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Early Leaf Health Prediction Using Deep Dense Convolutional Neural Network (Ddcnn) and Computer Vision

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Abstract
The control of plant diseases is a major challenge to ensure global food security and sustainable agriculture. Several recent studies have proposed to improve existing procedures for early detection of plant diseases through modern automatic image recognition systems based on deep learning. Disease detection in plants at early stage is hard and challenging task. The image database is increasing day by day. This all happens due to raid development in technology and high speed internet increasing in capacity and storage. Farmers are influenced with yield of agriculture product that emerges because of various leaf health diseases. Diagnosing the plant diseases caused in enormous farming regions by manually analyzing the plant diseases is tedious task. With the significant advancement and development in deep learning have opportunity to improve the performance and accuracy of object detection, recognition system. We designed a Deep Dense Convolutional neural network (DDCNN) system that automatically predicts the plant health in advance and alerts the farmer for the best spray of correct fungicide or insecticide at the right time to prevent the damage of plant health and leaves and hence to increase the yield

Keywords: Deep dense **C**onvolutional neural network (DDCNN), Computer Vision, Classification, Prediction

INTRODUCTION

Due to the current development in technology, there is an increase in the utilization of multimedia devices such as cameras, cellular phones, and internet. The shared and stored plant leaf dataset are growing and to look, classify and predict is a challenging research problem. At present the visual inspection done following the conventional technique by humans makes it impossible to classify and predict plant diseases and due to the advancement in computer vision models which address these issues and offers fast, normalized and accurate solutions. Numerous research papers from past five years involving plant classification and prediction using Convolutional neural network has been published and achieved the results not more than 93-95%.

In machine learning and cognitive science, ANN is an information-processing paradigm that was inspired by the way biological nervous systems, such as the brain, process information. The mind consists of a massive variety of particularly interconnected neurons running collectively to remedy particular problems. An synthetic neuron is a processing detail with many inputs and one output. Although synthetic neurons will have many outputs, simplest people with precisely one output may be considered. Their inputs also can tackle any cost among zero and 1. Also, the neuron has weights for every enter and an average bias. The weights are actual numbers expressing significance of the respective inputs to the output. The bias is used for controlling how smooth the neuron is attending to output 1. For a neuron with actually massive bias, it is simple to output 1, however whilst the prejudice may be very terrible then it's far tough to output 1. The output of the neuron isn't zero or 1. Instead, it's far $\alpha\cdot\ (w{\cdot}x\ +\ b)$, in which α is known as the switch function. There are distinctive styles of switch function: step, linear, sigmoid, and so forth. The smoothness of α way that small modifications $\Delta\ wj$in the weights and Δb with inside the bias will produce small extrade Δ output with inside the output from the neuron. Small output modifications approximated by

$$\Delta output \approx \frac{\sum \Delta output \Delta w_j}{\delta w_j} + \frac{\sum \Delta output \Delta b}{\delta_b} \quad (1)$$

Neural networks, with their incredible cappotential to derive which means from complicated or imperfect data, may be implemented for extracting styles and detecting tendencies which might be too tough to note with the aid of using human beings or laptop techniques. Other benefits of ANNs are adaptive learning, self-organization, actual time operations, and so forth. There are foremost classes of ANNs while speakme approximately architecture: feed-ahead ANNs wherein the output of any layer is not likely to steer that identical layer and comments ANNs wherein indicators tour in each instructions with the aid of using regarding loops withinside the network.

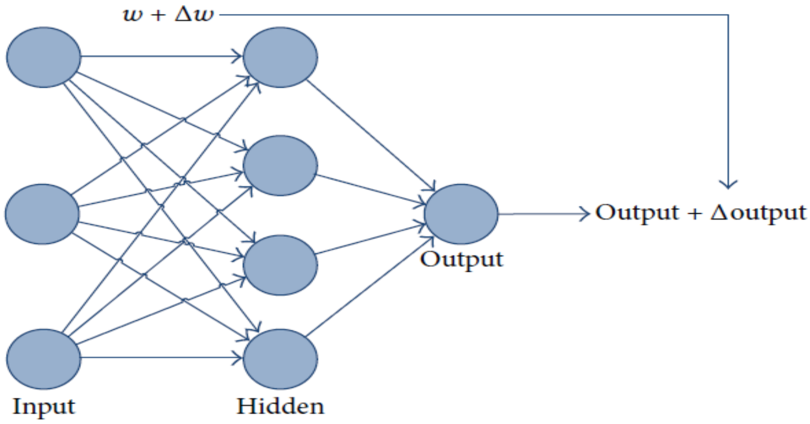

Fig-1: Simple Model of ANN

The research gap exists as most of the research published from past five years based on leaf diseases prediction and classification uses simple Convolutional neural network, region based Convolutional neural network etc. The advance and novelty of the developed model lie in its simplicity; health leaves and background images are in line with other classes, enabling the model to distinguish between diseased leaves and healthy ones from the environment by using redesigned deep Convolutional neural network (RDCNN) for our work we have used Kaggle pretrained dataset. The dataset consists of 3200 leaf images of size 256×256. The dataset is divided is divided into four classes like healthy, unhealthy. The overall composition of dataset is shown in figure 2.

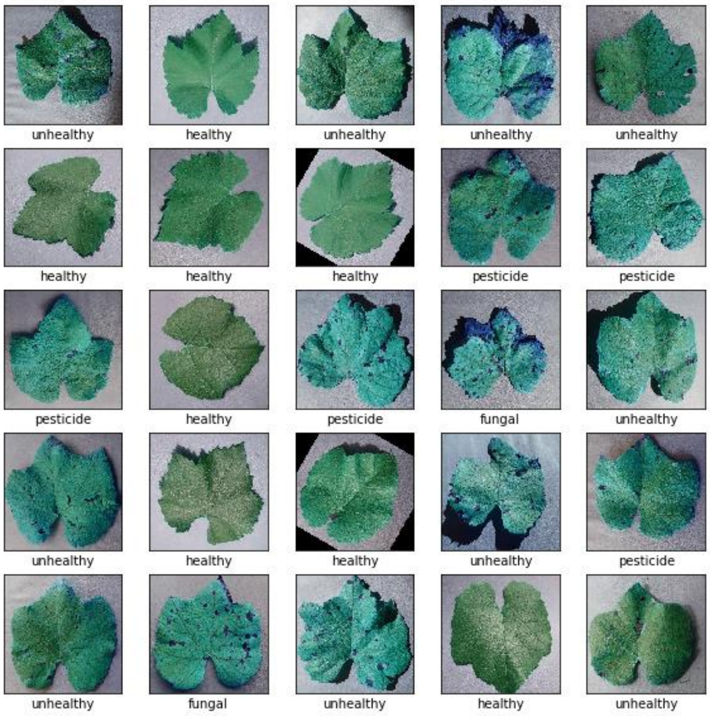

Fig-2: Overall Plant leaf Dataset

Background and Existing System

Several researchers have completed their studies primarily based totally on plant sicknesses identity, type and prediction the use of numerous deep studying strategies and, in our studies, we've analysed and reviewed the today's techniques and strategies of the studies completed from closing 5 years and for this reason the general paintings is summarised as below:

In [1] the authors the authors proposed hybrid version to hit upon bacterial spot sicknesses found in peach flora the use of their leaf snap shots, however, it may be utilized in plant disorder detection. They used publicly to be had dataset named Plant Village to get the leaf snap shots of peach plant. This machine completed an mixture overall performance of 98.38%.

In [2] the authors describe the techniques in excellent tuning pre-educated technique on plant identity assignment in preference to a standard item reputation assignment. The authors confirmed thru visualization strategies, that the traits discovered fluctuate in keeping with the method followed and they do now no longer always consciousness at the component suffering from the disorder. The authors proposed an intuitive technique that considers sicknesses independently of plants and contributed their paintings on crop disorder categorization. They used Image Net and Plant CLEF2015, and completed standard overall performance of 45%.

In[3] the authors advanced version to understand thirteen unique kinds of plant sicknesses out of wholesome leaves with the cappotential to differentiate plant leaves from the surroundings. They educated CNN via way of means of the use of Berkley Vision and studying centre and completed the general overall performance of 91%.

The authors describe an method in detecting plant sicknesses [4] the use of deep Convolutional neural community educated and excellent-tuned to healthy appropriately to the database of the plant leaves that changed into collected independently for various plant sicknesses and the general overall performance completed via way of means of the version is 96%.

Implementing the perfect control techniques like fungicide programs, disorder-particular chemical programs, and vector manage thru pesticide programs should cause early facts on crop fitness and disorder detection. This should facilitate the manage of sicknesses and enhance productivity. In [4], authors present, review, and understand the call for for growing a fast, cost-effective, and dependable fitness-tracking sensor that allows improvements in agriculture. They defined the presently used technology that encompass spectroscopic and imaging-primarily based totally and risky profiling-primarily based totally plant disorder detection techniques for the motive of growing ground-primarily based totally sensor machine to help in tracking fitness and sicknesses in flora below discipline conditions. After evaluation in their paintings and evaluation provided via way of means of the authors of [5, 6, 7, 8] it changed into determined to apply picture processing disorder reputation method amongst different processes generally used for plant disorder diagnostics, for instance, double-stranded ribonucleic acid (RNA) evaluation, nucleic acid probes, and microscopy.

Numerous methods are presently in use for plant disorder detection making use of laptop vision. One of them is disorder detection via way of means of extracting shade characteristic as authors in[9] have provided. In this paper YcbCr, HSI, and CIELBcolourmodels have been used withinside the study; as a result, disorder spots Computational Intelligence and Neuroscience 3were correctly detected and remained unaffected via way of means of the noise from unique sources, inclusive of digital digicam flash. In addition, plant disorder detection may be completed via way of means of extracting form capabilities technique. Patil and Bodhe carried out this method for disorder detection in sugarcane leaves in which they have got used threshold segmentation to decide leaf place and triangle threshold for lesioning place, getting the common accuracy of 98.60% on the very last experiments [10].Furthermore, extracting texture characteristic may be utilized in detecting plant sicknesses. Patil and Kumar proposed a version for plant disorder detection the use of texture capabilities inclusive of inertia, homogeneity, and correlation received via way of means of calculating the grey degree co-incidence matrix on picture [11]. Combined with shade extraction, they experimented on detecting sicknesses on maize leaves.

Furthermore, extracting texture characteristic may be utilized in detecting plant sicknesses. Patil and Kumar proposed a version for plant disorder detection the use of texture capabilities inclusive of inertia, homogeneity, and correlation received via way of means of calculating the grey degree co-incidence matrix on picture [11]. Combined with shade extraction, they experimented on detecting sicknesses on maize leaves.

Combination of a majority of these capabilities presents a sturdy characteristic set for picture development and higher type.In [12], the authors have provided a survey of famous traditional techniques of characteristic extraction. Due to the fast development of Artificial Intelligence (AI) science, paintings on this paper is specifically centered on making use of those methodologies and strategies. There are a few processes which observe the feed-ahead again propagation of neural networks consisting of 1 input, one output, and one hidden layer for the desires of figuring out the species of leaf, pest, or disorder; this version changed into proposed via way of means of the authors in [13]. They advanced a software program version, to indicate remedial measures for pest or disorder control in agricultural plants.

Another method proposed via way of means of the authors in [14] includes the capabilities extracted via way of means of Particle Swarm Optimization (PSO) [15] and ahead neural community in path of figuring out the injured leaf spot of cotton and enhancing the accuracy of the machine with the very last standard accuracy of95%.

Also, detection and differentiation of plant sicknesses may be completed the use of Support Vector Machine algorithms. This method changed into carried out for sugar beet sicknesses and provided in (24), in which, relying on the sort and degree of disorder, the type accuracy changed into among 65% and 90%.

Likewise, there are techniques that integrate the characteristic extraction and Neural Network Ensemble (NNE) for plant

disorder reputation. Through education a exact variety of neural networks and mixing their outcomes after that, NNE gives a higher generalization of studying cappotential (25).Such technique changed into carried out best for spotting tea leaf sicknesses with very last trying out accuracy of 91% (26).

Another method primarily based totally on leaf snap shots and the use of ANNs as a way for an automated detection and type of plant sicknesses changed into used along with K-way as a clustering process proposed via way of means of the authors in (27). ANN consisted of 10 hidden layers. The variety of outputs changed into 6which changed into the variety of lessons representing 5 sicknesses in conjunction with the case of a wholesome leaf. On common, the accuracy of type the use of this method changed into 94.67%.

The authors in (8–31) provided the deep studying techniques for fixing maximum complicated responsibilities in unique regions of studies in biology, bioinformatics, biomedicine, robotics, and 3-D technology. In our study, we make the most the deep studying.

In our study, we make the most the deep studying technique for plant fitness prediction, pushed via way of means of evolvement of deep studying strategies and their utility in practice. Extensive studies of the ultra-modern literature yielded no proof that researchers explored deep studying method for plant fitness prediction from the leaf snap shots. Our technique of prediction via way of means of making use of deep dense Convolutional neural community (DDCNN) is provided in those sections below.

Proposed Methodology

The entire procedure for developing the model for plant disease classification and prediction using DDCNN is described further in detail. The complete process is divided into several necessary stages in the subsections below, starting with image classification process using DDCNN.

1. ***Dataset.*** Appropriate datasets are required at all stages of plant classification and prediction starting from training phase to evaluate the performance of recognition algorithms. All the images collected for the dataset were downloaded from the website (Kaggle.com). Images in the dataset were grouped into four different classes. Two classes represent healthy and unhealthy, while as other two represent pesticide affected, and fungicide affected leaves [14].
2. ***Image pre-processing and Labelling. Images*** downloaded from the website (Kaggle.com) possess varying size, resolution and quality. In order to get better feature extraction, final images intend to be used as dataset for deep dense convolution neural network (DDCNN) were pre-processed in order to gain the consistency the details are included in the below table 1.

Table-1: Dataset for image classification and prediction leaf health

Class	Trained images	Tested images
Healthy	2000	1692
Unhealthy	2000	1722
Pesticide	1000	834
Fungal	1000	800

Many resources can be found by searching across the internet, but their relevance is often reliable. In the interest of confirming the accuracy of classes in the dataset, initially grouped by keywords search agriculture experts examined leaf images and labelled the images with appropriate disease acronym. As it’s known, it is important to use accurately classified images for training and validation dataset. Only in that way may an appropriate and reliable detecting model be developed.

The convolution is essential building block of Convolutional neural network. The layer parameters are comprised of a set of learnable kernels which possess a small receptive field but extend through the full depth of input volume [16].

Each convolution layer has M maps of equal size, M_x and M_y and Kernel of size K_x and K_y is shifted over the certain region of input image. The skipping factors Sx and Sy define how many pixels the filter/kernel skips in x- and y-directions between subsequent convolutions (46). The size of output map could be defined as:

$$M^n{}_x = \frac{M^{n-1}{}_x - K^n{}_x + 1}{S^n{}_x + 1} \qquad (2)$$

$$M^n{}_y = \frac{M^{n-1}{}_y - k_y{}^n + 1}{S^n{}_y + 1} \qquad (3)$$

Where ‘n’ indicates the layer. Each map in layer L_n is connected to most M_{n-1} maps in layer Ln1. Rectified linear unit (ReLU) are used as substitute for saturating nonlinearities. This activation function adaptively leaves the parameters of rectifiers and improves the accuracy at negligible extra computational cost [47] and is defined as.

$$f(z_i) = max(o, z_i) \qquad (4)$$

Where z_i represents the input of nonlinear activation function fon ith channel. DDCNN trains several times faster. This method is applied to the output of every convolutional and fully connected layer. Despite the output, the input normalization is not required; it is applied after ReLU nonlinearity after the first and second convolution because it reduces top -1 and top 5 error rates. In DDCNN neurons within a hidden layer are segmented into “feature maps”. The neurons within a feature map shares the same weight and bias. The neurons within the feature map shear the same feature. These neurons are unique since they are connected to different neurons in the lower layer. So, for the first hidden layer, neurons within the feature map will be connected to different regions of input image. The hidden layer is segmented into feature maps where each neuron is a feature map looks for the same feature but a different position of input image. Basically, the feature map is the result of applying convolution across an image. Each layer’s features are displayed in a different block, where visualization represents the strongest activation for the provided feature maps, figure 3.

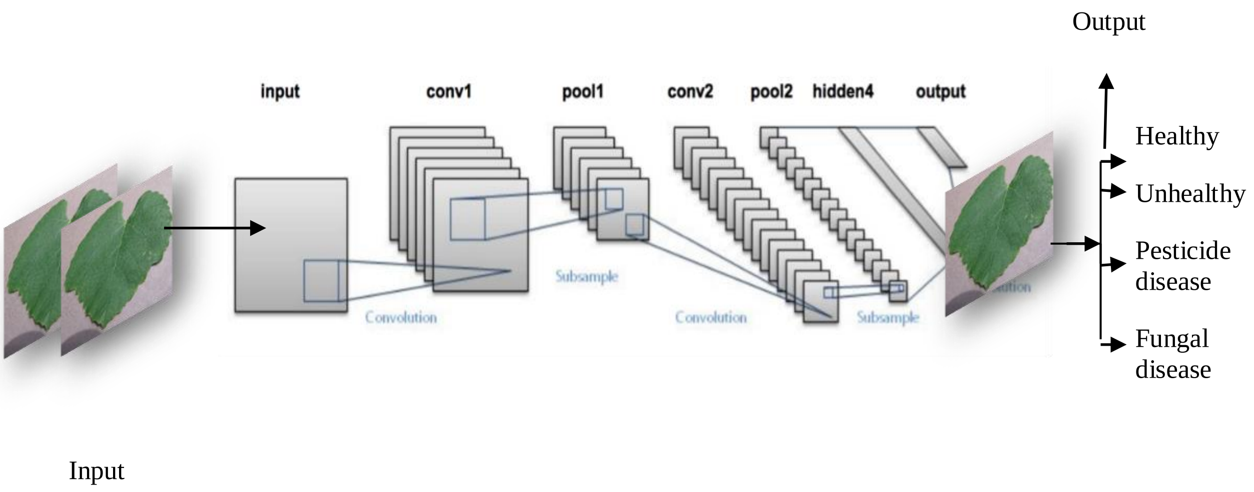

Fig-3: Architecture of DDCNN

Architecture Description: The DDCNN architecture consists of input layer, convolution layer, pooling, and output layer respectively. Here the input images of size 256*256 are fed to the input layer, and then the input will be passed to the Convolution layer. The main purpose of the convolution step is to extract features from the input image. The pooling or sub sampling layers comes after the convolution layers; it has same number of planes as the Convolutional layer. The purpose of this layer is to reduce the size of the feature map. It divides the image into blocks and performs max pooling. Sub sampling layer preserves the relative information between features and not the exact relation. Pooling is of three types namely minimum pooling, Max pooling, Average pooling respectively. Minimum is to choose the minimum value from the feature map, Max pooling is to select the maximum value from the feature map and average is select the average value from the feature map of an image and hence we are estimating the excellent predictions in terms of Healthy, Unhealthy, Pesticide disease, Fungal disease.

Machine used:

A single PC was used for the entire process of training and testing the plant disease detection model described in this paper. Training of the CNN was performed in Graphics Processing Unit (GPU) mode. Every training iteration took approximately eight hours on this specified machine whose basic characteristics are presented in Table 2.

Table-2: Machine characteristics

Hardware and software	Characteristics
1) Memory	8GB
2) Processor	Intel(R) Core(TM) i3-7020U CPU @ 2.30GHz 2.30 GHz
3) Graphics	Intel (R) HD Graphics 620
4) Operating System	Windows 10 64 bit

RESULTS AND DISCUSSION

This section analyzes the performance of the proposed and existing methods using the plant dataset .The dataset is trained and tested from Annamalai University Deep learning laboratory using python executable code in Jupyter notebook. The dataset samples are divided into 70% for training and 30% for testing. The methods are implemented using Anaconda with Jupyter notebook in windows. Dataset training and testing done in a laboratory environment using and the results including percentage of data used , classification (in terms of varieties like fungal(3), healthy(0) , unhealthy(1) , pesticide(2)) shown in Figures 4(a),while as summary of the model is shown in 4(b) and The performance of the classifier can be evaluated using measures like precision, recall, F1-score, and accuracy. The precision, recall, F1-score, and accuracy for testing images are shown in Table 3 for every 4 consecutive leaf images.

The overall confusion matrix using generated by the model using precision, recall, F1 score is shown in 4(c).

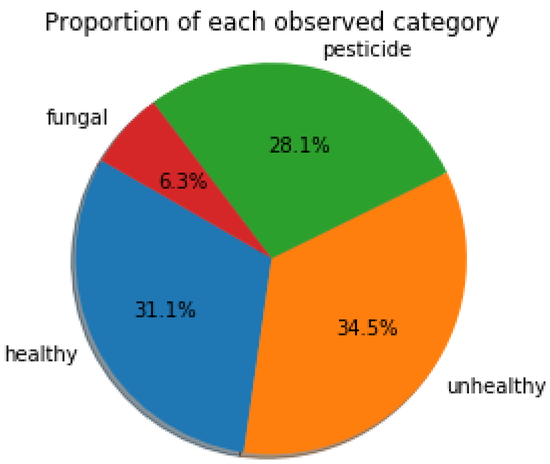

Fig-4: (a) Plant classification, percentage of data used in classification

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 254, 254, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 127, 127, 32)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 125, 125, 32)      9248
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 62, 62, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 60, 60, 32)        9248
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 30, 30, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 28800)             0
_________________________________________________________________
dense (Dense)                (None, 4)                 115204
=================================================================
Total params: 134,596
Trainable params: 134,596
Non-trainable params: 0
```

Fig-4: (b) Summary of the DDCNN generated by the model

The results of the proposed system and the existing methods such as Support Vector Machine (SVM), and Convolutional neural network Probabilistic (CNN) are measured via the metrics like macro precision, macro recall, macro f1-score, and accuracy. These metrics have been generated via a confusion matrix. A confusion matrix needs to be computed for each class $g_i \in G = \{1, \dots, K\}$, in such a way that the i[th] confusion matrix assumes class g_i as the positive class and the remaining classes g_j with $j \neq i$ as negative class. As each confusion matrix pools together the entire observations labelled with a separate class apart from g_i as the negative class, this method increases the number of true negatives. This gives us:

- "**True Positive (TN)**" for event values that are correctly analyzed.
- "**False Positive (FP)**" for event values that are incorrectly analyzed.
- "**True Negative (TN)**" for no-event values that are correctly analyzed.
- "**False Negative (FN)**" for no-event values that are incorrectly analyzed.

Let us TP_i, TN_i, FP_i and FN_i to indicate the true positives respectively, true negatives, false negatives and false positives, in the confusion matrix associated with the i[th] class. Let the recall here be indicated by R and precision by P. Micro average pools the performance over the least possible unit. It is computed by equation (5,6),

$$P_{micro} = \frac{\sum_{i=1}^{|G|} TP_i}{\sum_{i=1}^{|G|} TP_i + FP_i} \quad (5)$$

$$R_{micro} = \frac{\sum_{i=1}^{|G|} TP_i}{\sum_{i=1}^{|G|} TP_i + FN_i} \quad (6)$$

The micro-averaged precision, P_{micro}, and recall, R_{micro}, give rise to the micro F1-score. It is computed by equation (7),

$$F1_{micro} = 2.\frac{P_{micro}.R_{micro}}{P_{micro} + R_{micro}} \quad (7)$$

Given that a classifier gets a large $F1_{micro}$, it denotes that it performs exceedingly well. Here, micro-average may not be sensitive to the overall predictive performance. Due to this, the micro-average can be misleading when there is an imbalance in the class distribution.

Macro average averages over bigger groups and over the performance of individual classes than observations.It is computed by equation (8,9),

$$P_{macro} = \frac{1}{|G|}\sum_{i=1}^{|G|} TP_i/TP_i + FP_i \tag{8}$$

$$R_{macro} = \frac{1}{|G|}\sum_{i=1}^{|G|} TP_i/TP_i + FN_i \tag{9}$$

The recall and macro-averaged precision leads to the macro F1-score.It is computed by equation (10),

$$F1_{macro} = 2.\frac{P_{macro}.R_{macro}}{P_{macro} + R_{macro}} \tag{10}$$

If $F1_{macro}$ has a bigger value, it points out to the fact that a classifier is able to perform well for each of the individual class.Multi-class accuracy is termed as the average of the correct predictions. It is computed by equation (11),

$$accuracy = \frac{1}{N}\sum_{k=1}^{|G|}\sum_{x:g(x)=k} I(g(x) = \hat{g}\,(x)) \tag{11}$$

Where I is defined as the indicator function, which returns 1 when there is a match between the classes and 0 otherwise. The proposed system is tested with real-time video for varying numbers of hidden layers. For authentication, 5000 images are extracted from the live webcam and it is used to evaluate the performance of the system for consecutive ‘n’ images (n= 1, 3, 7 and 10). Similarly, when the model is tested for every 3 frames and 7 frames gives 90.32% and 92.17% respectively. The proposed model with three dense layers achieves an accuracy of 94.15% for every 10 frames. Among the classifiers, the proposed algorithm gives the highest validation accuracy and these models are tested in the real time video to evaluate the performance of the system.

Table-3: Performance of Early leaf health and disease classification and prediction

Methods	n=1(in %)	n=3(in %)	n=6(in %)
SVM	75.62	78.32	84.21
CNN	78.22	81.21	85.78
VGG3	82.12	85.63	90.14
VGG7	84.52	86.93	92.75
DDCNN	88.36	90.32	96.78

Table-4: Performance evaluation metrics under classification and prediction

METHODS	Results (%)			
	Precision	Recall	F1-Score	Accuracy
SVM	80.12	82.72	81.42	84.21
CNN	83.79	84.81	84.30	85.78
VGG3	87.51	89.17	88.34	90.14
VGG7	89.23	91.28	90.255	92.75
DDCNN	92.62	93.71	93.165	94.15

The overall performance obtained is 96.78 % when compared this four class problem with other methods is shown in below table 3 and the analysis is shown in Fig. 4 (c)

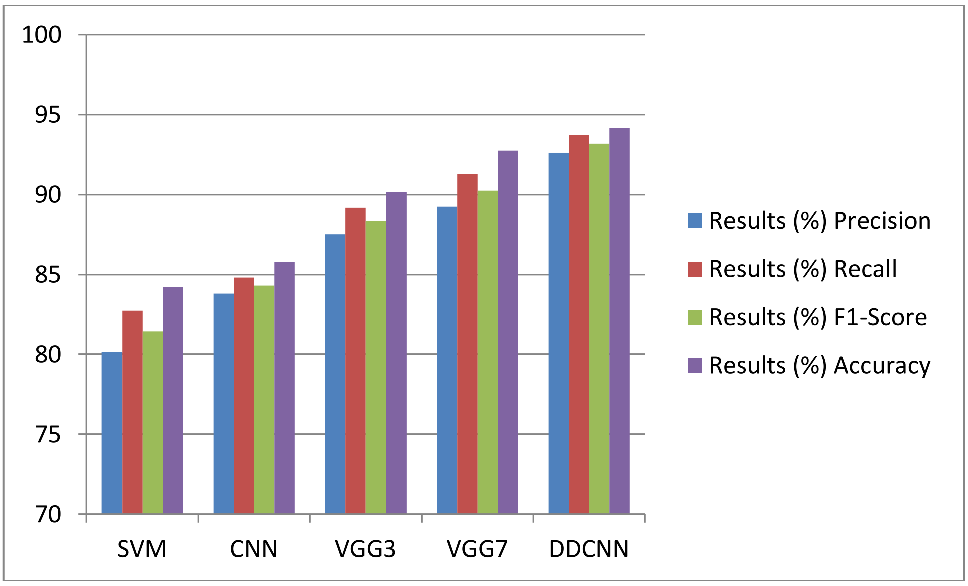

Fig. 4(c)

Conclusion and future work

In this paper a novel and effective method is carried out about the plant early leaf health and affected disease classification and prediction diagnosed. The whole method changed into described, respectively, from gathering the pix used for education and checking out and subsequently the method of education the deep DDCNN and fine-tuning. Different exams have been accomplished so as to test the overall performance of newly created version. The experimental consequences executed precision among 92% and for separate magnificence exams. The very last average accuracy of the educated version changed into 94.3%. An extension of this have a look at may be on amassing pix for enriching the database and enhancing accuracy of the version the use of one of kind strategies of fine-tuning and augmentation. The major aim for the destiny paintings may be growing whole device along with server aspect additives containing a educated version and an software for clever cell gadgets with functions which include showing diagnosed illnesses in fruits, vegetables, and different plants, primarily based totally on leaf pix captured with the aid of using the cell telecell smartphone camera. This software will function an resource to farmers (no matter the extent of experience), allowing speedy and green popularity of plant illnesses and facilitating the decision-making manner in relation to the usage of chemical pesticides.

Furthermore, destiny paintings will contain spreading the use of the version through schooling it for plant disorder popularity on wider land areas, combining aerial images of orchards and vineyards captured through drones and convolution neural networks for item detection. By extending this research,

Conflict of Interest: The authors declare that there is no conflict of interest among them.

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