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Convolutional Neural Networks in Detection of Plant Diseases

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Abstract:

Pests and illnesses that affect plants can drastically lower crop yields and quality, endangering consumers' health. Some plant diseases can be so bad that they totally ruin grain harvests. Therefore, there is a great need in the agricultural data sector for systems that can detect and diagnose plant illnesses automatically. Color features, vein features, Gray-Level Matrix techniques, and Fourier descriptors are few of the feature extraction-based image processing approaches used here. The results concluded here support the utilization of the features obtained from divided leaves instead of the entire leaf. Combining CNN with SVM and KNN was suggested in this study. It evaluated and collated the suggested method's accuracy with approaches from other studies after using 10-fold cross-validation to assess its accuracy.

Keywords: Image processing, Image classification, Disease classification, Convolutional Neural Networks (CNN)

1.Introduction:

Food safety and plant health are closely related. Following the statistics of the United Nations, twenty to forty % of food supply has been destroyed by pests and illnesses, posing a danger to food security (Cooper 2007). The use of pesticides allows farmers to shield their crops from these pests while simultaneously maintaining harvest yields. Their utilization has contributed to the rise in food production since the 1950s, which in turn has helped to fulfill the demands of an expanding population (Knillmann, S. and Liess, M. 2019). Nevertheless, these compounds are not eco-friendly when used. Insect, avian, and fish populations, along with air, water, and soil quality, are all adversely affected by the use of these compounds . Additionally, their use poses a risk to human health, resulting in both short-term and long-term repercussions (Kim, K.-H., Kabir,. 2016). Still, from 1990 to 2016, the amount of pesticides used increased by 78% in terms of tons of active chemicals . This is why automated plant disease detection systems can be a great asset to farmers' decision-making processes . (Barbedo, J. G. A., 2013). Continual on-site monitoring is impossible in large properties and areas without easy access to specialized technological support. Problems abound, though, and none of the current approaches seem to be working.

However, it is not easy to tell if a plant is healthy just by looking at it. Indeed, agricultural areas are diverse and intricate habitats. As the seasons change, so do their leaves, blossoms, and fruits, demonstrating their ongoing evolution. The amount and direction of sunlight also has a small impact on how they look at different times of the day.

Incident solar energy affects crop spectral response. Various methods for detecting agricultural diseases have been developed by researchers, both in controlled environments and in the real world. The creation of vegetation indices, pattern analysis, and visible and near-infrared reflectance analysis were all major components of such tools. These also show a number of barriers to the automated illness detection potential of these techniques. However, there are certain restrictions and challenges with regard to the possession of pictures, climatic restrictions, costs, disposition, quick utilization, and diagnosis abilities.

Additional challenges arise when processing field pictures, such as handling complicated components like foliage or uneven backdrops. Additional problems may develop with the multi-faceted nature of phytosanitary issues, such as the fact that symptoms can differ among different types and over time, or that numerous diseases could manifest at the same time. For automatic illness identification systems to be useful, we need methods that can get beyond these obstacles. Since 2012, biometry, object recognition, and classification are fashionable functions which successfully worked across convolutional neural networks (CNNs) and deep neural networks (DNNs), which also have succeeded on different computer vision applications. Convolutional neural networks (CNNs) have convolution layers that work similarly to data-driven matching filters. Convolutional neural networks (CNNs) maximize a hierarchical representation of a task-specific visual. A model is constructed with combined weights and biases during CNN training. The model is subsequently instructed to perform the task for which it was originally designed. The ability to generalize, or handle data that has never been seen before, is one of CNNs' main capabilities. As a result, it can withstand intra-class variability, picture capture conditions, and backdrop heterogeneity to an extent. But developing those graphical representations requires training data on a massive scale. Overfitting the training data occurs when DNNs, due to their high parameter count, fail to generalize, which is a typical issue with DNNs (. Abdulrahman, sh 2020). Two additional challenges associated with CNNs are how training outcomes are interpreted (the black box effect) and the selection of problem-specific architecture, as in (LeCun, Y.,2015), which reported further information regarding CNNs. This paper introduces the related works, methodology, findings, and discussions.

2.Related works:

In (SH.Goeau , 2020), the author proposed K-Nearest Neighbor (KNN). based method for identifying leaf diseases in vine plants. While investigated machine learning methodologies for the identification and diagnosis of plant diseases in a variety of domains by (Chen, J. ,2020), such as the classification of plant leaf diseases and the detection of plant genes. A study (shaymaa.a 2020) proposed a Naive-Bayes classification to photographically diagnose plant diseases. Automated disease diagnosis is the main focus of medical image analysis, which mainly suggests applications based on deep learning Despite its potential, deep learning for the identification of plant leaf diseases has garnered limited attention in the literature (Yong Bijo ,2023) . It is necessary to employ new methods in this field. In order to combat several plant leaf diseases, the authors (Kamilaris A, Prenafeta-Boldú FX. 2019) utilized deep CNNs with different datasets and layers to tackle these issues. In (Zhang Y-D, Dong Z, 2019), the authors employed plant leaf photographs and diverse data quantities to develop a comparable deep convolutional neural network approach for multiple plant identification tasks. Furthermore, deep convolutional neural networks can identify plant pests and diseases. To identify pests and diseases in tomato plants, we used this method (Zhong L, Hu L, Zhou H. 2019). The authors of (Shaymaa Adnan tal 2020) used deep learning approaches to solve a variety of agricultural problems after reviewing 40 separate research publications. Here are a few ways to go about it. The authors utilize a convolutional neural net with fourteen layers, batch normalization, dropout, and stochastic pooling to present a model for MS brain detection in (X. Wang, and N.D. Georganas, 2020). Accuracy in classification with this method averaged 98.77%. In a recent endeavor to identify fruits in images, a multi-layer neural net was trained by the above-mentioned methods and features(Leith Sabbar Jabeer, ,2024) . The last trial produced a classification accuracy of 94.94%. Crops grown across multiple time periods can also be classified depending on these networks. This method was proposed by (, Ehsan Qahtan 2023) and used on commercial crops. This method achieved a maximum classification accuracy of 85.54%. Using a collection of plant leaf pictures, our work trained and tested a deep identification model for plant diseases employing CNN_K-NN and CNN_SVM.

3.PROPOSED MODEL:

The suggested approach is divided into various phases for the aim of identifying plant disease cases. The suggested stages are shown in Figure 1 below.

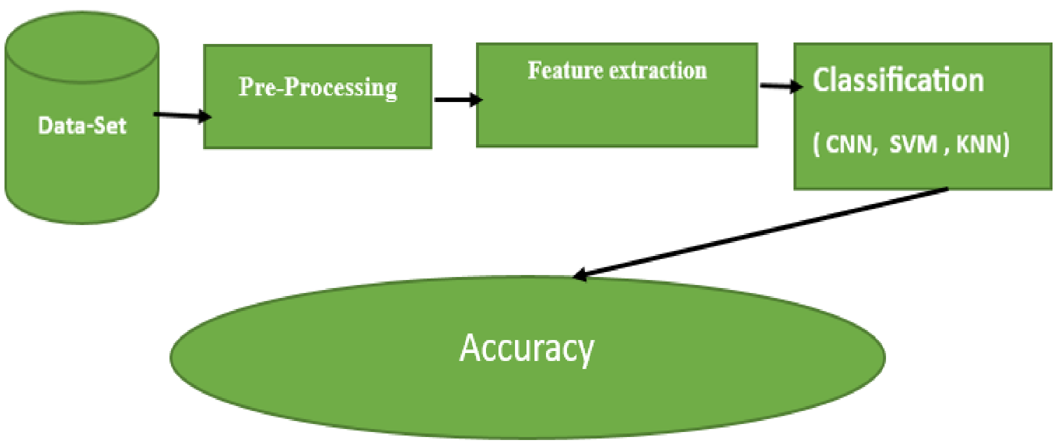

Figure 1:, proposed work

A. Data-Set:

When it comes to identifying plant leaf stress, Digipathos is another popular dataset (Rafah Amer ,etal , 2019).. Almost 167,3,000 digitized images of major cash crops like soybeans, coffee, rice, beans, wheat, corn, and other fruit species are included in the database. Anyone can utilize the 168 database for their own academic, technical, or research projects, and it's free to do so. The original intent behind its creation was to establish it as a standard for identifying leaf stress in plants. The original plan was to include 170 different types of stress and their symptoms along with

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extensive discussions of each stress's sources and effects. Skilled botanists have placed ground truth labels on all of the database photos. Show Figure 2

Figure 2: Examples of image from the Plant dataset

B. Pre-Processing of images:

As part of the preprocessing stage, the leaves are extracted from their backgrounds. During the segmentation process, the following techniques were often followed:

• Photos with colorful foliage were converted to monochrome from RGB.

• By experimenting with different thresholding values, we were able to successfully segment photos of leaves.

• Pixel blocks can be removed using the erosion and filling processes.

The following Figure 3 shows the basic steps to implement the processing algorithm (Abdulrahman sh , 2020)

1: Read image
2 : Convert RGB image to grayscale
3 : Convert image to double precision .
4 : Convert to 8 bit unsigned integer
5 : Obtained <A % A refer to best thresholding
6: Erode process of image
7: Finally "Select objects in binary image"

Figure 3: algorithm of Image pre-processing

C. Feature Extraction:

Four feature extraction approaches with a high degree of performance and ease of application were utilized in this work; These techniques are widely recognized and implemented in the field of image processing .

C1. Vein features:

Morphological operations, such as opening, can be used to derive vein features (Barbedo, J. G. A., 2013). The steps involved are as follows:

(a) transforming color leaf photographs into grayscale ones.

(b) A disk-shaped structural element with radii 1, 2, 3, and 4 is generated in this way.

(c) The opening operation is that which executes these structural parts.

(d) The procedure generates leaf images in grayscale with the addition of subtraction.
(e) Thresholding transforms these into binary pictures.
If we add up all the pixels, we get b1, b2, b3, and b4.
The five main vein characteristics are as follows:

$$z_1 = \frac{b1}{b} \;, z_2 = \frac{b2}{b} \;\; z_3 = \frac{b3}{b}, z_4 = \frac{b4}{b}, z_5 = \frac{b4}{b1} \quad \ldots\ldots(1)$$

b denotes the area of the leaf vein; b1, b2, b3, and b4 collectively provide the vein's total pixel count. The results showed that when used in conjunction with other feature extraction approaches, the mouth attributes improved performance.

C2. Co-occurrence matrix with gray-levels (CMGL):

To statistically analyze and extract textural information from photos, one can use a co-occurrence matrix with gray levels (CMGL). Two adjacent grayscale pixels in a picture form the basis of this technique (Ehsan Qahtan, 2023). For texture descriptions, Haralick and Shanmugam suggested GLCM, which has been well-received due to its performance up until this point (Kim, K.-H.and Kabir,. 2018).. According to Haralick, there are fourteen characteristics of grain texture, including homogeneity, entropy, energy, and contrast. Five Haralick characteristics were utilized in this study.

Homo=$\sum_{i,j} {p(i,j)}/{1+i-j}$ …….(2)　　Cons =$\sum_{i,j} \| i-j \| \, p(i,j)$ … … (3)

Entr=$\sum_{i,j} p(i,j) log_2\, p(i,j)$ …. . (4)　　Ener $\sum_{i,j} p(i,j)^2$ … … (5)

While correlation =$\sum_{i,j} \frac{(i-\mu)(j-\mu)p(i,j)}{\tau i,\tau j}$ …..(6)

The deviations of the rows and columns of the probability density function p(i, j) where μ, μ,, τi, τj values

C.3 Colour qualities:

Statistical measurements including mean (μ1), standard deviation (1σ_1), skewness (θ_1), and kurtosis (γ) are employed to ascertain color attributes. This statistical analysis reveals four properties shared by the R, G, and B components of each plane. The four statistical formulas are as follows: (Ehsan Qahtan, 2023)

$$\mu 1 = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} pi, j \ldots \ldots (7) \qquad \sigma = \sqrt{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (pi,j) - \mu 1)} \ldots\ldots(8)$$

$$\theta 1 = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (pij - \mu 1)^3}{MN\sigma^3} \ldots . . (9) \qquad \gamma = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (pij - \mu 1)^3}{MN\sigma^4} - \ldots\ldots.(10)$$

c.4 Fourier descriptors:

They are utilized to depict an object's outline. The border points of the leaf region are used to calculate these procedures. Pictures of plant leaves are first transformed into binary pictures and then into grayscale before the Fourier descriptors approach is employed. We determine the border coordinates (x, y) for every binary picture of a leaf. Then, the Fourier transform (FT) is used for every x and y coordinate. One way to describe FT is:

F(i) = FFT{p}i ……..(11)

Where $p(j) = \sqrt{(x(j) - x_c)^2 + (y(j) - y_c)^2}$

The coordinates of the centroid are (xc, yc), those of the border are (X_j, Y_j), and the vector of the radii is denoted by p.

4.Principles of Machine Learning Image Classification Techniques:

4.1.Convolutional Neural Network (CNN). As seen in Algorithm 1, the Conv._Net, or CNN for short, is an algorithm of deep learning that retrieves the input, applies bias and weights to its many components, and subsequently differentiates between them (X. Wang, N.D. Georganas, 2020). The main advantage of convolutional neural networks (CNNs) over other algorithms is the reduced amount of work needed for data preprocessing that they enable. This is because CNNs can automatically learn to refine their filters. One way to determine the CNN's output layer is by applying the following formula:

size of output layer + input size - (filter size - 1)…….…(12)

The Sallow convolutional neural network (S-CNN) consists of two-layer convolutional layers, two-layer max-pooling layers, a connected layer. Show Figure 4

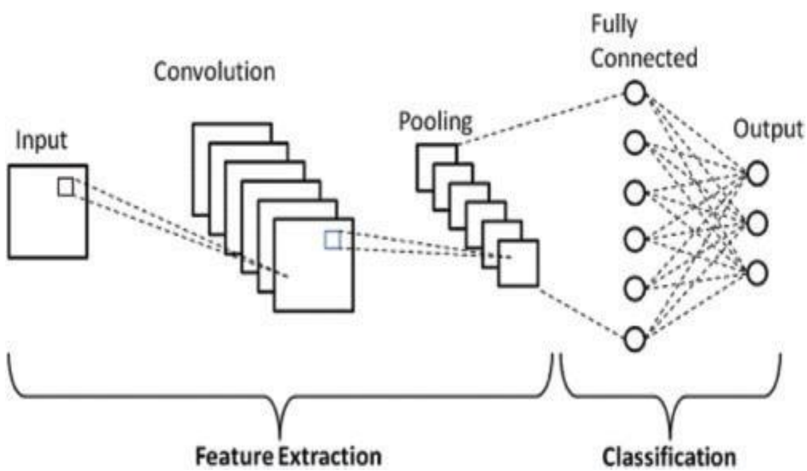


Figure 4: CNN's basic architecture

a SoftMax layer Identifying edges, both vertical and horizontal, is one difficulty. We develop the concept of a filter, often known as a kernel. as follow

$$\begin{matrix} 3 & 0 & 1 & 2 & 7 & 8 \\ 1 & 5 & 8 & 9 & 3 & 1 \\ 2 & 7 & 2 & 5 & 1 & 3 \\ 0 & 1 & 3 & 1 & 7 & 8 \\ 4 & 2 & 1 & 6 & 2 & 8 \\ 2 & 4 & 5 & 2 & 3 & 9 \end{matrix}$$

After that , take filter like .(aka- and a kernel)in mathematic . as follows:

$$\begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix}$$

Now used “.convolution.” Show bellow

$$\begin{matrix} 3 & 0 & 1 & 2 & 7 & 8 \\ 1 & 5 & 8 & 9 & 3 & 1 \\ 2 & 7 & 2 & 5 & 1 & 3 \\ 0 & 1 & 3 & 1 & 7 & 8 \\ 4 & 2 & 1 & 6 & 2 & 8 \\ 2 & 4 & 5 & 2 & 3 & 9 \end{matrix} * \begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix}$$

Finally, we obtain

$$\begin{matrix} 3 & 0 & 1 & 2 & 7 & 8 \\ 1 & 5 & 8 & 9 & 3 & 1 \\ 2 & 7 & 2 & 5 & 1 & 3 \\ 0 & 1 & 3 & 1 & 7 & 8 \\ 4 & 2 & 1 & 6 & 2 & 8 \\ 2 & 4 & 5 & 2 & 3 & 9 \end{matrix} * \begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix} = \begin{matrix} -5 & -4 & 0 & 8 \\ -10 & -2 & 2 & 9 \\ 0 & -2 & -4 & -7 \\ -3 & -2 & -3 & -16 \end{matrix}$$

5. Deep Learning Architectures for Plant Leaf Classification Based on SVM and KNN:

1. CNN-SVM Support Vector Machines,, are a popular and straightforward classification technique with many applications. According to Vapnik and Cortes , it has been suggested. In addition, the principle of reducing structural risk has been its foundation. Support vector machines (SVMs) are useful supervised machine learning devices that look for patterns in data to use for categorization goals. There is an excellent medium between the accuracy gained with a small amount of training data and the ability to generalize the test data, and SVM-based classifications have been recognized for this (shaymaa , et.al. 2020). One way to represent the SVM classifier is as:

$$g(x) = \omega.\theta(x) + b \ldots\ldots (13)$$

Where “ω" is the normal to separate the hyper plane represented by $\theta(x)$

$$\text{b}= \sum_{k=0}^{n} \alpha iyi\varphi(xp_j) + yi, \forall I \;\ldots\ldots.(14)$$

When considering a set of data points (xpi), the margin between two classes is denoted as 2 ‖w2‖, and the interval (y = +1, −1) reflects this margin. Minimizing the constrained optimization problem and then solving it using the Radial Basis Function (RBF) yields the optimal margin. This kernel function is widely used in many kernelized learning techniques, especially in support vector machine (SVM) classification.

In this study CNN_SVM used for plant classification tools combines the advantageous aspects of CNN + SVM. Figure 5: refer to architecture explains the CNN-SVM hybrid plant image categorization technique

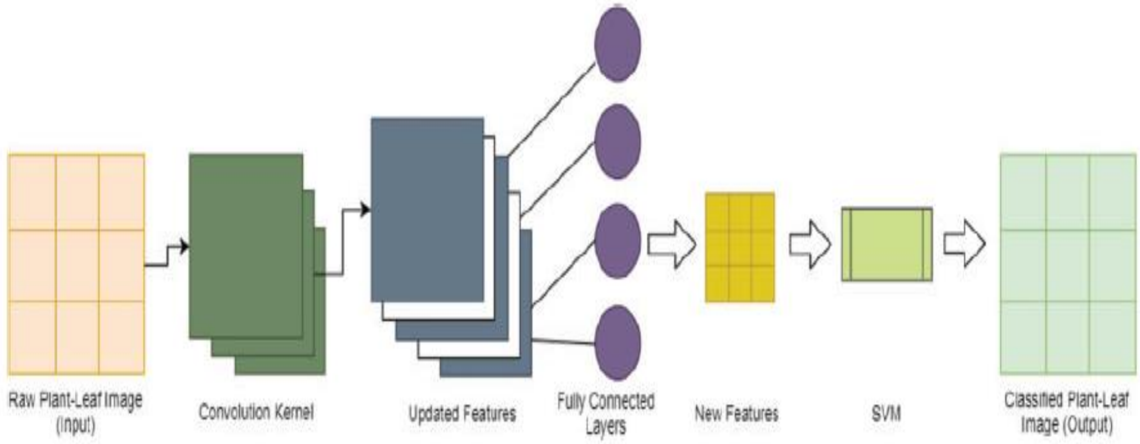


Figure 5: Hybrid (CNN-SVM)Classification

2. K-Nearest Neighbor (KNN). Algorithm 2 demonstrates how KNN, a supervised machine learning algorithm, compares fresh data to preexisting data and places it in a category that is quite similar to the existing categories (Rafah Amer ,etal , 2019). Although the KNN is most often utilized for classification jobs, it is also capable of doing regression analyses. The technique is the lazy learner algorithm as it maintains the training data set and performs its action during the classification process rather than instantly learning from it. Here is the mathematical expression for the calculation of the Euclidean distance:

$$x^2 = c - a^2 + d - b^2 \dots\dots\dots.(15\,)$$

Figure . 6 's architecture explains the CNN-KNN hybrid plant image categorization technique. A non-parametric classification method for identifying plant leaves in images is called kNN (K-Nearest Neighbor). (X. Wang, N.D. Georganas, 2020)

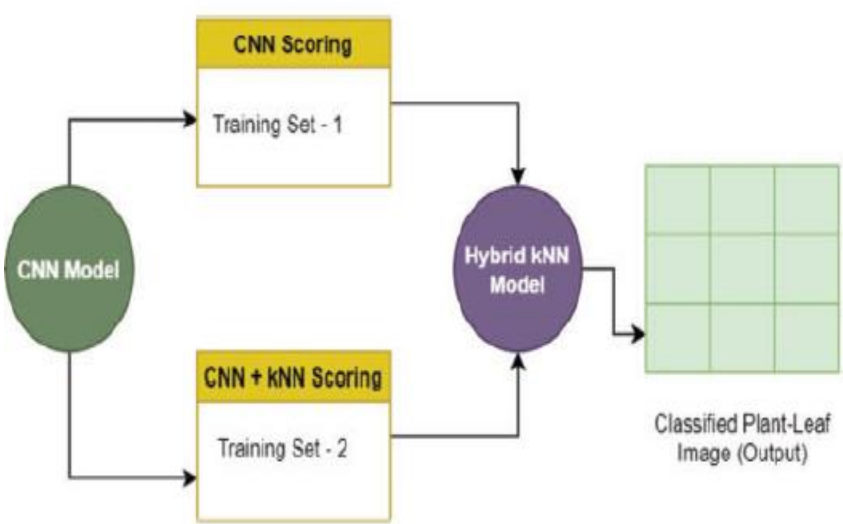
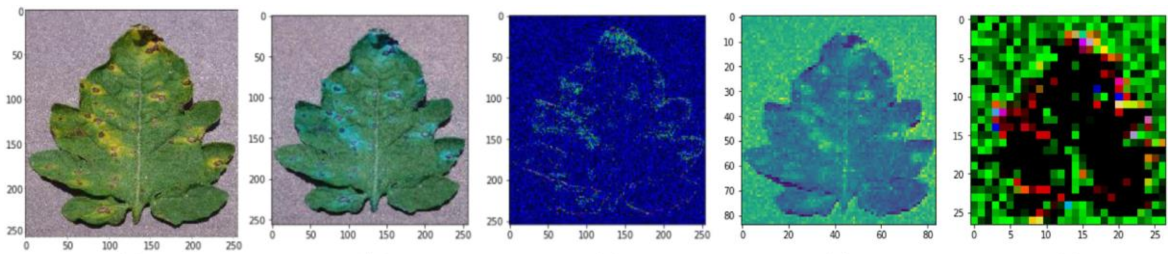


Figure 6: (Hybrid CNN-KNN)Classification

Results:

The CNN is a feed-forward artificial neural net representing deep learning. There are many agricultural picture categorization projects using it . The reduction of the necessity for the feature engineering procedure is a main advantage of utilizing Deep CNN to classify images. A proposal was devised to train the Deep CNN to classify images of plant leaf diseases by utilizing the data reported above. Deep CNN employs multiple convolutions that are layered multiple times. In the initial larger layers, starting with the most common ones and working their way down to more complex ones, they provide a wide range of representations of the training data. At first, the convolutional layers just take the training data and use it to extract features. A subsequent step is the reduction of dimensionality by these layers. Other distinct qualities are produced by the convolutional layers from various lower-level characteristics. Moreover, the basic construction blocks of the deep CNN are convolutional layers (shaymaa, 2020). A very special element of deep learning, feature engineering marks a major development over traditional machine learning. The outputs of the various layers of the proposed model are visually represented in Figure 7.



(a) (b) (c) (d) (e)

Figure 7 . (a) Input image, (b) convolutional layer – 1, (c) convolutional layer – 2, (d) convolutional layer - 3 and (e) flattening layer.

The pooling layer employs the spatial dimensions to perform the down sampling operation. It advocates for a smaller set of parameters. The suggested model's pooling layer used the maximum pooling method. When it comes to the suggested CNN, max pooling is more effective than average pooling. Dropout is another important layer concerned with the clearance of objects off the network. Overfitting can be reduced by using this organization procedure. The deep convolutional neural network (CNN) training method is quite iterative, requiring the training of numerous models to find the best one, in contrast to the dense layer's classification process, which uses the output of such layers. It is also referred to as bulk gradient descent, and it is a straightforward optimization technique that employs all of the training data on each step to perform the gradient steps (Rafah ammer ,2019). Training and evaluation of the proposed deep CNN model used the Digipathos dataset. Three sets—training, validation, and testing—were formed out of the dataset. Thirty percent(30%) of the entire data is utilized for testing, while seventy percent(70%) is used for training. Each batch included 1950 photos, 3900, and 55,636 images accordingly. Along with backdrop photos, The dataset included 39 distinct categories for identifying diseased and disease-free plant leaves. A number of models were compared to the proposed one, including CNN _SVM , and CNN_K-NN. Furthermore, the performances of the models are assessed in respect to the later testing protocols. In the end, the data show that the suggested model is better than all the others described. The subsection on average testing accuracy will come next. Table 1 illustrates a comparison between the results of prior research and the proposed methodology . While Figure 8 displays the Digipathos dataset's performance over 25 epochs. (FN) and all models' true positive (TP) values. In regard to all positive data, the TPR is a statistic reflecting the proportion of accurately anticipated positive data. As far as the entire negative data, the FPR gauges the percentage of negative data items mistakenly projected as positive. Calculated from the following equations, the FPR and TPR span 0 to 1

$$\text{TRP}=\frac{TP}{TP+FN} \quad \ldots\ldots(16) \qquad\qquad \text{FPR}=\frac{FP}{TP+FN} \quad \ldots\ldots(17)$$

Furthermore, the ratio of the outcomes of true positive outcomes (TP) to positive results (TP + FP) the model forecasts defines the precision. It is determined by the following equation and falls within the range of 0 to 1:

$$\text{Precision} =\frac{TP}{TP+FP} \quad \ldots\ldots(18)$$

The proportion of precise affirmative identifications is determined by the accuracy. Table 3 demonstrates that the Deep CNN model, which was recommended, obtained highly accurate outcomes than other machine learning devices. Moreover, recall is computed by means of division of the total number of pertinent sample data (TP + FN) by how many TPs there are. Using this equation helps one to ascertain the retrieval:

$$\text{Recall}=\frac{TP}{TP+FN} \quad \ldots\ldots(19)$$

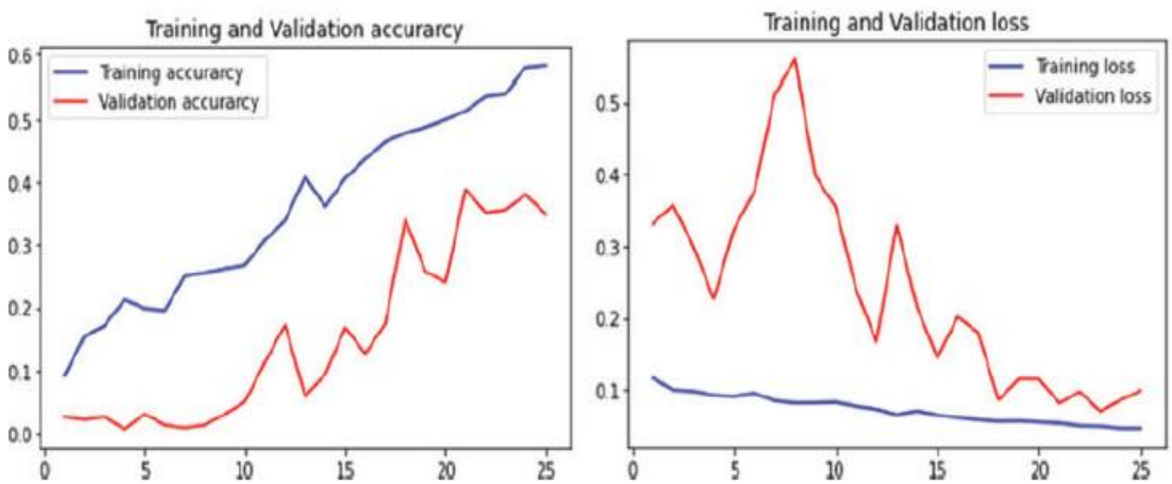


Figure 8: Performance on. Digipathos datasets when applied (25) epochs

Table 1comparison between the results of previous studies and the proposed method

#	Authors	Methods	DataSet	Accuracy%	Years
1	Zhang Y-D et. al	PA-NPA classifier	PIFAR http://bacterial-virulence-factors.cbgp.upm.es/PIFAR.	78%	2019
2	Sachin D. Khirade and A. B. Patil	ANN, Back propagation	captured through the camera.	-	2020
3	Ehsan Qahtan ,et.al	statistical inference methods	Wheat 2014 , Wheat 2015, Pilot	0.80	2023
4	Rafah ammer	SVM	-	-	2019

	et.al	Deep learning			
5	Zhou H , et.al	CNN	open database containing 87,848 photographs of leaves	99.53	2021
6	Ferentinos KP et.al	Deep learning ,CNN	-	0.712	2022
7	Shaymaa ,et.al	deconvolutional networks (DN)	The images were collected from the web	92.6∓2	2020
8	(Kamilaris A, et.al .	CNN, SVM RF,PDA	The images were collected from the web	-	2022
9	**Proposed method**	**[CNN-SVM and KNN]**	**Digipathos Dataset**	**SVM 0.5069065** **KNN 0.8786803**	-

Conclusion:

In order to safeguard agricultural productivity and quality, farmers benefit from prompt and early diagnosis of plant diseases. Features such as color, vein, Gray-Level Matrix, and Fourier descriptors are used for feature extraction. In this study, we identified plant diseases using CNNs, convolutional neural networks. Considering several assessment metrics, our approaches show that on a single dataset they can outperform current deep learning models. With fewer parameters and improved performance, the suggested solutions allow for quicker operating speeds on the same hardware platform. Starting with the proposed SVM, KNN, is advised for plant disease recognition due of their simple structure, strong performance, and low processing cost. Should the CNN fall short of the requirements, deep learning network modification should be taken under thought. In addition, it is worth mentioning that deep learning approaches remain unparalleled when it comes to handling many other complex jobs, such as agricultural object segmentation or detection.

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