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Transformative Breakthroughs: Revolutionizing Potato Disease Detection Through Machine Learning

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Abstract

Advancements in agricultural technology and the integration of artificial intelligence for diagnosing plant and leaf diseases are crucial for sustainable agricultural development. Conditions like early blight and late blight exert a notable influence on both the quality and quantity of potato harvests. Identifying these leaf diseases manually demands significant labor and a considerable level of expertise. Therefore, efficient, and automated methods for disease detection are essential to improve potato production. This study introduces a model that utilizes pre-trained models like VGG16 for fine-tuning via transfer learning to extract relevant features from the dataset. The dataset is sourced from a publicly available plant database. Several trained models are employed to detect and categorize both diseased and healthy leaves. The system achieves an impressive testing accuracy of 99.23%, with 25% test data and 75% train data split. The results demonstrate that machine learning surpasses existing methods in potato disease detection. This research underscores the significance of leveraging advanced technologies in agriculture to address crucial challenges and improve productivity.

Keywords: Feature extraction, VGG16, convolutional neural network (CNN), transfer learning fine-tuning

INTRODUCTION

Agriculture is a significant sector in India's economy, and one of the most versatile crops in the country is potato, which contributes almost 29% to the total agricultural crop production. Potatoes hold the position of the fourth largest agricultural food crop globally, trailing behind maize, wheat, and rice. India ranks as the second-largest producer of potatoes globally, with a remarkable yearly output of 48.5 million tons. Uttar Pradesh leads in potato production, as reported by the Agricultural and Processed Food Products Export Development Authority (APEDA). production within India, contributing more than 30.33% to the country's total output. Potato starch also referred to as farina, finds application in the textile industry for sizing cotton and worsted materials. Potatoes serve as a significant source of potassium, vitamins (particularly C and B6), and dietary fibers. Their consumption is associated with a reduction in overall cholesterol levels, contributing to the prevention and management of conditions such as high blood pressure, heart disease, and cancer [1–5].

Diseases can indeed have a detrimental impact on plant growth and agricultural lands. Microorganisms, genetic abnormalities, and infectious agents such as bacteria, fungi, and viruses are the principal contributors to these ailments. In the context of potato plants, fungi and bacteria are primarily responsible for leaf diseases. Late blight

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and early blight are fungal infections, whereas soft rot and common scab are bacterial infections. Detecting and diagnosing these diseases early on is crucial to improving crop yield, increasing profits for farmers, and contributing to the overall economy of the country. An automated strategy that can help identify and treat these diseases could be a significant step forward in achieving these goals [6–10].

LITERATURE REVIEW

To detect leaf diseases, a lot of effort has been made. Here is a discussion of many approaches to leaf disease detection that have been examined by numerous researchers. Sandika Biswas et al [11]. proposed a neural network and image processing system to assess the severity of potato late blight disease on potato leaves. The disease-affected area is segmented using fuzzy C Means clustering, and the photos are then added with a background that has similar color characteristics. For 27 photos, their suggested algorithm produces results with a 93% accuracy rate.

A technique for image processing was proposed by Md. Selim Hossain et al [12]. To detect and categorize two diseases that affect tea plants: brown blight and algal leaf diseases. A support vector machine classifier was employed to identify these diseases. The classification procedure employed eleven features, and the system produced results with an accuracy rate exceeding 90%. Citrus leaf diseases may be analyzed and classified thanks to work done by R. Meena Prakash et al [13]. Four components make up the entire system: feature extraction and classification, k-means clustering for segmentation, and image preparation. 35 photos of diseased and 25 photographs of healthy citrus leaves are used to train and test the classifier in a support vector machine. The accuracy range of the suggested system is 90% to 100%.

An automated deep convolutional neural network (D-CNN) based method was developed by Md. Rasel Howlder et al [14]. To identify the three main guava leaf diseases: rust, whitefly, and algal leaf spot. They produced their dataset, which included 2705 photos divided into four groups—three for diseased leaves and one for healthy leaves. The D-CNN model in this proposed method is built on eleven layers and was created using the Alex Net framework. The accuracy rate on average for the suggested system was 98.74%. A method for identifying grape leaf disease based on texture analysis and pattern recognition was developed by Harshal Waghmare et al [15]. The support vector machine performs the classification. Two main diseases affect grape plants: black rot and downy mildew. The accuracy of the suggested method was 96.6%.

PROPOSED MODEL

In the first module, we developed the system to get the input dataset for training and testing purposes. We give the data set in the model folder as shown in Figure 1. The dataset comprises 2311 images for potato disease detection, sourced from various internet platforms. We have not used any dataset from Kaggle or other websites, as it is not available. The collected data consists of five classes: Hollow heart of potato, potato leaf roll virus, early blight, scab of potato & Soft rot of potato [16–20]. Each folder in the dataset contains two types of images - colored and grayscale. Moreover, each crop exhibits various types of leaf diseases, and for classification purposes, each type is treated as a distinct disease class. The dataset is segregated into two categories, wherein each image includes a leaf picture both with and without background as shown in Figure 2.

It has taken the help of image processing to diagnose potato disease and potato leaf disease as shown in Table 1. Here we have used these parameters to diagnose the disease which can be identified by looking at the characteristics of the disease and the type of disease and we have tried to give more antidotes here. Accuracy is very good with training data in the project and accuracy with sample data is above 99%. So, our project will be able to accurately diagnose potato disease and leaf disease [21–23]. All through the proposed model, the VGG16 Architecture is utilized to recognize various kinds of potato infections, having five classes of potato sicknesses and an accomplished 100% accuracy rate. VGG16 stands out as a convolutional neural network (CNN) architecture renowned for its excellence in vision models. What sets VGG16 apart is its emphasis on simplicity in hyper-parameters, opting for convolution layers with 3×3 filters, a stride of 1, and consistent use of the same padding, alongside max-pooling layers with 2×2 filters and a stride of 2. This configuration of convolutional and max-pooling layers remains uniform across the entire architecture. Towards the conclusion, it incorporates two fully connected layers (FC) succeeded by a SoftMax layer for output [24, 25].

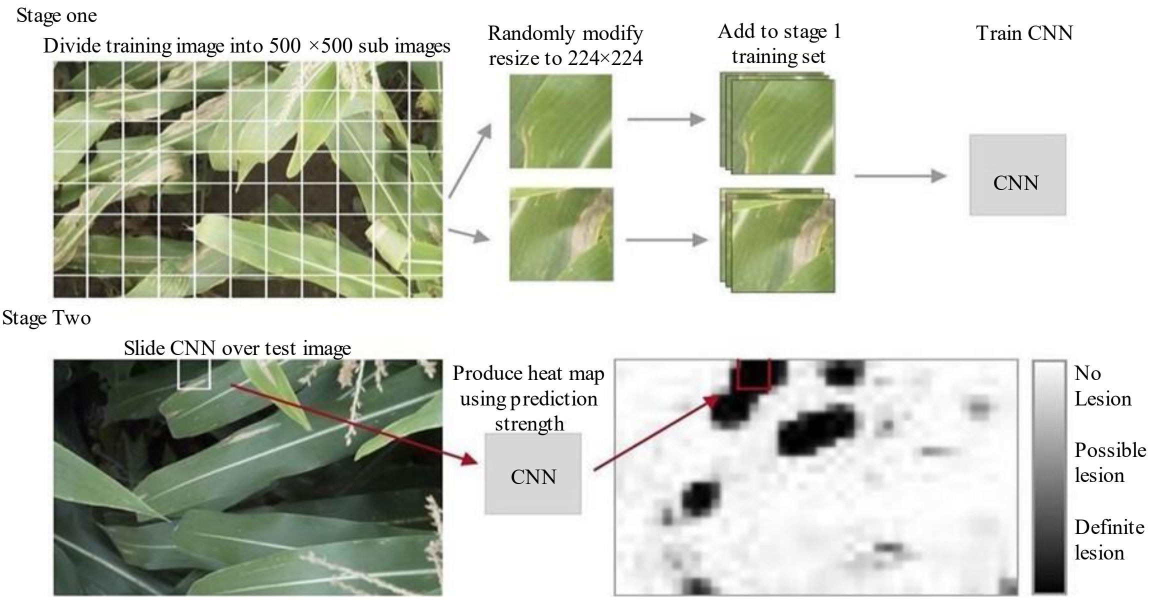

Figure 1. Stage classification.

Figure 2. Representative images from each class.

Table 1. Showing the number of samples in the training and testing set of models.

Label	Category	Number	Training sample	Test sample
1	Early Blight	1000	787	213
2	Late Blight	1000	791	209
3	Healthy	152	122	30
Total		2152	1700	452

Proposed Architecture

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a yearly contest focused on computer vision. It involves two tasks: object localization, where teams detect objects within images from 200 classes, and image classification, where images are classified into one of 1000 categories. The network's input is an image with dimensions of (224,224,3). The first two layers have 64 channels and utilize a 3×3 filter size with the same padding. Next, there's a max-pooling layer with a stride of (2, 2), followed by two layers containing convolutional layers with 256 filters and a filter size of (3, 3). Afterward, there's another max-pooling layer with a stride of (2, 2), similar to the preceding layer.

Following the initial layers, there are two convolution layers with filter sizes (3, 3) and 256 filters each. Subsequently, there are two sets, each comprising three convolution layers and a max-pooling layer. Each convolution layer within these sets employs 512 filters of size (3, 3) with the same padding. The image is subsequently passed through a series of two convolutional layers. Throughout these convolution and max-pooling layers, 3×3 filters are used instead of 11×11 in AlexNet and 7×7 in ZF-Net. Moreover, 1×1 pixel manipulation is employed in specific layers to modify the quantity of input channels. A 1-pixel same padding is applied after each convolution layer to preserve spatial features. The resultant feature map is flattened to generate a feature vector of dimensions (1, 25088). This vector traverses through three fully connected layers: the initial layer yields a vector of dimensions (1, 4096), the second also yields a vector of dimensions (1, 4096), and the third generates a 1000-channel output corresponding to the 1000 classes in the ILSVRC challenge. The output of the third fully connected layer then undergoes normalization via a SoftMax layer to create the classification vector. The top five categories are determined based on the values of the classification vector. ReLU is employed as the activation function in all hidden layers due to its computational efficiency, faster learning, and mitigation of the vanishing gradient problem.

CNN Architecture

An architecture for deep learning that learns directly from data is the CNN. CNNs are especially helpful for object recognition in images by identifying patterns. They can also be very useful in the classification of non-image data, like time series, and signal data as shown in Figure 3.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure 3. Different VGG Configuration.

The intermediate layers of a CNN include convolutional layers, pooling layers, fully connected layers, and normalization layers. where the activation function receives the output from the hidden layers.

The activation function increases the network's strength and gives it the capacity to express nonlinear, complex, arbitrary functional mappings between inputs and outputs as well as learn complex and complicated things from data. Therefore, we can create nonlinear mappings from inputs to outputs using a nonlinear activation. In this instance, ReLU is the activation function utilized in the hidden layers and SoftMax in the output layers.

As noted earlier, pooling is employed to either decrease the dimensionality of the input representation or to perform downsampling. Different varieties of pooling exist, such as min pooling, max pooling, and average pooling. The names of these types of pooling indicate the functionality associated with them; for example, min pooling refers to extracting the smallest value from a matrix of a certain dimension, while max pooling involves obtaining the maximum value from the same matrix. An illustration of max pooling via the 2×2 window.

Convolutional neural networks use pooling, a technique that helps the network recognize characteristics regardless of where they are in the image by generalizing data retrieved by convolutional filters.

Figure 4 explains how to reduce the dimension from 4×4 to 2×2 and max-pool from the 2×2 window deep convolutional neural network applications are now widely utilized in medical, agricultural, and other industries for a variety of objectives, and we used a pre-trained model like VGG16in our case to extract the important characteristics of the dataset. In this manner, we avoid beginning from scratch and make use of prior knowledge. Numerous pre-trained models, including VGG16, are accessible. By feeding the pre-trained models with the photos, we were able to extract features from them. These features are now fed into a variety of classifiers, including SVM, CNN, and logistic regression. After analyzing the outcomes of all the methods, we discovered that the state-of-the-art answer was provided by VGG16 in conjunction with logistic regression as shown in Figure 5.

CLASSIFICATION

The initial layer is in the process of extracting different features from the input photosynthesis one. We extract features from the input image in this layer using a filter or kernel approach.

$$(A)= \text{Prob}(B=1|A;\boldsymbol{\alpha}) \quad (1)$$

Equation (1) above provides the chance that, given an event A, another event B=1, which is parameterized by the variable "$\boldsymbol{\alpha}$," will occur.

$$\text{Prob}(B=1|A;\boldsymbol{\alpha})\text{Plus}\text{Prob}(B=0|A;\boldsymbol{\alpha})=1 \quad (2)$$
$$\text{Probability}(B=0|A;\boldsymbol{\alpha})=1-\text{Prob}(B=1|A;\boldsymbol{\beta})$$

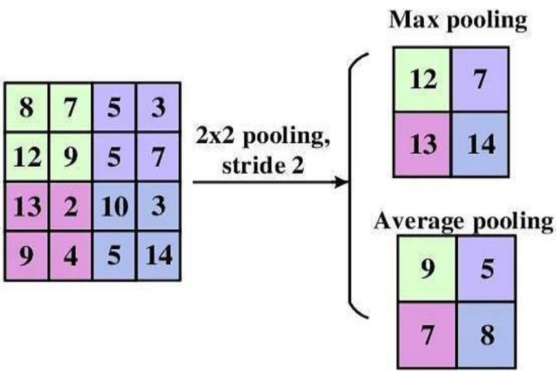

Figure 4. Characteristics of the dataset dimension.

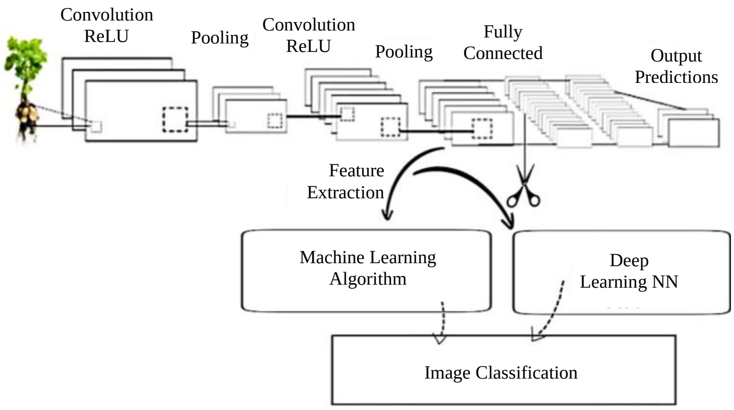

Figure 5. Process model.

Equation (3) below illustrates the cost function that is used to translate probabilistic outcomes into categorical results.

((A),B)=-B*log(HJ(A))-(1-B)*log(HJ(A))__ (3)

The only term that will exist if B=1is-log(**Ψ**(A)), as the (1-B) term will become zero. Log(1-**Ψ**(A)) by itself will appear if B=0, as the (B) term will also become zero.

RESULTS AND DISCUSSION

The proposed model utilized a dataset comprising 2152 images of potato leaves. The dataset, which originated from a plant village, contained 1000 images of late blight and 1000 images of early blight in addition to 152 images of potato leaves that were in good condition [13, 26] as shown in Figure 6. The dataset is divided into two parts: the training section contains 1700 photographs (70%), while the test section has 452 photos (30%). Several pre-trained models, such as VGG16 and InceptionV3, are employed for feature extraction. Several classifiers are used for classification, including neural networks, KNN, SVM, and logistic regression. With a 99.23% classification accuracy, Logistic Regression offers the most sophisticated answer out of all of these. AUC (area under the curve), and CA (classification accuracy) as shown in Table 2. Precision, Recall, and F1Score are performance metrics used to assess the model's efficacy as shown in Table 3.

Table 2. A report comparing this model to others.

Model proposed	Classification accuracy
Image segmentation + back propagation neural network	92%
Image Segmentation + Support Vector Machine	95%
Proposed Approach	99.23

Table 3. Using VGG16 and InceptionV3, AUC (area under the curve), CA (classification accuracy), Precision, Recall, and F1-Score.

Model	Classifier	AUC	CA	Precision	Recall	F1-Score
VGG16	KNN	98.9	98.8	98.6	98.9	98.9
	SVM	99.8	99.6	99.9	99.7	99.8
	Neural Network	99.6	99.9	99.8	99.6	99.6
	Logistic Regression	99.23	99.23	99.23	99.23	99.23
InceptionV3	KNN	98.8	98.9	98.6	98.7	98.9
	SVM	99.6	99.7	99.9	99.9	99.8
	Neural Network	99.9	99.6	99.8	99.7	99.6
	Logistic Regression	99.23	99.23	99.23	99.23	99.23

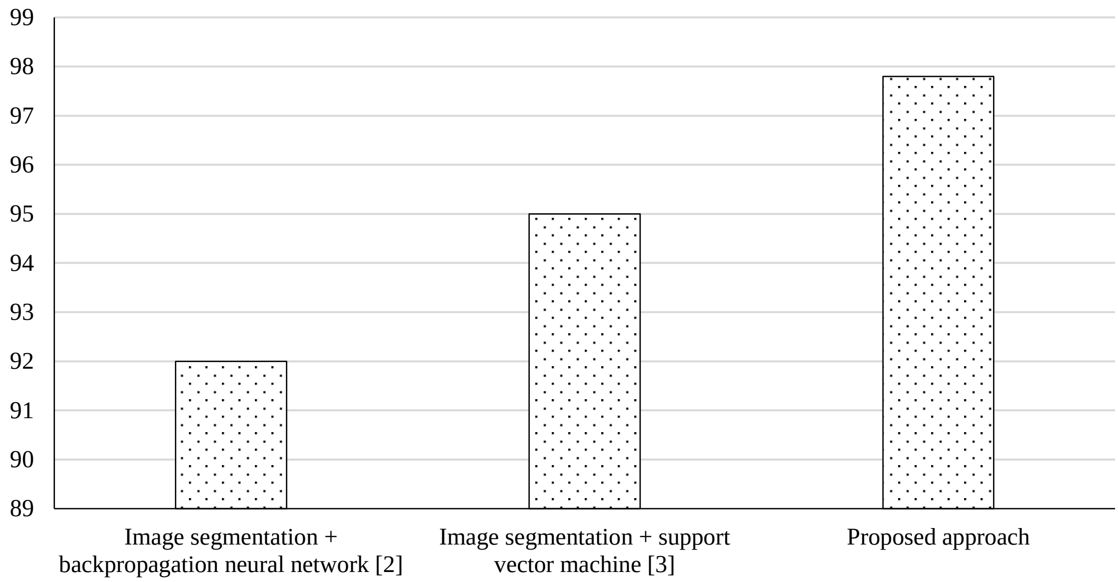

Figure 6. Accuracy of classification.

CONCLUSION

In this study, we used transfer learning to build a novel automated system that is designed to identify and classify diseases that are common in potato leaves, with a focus on early blight, late blight, and healthy conditions. Our efforts resulted in an outstanding 99.23% CA when measured against an extensive test dataset. Notably, our solution demonstrated significant improvements over the approaches cited in citations [2] and [3] of 5.8% and 2.8%, respectively, demonstrating the effectiveness and originality of our approach. Our method's practical applications also reach the agricultural sector, where it can greatly help farmers maximize crop yields and speed up early disease diagnosis. In our investigation, Figure 6 shows the classification accuracy of our method compared to other implementations, highlighting its superiority, and confirming its potential as a reliable tool for potato crop disease identification. Because of its high level of accuracy, our model is a useful tool for precision agriculture. It provides a proactive approach to disease control and can help improve crop health and productivity in general.

FUTURE SCOPE

Nowadays, the most important thing for increasing crop production and productivity in agriculture is to identify plant diseases early. Understanding how important it is to act quickly, we offer a unique solution that takes advantage of farmers' access to cell phones to help them identify diseases. To fulfill our vision, we want to install our automated system on cell phones and enable farmers to take pictures of plant leaves when they are just blossoming. These photos would then be quickly sent to a server, where our sophisticated, experience-based illness detection program would examine the leaves. Our approach democratizes access to precise disease diagnosis by automating the categorization process, removing the requirement for in-depth knowledge. After processing, the server quickly provides the farmer's smartphone with the results and suggested treatments. With this streamlined method, farmers receive meaningful data to help them make informed decisions and promptly implement interventions, all while speeding up the diagnostic process. Fundamentally, our system's incorporation into cell phones acts as a revolutionary instrument, democratizing agricultural knowledge and making a substantial contribution to increased crop productivity and yield quality.

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