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Plant Disease Detection Comparative Study

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ABSTRACT:Plant disease detection is an important task when it comes to improving productivity. The recognition of crop diseases are critical for preventing to yield and to lose argon-products. Crop health detection and monitoring of diseases are essential for agricultural operations. Manually observing plant diseases is a tedious task. It requires tremendous work, expert in this subject, and it requires prolonged time. As a result, processing of image is applied to detect illness of plants. Acquiring images, pre-processing, picture subdivision, classification and extracting the features, are the steps involved in disease detection. This paper discussed the methods for identifying diseases in plants using images of the leaf.

KEYWORDS: Plant Disease, VGG-19, ResNet, Alex Net, CNN etc.

I. INTRODUCTION

Asia is a cultivated continent, with agricultural production employing roughly 69percent of total of the population. Farm owners have a wide range of options for considering multiple appropriate crop production and locating appropriate insecticides. Illness reduces both the quality and quantity of farm commodities significantly. Crop diseases research is concerned with the inspection of visibly detectable crop pattern.

Keeping watch on plant health and disease is critical to successfully growing the farm. Initially, analysis and observing of plant illness were performed manually by the experts. This needs a lot of work as well as a large computational time. Image processing techniques can be applied in classification of the diseases in majority of cases, the signs can be found on the fruit, leaves and stem. The leaf of a plant it is viewed for detection of disease, that also shows the signs of a malady This study gives an overview of image. A leaf disease detection processing technique.

In the paper [1] the Authors Rutu Gandhi, Shubham Nimbalkar, Nandita Yelamanchili and Surabhi Ponkshe derive the suggested system designed on Convolutional Neural Networks (CNNs), a well known deep learning method used for image classification in specific. Two CNN designs models – MobileNets and Inception v3 – were tested to compare their accuracy, training speed, and model size, among other things.

To provide finite datasets of Indian plants and diseases, the system also employs Generative Adversarial Networks (GANs). Each of these techniques are discussed in more detail in the following.

A Convolutional Layer (CNN) [1], which is a network consisting of several sorts of layers in the neural or perceptrons, seems to be the system's principal classifier. All of the levels work together to retrieve the most significant information from the dataset's photos. Following are the layers: y Convolution Layer: This layer produces a stack of filtered pictures by convolving a weighted matrix with the given image. The filtering is combined using array of matrix patches chosen over a specific stride.

Pooling Layer: This layer is in charge of lowering the number of parameters in the picture stack and hence

Activation Layer: The rate at which neuron fires i.e application of non linearity to input, so the below are the activation functions, the quantity of processing necessary. MaxPooling is the most prevalent type of pooling.

Equations from [1]

- ReLU(Rectified Linear Units: nonlinearity is thresholded at zero)

$$f(y) = \max(0, y)$$

- Sigmoid: Range of input between zero to one.

σ(y) = 1/(1+e^(-y))

- Tanh: Range is fitted from -1 and one

Tanh(y) = 2σ(2y)-1

Softmax Classifier: This gives the probability distribution function.

Inception v3: This form of Inception model (Szegedy et al)[1] expands on the concept of selecting several convolutions. Nevertheless, it improves the operational cost of running the model in a number of ways. Bigger spatial convolutions take more time to in computation, and makes the design as a whole slow and heavy to train. These larger convolutions are replaced in Inception v3 with a comparatively network of lesser convolutions. 5 x 5 convolutions are substituted with a 2 design consisting of one 3x3 convolution followed by a fully linked layer on top of the preceding 3x3 layer's 3x3 outcome grid. This effectively entails replacing all 5x5 convolution operation with two 3x3 convolutions. 3x3 layers are also changed with two leve: a 3x1 accompanied by a 1x3, resulting in a 33 percent reduction in computing time. Convolutions of 7x1 and 1x7 are also used to substitute 7x7 layers. An Inception v3 model was tried and tested on the ImageNet database for the present scheme, and the final layer was retrained on dataset of plant illnesses. The unbranched picture data was trained over 4000 epochs using 75: 5 :20 learning, testing, and validating the ratio. The rate of learning was 0.01. The accuracy of the model was 88.6 percent.

Mobilenets: In comparison to normal convolution, which involves filtering and merging outputs in a single step, this 2-stage convolution techniques dramatically decreases computing time and model size. A full convolution is the first layer, proceeded by depth-wise separable convolutions. A batch normalising layer and ReLU non-linearity follow each layer. The final completely linked layer is the only one that does not have any nons, and it is preceded by a softmax layer that is classified. To decrease spatial resolution, the fully-interconnected layer are nothing but average pooling. The Mobilenets network for plant disease was trained on the ImageNet dataset, then trained up over four thousand epoch to deal with the plant disease dataset, with a 75:5:20 tr .

The model is developed on a smart phone app and require physical movement but we can take pictures from UAVs and this images will be worked upon. Further research is going on the multi classification using the discriminator in GANs so this can be the further scope of this work.

In the paper [2] the Authors Prakruti Bhatt, Sanat Sarangi and SrinivasuPappula derive that crop yield management relies heavily on timely and accurate identification of plant diseases and nutritional shortages. Automation is a low-cost alternative to human expertise, and it may assist detect crop illnesses, allowing for speedier judgement and offering farmer suggestions to reduce output loss. Farmers employ a mobile phone application for agriculture to explore their farms for interesting events, particularly those connected to plant condition. DCNNs have recently become popular technique in machine vision difficulties, and such as models based on learning could be a useful tool for doing just-in-time crop health assessments. Offer an examination of CNN models in terms of inference time, accurate, and size in order to construct state-of-the-art diagnostic capabilities on the phone. The precision of the effects of changing hyperparameters has been assessed. Different machine learning methods have traditionally been used to classify diseases using features derived from picture data. Plant diseases have been studied using machine learning approaches, and SVM has been demonstrated of having the best classification accuracy of around 93 percent. The threshold settings for image preprocessing, feature derivation, and classification can vary depending on the type of image data collection, makes it very difficult to put up a generalised solution. In 2012, Krizhevsky A. et al. developed AlexNet, which outperformed conventional classification techniques on a large imagenet database with around thousand classes in the ILSVRC by a large margin, demonstrating that supervised training of DCNN with pictures as input is possible, increasing classification accuracy and reducing the need for feature calculation steps. Transfer learning assists CN N in calculating image characteristics from the data, when data is less. We only delicate the weights of the connected layer, accompanied by the softmax activation, in all models for our experiments using batch training and transfer learning. This allows us to use the right weights for the architecture learned from big amounts of dataset.

Three distinct optimizers were used to evaluate model training and test precision. I Stochastic Gradient Descent (SGD) optimizer (ii) RMSProp optimizer (iii) Adam optimizer to minimize the loss function and update parameter values. The goal is to find the weight w' that minimises loss. The weights are iteratively updated for each training example z across the entire training set. Transfer learning has hyperparameters and optimizers, as discussed. These figures are slightly higher than the 98.4 percent acquired with SGD. SGD optimizer while training on color images were used for further experimentations: Batch size: 32, Learning rate: 0.0001, Optimizer: SGD, momentum: 0.9 for 30 epochs The losses

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have nearly the same curves and does not differ, indicating that the network did not overfit.

The accuracy of ResNet-5 0 is more as compared to the Inception v3, VGG19 and Xceptino. But on other hand the VGG acquires more memory as it has more number of parameters. Below both the figure shows the insight.

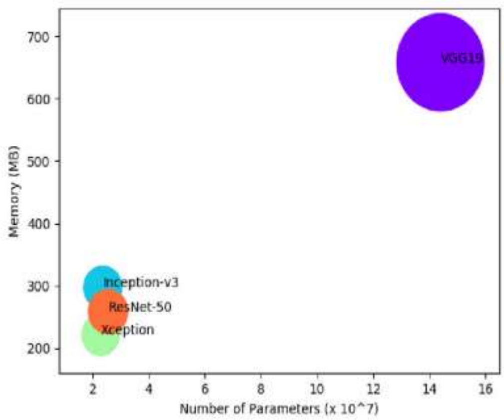

Fig. 1: Memory utilization of model in (MB) [2]

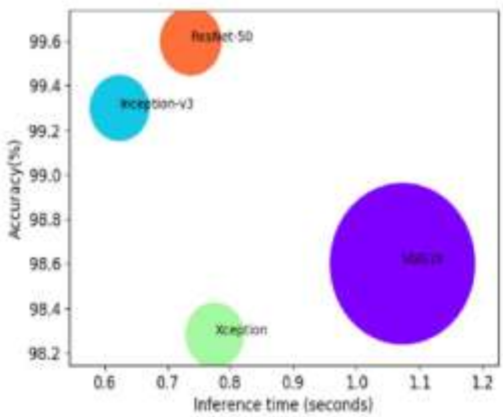

Fig 2: Accuracy v/s Inference time [2]

For its applicability at the edge with participatory sensing, we compared the performance of different CNN architectures in terms of how the design is accurate, size, memory usage. The use of crowd sourced photos to train deep learning models appears to be a potential method for a reliable automatic categorization. We're building the models from the ground up using massive amounts of data acquired by RuPS. The accurate methodology can be chosen based on the device's hardware limitations, such as storage and computing effectiveness. We hope to exploit the findings of this study to develop smart application features that will assist farmers in extracting relevant meaning from photographs captured in uncontrolled environments, even when cell network availability is a concern.

The Author of the paper[3] HalilDurmus, EceOlcayGüneú and MürvetKÕrcÕ has proposed that, the goal is to detect diseases in tomato plant farms or greenhouses. The study's goal was have the algorithm run on the robots. As a result, the robot will classify plant illness while roaming the field or greenhouse manual process or autonomously. Diseases can also be detected using pictures of leaf chosen to take by terms of the scope into fields. The illness investigated in this work cause physical changes in the tomato plant. The conventional characteristics extraction techniques on leaf photos were utilised in prior studies to detect illnesses. Deep learning approaches were employed to detect disorders in this study. The implementation's most important issue was choosing a deep learning architecture. As a result, two distinct deep learning network topologies, SqueezeNet and AlexNet were tried. The Nvidia Jetson TX1 was used to train and validate learning networks. The training was done with photos of tomato leaves from the PlantVillage dataset. There are ten separate classes with healthy photos. Images from the web are also used to test trained networks. The goal of this project is to use machine learning to detect plant illnesses. The goal of this project is to use robot platforms to identify plant diseases. The leaves of the crops are harmed by diseases and pests that must be discovered. These adverse consequences alter the physical look of the leaf, allowing the source of the harm to be identified using photos captured by the cameras. In this situation, a portable pc and a conventional color camera are required for illness detection by a machine. Because this type is performed by the machines, the mobile computer must be capable of doing computational tasks. Additionally, mobile computers can perform activities such as autonomous navigation, motor driving, and picture analysis.

1) AlexNet:

AlexNet was introduced by Krizhevsky in 2012 ImageNet picture categorization contest with their AlexNet network infrastructure and won with flying colours. AlexNet was the birthplace of the new CNN trend. AlexNet makes advantage of ReLU, local response normalisation, overlapping pooling, and several GPUs to train the network. Deep learning was employed by ImageNet champions in the subsequent years. Training on GPU is one of AlexNet's innovative features. GPUs with several cores have improved training times for very large datasets. ImageNet, for example, has one million higher resolution photos. AlexNet has five convolutional layers, which are accompanied by a ReLU layer. To aid generalisation, normalisation layers are stacked [9]. After pooling, features from the convolution level five are given to the fully connected network. Fully connected layers, as stated earlier, determine the class probability. To minimise overfitting, fully connected layers have dropout layers. The class probabilities of the input image are stored in the last fully connected layer (FC8). Softmax classifier is used to classify these probabilities.

SqueezeNet:

Several CNN designs have been proposed since the publication of AlexNet. The main objective of these strategies is to enhance the accuracy. In addition to these studies, reduction of dnns is becoming increasingly important. That one of the most important DL applications will likely be on smart phones, cameras, and automated vehicles.

Identifying infections on cellular device or pc is one of the goals of this research. As a result, the initial goal of this research is to find a network design that is relatively small in size. SqueezeNet has indeed been selected and implemented. SqueezeNet is an excellent example of networking. SqueezeNet used three design strategies to reduce model size.

As a result, detecting code must be small in in time complexity and random memory usage. CNN are trained using the Caffe foundation. Caffe is in Cpp and includes bindings of python for convenience. The network architecture in Caffe is defined in the prototype files. These are tested on prebuilt programmes. The dataset is described as a lmdb file. The training parameters are changed in the solver file. The AlexNet based on the Caffe framework, and SqueezeNet v1.1 can be downloaded. Typically, training takes place on workstations equipped with GPUs or GPU clusters. This job requires on-the-job training. This constraint limits training. Training time is longer, and training batch sizes are smaller.Because of its lightweight and low computation complexity, SqueezeNet is a suitable candidate for smart phone DL classification. The updating model is another advantage of using a smaller network. When the mobile application is updated via mobile communication, the data price is cheaper and the automatic update speed is faster.

Network	Alex Net	Squeeze Net
Test set Accuracy	0.95	0.943
Size	2 2 7.6 Mbyte	2 .9 Mbyte
Inference Time	~150ms	~50ms

TABLE 1: Comparison of AlexNet and SqueezeNet [3]

In the paper [4] the Authors Prajwala TM, AllaPranathi, Kandiraju Sai Ashritha, NagaratnaChittaragi*, Shashidhar G Koolagudi derive because of its lightweight and low computational complexity, SqueezeNet is a good candidate for portable deep learning categorization. The updating model is another advantage of using a smaller system. When the mobile application is revised via communication devices, the information price is cheaper and the updating pace is faster. On-board training offers the functionality of field exercises. When an unique disease is diagnosed or new picture for previously trained diseases are discovered, a DL network can be constructed on the field of art techniques. Automated extracted features is used in neural network models to assist in the categorization of input images into illness classifications. The current proposal attained an accuracy average percentage of 94-95 percent, demonstrating the neural net approach's viability even when under adverse conditions. Information gathering, data pre-processing, and classification are all critical stages in the suggested approach. The flowchart is illustrated in the current part, and it is discussed briefly.

The photos of tomato leaf disease were collected from the Village library. A python script was used to obtain pictures for such diseases. About 18160 photos from ten separate classes make up the collected dataset.

Pictures among all major types of plant disease that potentially harm the tomato production are included in the dataset. Each of the downloaded photographs was saved within uncompressed

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Digital form and used the RGB color space by default.

Because the collected data contained photos with little noise, noise removal was not required as a preprocessing stage. To accelerate up the learning process and make model training operationally possible, the photos in the dataset were scaled to 60 by 60 resolution. Classifying the input or target variables has the effect of speeding up the learning process. It is accomplished by improving the optimization problem's numerical condition. It's also double-checked that the various default settings used in initialization and termination are correct. We use the mean and standard deviation to normalise the photos such that all of the pixel values are in the same range. In deep learning terms it is called as Z-score.

Convolutional neural networks (CNN) could be utilize to build a computer model that takes unorganized picture inputs and transforms them to classified output items. They are multi-layer neurons that may be taught to acquire the necessary classifiers features. In compared to traditional methodologies, they require fewer pre-processing and execute autonomous extraction of features, improved performance.

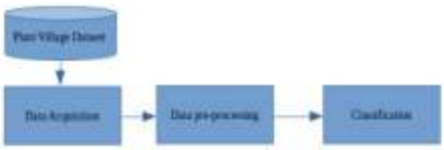

Fig. 3: Proposed methodology [4]

We tested various popular deep learning approaches for tomato plant leaf ilness, including AlexNet&GoogleNet, & found that a variant of the LeNet design produced the best results. Convolutional, activation, pooling, and fully linked levels make up LeNet, a simple CNN model. The LeNet framework has been used to create the framework for categorization of tomato leaf ilness identification.

When compared to the initial LeNet model, it adds an extra block of convolutional, activation, and pooling layers. A convolutional, activation, and max pooling layer are included in each block. This model employs three of these blocks, as well as completely connected layers with softmax activation. Feature extraction is done using convolutional and pooling layers, whereas categorization is performed using final fully connected levels. Activation layers are worn for establishing non-linearity into the network.

The intricacy of the retrieved characteristics grows as the depth is increased. The size of the filter is fixed at 5 5, but the number of filters increases as we advance through one block to the next. The very first convolutional block has twenty filters, which is expanded to Fifty in the next & eighty in the third. The rise in the number of filtering is required to recompense for the fact that the usage of max - pooling in every block reduces the dimension of the characteristic maps. The extracted features are additionally zero padded in sequence to maintain the picture's size after applying the convolution operation.

The maximum pooling level is used to reduce output feature size, speed up the train, and make the design less susceptible to slight input changes. The maximum pooling filter size is 22. For the identification of non-linearity, the ReLU activation layer is utilised in every block. To avoid overfitting the train set, the Drop - outs regularisation technique was utilised with a keep probability of 0.5. Dropout regularisation lowers neurons in the network at random throughout each training step to minimize model variation & simplifies the network, which aids in preventive.

The farming sector continues to be one of the most important sectors upon which maximum of Indians rely. Disease diagnosis in these crops is thus important to the economic growth of a country. Tomatoes are a staple crop that are grown in big quantities. As a result, the goal of this work is to percieve& identify ten distinct illnesses in tomato plants. To systematize tomato leaf diseases from the dataset, the suggested technique employs a cnn model. To classify tomato leaf illnesses into ten dissimilar classifications, a simple CNN with a small hidden layers was used.

As part of these efforts, various learning rate and optimization techniques could be utilised to experiment with the suggested model. It might include experimenting using newerdesigns in order to improve the effectiveness of algorithm on the train set. As a result, the aforementioned approach can be used as a resolution tool to assist and keep up farmers in recognisingilness that affect tomato plants. With a 94-95 percent accuracy, the suggested technology may accurately detect leaf diseases with low computation complexity.

In the paper [5] the Authors Shima Ramesh Maniyath, Hebbar Ram and 7 other proposed that crop illness pose a significant ultimatum to food security, yet their swift detection remains tough in many regions of the world caused by a lack of infrastructure. The essential foundation's attendance emergence of precise information approaches have been developed in the

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field of leaf-based image categorization. Exhibited outstanding performances Random is used in this paper. Identifying healthy and sick leaves from the woods generated data sets. The implementation phases in our proposed study include dataset development, characteristics production, training the classifier, and classification. To categorise infected and healthy photos, the produced datasets of sick and healthy leaves are combined and trained under Random Forest. We use the Histogram of an Oriented Gradient to extract image characteristics (HOG). All inclusive, enlist machine learning to train big publicallyacessible data sets provides a understable technique for detecting disease in plants on a gigantic scale. Agronomists in the local areas believe that it is quite difficult to identify the illness that may have happened to the plants. Also it is irreasonable for them to go to the office to investigate the direction of the illness. The main goal is to use picture processing and ML to distinguish the illness.

Insectiside and illness cause the demise of crops or parts of plants, resulting in lower production and lower quality. In addition, understanding of pest management and disease control is lacking in a number of developing countries. Toxic infections, improper illness control, and extreme change are only a few of the major causes of declining food supply. A variety of current techniques had arisen to reduce postharvest filtering, improve agro sustainability, & increase output. Various laboratory-based methodologies for illness identification have been used, involving polymerization chain reaction, gas chromatographic, mass spectroscopic analysis, thermometry, and excitable spectral techniques. These methods, on the other hand, are inefficient and time-consuming.

In recent years, a server-based and mobile-based approach to disease identification has been used. The added advantages of various technologies, such as the high resolution camera, high performance processing, and various built-in accessories, result in automatic disease recognition.To improve the recognition rate and accuracy of the results, modern technologies such as machine learning and deep learning algorithms were used. Various studies in the field of machine learning for plant disease detection and diagnosis have been executed, with traditional machine learning approaches such as random forest, artificial neural network, support vector machine(SVM), fuzzy logic, K-means practice, Convolutional neural networks, & so on....

Random forest is a learning process for classification, regression, and some tasks that spade work by constructing a forest ofdecision trees throughout the training period. Random forets, unlike decision trees, solve the problem of overfitting their training data set and can handle both numeric and categorical data. The histogram of positioned ramp (HOG) is an element descriptor used for item identification in computer perception and image processes. We are currently constructing three component descriptors are used:

1. Hu occasions
2. Texture of haralick
3. Histogram in colour

Hu moments are mostly used to determine the form of an object. The texture of the leaves is created using the Haralick texture.

The distribution of the data is represented as a colour histogram. Certain processes must be taken to determine whether the leaf is infected or healthy. Preprocessing, Feature extraction, and so on. Classifier training and classification Preparation of image, is reducing the size of all images to a uniform size. The next step is to extract features from a initialized image. It is accomplished by the assistance of HOG is a characteristic. This descriptor is used to detect objects. This feature description includes the object's look and the image's outline are both its frequency levels describe it. One of the benefits of the HoGcharasteristics extraction works on the cells that have been produced. This is unaffected by any alterations. Three feature descriptors were used in this example.

Color Histogram: A colour histogram shows how the colours in a picture are represented. The RGB colour space is transformed to HSV colour space before the histogram is computed. The RGB image must be converted to HSV because the HSV model is similar to the human eye perceives color in an image.

Algorithm description: The random forests classifier is used to implement the algorithm. They are adaptable and can be used for both classification and regression methods. Random forests outperformed other machine learning approaches such as SVM, Gaussian Nave Bayes, logistic regression, and linear discriminant analysis using fewer picture data sets. Training and testing information are separated from labelled datasets. HoG characteristic extraction is used to build the characteristic vector for the training informationset. A Random forest classifier is used to train the obtained feature vector. The feature vector for the testing data obtained using HoGcharactiristic unsheathing is sent to trained classifier for prediction. HoG characteristic extraction is used to transform labelled training datasets into their corresponding characteristic vectors. The characteristic vectors extracted are kept in the datasets for training the developed characteristic vectors are further instructed. Under Random forest classifier the characteristic vectors are retrieved from the HoG feature extraction on the test image.

To begin, any image must first be converted from RGB to grayscale. Because Hu moments figure descriptor and Haralickcharacteristic can only be obtained across a only one channel, this is done. As a result, before determining Hu moments and Haralick features, RGB must be converted to grey scale. To construct the histogram, the picture must initially be transformed to HSV (hue, saturation, and value). Finally, the major goal of our project is to use a Random forest classifier to determine if a leaf is ill or healthy.

Various ML model	Accuracy (%)
Logistic regression	65.35
VectorMachine	40.4
K-nearest neighbor	66.8
C A R T	65
Random Forest	70
Naivee	57.61

TABLE 2. Comparison [5]

The goal of these series of steps is to detect anomalies on crops in greenhouses or natural surroundings. To avoid occlusion, the image is normally captured having clean background. For accuracy, the series of steps was compared to other machine learning approaches.

This approach was developed including 160 photograps of papaya leaves and a Random forest classifier. The approach had a classification accuracy of about 70%. When using a large number of pictures and other local characteristic in concureence with global features like SIFT (Scale Invariant Feature Transform), SURF (Speed Up Robust Features), and condensed, together with BOVW, the accuracy can be improved (Bag Of Visual Word)

In the paper [6] the Authors Pranesh Kulkarni, Atharva Karwande, TejasKolhe, Soham Kamble, Akshay Joshi and MedhaWyawahare proposed that, identifying disease on crops is an important and time-consuming task in agricultural techniques. It takes a lot of time and specializedlabour. This research provides a clever and effective agricultural disease detection technique deploys machine learning and computer vision techniques The system proposed is 93 percent accurate in diagnosing 20 distinct illnesses in 5 common plants.

We used the PlantVillage public informationset for crop leaf disease identification focused by Sharada P. Mohanty et al. for this experiment. The dataset includes eighty-seven thousand Red Green Blue photographs of healthy and diseased plant leafs divided into thirty eightgroups, of which we have chosen just twenty five to test our method.

From every computer percieved-based system, information gathering is condemning. Before taking out characteristic, some background noise must be vanished to get perfect results. So the RGB photograph is transformed to greyscale first, and then the photograph is smoothed with a Gaussian filter. The photograph is then binaries using Otsu's thresholding procedure. Then, on the binarized image, a morphological conversion is utilized to close all small holes in foreground.

Following foreground recognition, the RGB photo of separated data is achieved by processing a bitwise AND operation on the binarized image and the original colour image leaf. Following photograph segmentation, the shape, texture, and color characteristics of the image are retrieved. The picture the area and circumference of the leaf are computed using outline. Contours are lines that connect all points along the borders of objects that have the same shape. Intensity or colour the mean and standard deviation of each RGB channel are also estimated. To calculate the amount of green colour in an image, it is first converted to HSV color space, and the ratio of number of pixels with hue (H) channel pixel intensity between thirty and seventy and total number of pixels in one channel is calculated. The image's The image's non-green portion is calculated by subtracting the green colour portion from following the extraction of color characteristics from the image, texture features were recovered using the image's gray level co-occurrence matrix (GLCM). The GLCM describes the spatial relationship underlying pixels in an image. Out of many method in computer vision is extracting texture characteristics through GCLM. The given features re below GCLM:

• Energy
• Correlation
• Contrast
• Dissimilarity
• Homogeneity

When all the characteristics from the photos were extracted, characteristics selection was done.

In all ML tasks, characteristics selection is important. We are selecting characteristics in this project it measures the correlation between target and variable. This indicates that both changeables are dependent on each other. Hence, one is dropped. As a result, we've also removed these variables. After characteristics selection, the data is analysed and it detects patterns in the data using machine learning classifiers.

Plant	Accuracy	F1
Apple	0.91	0.91
Corn	0.94	0.94
Grapes	0.95	0.95
Potato	0.98	0.98
Tomato	0.87	0.87

TABLE 3. Performance Table for models [6]

Decision trees are commonly used to attain improved accuracy. However, they can overfit. To solve problem, a random forest identifier, which is a composite of many decision trees, is adopted. Every tree is educated on distinct subsets of the entire dataset, which reduces overfitting and improves classifier performance.

The dataset was split into 2 parts: first the training which consists of 80percent and the second is validation which has 20percent data. The accuracy percent is computed using the K-fold cross validation technique. The technique can estimate the correctness of a dataset in its entirety.any bias. Precision, F1, accuracy, and recall were computed after fitting the data to examine the model's performance using test data Confusion and the ROC curve to investigate between fake positives and negatives, matrix is generated.

Average accuracy is 93 percent and an F1 value of 93, for plant disease diagnosis they have made a efficient CV system. The suggested system is also computationally efficient.

In the paper [7] the Author R K Tripathi has proposed that plant Material Infection Food safety depends on proper identification. The right handling of crops is necessary to boost crop production for the world's rising population. When is the best moment to save the plant? As a result, timely disease diagnosis is critical. This document is To diagnose the plant disease, a deep learning convolutional neural network method is used. The prevailing situation model of deep learning Alexnet is used to determine plant diseases in the past. The deepest totally connected is passed an outward characteristic of segmented plant material (leaves) layer. This fusion of Alexnet-extracted features and exterior features from segmented plant aids the diagnosis of plant diseases. Plant Village, a typical dataset with 54,306 leaf images of fifteen different plants and thirty five illnesses, was used for the experiment. The proposed CNN method worked effectively and outperformed the previous method.

Identification of plant material diseases and timely treatment are critical for improving food supply and food management for world's huge population. Because of the world's growing population, agriculture production will need to expand by a significant amount in the coming decade to meet food demands. Farmers commonly employ fungicides, bactericides, and nematicides to treat plant diseases without first identifying the disease. This is attributable to a shortage of information about plant diseases. These chemicals cause cancer in humans and have a negative impact on the agricultural ecology. As a result, a plant disease detection system is needed which can identify and recognise illness at an early stage, allowing for timely treatment without the use of toxic chemicals while also preserving the agro ecosystem. The illness with the plant material influence the standerd of vegetables, cereals, legumes and fruits, resulting in significant crop losses. In the contemporary context, advances molecular biology and biotechnology have ushered in a change in field of plant illness detection .Plant disease's future prospects The purpose of finding to assist farmers throughout the world in diagnosing disease at an early stage so that solution can be administered to boost yield. The projected deep excavation is given learning approach is robust in recognising plant illness; its is as follows: After integrating the two approaches, the suggested deep learning approach boosted discriminative capability. outward characteristics of subdivided plant material (leaves) to the deepest totally activated layer that's connected Colored plant leaves and it's divided plant leaves outperformed previous segmentation-based techniques and other algorithms in terms of disease recognition accuracy. This method outperformed the competition on PlantVillage, a big standard dataset.

Approach: We addressed the multilayer design of a convolutional neural network in this section, which aids in the classification of plant diseases. Convolutional Neural Networks are more accurate and work better with large datasets. The given deep learning method have of three main steps: plant material (leaves) pre-processing with coloured segmentations, Alexnet architecture carried out to coloured input images, and segmented function at fully connected layer to enhance the system's accuracy.

Pre-Processing: Plant images are scaled to 200x200 pixels and used to train and test deep convolutional neural networks. Plant material that is coloured (leaves) is transformed to a grayscale dataset. For colour segmentation, a hybrid Otsu and median filter approach was used on plant material (leaves).

In terms of accuracy, a deep CNN is the best strategy to recognising plants diseases. Deep Alexnet CNN architecture was applied in this study, and an outer feature was sends to the extreme layer of given architecture to enhance the quality of discriminative and improve plant disease recognition. five convolutional, three pooling, and three totally linked layers placed in this deep learning architecture, with every convolutional layer being used after rectified linear unit (ReLU). Afterward, to manage illumination variations, two local layers for normalisation are added. Due to the high parameters in the Plant Village dataset, a regularisation technique is done utilising dropout over all fully connected layers. Plant disease representation is based on the retrieved characteristics from the fully linked layer.

On the standard dataset Plant Village, the proposed deep learning approach was evaluated.

The total number of plants in this dataset is 54,306 leaves with 15 types of plants and 38 types of plant disease .This method was tested on a system with the following specifications: 8th Gen i7, 2.20 GHz processor, 8 GB RAM, and 4GB NVIDIA GEFORCE GTX. Against assess of effectiveness of proposed method, it was compared to the top performer of plant disease detection on the Plant Village Dataset Deep CNN, as well as nearest performances- Inception V3, ResNet-50, DenseNet169, and VGG-16 using Gaussian method. The suggested technique used the coloured picture as a straight input for deep CNN and section image characteristics as an exterior feature for Alexnet's totally connected layer. Recall evaluates how many of the disease-related demo photos were correctly identified. The number of samples accurately identified that do not show the specified disease is measured by specificity. Precision, recall, F-measure, and total accuracy have all been evaluated.

The suggested deep CNN approach is integrated with external features to increase plant disease recognition accuracy, recall, precision, and f-measure. The Alexnet model receives a coloured input image, and the coloured segmented image is mixed at the fully connected layer, which improves overall accuracy. This method is more accurate and outperforms the state of the art method by a little margin. The accuracy was increased by combining the features of coloured and segmented images along with Alexnet model. Plant disease identification's future prospects include assisting farmers around the world

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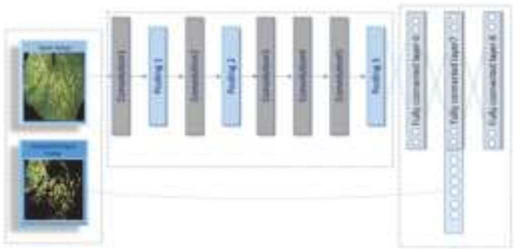

Fig. 4 Alexnet using Segmented feature fusion [7].

in diagnosing disease at an early stage so that treatment may be administered to boost yield. On the Plant Village dataset and other hard datasets with complex backgrounds and unconstrained environments, future improvements can be made utilising other CNN models. The suggested system would provide treatment information for diagnosed diseases, which would benefit illiterate peasants.

In the paper [8] the authors Namita M. Butale and Dattatraya V. Kodavade has proposed that the most important sector of the Indian economy is agriculture. As a result, plant detection is important in agriculture. A major factor is sickness. If good plant care is not done, then it has major consequences to plants, as a conclusion of which product quality, quantity, and productivity are all affected. Farmers in some countries lack adequate facilities, if they have any at all. They have the notion that they can call specialists. As a result of this consultation. Plant leaf disease monitoring is done manuallyit is an extremely important duty that is also time consuming the outcomes the results achieved are also unsatisfactory. Automatic illness detection is helpful in the early stages of disease detection. It will take less effort, time, and provide more reliable findings if an automatic illness detection technique is applied. Image acquisition, picture pre-processing, image segmentation, feature extraction, and classification are all steps in a disease detection system.

Automatic illness detection is helpful in the early stages of disease detection. Expert naked eye observation is the current way of identifying disease in plants. This necessitates a large team of specialists and ongoing plant monitoring, which is prohibitively expensive for large farms. Farmers in some countries lack proper equipment or even the knowledge on how to contact professionals. As a result, engaging specialists is both expensive and time consuming. In such circumstances, the recommended method is useful for monitoring huge crop fields. It is easier and more cost effective to detect diseases automatically by simply glancing at the signs on leaves. This enables image-based automatic process control, inspection, and robot guiding using machine vision. Plant disease detection by visual means is difficult and inaccurate. Automatic illness detection, on the other hand, will provide more accurate results in less time and with fewer resources. Image segmentation be done in many ways, from simple thresholding to complex colour image segmentation. This is anything that the human eye can clearly distinguish and view as a separate item. Because computers are unable to distinguish objects, image segmentation algorithms have been created.

The first phase, image acquisition, is dependent on the hardware device. Photos of leaves are captured using a digital camera or similar device, and images from datasetsutilised as given input to algorithm to find sick areas on the leaf.

1. Image acquisition
2. Image Preprocessing
3. Image Segmentation
4. Feature extraction
5. Disease classification

Image acquisition refers to taking a photograph of a real-world scene with a camera. In today's society, shooting photos with a digital camera is a frequent way. However, there are alternative options. Images from dataset will be used from respective project, and the algorithm will be trained and tested.

Image acquisition refers to taking a photograph of a real-world scene with a camera. In today's society, shooting photos with a digital camera is a frequent way. However, there are alternative options. Images from the plant village dataset will be used from respective project, and the algorithm will be trained and tested.

In Image segmentation an image will separated or group into different parts. Image segmentation are divided in to 3 types

1. Edge based
2. Region based
3. Clustering based

The image segmentation in this paper is based on clustering. Clustering divides the data into a small number of homogeneous groupings. The segmentation process is based on the image's numerous attributes. This could be colour information, image boundaries, or a segment.

The most used Kmeans clustering algorithm is used to go with image segmentation. It's utilised to separate the focus from the backdrop. The K-means technique is used to segment images in this paper. The genetic algorithm is an optimization method that is applied after k-means

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segmentation in order to achieve an optimum outcome. In a vast solution space, GA has been shown to be the most powerful optimization approach. The steps of a genetic algorithm, which is a heuristic search approach, are as follows:
1. Population initialization
2. Function of fitness
3. Crossover and mutation in selection Operations

The genetic algorithm produces the best results. The extraction of characteristics is a crucial part of accurately estimating the affected region. The process of feature extraction entails minimizing the number of resources required to describe a huge dataset. It's a technique for identifying image features and groups of characteristics that can be used to convey important categorization and analysis data. It is assumed that the extracted feature will having relevant knowledge from the input data, despite the fact that the needed job can only handle a reduced representation of the original data. The main strategy for region description is counting the texture counting. The Gray Level Co-occurrence Matrix (GLCM) of leaf is calculated during the texture analysis. Texture-specific features such as contrast, energy, and homogeneity are calculated.

The extraction and comparison of co-occurrence features for the leaves with attribute values are kept in the feature dataset throughout the classification phase. The Support Vector Machine is used to classify images. SVMs (support vector machine) are group of supervised learning methods for identification and regression. The data is separated into train and train test sections. 80 percent of the photos are used to train the SVM, while the remaining 20% are used for testing purposes. SVM compares the features of an image and performs classification based on the trained images. The disease name and the solution for that disease are the outputs of SVM.

Image processing-based plant leaf disease detection is usefull for early disease identification. Automatic illness detection saves time and money by detecting diseases at an early stage. Tomato, corn, grape, peach, and pepper bell have infected leaf image datasets.

II. COMPARISON

Table:

Sr No.	Year	Approaches	Accuracy (%)	Future Scope	Unique Features (if any)
[1]	2018	1) INCEPTION v3 2) MOBILENETS	1) 88.6 2) 92	The future scope is that rather than physically moving in the field the drones may capture the the images. Use of GANs for multi class classifier is one of the area under research.	The trained model was deployed on a smart phone where the camera was used to further predictions.
[2]	2017	1)VGG-19 2)INCEPTION v3 3)Xception 4)ResNet-50	1) 98.2 2) 98.4 3) 98.6 4) 99.7	The research and the results discussed can be used to build smart applications that would definitely help the farmer under uncontrolled conditions even if there is no network.	The authors have compared various models mentioned on parameters like memory requirement, model size, accuracy. Also the data is collected from Ru PS. Suitable design can be implemented based on computing availability.

[3]	2017	1) AlexNet 2) SqueezeNet	1) 95.65 2) 94.30	On board training is beneficial as if a new illness comes across the model can be trained on the spot. Presently they have navigation, control, and data acquisition so the further work is to done of implementing it on a robot	The paper has made it very clear, SqueezeNet can be good model for mobile based DL classification as compared with AlexNet. As AlexNet takes around 227.6MB and SqueezeNet takes 2.9MB only.
[4]	2018	1) LeNet	1) 94	The future scope as per the discussion is that, various learning rates and optimization can be implemented for future work.	Authors has given that the experimentation requires minimum hardware because of less number of dependents, lesser layer. Also this aims to classify 10 different diseases related to tomatoes.
[5]	2018	1) HOG feature extraction 2)Load RF Model 3)Classify HOG using Model 4)Display Results	1) 70	The algorithm was compared with ML models to know the accuracy, it will improve if it might be trained with large dataset and global and local features.	—
[6]	2021	1)Original - Grey scale 2)Gaussian filtering 3)Otsu's thresholding 4)Morphological Transform 5)ANDING operation 6)Classification	93	The authors has the vision that it can be deployed on a robot with complex processors for real time plant illness identification.	Random forest classifier is used for identification tasks. K-fold cross validation used to know the accuracy percent of the model. It is inexpensive computationally. The model is deployed on a website
[7]	2021	1) AlexNet	97.38	The diagnosis can be done at an early stage to treat the disease and increase the yield to the full potential.	This technique surpasses the state art by a very little difference. Model is fused by recall and improves accuracy, feature extraction.

[8]	2019	1)K-means And Support vector machines	63	—	Helps detect illness at starting phase. The crops utilized are corn, grapes, peach and pepper, bell.

III. CONCLUSION:

Various research work in the plant disease detection has took place over the period of time. One can choose his approach while building a classification model for this problem according to the requirement and application.

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