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Research Article

ANALYSIS OF GRAPE LEAF DISEASE BY USING DEEP CONVOLUTIONAL NEURAL NETWORK

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Abstract

Smart agriculture is a strategy for restructuring and reorganizing agricultural systems to ensure food security in the face of emerging climate change challenges. Diseases cause problems on agricultural development and yield and they're generally tough to control. It is necessary to have a precise diagnosis of the grape leaf diseases and preventative measures before time. In order to diagnose grape leaf diseases, this research suggests a novel recognition method that is based on enhanced convolutional neural networks. Firstly; addressed the grape leaf disease types into four categories such as Esca, black rot, Leaf Blight, and healthy which cause loss for grape industry every year. A large dataset of labeled images is collected and prepared for training. The images are typically pre-processed to enhance their features and remove any noise or artifacts that might interfere with the CNN's ability to recognize patterns. Data collection, data pre-processing, and image categorization are the three main phases of the study's approach. Secondly; Images are classified and mapped to their respective disease categories on the basis of three features namely, color and texture. Extensive experiments performed on MATLAB using CNN model AlexNet. The CNN training process used learning rate 0.0001 which produced better results and obtained better accuracy. Overall, an accurate diagnosis of grape leaf diseases and the implementation of effective preventative measures will help to reduce the impact of diseases on agricultural development and yield. This will help to ensure a sustainable and profitable grape production industry for farmers and communities.

Keywords: Smart agriculture, AlexNet, Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Deep Learning
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1. INTRODUCTION

Agriculture is the culture base upon which every human community is built. The enhancement of production is the primary emphasis, but the ecological repercussions that have led to the deterioration of the ecosystem are not being taken into consideration. Because plant diseases are unavoidable, the detection of leaf diseases is an extremely necessary part of agricultural industry. Fungi, organisms, bacteria, viruses, and other microorganisms may all infect plants and cause disease. Grapes, which are one of the most frequently planted economically valuable fruit crops, are utilised in wine, and other fermented beverages, and they are also consumed fresh or dried in the form of raisins (Kole et al., 2014). Early identification of grape diseases might possibly decrease losses and manage expenses and subsequently can enhance the grape fruit quality. For decades, the illness diagnosis is accomplished by human. The diagnosis of diseases in their earliest stages is very important for maximizing crop output. Plant diseases like black measles, bacterial spot, black rot, and, amongst others, have an influence on the development of plants, and the economic repercussions of the agricultural sector. The application of chemical techniques causes harm to both the plant as well as the environment around it. The most essential era for effective illness treatment is the early detection phase, which occurs while diseases are first manifesting themselves. It is common practice in the agricultural industry to conduct manual disease detection using human expertise in order to identify plant diseases (Park et al., 2017).

According to this research, CNNs have achieved results that may be considered good in the recognition of plant diseases. However, CNNs are employed in the diagnosis of grape leaf diseases very seldom at this time. In addition, the majority of application-oriented image recognition algorithms are derived from well-known transfer learning methods, and the algorithms themselves have had very little development in recent years. Therefore, the avoidance of agricultural production losses and the preservation of product quality is heavily dependent on the correct diagnosis of these diseases so that the appropriate pesticides may be used in accordance with that information. As a result, an appropriate solution is necessary in order to precisely identified the illness and investigate features of the disease in order for appropriate steps to be performed in order to treat the plant that is afflicted. CNN is a method that is widely used in deep learning, and it trains several layers of an algorithm in a robust manner. It has been reported to be really successful, and in addition, it is the method that is used the most often in a variety of computer vision applications.

The goal of current work is to identify disease in grape leaf plants and deal with grape diseases more promptly. As a result, the following are the objectives of the proposed work:

Firstly, the structure of CNN is investigated in this study. The dataset was acquired from the database at Plant Village. There were 4062 photos in the dataset, of which 80 percent were utilized for training and 20 percent were used for testing. CNN demonstrates superior performance in terms of feature representation, and it is capable of achieving complicated picture classification.

Secondly, this research presents a strategy for enhanced picture categorization that is based on deep learning as a potential solution. CNN model named Alexnet and improved the result in order to get a higher level of performance in the classification.

Thirdly, a performance study and evaluations of the suggested method is carried out, at the end results are compared with the total number of epochs. The experiments show that the proposed algorithm that is described in this research achieves a greater level of accuracy.

2. LITERATURE WORK

Early plant disease detection plays a significant role in efficient crop yield. Plant diseases like black measles, black rot, Esca, Leaf Blight, etc. affect the growth, crop quality of plants and economic impacts in the agriculture industry. With the rapid growth in technology, automatic revealing of plant diseases is possible with the use of computer vision and artificial intelligence studies. They gained adequate results on their suggested procedures. Some of the achievements as below:

Ertam and Aydın (2017) conducted the comparative research on the effects of a number of activation functions, including tan ReLU, sigmoid, and soft plus, on classification. A classification rate of 98.43 percent indicates that the ReLU activation unit has a highest accuracy. The results of this experiment show that increasing the time complexity or epochs results in an increase in the accuracy values.

Pooja et al. (2017) applied ML processes and IP technologies for illness identification and categorization with the use of SVM classifiers are used in order to do illness classification. Training and testing with five different illnesses and pests have been completed. We employ a data training process consisting of 227 photos and a testing process consisting of 121 images. A recognition rate of 92.4 percent was determined to be the overall average. The retrieved characteristics were expressed using a variety of different criteria, including color, shape, and texture. Only the most important aspects of these 38 characteristics were taken into consideration throughout the training.

Wiesner-Hanks et al. (2018) used data from a corn database obtained from a flying drone at a height of 6 meters. They picked areas of the picture that are 500 by 500 pixels and called them based on the premise that there was a condition in the most central part of the 224-by-224 region in each of the original photographs of 4000 by 6000 pixels. During the classification phase, a 500 by 500pixel classification technique is used to introduce the ResNet model, which is a CNN model.

Ma et al. (2018) developed a model depends on DNN for detection of illnesses seen on cucumber leaves. Before the data is processed by DNN, an augmentation of the data is carried out, and it separates the symptoms that differentiate the cucumber illnesses from the complicated backdrop. In order to test the approach that is described, a total of 14,208 photos of cucumber leaves are employed, and the results reveal that the method performs well.

Wu et al. (2019) Used trained models it was possible to categories the many forms of illness that may affect the soy bean plant. Data are collected by hand on a wide range of factors that may have an effect on soy bean plants. These factors include bacteria, downy mildew, pests, insecticides, spider mites, viral infections, and health. In order to prevent overfitting, the author used a method called back propagation algorithm. The accuracy rate of Reset is higher than that of both AlexNet and GoogleNet at 94.29 percent. By using an F1-score confusion matrix, it was discovered that downy mildew are better categories in comparison to those that are not included. Using t-distributed stochastic neighborhood embedding, the researchers were able to show the characteristics that were produced from completely linked layers (t-SNE).

Ozguven and Adem (2019) modified the input layer such that it now has 600 by 600 pixels rather than 32 by 32 pixels. In addition to this, a method that is capable of automatically detecting and identifying leaf spot disease in all three phases of sugar beet disease was developed. In comparison to the precision of Faster R-92.89 CNN, the newly developed version of Faster R-CNN achieved a rate of 95.48 percent.

Cruz et al. (2019) assessed six different neural network topologies that showed great potential for analyzing images of the Grapevine Yellows condition. They revealed that DL delivers predicted values that are 35.97 percent and 22.88 percent better than a baseline technique that did not use deep learning. The baseline method was used to recognize GY from sight. This approach achieves a true positive rate that is 98.60 1.47 percent higher than that of trained people, accordingly.

Ji et al. (2020) proposed a model after taking into account the results of several deep neural networks. They created a single model by combining the Inception v3 and Recurrent neural networks models into the single model in order to find grape leaf disease. They implemented the dataset from Plant Village as their point of departure. The model has an accuracy score of 99.05 percent, a recall score of 98.88 percent, and an F1 score of 98.96 percent, respectively. According to the findings of the researchers, VGGNet is the algorithm that performs the worst, with a result of 94.16 percent, a recall score of 93.32 percent, and an F1 score of 94.40 percent.

Sethy et al. (2020) developed an SVM classifier by using deep features gathered from thirteen different CNN architecture. On the test dataset, a Score of 0.9838 was achieved, which demonstrates that the classifier that was trained using characteristics extracted by 50 iterations is superior to other networks when it comes to identifying rice sickness. This method has been used by the researchers so that they could determine the degree to which rice lacked nitrogen that year.

Joshi et al. (2021) developed the VirLeafNet identification system, which is capable of identifying leaves with an accuracy that reaches 97 percent. In the study described above, the majority of the crop disease identification was carried out with the use of a standard sample database. When trying to present serious disease qualities in the normal sample database, it is common practice not to take into account the complexity of illness images that have been gathered in the field. As a result, the applicability of disease identification modeling techniques in actual production has been reduced as a result.

Gokulnath et al. and Mumtaz et al. (2021) hypothesized that an effective loss fusion deep neural networks model might be created by combining the better of the two separate loss functions. This model was then used to categories five, seven, and ten distinct disease-related photographs found in Plant Village. For the purpose of identifying leaves affected by grape diseases, a combined model was constructed. They merged the CNN models and they employed multilayered feed - forward neural and sigmoid layer for classification. The Convolutional networks Inception-v3 and Resnet50 were integrated.

The majority of grape plant diseases are serious and spread quickly. Grape plant infections begin on the leaf and spread to the stem, fruit, and root. Because of restricted access to human specialists in underdeveloped nations, it is time consuming and difficult for farmers in remote places to categorize grape leaf diseases. Recent study has categorized grape leaf diseases using several models. However, the categorization did not yield excellent accuracy results. The suggested method produced more accurate illness classification results by employing the AlexNet model with a variable number of epochs.

3. RESEARCH METHODOLOGY:

3.1 Grape Leaf Disease Images Collection:

The dataset that was employed in this research consisted of 4062 photos of grape leaves, with 2474 of those images serving as training data and 1588 serving as testing data, as shown in Table 3.1 are obtained from the dataset provided by Kaggle by Plant Village (https://www.plantvillage.org/). The data set is separated into four categories: three of the categories represent diseased grape leaves (Black Rot, Esca, and Leaf Blight), while the fourth category represents healthy grape leaves shown in Figure 3.1.

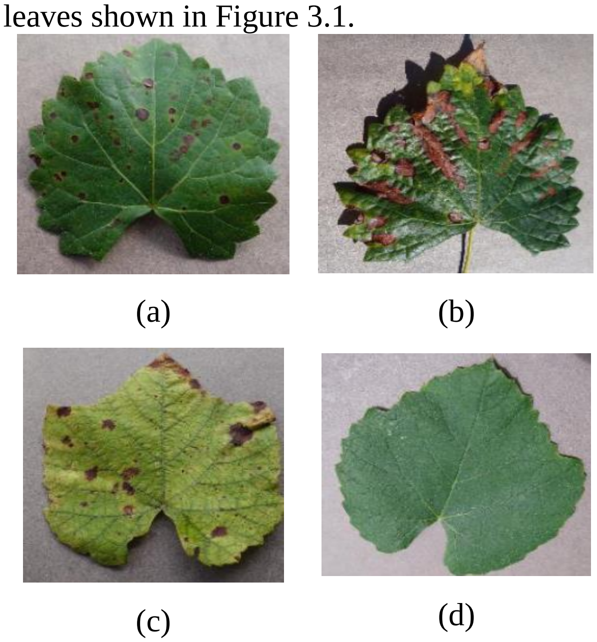

Figure 3.1. Black Rot (a), Esca (b), Leaf Blight (c), and Health (d)

Table 3.1: Grape Leaf Image Collection

Class	No of images	Training Images	Testing Images
Black Rot	1180	944	236
Esca	1383	1106	277
Leaf Blight	1076	860	216
Healthy	423	338	85

3.2 Image Preprocessing and Labelling:

Image preprocessing is done even before model is trained in order to enhance the image consistency that is present in the dataset so that it can be processed by the CNN classifier. The first thing to do is standardize the size of the picture. After that, a grayscale version of the picture is created. The next thing that has to be done is classify the photos of grape leaves into the appropriate groups, and then label each image with the abbreviation that corresponds to the disease. At this point in the process, the dataset's trained model and test set each include four classes that have been marked. The test picture has to be processed in this stage so that its dimensions, colors, and overall quality may be brought up to par with those of the photographs that make up our dataset. This process includes the picture going through different steps. These steps are as follows:

3.2.1 Image Resizing:

Through the use of the imresize () technique in MATLAB, the dimensions of the picture are scaled up until they match those of the training images. Resizing an image is an essential step because the values may shift in a significant way if all of the training photos and the images were not identical.

3.2.2 Smoothening:

The smoothing of the image causes the number of pixels to gradually become more uniform across all of the image's points, which enables the creation of an image that is continuous. In addition to this, the picture undergoes a transformation that changes it from a colorful image to a grayscale image.

3.2.3 Convolutional Neural Network (CNN):

A neural network used in the processing of image data is referred to as a CNN. The matrix performs the function of convolution, sometimes known simply as convolution, is responsible for filtering the picture. The CNN is comprised of many layers, each of which serves to filter the subsequent process. The method is often referred to as the training process.

3.2.4 Convolutional Layer:

The convolutional procedure will be applied to each and every data that makes contact with the convolutional layer. A two-dimensional feature map or an activation map will be produced as a consequence of the layer's processing of the incoming data. The length, height (in pixels), and thickness of the filter that is included in the Convolutional Layer are determined by the data that is supplied from the channel. Between the data that is entered and the value that is produced by the filter, each filter will go through a shift and a "dot" operation. Through modification of the output, the convolutional layer substantially increased the complexity. Convolution can accomplish calculations from two-dimensional images that mapped to a continuous sliding convolution window to get the corresponding convolution value. Apiece map feature is convoluted by several graphical input features. For input x from the i-th convolutional layer, calculated as follows using equation (1)

$$hic = f\ (Wi * x) \qquad 3.1$$

Where f is an activation function, * is a convolution operation, and W is the convolution kernel at the layer. Wi= [Wi1, Wi2...WiK] K is the number of kernel convolution at the layer. Each WiK kernel is a weight matrix M x M x N. M as the window size and N is the number of input channels

3.2.5 Pooling Layer:

The activation map contains various features that can cause overfitting and computing loads. The pooling layer is often applied to reduce dimensions and can help get invariant for translation. Pooling methods commonly used are max pooling (MP) and average pooling (AP) and can be calculated using eq 3.2 and 3.3 (Abhirawa et al., 2017). For example, region R contains pixel max pooling, and average pooling can be defined as follows:

$$MP = \{y_j \ = \max_{i \in R_j} xi\} \qquad 3.2$$

$$AP = \{y_j \ = x_i / \sum ieR_j \, xi\} \qquad 3.3$$

3.2.6 Fully Connected Layer:

At completely connected layer, every layer has a direct connection to every other layer in both layer below it and the one above it. Each node that is present in the last frame of the fully - connected layers is linked as a vector to first level of the fully connected layer.

3.2.7 Training:

The process of training a network involves collecting kernels for use in convolution and weights in order to minimize the amount of variation on a testing set that exists between exportable and the ground truth labels that have been given. In the work that we have done, 80 percent of the data used for training have been processed through this stage.

3.2.8 Testing:

The testing dataset is one that is employed to carry out an objective final assessment of the design's appropriateness for the training data. In this step, we use the organizations that were trained data in previous step that has received training in CNN, 20 percent of the data were used for testing. In the previous step, CNN was used to train the groups, and the features were learned by the network. The flow of proposed system is shown in Figure 3.2.

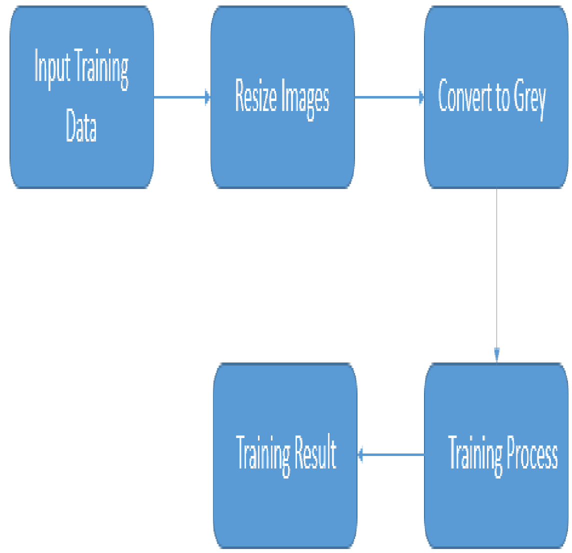

Figure: 3.2 Training Flow

3.3 Classification:

The fully connected layers are being used for classification, whereas convolution layers employed for feature extraction in this model. During this procedure, the plant leaf is evaluated to determine whether or not it is afflicted with the disease, the specific kind of identified a plant disease, and the plant variety is recognized.

Classification is last stage in the image processing Phase involves training the dataset and then evaluating the pictures to see how they compare to the model that has been developed. The CNN is the algorithm that is used in this particular categorization model. This is because it can be employed to discover solutions to these problems.

4. RESULTS AND DISCUSSION

4.1 Testing the Number of Epochs:

Experiments were carried out to investigate how the number of epochs used impacts the overall system performance. One full display of a machine learning algorithm is referred to as an epoch. This allows the machine to gain

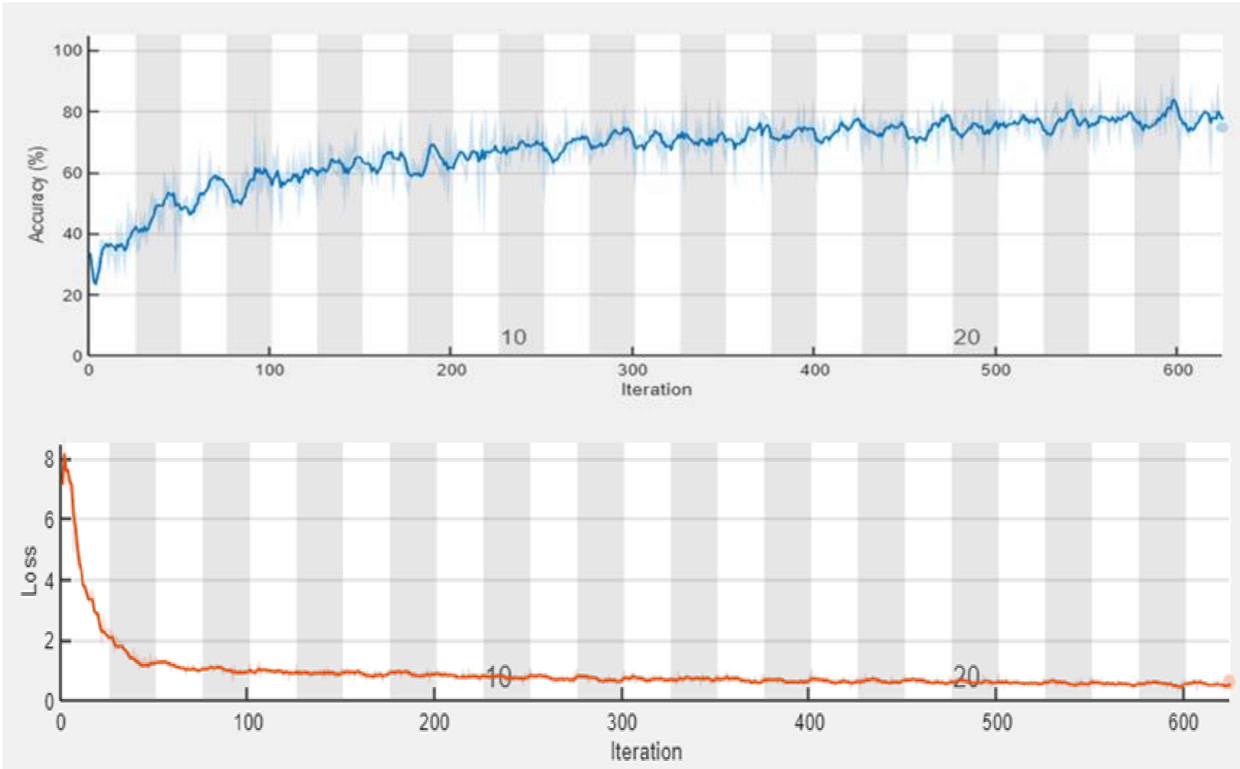

Figure: 4.1 Accuracy and Training loss using 25 epoch and a learning rate of 0.0001

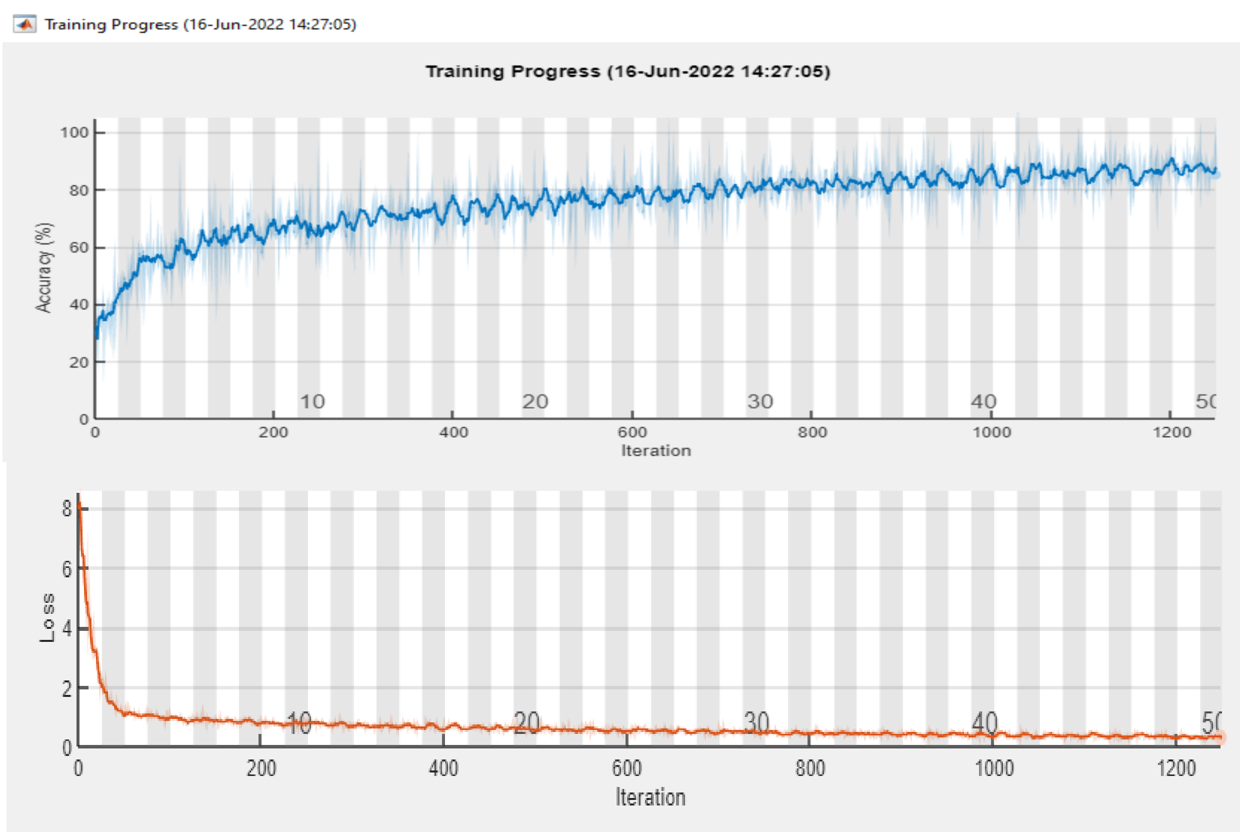

Figure: 4.2 Accuracy and Training loss using 50 epoch and a learning rate of 0.0001

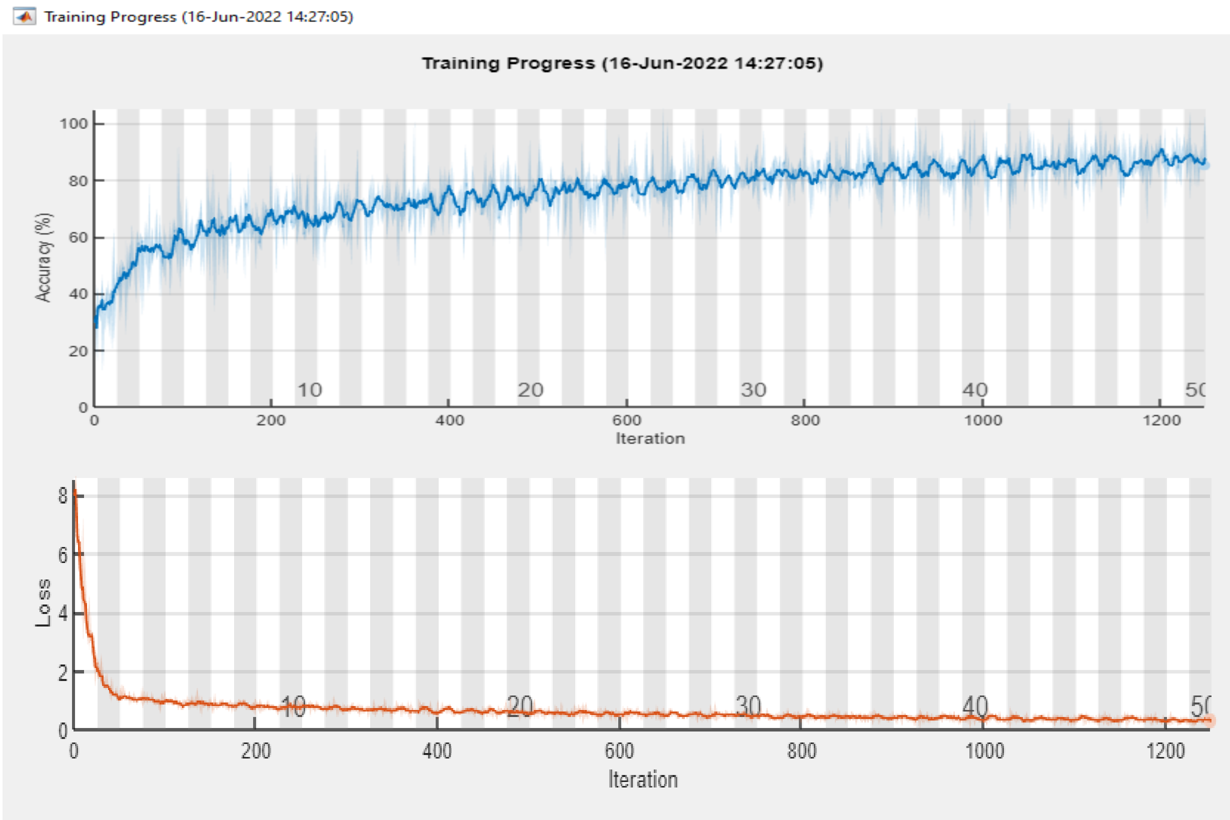

Figure: 4.3 Accuracy and Training loss using 75 epoch and a learning rate of 0.0001

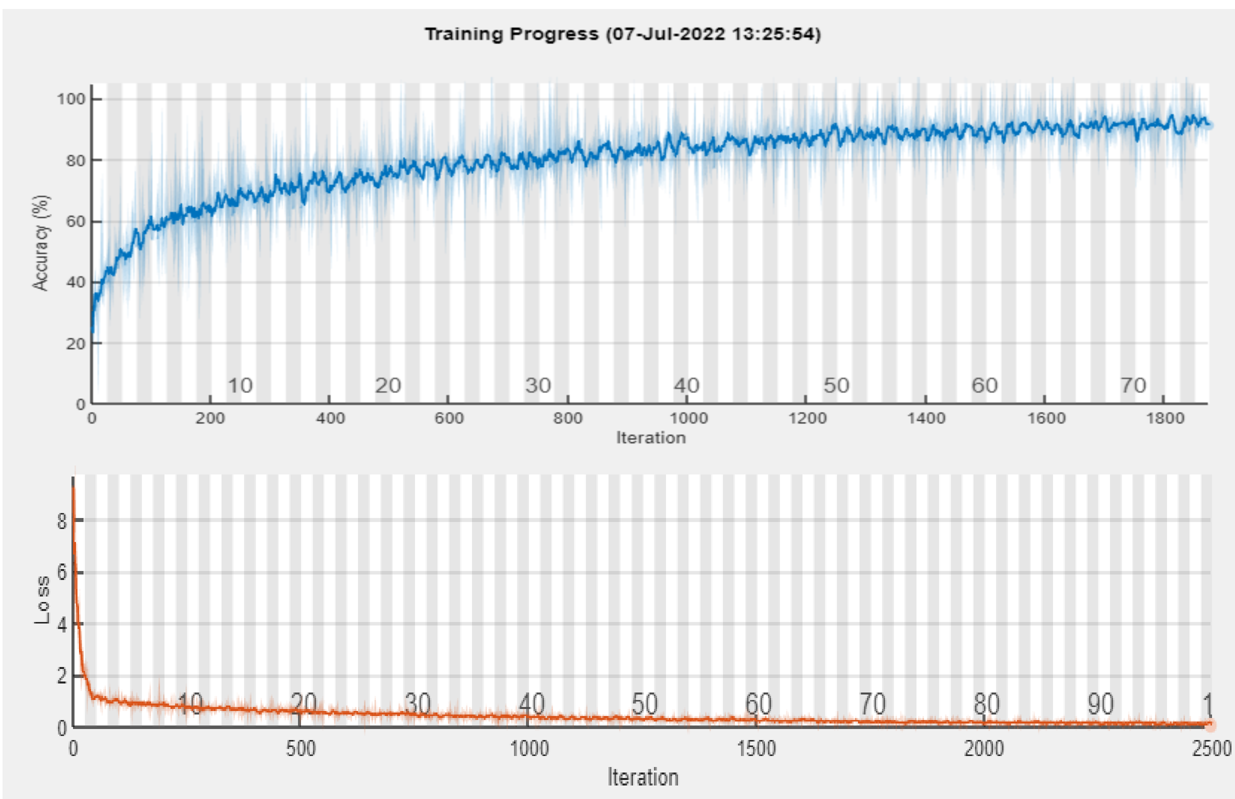

Figure: 4.4 Accuracy and Training loss using 100 epoch and a learning rate of 0.0001

Figure 4.5: Confusion Matrix of Grape Leaf Disease Detection

new knowledge. As a point of reference, this analysis makes use of the numbers epoch 25, 50, 70 and epoch 100, although the learning rates used are 0.0001.

Figure 4.1 illustrates that an accuracy rate of 84.99% is achieved by utilizing the training step 50 epoch and a learning rate of 0.0001.

Figure 4.2 shows that an accuracy rate of 92.91% is produced utilizing the training step 100 epoch and a learning rate of 0.0001.

Figure 4.3 illustrates that an accuracy rate of 96.93% is achieved utilizing the training step 75 epoch and a learning rate of 0.0001.

According to Figure 4.4 an accuracy rate of 97.19 is produced by employing the training step 100 epoch and a learning rate of 0.0001.

Based on the results of the testing process, it can be stated that a higher learning rate can result in a higher percentage of data accuracy.

4.2 The Evaluation Index:

The scenario that a model properly identifies as positive is referred to as a true positive (TP). A model is said to have a false positive (FP) when it wrongly identifies as positive things that are, in fact, negative. The situation that the model properly identifies as negative is referred to as a true negative (TN). A false negative (often abbreviated as FN) is an erroneous prediction of something that is really positive (Hari et al., 2019). The rate of right predictions as a percentage of total forecasts is what accuracy measures mentioned in equation 4.1.

$$\textbf{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \qquad \text{Eq 4.1}$$

The term "precision" refers to the proportion of positive outcomes that were correctly anticipated (TP) to the total number of positive results that were obtained (TP+FP). Precision refers to the fraction of good attributes that were accurately detected by utilizing equation 4.2.

$$\textbf{Precision} = \frac{TP}{TP+FP} \qquad \text{Eq 4.2}$$

When we refer about recall, what we really mean is the proportion of correctly predicted positives, or TP, to the total number of samples in the actual class, which includes TP and FN. Accuracy of recall is determined by applying equation 4.3.

$$\textbf{Recall} = \frac{TP}{TP+FN} \qquad \text{Eq 4.3}$$

The F1 score is the average of the values for accuracy and sensitivity, and it places equal importance on both of these characteristics and is calculated by using equation 4.4.

$$\textbf{F1Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad \text{Eq 4.4}$$

On the basis of the data, calculations and comparisons were carried out with regard to accuracy, precision, recall, and F1- score show in figure 4.5.

4.3 Comparative Analysis:

The results, and the level of accuracy was achieved by using learning rate of 0.0001. Accuracy rate of 84.99 is achieved by utilizing 25 epochs at a learning rate 0.0001 as shown in figure 4.1 and accuracy rate 92.91 percent is achieved by utilizing the 50 epochs at a 0.0001 learning rate, as shown in Figure 4.2 and accuracy 96.93 percent is achieved by using 75 epochs at learning rate 0.0001 as shown in figure 4.3. An accuracy rate of 97.19 percent is achieved while utilizing 100 epoch and 0.0001 learning rate, as shown in Figure 4.4. It is possible to assess that better accuracy can be achieved by using a greater number of epochs. The results of this comparison make it clear that the amount of epochs and the learning rate both play a significant role in determining the degree of accuracy It has been proved that this technique achieved a greater level of accuracy while compare to other stat of art. According to Table 4.1, the methodology that used in experiment produced good performance in terms of accuracy.

Table 4.1: Comparative Analysis

Dataset	Image Size	Epoch	Learning rate	Accuracy
4062	227*227	25	0.0001	84.99
4062	227*227	50	0.0001	92.91
4062	227*227	75	0.0001	96.93
4062	227*227	100	0.0001	97.19

5. CONCLUSION

In this research four types of grape leaves have been identified. Based on computer resources and Deep Learning Techniques this study provided a robust way to identify and categories these diseases and provide fast and accurate results. MATLAB was used to carry out the implementation of the CNN-based identification strategy that was suggested for grape leaf diseases. 80% data is used for training while 20% data is used for testing. The system achieved an accuracy of 84.99% with 25 epochs, 92.91% with 50 epochs, 96.93% with 75 epochs, and 97.19% with 100 epochs. It is worth noting that increasing the number of epochs during training can often lead to higher accuracy rates. According to the experiments the suggested algorithm achieves a recognition rate of 97.19% using 100 epoch which provides superior performance in comparison to other well-known transfer learning algorithms it was noticed that executing more epoch may yield greater accuracy.

Findings of this research show that the suggested algorithm is capable of classification of grape leaf disease. The identification system can help farmer identify and treat disease early, which can prevent crop losses and improve yields. This can help to improve food security and reduce poverty in communities that rely on agriculture. Farmers will have an easier time planning strategies and sharing helpful information if they have access to a decision-making system that is built on high-tech platforms and is based on technologies that are applied in everyday practices. The identification system can help reduce exposure to harmful chemicals by minimizing the use of pesticides and fungicides. This can help improve the health of farmers and other community members who may be exposed to these chemicals. The purpose of this work was to identify and recognize plant diseases using CNN. In the future, more plant kinds and plant diseases of various sorts may be added to the existing dataset to improve the trained models. Other CNN designs may also utilize alternative learning rates and optimization techniques to test the model's performance and accuracy

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