

Transfer learning Model for Plant Disease Detection

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Abstract : The significant task in image processing is to detect the diseases in plants as the data utilized for input is complex in nature. The infected plants are diagnosed in diverse phases. For this purpose, various algorithms are available. The prior work presented SVM (Support Vector Machine) algorithm in order to detect the disorder. This research work introduces a transfer learning system for enhancing the diverse metrics such as accuracy, precision and recall obtained from the earlier work. The Python is applied to deploy the introduced and traditional technique. Some parameters are considered for analyzing the outcomes. The results of analysis depicted that the introduced approach outperforms the traditional approach concerning accuracy, precision and recall.

Keywords : Plant Disease, SVM, KNN, Transfer Learning, CNN

1. Introduction

The farming sector has developed to the point where it cannot be trusted to serve the world's expanding population. However, this important source of income is threatened by plant diseases. Plant diseases drastically lower forestry and farming productivity and are expensive. For instance, by eradicating just 20% of the fungus that causes severe financial losses in crops, leaf rust, growers might make a profit of almost \$11 million [1]. Early detection and diagnosis of plant pathogens are therefore essential for the application of prompt therapies. There are numerous methods for detecting deformities in plants. Certain diseases either don't show any symptoms at all or only do so after it's too late to take any action. A thorough investigation utilizing the available microscope is essential in circumstances like this. Signs of a certain diseases can only be found in portions of the electromagnetic spectrum that are undetectable to humans. However, the majority of diseases have obvious symptoms. Plants' leaves, stems, fruits, seeds, and other sections can all display the disease's symptoms [2]. Depending on symptoms that show up on a plant's leaves, this study aims to identify and investigate plant infections. Monitoring by people frequently leads to the diagnosis, or at the very least, the initial hypothesis regarding the illness. A skilled doctor may be able to diagnose the condition. Unfortunately, there aren't many professionals in the area who can help producers by using data-based analysis. It is essential to look for a quick, mechanized, affordable, and accurate way to identify plant pathogens. The use of computer vision-based image processing methods for agronomic engineering research since the late 1970s has drawn a lot of attention from researchers [3].

1.1 Plant Disease Detection based on Images

Leaf photography is an excellent and thorough source of data on phytopathology and morphological behaviour. It is essential to thoroughly extract and analyse such data as a result. Image processing has a significant positive impact on foliar problem inquiry and diagnosis. Figure 1 depicts the procedure used for identifying and categorising leaf disease. It sheds light on the various methods researchers have employed to use machine learning and image processing to identify diseases [4].

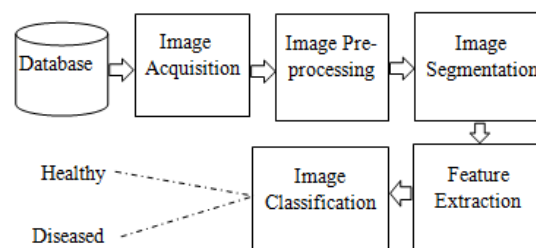


Figure 1: Plant Disease Detection

As shown in Figure 1, taking photos is the initial step in the disease identification process. The majority of the time, taking images can be done using either a digital camera or an imaging platform. Rough photos contain noise; as a result, these mistakes must be removed. The following step is called "image pre-processing" and it entails removing unnecessary distortions and boosting contrast to make image details more lucid and brighter. For instance, it's rather common to use a Gaussian function to add a light blur to images in order to reduce noise [5]. In the third stage, known as picture segmentation, the image is separated from its background while being divided into the necessary sections to emphasize key features. The fourth stage, feature extraction, reveals the information and details

in an image. The primary leaf characteristics that are significant for diagnosing plants are size, texture, and colour. The classification system thus gets an input feature vector composed of these selected attributes. It is possible to distinguish between various item categories using this vector. Sorting into categories is the previous step. It's critical to keep in mind that the ideal classification architecture relies on the particular issue. Using the final feature vector derived in step 4, the classification system's objective is to classify the photos into a number of specified categories. This is why the categorization task's training and assessment phases were developed [6]. Using the training dataset, the classification system's development is the main objective of training. This suggests that as training sets are added, accuracy rates rise. It is essential to bear in mind that the goal should be reached as quickly as possible, which is the crop's status as healthy or diseased, depending on the species.

1.2 Detection and Classification Algorithms for Plants' Diseases

Digital pictures of disease-carrying organs and agricultural plants are now more accessible because to quick technology advances in mobile devices and cameras. Meanwhile, as demonstrated in a number of studies, the viability of image processing and disease diagnosis has increased with the deployment of machine learning and deep learning technologies. Artificial neural networks (ANNs), decision trees, random forests, and support vector machines are just a few examples of the machine learning methods that have been extensively used in agricultural research (SVMs) [7]. The descriptions of all of these algorithms are as follows:

Decision Tree: A decision tree, a non-parametric algorithmic architecture, iteratively partitions the entire sample space into equally tiny and full subsets (or levels). Any subset is defined and distinguished from other subsets by the set of choice rules that go into its development. For target variables that are both nested and constant, decision trees are useful. The two essential components of the DT algorithm are the selection criterion and the halting rule. Information entropy, the Gini index, or misclassification error may be used as selection criterion for an explicit objective. The selection criterion is frequently the least squared error for a constant target [8]. Starting with the entire training dataset, DT explores all predictor variables at all feasible divided sites to discover the optimal divisions that fulfil the selection criteria. This cycle of repetition continues until the withholding rules are put

into place. Because it is non-parametric, the DT does not presuppose the distribution, and neither do the predictors need to employ a functional method.

Random Forest: Because a small change in the training dataset can have a large impact on the structure of the tree, decision trees are fundamentally unbalanced. Volatility is often used to uncover more signals in the data than a single tree can, according to conventional wisdom. RF is made up of numerous models that cooperate, which is why it is known as an ensemble framework [9]. By using many trees constructed on various samples that have been made much more random to decrease the influence of correlations between samples or across trees, RF attempts to demonstrate higher resilience than a single tree.

Support Vector Machine: SVM separates the mapped points in a high-dimensional space linearly using hyperplanes. These hyperplanes are built using the acquired data points as support vectors. In order to maximize the lowest margin and isolate the dependent variable along a hyperplane, the SVM aims to achieve greatest margin data splitting. The margin represents how the senses and the hyperplane are divided. It can occasionally be impossible or too difficult to locate the hyperplane that entirely isolates the response, though. We employ softer hyperplanes instead of stiff ones to allow for a lower rate of misdiagnosis [10]. A larger dimensional feature space (number of explanatory variables and their resulting terms) results in the production of more descriptive phrases. If the size of the feature space is greater than the number of perceptions, it will be difficult to formulate a solution to an objective function. SVMs naturally employ a kernel method to solve this problem by implicitly translating data to a separate feature space using kernel functions. This feature space can be described by having a sufficient comprehension of the pairwise internal products of the perceptions in the data. To train the SVM, the vectors or particular sensations that will support the hyperplane are selected.

ANN: ANN was primarily developed in 1943 by two academics by the names of McCulloch and Pitts. By fusing numerous condensed processing modules (sometimes referred to as perceptron, neurons, or nodes) into a densely networked architecture, artificial neural networks (ANNs) sought to mimic the neurophysiology of the human brain. The single-hidden layer feedforward network (SLFN) is the most prevalent kind of neural network system [11]. It is applied when conducting a neural network analysis. A

hypothetical mathematical illustration of SLFN is as follows:

$$y = G \left(a_0 + \sum_{j=1}^h a_j v_j \right)$$
$$v_j = F \left(\beta_{0j} + \sum_{i=1}^k \beta_{ij} x_i \right)$$

where $x_i, i = 1, \dots, k$ and $v_j, j = 1, \dots, h$ represent the input units and the hidden units respectively. The term β_{ij} denotes the weight of the like between the input-layer unit x_i and the hidden-layer unit v_j . Also, a_j signifies the connection's weight between the hidden-layer unit v_j and the output y . The bias of hidden-layer unit v_j is β_{0j} and the bias of the output y is a_0 . $F(\cdot)$ and $G(\cdot)$ respectively indicate the activation function of the hidden-layer units, and the activation function of the output. Activation functions are often sigmoid functions: s-shaped functions like logistic and hyperbolic tangents that create limited values within the range of $[0, 1]$ or $[-1, 1]$ [12]. Sigmoid functions are chosen as activation functions, as they are distinguishable, which lets Hessian-reliant optimization algorithms to be used in solving the weights.

2. Literature Review

V. Tiwari, et.al (2021) suggested a DL (deep learning)-based technique to detect and classify the plant disease from leave images taken at different resolutions [13]. An enormous dataset, in which plant leaves images taken from various countries, employed to train the dense CNN (convolutional neural network) model. This model assisted in tackling the images suffered from various inter- and intra-class variations with complicated situations. A number of metrics were considered to test the suggested technique. The simulation outcomes reported that the suggested method was effective of classifying several kinds of plant leaves at an accuracy of 99.58% and processing time of 0.016s.

S. P. Singh, et.al (2023) suggested a custom CNN (Convolutional Neural Network) model for detecting and classifying the common diseases of rice plants [14]. A number of metrics related to the network were mitigated for this purpose. Furthermore, a dataset consisted of 1400 on-field images was utilized to detect the diseased plants. SGDM (Stochastic Gradient Descent with Momentum) and Adam (Adaptive Moment Estimation) methods were implemented to compute the suggested model. The experimental

results demonstrated that the suggested model offered an accuracy of 99.66% with initial method and 99.83% with the second method.

M. H. Saleem, et.al (2022) projected an optimized DL (deep learning) approach recognized as RFCN (region-based fully convolutional network) for diagnosing the plant disease on the newly developed dataset [15]. An appropriate model was discovered to quantify the methods of augmenting the data. Thereafter, an analysis was performed on the impact of image resizers using interpolators, WIs (weight initializers), BN (batch normalization), and DL optimizers. At last, the position-sensitive score maps and anchor box specifications were observed to improve the efficiency. The testing results on external dataset indicated that the projected approach was robust and practical, and offered a precision of 93.80% as compared to other methods. Moreover, it assisted in controlling disorders occurred on various plant species automatically.

R. Nalawade, et.al (2020) introduced an innovative system with the objective of diagnosing the leaf disease along with complete surveillance of the field having real-time values of field components such as temperature, humidity, moisture, etc. [16]. User were capable of controlling the flow of water in automatically way with the help of application that helped to track the real-time values. This application was useful to attain the information related to the need of plant fertilizers, soil factors and pesticides for curing the diseases. The results depicted that the introduced system yielded an average accuracy of 98.07%. This system also allowed user to observe the outputs such as the field report, and diagnose the diseases on the app.

J. Zhao, et.al (2019) developed a CNN (convolutional neural network) known as YOLOv2 (You Only Look Once version 2) to diagnose the healthy and diseased tomato fruits [17]. This algorithm was planned on the basis of regression framework and detected the disease quickly and accurately. Primarily, the DA (data augmentation) techniques employed to expand the image datasets for alleviating the chance of overfitting, and to acquire the augmented datasets in which 1000 images of tomato fruit were comprised. Subsequently, the image data kind was explored using the grayscale processing and foreground extraction modules. Eventually, KMC (k-means clustering) algorithm was put forward for lessening the time to train the model and enhancing the detection effects. The developed model offered mAP (mean Average Precision) up to

97.24%. The experimental outcomes validated the efficiency of the developed model for detecting physiological diseases on tomato plants.

P. Bedi, et.al (2021) investigated a new hybrid framework in which CAE (Convolutional Autoencoder) algorithm was integrated with CNN (Convolutional Neural Network) to detect the plant diseases automatically [18]. The leaf images of peach plants were employed for detecting Bacterial Spot disease. A public dataset called PlantVillage, consisted of images of peach plants, executed for computing the investigated framework in the experimentation. The investigated framework offered an accuracy of 99.35% to train the system and 98.38% to test the system on 9,914 training parameters. Moreover, this framework consumed least time for recognizing the disease in plants.

S. Datta, et.al (2023) recommended a DCNN (Deep Convolutional Neural Network) having multiple hidden layers in order to classify the diseased tea leaves into dissimilar categories [19]. This technique was useful to diagnose more amount of attributes and enhance the accuracy to diagnose the diseases. This technique implemented to classify the infections in diverse classes such as Gray Blight, Algal Spot, Brown Blight, Helopeltis, Healthy Leaves and Red Spot. The next focus was on generating a labelled dataset, in which 5867 unhealthy and normal tea leaf images involved, and uploading it on Kaggle. The recommended technique was capable of detecting diverse types of tea leaf disease and offered an accuracy of 96.56%. Furthermore, this technique was adaptable on several IoT (Internet of Things) devices to be exploited in real time.

S. Ashwinkumar, et.al (2021) designed an automated mechanism to diagnose and classify the plant leaf infections in which an OMNCNN (optimal mobile network-based convolutional neural network) was exploited [20]. This mechanism had diverse phases such as to pre-process the image, segment it, extract the features and classify the disease. BF (bilateral filtering) based method was employed to pre-process the image. Kapur's thresholding-based segmentation method put forward for recognizing the infected parts of the leaf image. Moreover, MobileNet model helped to extract the attributes and the EPO (emperor penguin optimizer) led to optimize the hyperparameters. In the end, proper class labels were assigned to the plant images using ELM (extreme learning machine) algorithm. The experiments carried out to quantify the designed mechanism. The

experimental results indicated that the designed mechanism offered the precision of 98.5%, recall up to 98.92%, accuracy around 98.7%, F-score up to 98.5%, and kappa up to 98.5%.

H. Andrianto, et.al (2020) established a DL (deep learning) system with VGG16 in which ML (machine learning) application was implemented on a cloud server and an application on a smartphone [21]. The smartphone application adopted for capturing the images of leaves of rice plant, transmitting them to the application on the cloud server, and receiving the classification results as an information related to kinds of plant diseases. The results illustrated the applicability of this system in diagnosing the rice plants. The findings exhibited that the established system offered an accuracy of 100% and 60% when the system was trained and tested respectively. Additionally, this system was assisted in enhancing the production by controlling rice plant disease.

S. Anwarul, et.al (2023) formulated CNN (Convolutional Neural Network) algorithm on simple digital images of diseased and healthy plants for diagnosing the plant disease [22]. The major emphasize was on creating an efficient web application whose deployment was done on the basis of DL (deep learning) algorithm. A platform was provided to the user for recognizing and diminishing this issue. Seven conv (convolutional) layers, 2 DC (densely connected) layers, and 4 pooling layers were utilized in this algorithm. The experimental results on PlantVillage dataset revealed that the formulated algorithm offered an accuracy of 94% to recognize the diseased plants in comparison with the existing methods.

3. Research Methodology

This research work is focused on recognizing the diseases in plants. The entire cycle to detect the infection contains different functions that are discussed as:

1. Pre-processing: - The image is pre-processed in this function with the objective of diagnosing the diseases from leaves of plants. The images are captured to be fed in input. A consistent data source is considered to collect these images. A public dataset called Plant Village is generated in which all the collected are comprised. The Plant Village is a website that is helpful for deriving the information about the plant and its disease's kind. The images taken from wheat are involved in the dataset. This dataset consists of 3 portions in which images normal leaves, leaves

suffered from early blight and the images of late blight disease, are inserted. This process also focuses on transforming the input images into gray scale.

2. Segmentation: - The second function aims to split a digitized image into distinct portions. The process to segment an image is adopted to identify the objects and retrieve the information from the images. The images are easily analyzed in this stage. The technique of segmenting an image is put forward to locate the RoI and bounding line of pictures. every pixel is marked with a label. Every pixel having similar label leads to strengthen several features. This work adopts KMC (K-means clustering) for segmenting the pictures of plant leaves. Moreover, the samples are gathered into various clusters according to the distance using this algorithm. Two points having least distance amid them are assisted in offering compressed and independent cluster as a closing target. The 3 is taken as the optimal value for the input. The value of k is considered to segment an image. After that, this phase selects the essential portion from the part of input leaf which suffers from infection.

3. Classification :- To prediction the disease type model of transfer learning is applied which is the combination of VGG16 and CNN model. The VGG16 is used as the base model over which CNN model is used for the training.

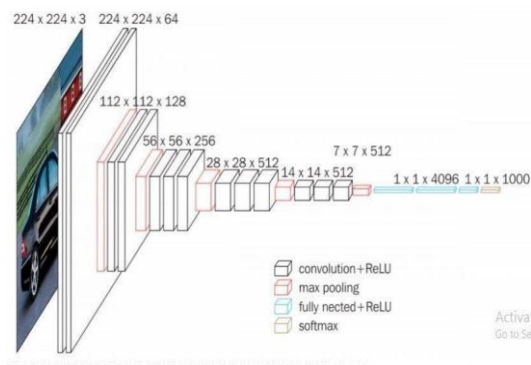


Figure 2: VGG16 Model Architecture

Following are the various specifications of VGG16 Model: -

1. This model illustrates sixteen layers with 16 and these layers contain weights. Around 13 conv layers, 5 MP layers and 3 dense layers are included. However, only 16 weight layers are there.
2. The tensor size as 224, 244 with 3 RGB channel is utilized for input in this model
3. This model does not contain a large number of hyper-parameters as it deploys conv layers of 3x3 filter with stride 1 and the same padding and max-pool layer of 2x2 filter having stride 2.

4. The arrangement of conv and max pool layers is done in consistent way in the entire framework.
5. 64 filters comprised in Conv-1 Layer, 128 in Conv-2, 256 in Conv-3, 512 in Conv 4 and Conv 5.
6. Three FC layers has a stack of conv layers: 4096 channels are included in primary two, the last leads to perform 1000-way ILSVRC classification. Therefore, one thousand channels are comprised. The last one is known as the soft-max layer.

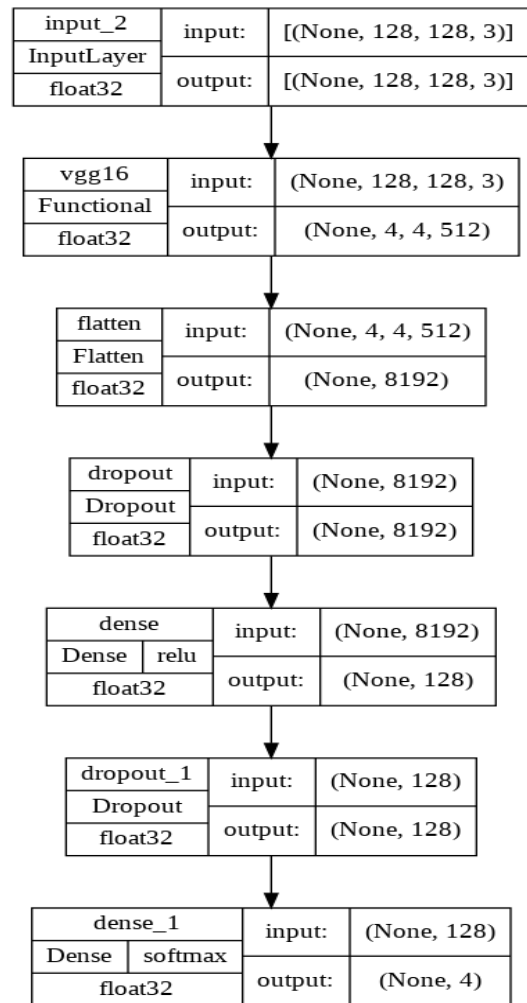


Figure 3: Proposed Transfer Learning Model

4. Result and Discussion

This research work is based on the plant disease detection using transfer learning model. The dataset is collected from kaggle and potato plant is considered for the prediction. The performance is analysed in terms of accuracy, precision and recall.

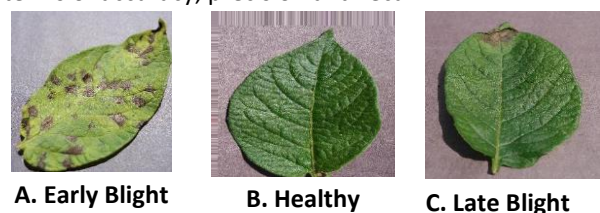


Figure 4: Dataset Samples

As shown in figure 4, the sample images of the dataset are illustrated which has different diseased images.

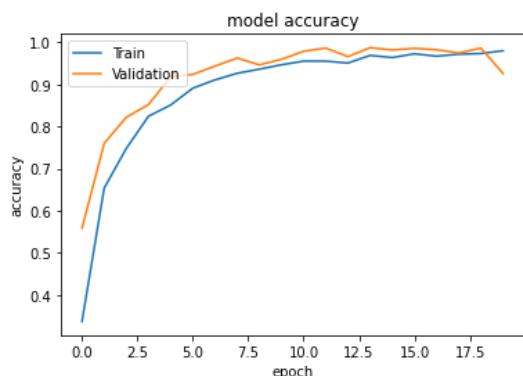


Figure 5: Training Accuracy

As shown in figure 5, the training and validation accuracy of the proposed model is shown which is raised upto 95 percent.

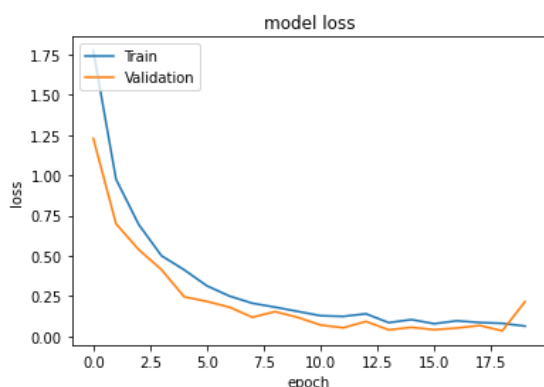


Figure 6: Model loss

As shown in figure 6, the model loss of the proposed model is shown which shows loss of 5 percent for the plant disease prediction

Table 1: Result Comparison

Model	Accuracy	Precision	Recall
Random Forest	66 Percent	56 Percent	66 Percent
SVM	77.59 Percent	78 Percent	78 Percent
KNN	69.88 Percent	70 Percent	70 Percent
Proposed Model	91 Percent	91.2 Percent	92 Percent

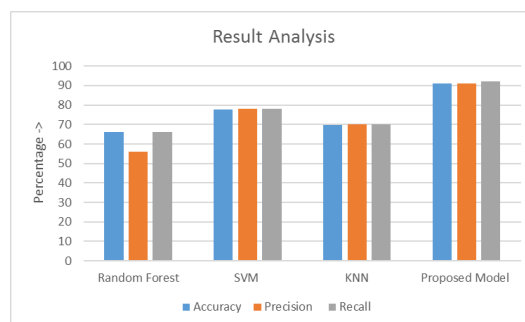


Figure 7: Result Analysis of Proposed Model

Figure 7 depicts that the results of the introduced approach are compared with the SVM, KNN and Random Forest. The proposed model achieves accuracy upto 95 percent, KNN Model, Random Forest Model and SVM Model has accuracy 69.88, 66 Percent and 77.59 percent respectively for the plant disease detection which proves reliability of proposed model.

Conclusion

This work concludes that the introduced approach is applicable to diagnose the diseases occurred on plants. This technique detects the infected plants in diverse phases. The K-Means is adopted to segment the plant image. The law textural technique is exploited to extract the attributes. The disease is predicted using transfer learning techniques. A comparative analysis is conducted on the introduced approach against the SVM (Support Vector Machine) for diagnosing the ailment of plant. The introduced approach offers more effectiveness in comparison with the conventional technique concerning accuracy, precision, and recall to detect the infected plants.

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