artificial vision system that extracts specific geometric and morphological features from plant leaves. The proposed system is made up of an artificial vision system, image processing algorithms, and a feed forward neural network-based classifier. For feature selection, a fuzzy surface selection technique was used. In [14], a prediction approach based on support vector machines is proposed for developing weather-based prediction models of plant diseases. The performance of multiple regression, artificial neural networks (back propagation neural network, generalized regression neural network), and support vector machines (SVM) was compared. The SVM-based regression approach resulted in a better description of the relationship between environmental conditions and disease level, which could be useful for disease management.

[15] proposed using a back propagation neural network to detect damaged leaves. It was demonstrated that a back propagation network and the shape of a leaf image are sufficient to identify the species of a leaf. To find leaf tokens as input to the back propagation algorithm, the Prewitt edge detection and thinning algorithm is used. It was reported that there is room for improvement in this work, which includes more experiments with large training sets to recognize various damaged leaves caused by different diseases.

Banana images from the PlantVillage dataset [18] were used in [16] to detect two common diseases. There were 3700 images in total, which were resized to 60x60 pixels, and the experiment was carried out on both colored and grayscale images. The model was built using the LeNet architecture [17], and it achieved an accuracy of 92-99% after several trainings on different proportions of the train and test split. However, because diseases are frequently identified by color deviation, the conversion to grayscale significantly reduced those results. The authors recognized the importance of taking images in real-world settings and emphasized that disease localization was an important step in the process. Another study addressing the same issue was conducted [19], but this time the experiment included testing five different CNN architectures: AlexNet, AlexNetOWTBn, GoogLeNet, OverFeat, and VGG, with the latter achieving the highest accuracy of 99.53% for 58 distinct classes. In contrast to the usual procedure, the authors avoided segmentation in favor of using CNN. However, it is important to note that the training and testing sets were from the same dataset, and the results would have been poor if the sources had been different.

Table 1. Comparison of various techniques

Sr No	Reference	Object	DL Frame/Techniques	Dataset	Sample size	Metric
1.	[5], 2010	A variety of plants like potato, tomato, onion, rice etc.	Non-invasive techniques like spectroscopic & imaging techniques and Volatile. Organic Compounds (VOC) profiling-based technique to detect diseases in the plants.	Review of various studies using different datasets and observing their results	Different size for different datasets	None
2.	[9], 2012	Various agricultural crops	SVM, ANN, PCA, SAM (Spectral Angle Mapper)	Self-acquired in field	Customized dataset	None
3.	[10], 2010	Wheat	SVM based multiple classifier system	Dataset acquired from NERCITA	800 images both in the training and the testing set	Accuracy
4.	[14], 2006	Rice	Conventional Multiple Regression (REG), Back propagation Neural Network (BPNN), SVM & Generalized Regression Neural Network (GRNN)	Data on weather and rice leaf blast severity were obtained from one-year historical data for the year 2000 and from a NATP project entitled "Development of weather-based forewarning systems for crop pests and diseases"	Various weather variables in the dataset	Mean Absolute Error (MAE) & Correlation Coefficient
5.	[15], 2007	Leaves	Back propagation Neural Network (BPNN), Prewitt edge detection and thinning algorithm	Self-acquired dataset	The training set contains minimum five spices for each type of leaf in each data file	A software model divided into various modules

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6.	[16], 2017	Banana Leaf	CNN and Image Processing	PlantVillage Dataset from [18]	3700 images which were later resized to 60*60 pixels	Accuracy, Precision, Recall and F1-score

3 PROPOSED WORK

3.1 Architecture

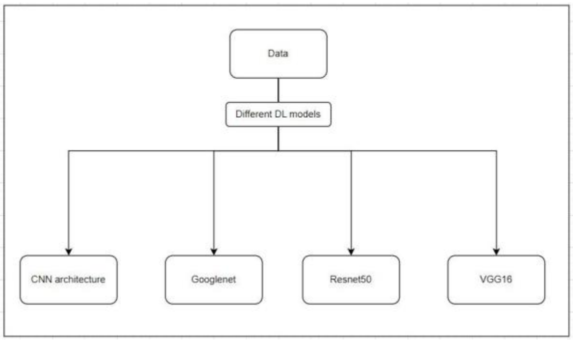

Fig. 1. System Architecture

3.2 Dataset

We have used only 900 images to train our model and 300 images for validation. The dataset used is a kaggle dataset: [PlantVillage Dataset | Kaggle]

The dataset has images belonging to classes like Early blight,late blight and healthy.

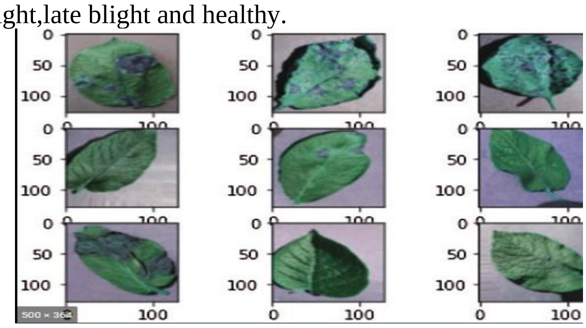

Fig. 2. Dataset Images

3.3 Data Preprocessing

We firstly augment the data to simply increase the quantity of data.Data Augmentation is a process that generates several realistic variants of each training sample, to artificially expand the size of the training dataset. This aids in the reduction of overfitting. In data augmentation, we will slightly shift, rotate, and resize each image in the training set by different percentages, and then add all of the resulting photos to the training set. This allows the model to be more forgiving of changes in the object's orientation, position, and size in the image. The contrast and lighting settings of the photographs can be changed. The images can be flipped horizontally and vertically. We may expand the size of our training set by merging all of the modifications. We then create batches of size 32 images each,3 channels and 50 epochs.

3.4 Model Building

We create a CNN neural network using Max Pooling and Conv layers. The Relu which is a non linear activation function is used in the hidden layers while the output layer has softmax activation function.

3.5 Validation

We fit our model over training data and find the results and based on it compute the accuracy scores. The train test validation is shown below.

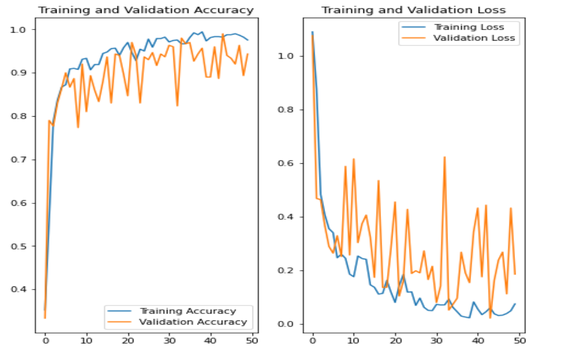

Fig. 3. CNN train-test accuracy visualization

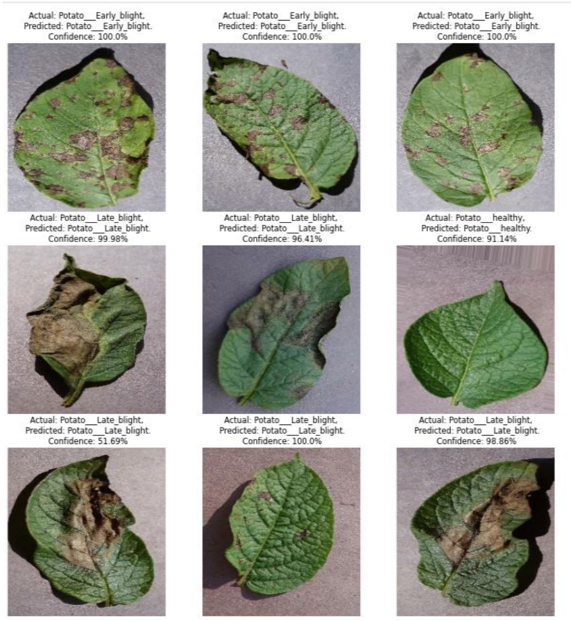

Fig. 4. Results of the Model created

3.6 Comparative Study

Now,we use various CNN architectures like Googlenet,Resnet and VGG over the above data and compute accuracy and their performance to find out the best neural network that can be used to predict the disease type of potato disease based on input image fed.

GoogleNet

GoogLeNet is a 22-layer deep convolutional neural network that's a variant of the Inception Network, a Deep Convolutional Neural Network developed by researchers at Google.The GoogLeNet architecture presented in the ImageNet Large-Scale Visual Recognition Challenge

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2014(ILSVRC14) solved computer vision tasks such as image classification and object detection.

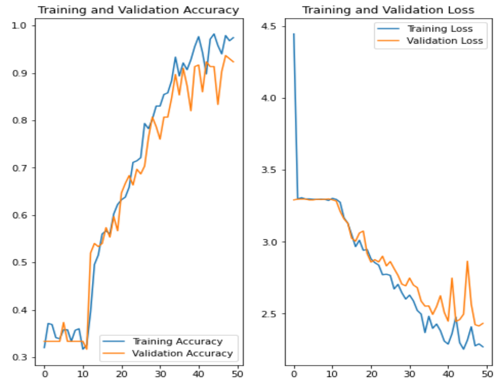

Fig. 5. GoogleNet Accuracy Visualization

Resnet

In order to solve the problem of the vanishing/exploding gradient, this architecture introduced the concept called Residual Blocks. In this network, we use a technique called skip connections. The skip connection connects activations of a layer to further layers by skipping some layers in between. This forms a residual block. Resnets are made by stacking these residual blocks together.

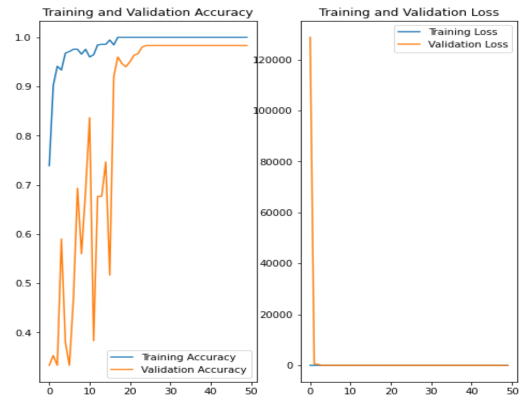

Fig. 6. Resnet Accuracy Visualization

VGG16

VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

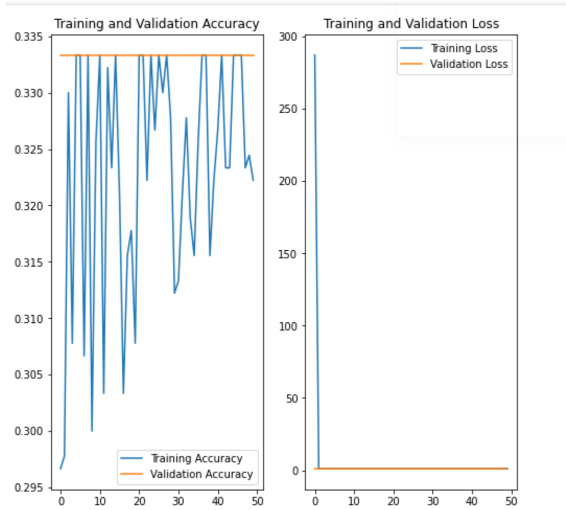

Fig. 7. VGG16 Accuracy Visualization

4 RESULTS

Here, we see a detailed comparative analysis of all the neural networks used.

Table 2. Accuracy of various models

DL model	Validation Accuracy			Average Training time per epoch (in sec) (Data was stored in cache memory)
	First 20 epochs	First 30 epochs	First 40 epochs	
CNN	0.95	0.92	0.97	2
GoogleNet	0.62	0.83	0.95	4
Resnet50	0.94	0.98	0.98	13
VGG16	0.33	0.33	0.33	17

It can be clearly seen that Resnet is the best model that can be used due to its high and near constant accuracy for each epochs. This can be well explained due to the fact that Resnet uses skip connections (Resnet blocks) to optimize deep layers processing so that issues like varnishing gradients can be solved.

Google Net, which had the best accuracy over Imagenet dataset, shown excellent accuracy in the final 50 epochs but however not initially. VGG16 performs the worst in terms of accuracy as well as processing time. The reason may be due to the same convolution filers used from time to time during each convolution layer operation. Plain CNN works fairly good with even less processing time but however for bigger datasets like ours, it might not be suitable in real time.

5 CONCLUSION

In this paper, we have used the concept of CNN and have developed a model to classify conditions in the potato leaves like early blight, late blight and healthy achieving classification accuracy of around 97%. The data augmentation process helps the model to be more robust. Our technique can help farmers in detecting diseases in their

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early stages and in enhancing their crop yields. figure 6 shows the classification accuracy of the proposed approach in comparison with other implementations.

6 FUTURE SCOPE

We could improve the robustness of our model by using Gan for data creation and Transfer Learning for improving model accuracy. Gan will help us to make the model more forgiving of changes in the object's orientation, position, and size in the image. Transfer Learning will help us to develop a model that is more robust and accurate.

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