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Machine Learning Algorithm to Classify the Tomato Plant Quality with Transfer Learning Feature Extraction

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Abstract

Numerous diseases that can drastically lower yield and quality affect tomato plants, including botrytis grey wilt, grey leaf spot, Verticillium wilt, Fusarium wilt, anthracnosesouthern blight, septoria leaf spot, early southern blight, bacterial speck, Fusarium wilt, and blossom end rot. For many illnesses to be effectively managed and prevented, early identification and precise diagnosis are essential. In order to sort or grade tomatoes, this study suggests an automated machine learning-based system for detecting plant diseases in tomatoes. Initially, a vast collection of photos showing both healthy tomato plants and a range of frequent illnesses is gathered. Next, using transfer learning of the dataset, a deep Convolutional Neural Network (CNN) architecture is created and trained. When it comes to identifying between healthy and unhealthy tomato plants, the trained model performs with excellent accuracy. Additionally, it can identify the particular disease that is afflicting the sick plants, allowing for more focused management and treatment plans. The suggested technique provides a practical and economical means of identifying diseases in tomato plants early on, which will increase yields and lessen farmers' financial losses. Future research may examine the integration of a robotic platform for autonomous disease monitoring and management, as well as the real-time deployment of the system in agricultural settings.

Keywords: Grading, feature extraction, Machine Learning algorithms, Image processing, sorting, neural networks.

1. Introduction

For many years, agriculture has been linked to the production of staple foods that are crucial to our diet and way of life. The majority of the nation's economic growth is being offset by agriculture. It might be regarded as the most important aspect of society. We might say that industrialization and its causes are ruining the course of agriculture because numerous industries have been established all over the world. Another factor contributing to the decline in farming activity is globalization. The necessity to adjust agricultural cultivation to the growing population as well as changes in the climate have had a significant impact on productivity since these factors can also encourage the establishment of numerous plant diseases. Therefore, reducing the usage of pesticides will be our primary goal in order to save the environment and lower farming costs. Plant disease prediction can now be done with the help of data mining, a potent and popular technique. Thus, it will be simple for us to identify if a crop is infected or not using data mining principles with image processing, classify disease according to numerous concerns and with the help of colours created due to disease, and then offer various therapies for it depending on degree of illness. Therefore, gathering information about plant illnesses and developing a model for disease detection are the main goals of the research. Deep Convolutional Networks, which aid in recognition and classification as well as Smartphone-based leaf size and Color detection for plant disease monitoring, have been used in recent sophisticated technology.

2. Related Work

The use of transfer learning, a general intelligent tomato classification system based on DenseNet-201 was presented. The model was trained using supplemented training sets that were acquired through data augmentation techniques. Even with photos with a lot of noise, the trained model was able to classify objects with a high degree of accuracy. Furthermore, the trained model was able to recognize and categories a single tomato image in just 29 milliseconds, demonstrating the high potential utility of the suggested approach in practical settings. The trained models' feature Visualization, or their acquired common and high- level features, demonstrates their comprehension of tomato imagery [1]. The trained models' strongest activations indicate whether a model recognized the correct or incorrect target throughout the classification process [2].

The enriched training sets acquired by data augmentation techniques were used to train the model in a generic intelligent tomato classification system based on Dense Net- 201 with transfer learning [3]. Even with high noise levels in the photos, the trained model was able to classify objects with excellent accuracy across a range of quality levels [4]. A single tomato image could be identified and classified by the trained model in just 29 milliseconds, demonstrating the high potential utility of the suggested approach in practical settings [5]. The trained models' feature visualization demonstrates their comprehension of tomato images, or the high-level and common features they have learned [6]. The most robust activations of the trained models demonstrate how a model's final classification accuracy is influenced by the target recognition areas it makes during the process. As a result, the study's findings may offer direction and inspiration for advancing the field of intelligent agriculture [7].

A typical stage in the development of fruits and vegetables is ripening. Deep learning models combined with computer vision (CV) provide various agricultural potential [8]. The ability to recognize and assess the ripeness of fruits and vegetables is one of CV's key uses. Additionally, farmers may harvest more effectively thanks to computer vision's ability to precisely recognize when veggies are maturing [9]. Deep learning models are employed for this purpose in order to extract detailed features from the photos in a faster manner than using previous methods [10]. However, these deep learning methods require a large dataset and take longer to classify images [11]. To address these problems, the transfer learning approach was suggested by numerous studies. This research presents a VGG16 model-based transfer learning model for tomato ripeness detection and categorization [12]. Additionally, a Multi-Layer Perceptron (MLP) is used in place of the top layer in order to increase the method's efficiency, and a fine-tuning methodology is applied [13]. The suggested model using the fine-tuning strategy performs better in terms of tomato ripeness classification and detection [14].

Humans are naturally adept at evaluating the freshness of fruit. Nevertheless, there hasn't been much work done on developing a deep learning fruit grading system based on digital photos. This article's suggested algorithm could be used to prevent fruit waste or salvage fruits from being thrown away. In this paper, we use deep learning and computer vision to offer a thorough examination of the freshness rating method. Our grading system is predicated on the visual examination of digital photos [15]. This project makes use of a variety of deep learning techniques, such as ResNet, VGG, and Google Net. The region of interest (ROI) in digital photographs is extracted using YOLO, with AlexNet used as the basis network. In light of multiclass fruit categorization, we therefore build a unique neural network model for fruit recognition and freshness rating. After we entered fruit photos into our model for training, AlexNet emerged as the top performer; in the meantime, the VGG scheme fared the best in validation[16,17].

3. Proposed Method

This model is a comprehensive initiative in the field of agriculture. Using an image, a Convolutional network model is trained to determine whether a tomato plant has a specific disease. This Convolutional network model uses an ensemblelearning strategy for classification and regression applications, combining random forest and support vector machines. During training, it constructs a number of decisiontrees, and it outputs a class that is the mean prediction of eachtree or the mode of the classes. The damaged plants are classified using vgg 16 and vgg 19.

The basic formula is

g(t) = 1− ∑ i = 1c p(i|t) 2 (1)

G(t) is the gini impurity of node t.

C is the number of classes.

P(i/t) is the proportion of instances of class iamong the instances in node t

When doing a classification task, the node containing all of the decision trees' predictions is used to make the final prediction. Regression tasks use the mode of all decision treepredictions to arrive at the final prediction. Compared to individual decision trees, random forests provide better resilience and generalization performance by merging numerous decision trees that were trained on various subsets of data and characteristics. Because of its simplicity and efficacy, it is frequently utilized in many different applications, including the detection of illness in tomato plants. To begin, numerous bootstrap samples are created from the original dataset using Random Forest. Every bootstrap is produced by selecting data points at random fromthe original dataset and replacing them.

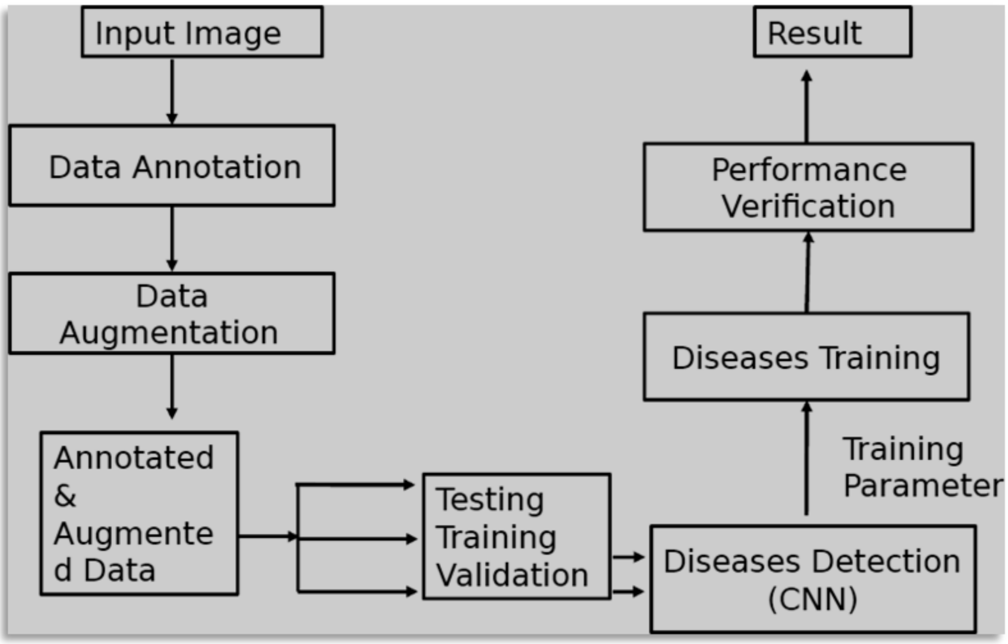

Fig 1 : architecture of the proposed system

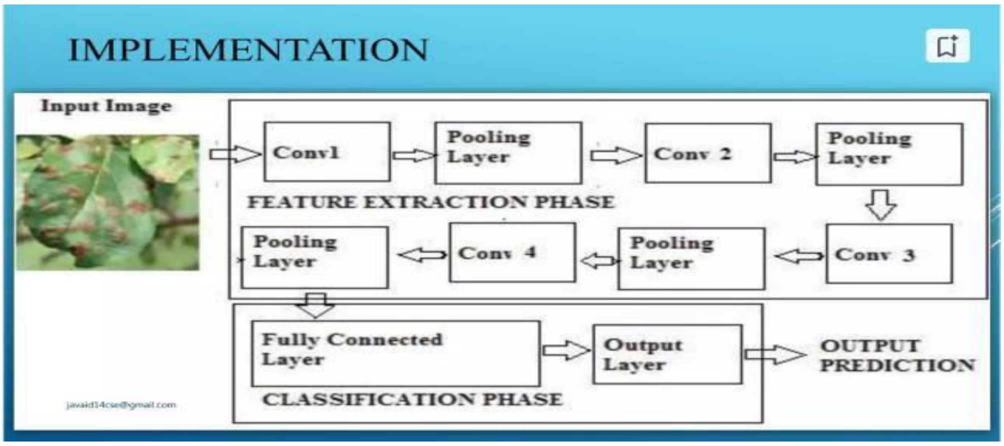

Fig 2: Implementation of the proposed system

In order to identify and categorize plant leaf diseases, some fundamental image processing steps are involved in plant disease identification. These processes include acquiring the image, pre-processing it, segmenting it, extracting features, classifying it, and detecting leaf disease. The following is a description of these steps.

3.1 Image Acquisition

The acquisition of images is the initial step in any vision system. The process of obtaining a plant leaf and using a camera to produce high-quality photographs is known as image acquisition. Photos are taken in the fields of agriculture or on the internet. The quality of the database photographs determines how effective the concept is. The format of this image is RGB (Red, Green, and Blue).

3.2 Image Pre-Processing

This includes filtering, RGB to Lab conversion, and image enhancement, among other operations. In this case, contrast is increased using picture enhancement. Filtering techniques are used for image smoothing. In image processing, a variety of filtering algorithms are available, such as the Gaussian, median, and average filters.

3.3 Image Segmentation

Image segmentation is the process of dividing an image into several sections with similar features. Numerous techniques, such as the otsu method, k-means clustering, turning RGB images into HIS models, etc., can be used to segment the data. A set of characteristics is used to classify an object into K number of classes using the K-means clustering algorithm. The process of classifying an object involves reducing the total squares of the distances between it and the associated cluster.

3.4 Disease Classification and Detection

Lastly, the datasets are trained and tested using classifiers. These classifiers could be neural network, fuzzy logic based, support vector machine (SVM), k-nearest neighbor, etc. These techniques are employed to identify and categorize the leaf disease.

4. Proposed Algorithm

Since our model uses raw photos as input, we extracted features using Convolutional Neural Networks (CNNs). CNNs are widely used in natural language processing, recommender systems, and image and video recognition. Similar to neural networks, CNNs consist of neurons that have biases and weights that can be learned. Every neuron gets many inputs, adds their weights, passes the result via an activation function, and produces an output in response.

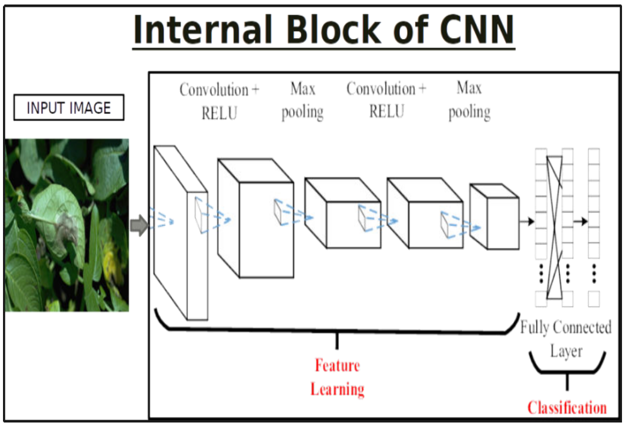

Fig 3: classification of CNN layers

Here, CNN 2D is being used. In essence, three- dimensional inputs—typically, images with three color channels—are fed into two-dimensional Convolutional layers. They examine a small window of pixels at a time, say 3x3 or 5x5, by passing a filter—also known as a convolution kernel—over the image. They keep moving the window until they have scanned the entire image. Seven Convolutional layers with a ReLU activation function make up our model. i.e, Most neural networks, especially CNNs, are designed using the Rectified Linear Unit (ReLU) activation function. For all positive values of input "x," it is the identity function, f(x) = x, and it zeros off for negative values. In order to effectively reduce the width and height of the feature maps while maintaining the number of channels, we have used ReLU for each hidden layer, which is followed by the Max-pooling layer, which maximally activates a small number of neurons from the feature. We have also defined the soft-max activation function for classification purposes.

4.1 Image Acquisition

The image-capturing apparatus intended to capture the tomato plant inside the controlled chamber is used to capture images. The captured image is in the Joint Photographic Experts Group (JPEG) format, with a uniform dimension of 680 x 480 and a horizontal and vertical resolution of 96 dots per inch (dpi). It also has a bit depth of 24. The system harvests tomato plants at 8:00 am, 12:00 noon, and 5:00 pm to create a dataset on the plant under various natural lighting scenarios. The camera is positioned 0.65 meters away from the intended plant in order to get higher-quality fruit shots. When it came to the presence of flowers and fruit in each image that was gathered, researchers gave the ground truth. The sample photos of the tomato plant are displayed in Fig. 4.

Fig. 4. Sample of plant images captured inside the chamber

4.2 Dataset Structure

The deep learning algorithms will be trained using the datasets that were taken from the growth chamber. The programme "Label IMG" will be used to process these data sets in accordance with the ground truth. This tool for tagging objects is used to annotate image datasets. The annotation process is used to pinpoint the locations of the classes (fruits and flowers) that need to be identified in the picture. Whereby, every flower and every tomato—whether green, turning red, or green—is encased in a box during the annotation process, and this box will determine where the image is saved as a.xml file. The dataset distribution for deeplearning training is displayed in Table 1.

Table 1.Dataset for the training of the object detection algorithms

Item	Quantity
Number of Gathered Image Datasets	**277**
Number of Sample Images Used for Training	**231**
Number of Samples Images Used for Validation	**46**
Number of Tomato Fruits in the Training Data-set	**1,193**
Number of Tomato Flowers in the Training Dataset	**421**

Additionally, the produced photos are used to train various machine learning models for maturity assessment. Green, changing, and red tomatoes are recognized and clipped based on the photos. The first class, known as "green tomatoes," is made up of tomatoes that are typically green in color up until they reach the breaking maturity stage. The second class of tomatoes, known as changing tomatoes, is descended from orange-colored tomatoes that turn pink as they mature. The third and final class of tomatoes, known asred tomatoes, is made up of tomatoes that are typically red in color from light red to crimson maturation stages. Followingthe application of the actual class sorting to the collected tomato images, the Hue-Saturation-Value (HSV) color space is extracted. Various machine learning algorithms will be trained using the mean data of the image's HSV color space. This generates a CSV file with 450 rows and 7 columns. The content distribution of the CSV file is displayedin Table 2.

Table 2. Dataset for the training of the machine learning algorithms

Item	Quantity
Number of Samples (No. of Rows)	450
Number of Samples for the GreenTomato Maturity (No. of Rows)	150
Number of Samples for the TurningTomato Maturity (No. of Rows)	150
Number of Samples for the RedTomato Maturity (No. of Rows)	150
Number of Columns	7
Column Label	Red, Green, Blue, Hue, Saturation, Value, Maturity

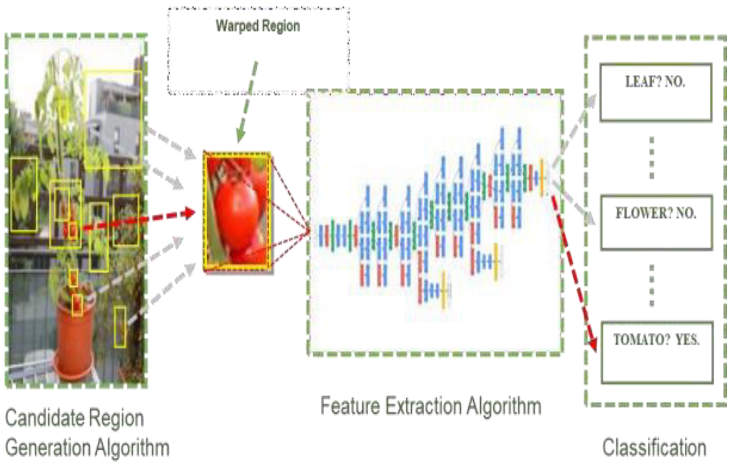

Fig. 5. Flower and fruit detection algorithm

The Open Source Computer Vision Library (OpenCV) and scikit-learn libraries were two of the libraries used by the system, which used Python programming in a console. For deep learning, machine learning, and image processing, those libraries are indispensable. The method of identifying the fruit and flowers in the image of the tomato plant was shown in Fig. 2. It is separated into three distinct processes: the creation of candidate regions, the extraction of features, and the classification of categories. Using the Selective Search Algorithm, an input image is examined at the candidate region generation step in order to identify a number of small areas, or candidate regions, that are more likely to contain a tomato or other fruit. Although the primary concept behind the Selective Search Algorithm is that up to 2,000 candidate boxes can be found in order to divide the input image into manageable halves. Additionally, it is due to selective search that the two most likely nearby areas repeatedly join to form a potential object that is led by the merge rule. The merging rule includes the following: size similarity, shape compatibility, texture similarity, gradient histogram, and color similarity.

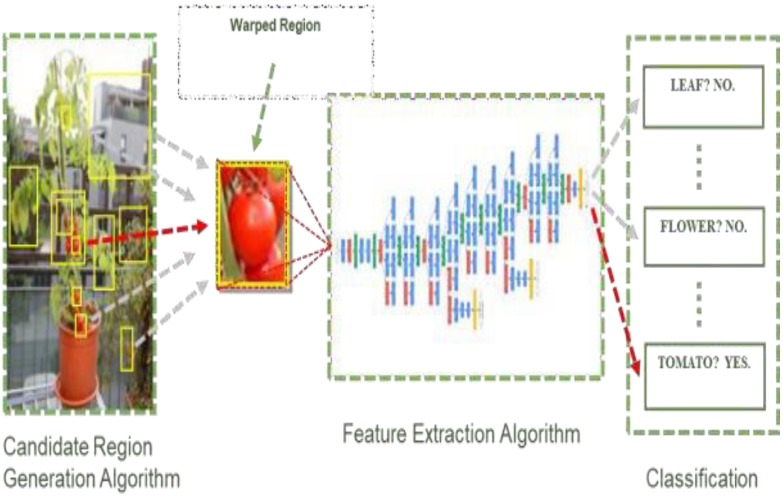

Fig. 6 Flower and fruit detection algorithm

Performance Assessment of SSD and R-CNN. The following scenarios are used to evaluate the RCNN and SSD models: flower only, fruit only, and both flower and fruit. Each condition requires the evaluation of thirty photographs. The features of SSD and RCNN for detection and determining the appropriate number of detections are summarized in Table 3. It can be concluded that for both flower and fruit detection, SSD outperformed the RCNN.

Image Features	**RCNN's Accuracy (%)**	**SSD's Accuracy (%)**
Image with FlowerOnly	0.00	100.00
Image with FruitOnly	26.98	96.62
Image with Flowerand Fruit	Flower: 3.33 Fruit: 11.98	Flower: 100 Fruit: 95.35
Over-all Accuracy	Flower: 1.67 Fruit: 19.48	Flower: 100 Fruit: 95.99

Table 3. Summary of accuracy performance for RCNN and SSD in flower and fruit detection.

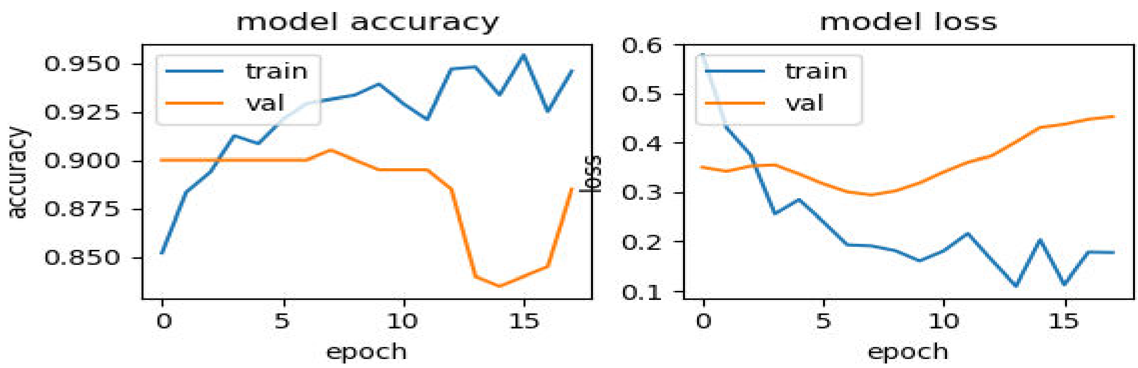

Figure 7: Comparison between accuracy and loss region generation step in order to identify a number of small

A portion of the disease dataset, which includes leaf illnesses in tomato plants, is used to evaluate the CNN-based classifiers. The tomato plant's leaf diseases make up the dataset. The used dataset has 520 photographs total, including pictures of healthy tomato leaves. The dataset is subjected to the first preparation and augmentation. The 412×412 dimensions, which are selected to be comparatively modest and about a fraction of the average size of all photographs, are scaled to accommodate the dataset's images. Following the 10% test set removal of photos, the remaining training set images are enhanced by adding a horizontally flipped copy of the images to minimize over fitting. A subset of these images is then further separated as the validation set pre-trained. First, the dataset that will serve as a benchmark for comparison is used to fine-tune the pre-trained YOLO models. Next, in order to compare the outcomes, a condensed CNN architecture is suggested and trained both with and without the residual learning framework (residual and plain CNN). Every pathogen that could hinder a tomato plant's growth has been examined. A convolution neural network (CNN) is trained with data to classify the visual symptoms of many diseases, each of which has unique traits and symptoms. A model that can identify every ailment is developed after training. The trained model's Mean Average Precision (MAP), as determined by testing it on the Pascal voice format, is 0.76. The system has the ability to forecast diseases at various image resolutions and scales. The output result is independent of size, orientation, or light intensity. Nonetheless, accuracy of image detection will be great on high resolution images. The system adjusts the pixel value at this ratio and resizes the input image to 412*412 (width * height).

5. Machine Learning Results

The ANN, KNN, and SVM classifiers—which will be in charge of categorizing the discovered tomato fruit—are trained and assessed. During the training phase, various distributions of training-testing datasets are taken into account. The 60%–40%, 70%–30%, and 80%–20% train–test dataset splitting are used to develop models. Ten-fold stratified cross-validation per model was used to assess the training accuracy performance. Grid SearchCV was also used for optimization in order to get the ideal values for hyper-parameter tuning. To choose the optimal machine learning and dataset splitting model, models were evaluated using the testing dataset. The accuracy percentage of each model in each split dataset, both during training and testing, was compiled in Table 4.

		Training			Testing Using Optimized Model				
Model	Splitting	No. of Samples	Default Parameter Accuracy (%)	Optimized Parameter Accuracy (%)	No. of Samples	Correct	Incorrect	Accuracy (%)	Over-all Accuracy(%)
	60-40	270	7.78	97.78	180	179	1	99.44	
SVM	70-30	315	7.78	97.78	135	135	0	100.00	99.81
	80-20	360	7.78	97.78	90	90	0	100.00	
	60-40	270	90.44	93.78	180	179	1	99.44	
KNN	70-30	315	90.44	93.78	135	133	2	98.52	99.32
	80-20	360	90.44	93.78	90	90	0	100.00	
	60-40	270	85.11	91.33	180	179	1	99.44	
ANN	70-30	315	85.11	91.33	135	133	2	98.52	99.32
	80-20	360	85.11	91.33	90	90	0	100.00	

Table 4. Accuracy performance of size classification models using machine learning

When optimization is carried out, all machine learning models perform noticeably better than when the default parameter values are used. The results also showed that every model performs consistently during the training phase, irrespective of the combinations of data splitting that are used. Cross-validation yields the same accuracy results: 91.33% for ANN and 93.78% for KNN.

Fig. 8. Comparison of training and testing accuracy of threedifferent machine learning models

Testing accuracy in Fig. 9 showed that all models performed well when tested on an independent dataset, which was also comparable with how well they performed during training. SVM emerged as the most optimal machine learning model after a performance comparison of the three models, with training accuracy of 97.78% and overall testing accuracy of 99.81%.

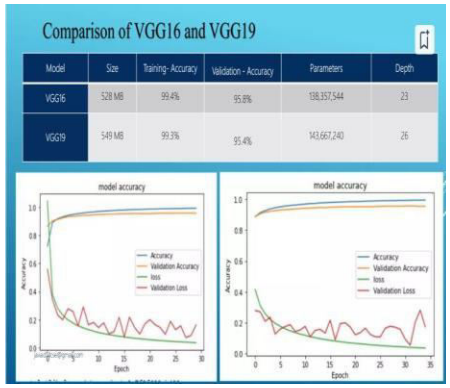

Fig 9: Comparison of results between VGG16 and VGG 19

6. Conclusion

Most of the nation's economic growth is offset by agriculture. It is seen as an essential component of society. Therefore, the primary goal of the suggested task is to reduce the usage of pesticides in order to conserve our environment and lower the cost of farming. Identifying the type of disease and its potential treatment, as well as whether a crop is affected or not, may be done easily by combining data mining ideas with image processing. This research presents multiple approaches, including pattern recognition, back propagation, neural networks, support vector machines, and others, for the identification and categorization of plant leaf diseases. The fundamental idea of plant leaf disease detection as well as the symptoms of different leaf diseases is covered in the suggested work. In accordance with our survey document, we began our investigation on every crop and component of it. However, as we were still in the learning and practice stage, we quickly saw that this was not something we could accomplish at this time. Specifically, we changed our focus to focus on the "tomato," the major crop of our own nation, and began researching every ailment and its causes that might be inferred from changes in the tomato plant's leaves.

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