A FULLY CONNECTED DEEP NEURAL NETWORK MODEL FOR DYNAMIC NATURAL VEGETATION ENVIRONMENT

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Abstract- With growing technological advancements, the significance of prediction of natural vegetation is paramount to the research community. There are diverse technical solutions that can predict the species of natural vegetation. However, these solutions fail to provide better prediction accuracy. To handle the drawbacks encountered by the existing model, this work concentrates on modelling an integrated approach for predicting the plant species. Voluminous data is gathered to produce a massive database with diverse characteristics (parameter observation) and temporal analyses. In this work, data is collected from an online resource to give the updated status of the plant species and to estimate the factors that influence the growth of the plants. Here, the vegetation index is measured to examine the species. The varied-size data is transformed into a fixed-size module to map the plant condition. Here, Deep Neural Network (DNN) is applied over the collected/available data to provide optimal accuracy. The prediction accuracy is higher when compared to the existing image processing approaches. The proposed model is preferred by the researchers as it provides a modern environment and gives better perspectives to the research community with the growing plant condition. The simulation is done in MATLAB 2020a. The proposed model offers better trade-offs compared to existing approaches. Various metrics like accuracy, F-measure, recall, precision, and error rate are evaluated to understand the vegetation in a better way.

Keywords- Deep Neural Networks, natural vegetation, prediction accuracy, parameter observation, factor evaluation

1. Introduction

Deep learning (DL) is a domain that offers significant scope for experts and researchers with learning approaches like naïve Bayes, support vector machine (SVM), and conventional neural networks (CNN). Several new algorithms are introduced that offer better performance when compared to the traditional machine learning algorithms [1]. The improved performance is attained by the simulation of the visual, brain, and auditory systems of humans. The area of deep learning has remarkable advancements as it offers advanced learning when compared to the machine learning models. Deep learning technology has attained a considerable and unavoidable part in pattern recognition applications, even though it is in the early stages of research [2]. Different areas and applications are interconnected to deep learning approaches like recognition and detection of an object, recognition of speech, NLP as natural language processing, CRM as customer relationship management and so on [3]. The algorithms of deep learning have various advantages that must be utilized efficiently to enhance and improve the present developed systems in the domains like agriculture, health, and robotics [4].

Plants have a significant role in modern research. Various experts are investigating plants for various applications such as agriculture and medicine. The plants are affected by ecosystems and climate directly or indirectly. Various applications such as energy, health, agriculture, medicine, and the environment are benefited from this research [5]. Since the twenty-first century, because of population growth and climate change, several challenges are faced by agriculturists to provide essential food, especially in a few areas. Hence, much emphasis is provided to the research and developments of new methods in agriculture for farmers [6]. While dealing with huge farms, automation and optimization is the most efficient solution to the problems related to classification. One significant application is to find the pests and weeds in the crop field to remove them efficiently, enabling the efficient utilization of the farm's total capacity, and the farm produce can be further optimized [7]. The wide variety of plants makes it very difficult for farmers to identify all kinds of weeds. The specialists hired to identify the plant types must provide appropriate justification and are expensive[8]. It is only possible to host experts around the world on farms to be able to provide a complete solution. Also, the observations of humans cannot be correct with the lack of knowledge due to the similarities in various plants and the leaves' shapes. Hence, automation helps separating the data in an efficient way with image processing along with data obtained from human experts.

The recognition of plants is complex, even for botanists and plant science experts. It is a critical study because of its importance in a few fields like the pharmaceutical industry, modern farming, medicine, etc. Tremendous efforts are invested to automate plant recognition, find a better solution, and create a precise and correct system. The conventional methodologies do not help recognize plants like this are costly, consume time, and human interaction is essential. A system must be developed to identify and recognize the plants in an automated way [9]. The characterization and generalization of the system is done based on the essential factors, limitations, and parameters for judging the applications. In addition, these systems are used and applied to support modern farming.

Prediction of plant species in the outdoor environments can be performed efficiently by implementing the proposed system. It depends on deep learning since the complex conditions are considered while working on real-time applications [10]. The implemented system has the novelty of identifying completely automated plant species prediction in complex and critical dynamic outdoor environments and natural conditions. Consider the instance that the theoretical deep neural network system identifies and finds the species at a longer distance, such as 200 cm. Despite the challenging weather conditions, this system offers a higher accuracy of 99.5%. The developed system uses the deep neural network (DNN) to recognise plants and classify tasks. The design needs to be evaluated to examine. A few experiments are conducted to evaluate the outcomes of conventional learning approaches and compared them with the proposed model. The proposed system also gives a flexible, unique feature which helps to lose the costly hardware equipment.

The work is structured as follows: section 2 provides a wider explanation regarding various prevailing approaches. The suggested model is explained in section 3, followed by numerical results in section 4. The summary is provided in section 5.

2. Related works

A more complex task with the direct measurement of the solar radiation is discussed in [10]. The evaluation of the other performance parameters related to the data-driven approaches like MT (model trees), SVR, GEP (gene expression programming), and the ANFIS (adaptive neuro-fuzzy inference system) is implemented [11]. Also, six equations to predict the GSR (global solar radiation) at a similar synoptic station are suggested, and these are empiric in an authentic way. It is essential to mention that the GSR was evaluated at the mentioned station from 2011 to the end of 2013. The real-time issue is relevant to the set of various regions like hydrology, agriculture, resources of water engineering and the food warning as suggested in [12]. The improved version of the EELM model is an extreme learning recommended driving forecasting flow. The proposed model is used in a tropical environment to perform the experiments and evaluate the different measures. It includes the evaluation of Willmott's Index (WI), determination of coefficient (r), mean absolute error (MAE), Nash-Sutcliffe efficiency (Ens) and root-mean-square error (RMSE) [13]. In 2019, the researchers Baghban et al. [30] suggested a new technique for developing a standard model to predict the relative viscosity. An adaptive network-based fuzzy inference system (ANFIS) is proposed in [14]. The suggested model is utilized to help the engineers and chemists who perform research in the nanofluid domain [15].

Consider the instance where windy weather results in the movement of the leaves when clicking the picture. It reduces the object's and the leaf's clarity and increases the number of deformed images of the leaves [16]. Consecutively, the final obtained images will be blurry in several ways. The fog reduces the contrast of the images, blocking and scattering the light due to the smaller droplets of water in the outdoor environment. It leads to the variation of other parameters, like contrast, visibility, and intensity of light [17]. Hence, the amount of absorbed, diffused light and the effects related to visuals are changed by the clouds, giving no direct sunlight in the environment. The proposed work addresses the various difficulties and the challenges in the plant recognition process [18].

The time for taking pictures in situations which are not controlled manually is an essential parameter. The image is obtained from the same plant under similar conditions of light source and shadow. Some difficulties are encountered in plant recognition [19] – [22]. The number of fresh and dried leaves is altered, and the colour of the leaves is not changed. The results of classification remain the same when particular parts of the plants captured as pictures in the region of interest [23] – [24].

The mentioned factors add new challenges in the process of plant recognition. These open research avenues to gather larger datasets of actual natural plants and develop real-life applications to find the species of plant. This model has the prepared dataset [25], which has specific features and is the key to resolving the problems related to the natural recognition of plants. It is more prominent in variability in the images, and it is essential to consider that the same dataset is unavailable. The information related to the current dataset is discussed in [26] – [30].

3. Methodology

The process of plant recognition helps to find the species of plant from the provided dataset. The dataset has images captured at various distances, weather conditions, backgrounds and lighting. Images are captured in the morning, evening, and noon. In addition, the perspectives and points of view are varied from one image to another. Hence, the illumination and intensity of light are inconstant in all the images. All the images in the dataset are in RGB format. The data is complex because of the diverse characteristics. Hence, the process of plant recognition is complex. Every observation is the captured image from one of the four species of plant in the natural environment.

3.1. Modern natural plant dataset

The dataset was created from https://flavia.sourceforge.net/, a modern natural plant dataset with colour images consisting of various features, percentages of the same plant regions, information, etc. A few regions are affected, and are considered to be included in the dataset according to the standard rules to prepare the dataset. The same protocols are not utilized to obtain the images. The checks must be performed to take images of the leaves of similar species from the unique plants in different situations and conditions at various times. No other factors are considered during the process of selection. The image sizes are inconsistent and differ from one image to another. Various aspects of the components of the natural environment need to be considered to take the useful natural dataset. The continuum aspects are added, which in turn creates and gives the practical and logical collection of information for solving the issue of identifying the plant species in a natural outdoor environment. There is a compensation for the lack of a dataset. The information related to careful exploitation can help enrich the many applications with wider insight towards plant identification. In addition, the dataset gives information related to capital which provides insights into the present difficulties.

3.2. Deep neural network

The features of the patterns are obtained with the help of the suggested approach from the evolutionarily related profiles given to the fully connected DNN presented in Fig 1. There are three fully combined hidden layers in the suggested DNN, followed by the output and concatenate layer for predicting the multi-label classes. The proposed model explores two evolutionary-based profiles, i.e. features. A set of features are extracted from every evolutionary-related profile. A sum of feature sets is examined, and the feature set is chosen such that the performance of the system is improved.

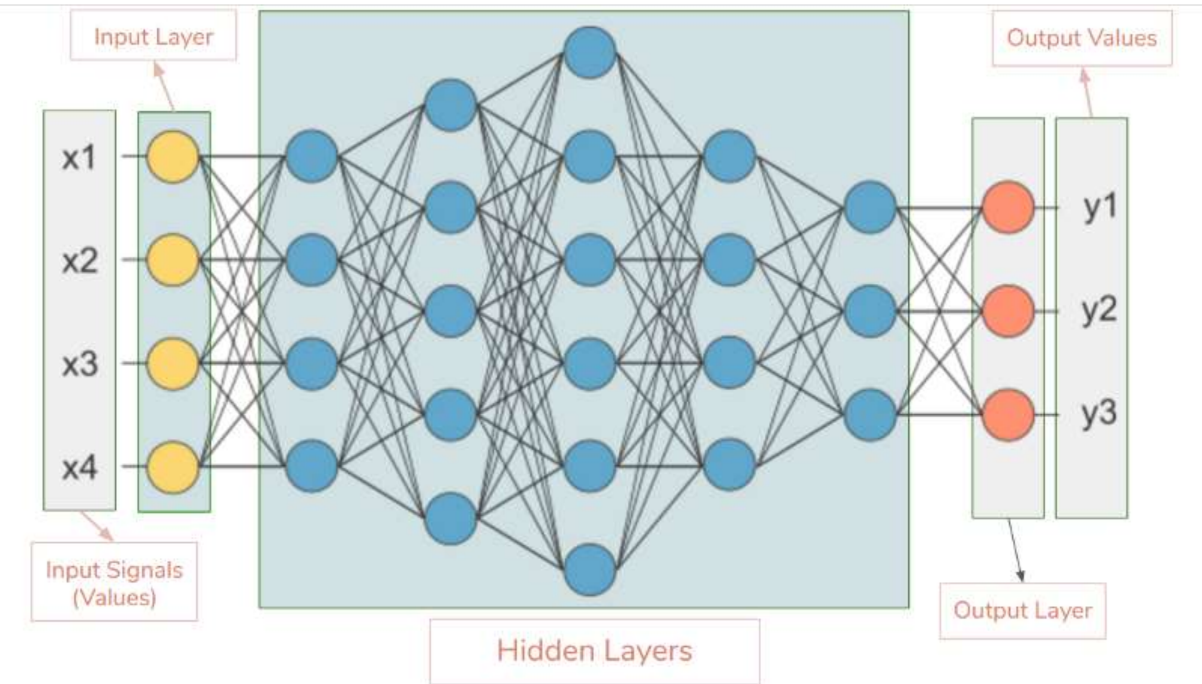

Fig 1 Deep Neural Network model

The feature vector is processed and provided to the hidden layers, presented in Fig 1, with 100 neurons, 25 neurons, and 400 neurons at the second, third, and first hidden layers. A sigmoid function helps to activate every hidden layer. The sigmoid function transforms the extensive range of input values in the interval (0 to 1) to the real numbers. The vital benefit of the sigmoid function is its ability to lower the computation cost to train and obtains constant performance in the prediction. This is achieved through the backpropagation for the multi-layer neural networks like the sigmoid function with an output range between 0 and 1.

$$sigmoid\ (x) = \left(\frac{1}{1+e^{-x}}\right) \tag{1}$$

Output layer: The softmax is adopted by the output layer, like the activation function, for predicting n probabilities of location for the data series. Then, the n neurons are obtained by the output layer. The last hidden layers are given to the output layer for predicting the probabilities of location for the provided data series. The softmax function output must be calculated using Eq. (2), and the output layer has output values from 0 to 1.

$$softmax\ (x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}} \tag{2}$$

Concatenate layer: The output layer has all the values of label probability rounded off in terms of the predetermined threshold and concatenated for attaining multi-label prediction. The training error is computed by choosing the stochastic gradient descent algorithm for the suggested network and updating weights through back-propagation. The critical goal of the proposed DNN training model is to lower the cross-entropy loss function. Here, several sub-locations are represented as Loc, the natural logarithmic function is defined as log, the actual locations for the i^{th} data sequence are presented as y_i, the predicted locations for the similar sequence of data patterns are shown as p_i, and the L2 regularization hyperparameter is given as γ, The Eq. (3) and (4) helps to perform the optimization of all the parameters, here the rate of learning is presented as β. The rate of the parameter is shown as φ.

$$L(\emptyset) = -\sum_{i=1}^{Loc} y_i(\log(p_i) + \gamma||\emptyset||^2 \tag{3}$$

$$\emptyset \leftarrow \emptyset + \beta \frac{\partial L(\emptyset)}{\partial \emptyset} \tag{4}$$

The number of hidden layers, the number of neurons in every hidden layer m with its activation functions and the hyper-parameters of the fully connected dense layers are optimized with the help of the proposed method. The range numbers are taken into consideration. The outcomes are noted for the three hidden layers and 1 to 10 for the number of hidden layers. Every layer has several neurons from 1024 to 8; the better-mentioned outcomes at the first, second, and third layers are 400, 100, and 25, respectively. Better results are achieved with the help of the sigmoid function. In addition, these hyperparameter values are maintained as constant over all the experiments mentioned further.

4. Numerical results

The experiments are performed on the DNN. The dataset is classified into two groups: testing and training datasets for the experiments, and the images are selected for every dataset. There are 800 training and 200 testing images. Some factors in the images include shadows, overexposure, nonuniform illuminations, underexposure, and pose. Background clutter differed considerably within the images in the dataset, and this more extensive range of variation in both the testing and training datasets are relevant for the exploration of different aspects of the issue and identifying the outcome pertinent to overcome the difficulties of recognizing the species of plant in the natural environments. Also, every image needs to be affected using different factors to ensure all aspects are covered. There is no concentration on the impacts of only one aspect, like there is no control during the recognition work on the environmental factors.

The used machine specifications for the experiment are CPU (central processing unit) of speed 3.70 GHz, Intel Core i7 (4820K), graphics GeForce GTX 760 and RAM of 16GB. The raw image has the inputs provided to the implemented network in the phase of the test without performing any extra pre-process operations like scaling, cropping and so on. It is mentioned that the Café is an efficient platform for network implementation. Hence, this is well-defined as an efficient platform for building deep neural networks. It gives the flexibility to implement the DNN, like the famous and active platform for the classification tasks and the deep model links to the extent of other suitable toolboxes. It is possible to switch between the GPU and CPU to select the Café. Café helps the implemented model obtain the outcomes that can be used in the absence of certain facilities related to the hardware equipment. In addition, the GPUs are lacking, which does not impact the application in the final natural plant recognition system. It is an extraordinary benefit when the system is used with the help of small field robots having restricted hardware equipment.

The first consideration is the measure of accuracy in the issues of image classification needs to have the quality of the natural plant recognition and needs to be evaluated. Accuracy is defined as the proportion of the number of accurately predicted images of natural plants based on the total amount of predicted images of the natural plant in the test dataset. It is the same as the 200 images from four plant species in the experiment in the uncontrolled outdoor environment. The testing dataset has no dependence on the image distribution of every plant species. The test images are chosen randomly from the state-of-the-art dataset, and some significant variations are obtained in every species' natural images of the plant. There is no concern regarding the number of images taken in the test dataset. The complete procedure is to choose the images to perform differently for the testing, and the one class species of plant have two images taken on sunny days.

Some other class species of plants have eight images taken from the particular plant on sunny days. When the user decides on every class of species on the selection of the test images, there is a benefit which creates the system having reliability as the outcome. The deep network has the accuracy presented in Fig 2 in various iterations. The higher accuracy and the iteration changes are introduced, and the first iteration gives lesser accuracy when compared to the last. In addition, the DNN has the total error, and the accuracy is obtained, represented in blue. In addition, higher accuracy is received in the 1056 iteration. The higher accuracy is attained in the iteration of 1056 which is constant in the subsequent iteration. The training phase in this iteration is completed and the final model is achieved.

The suggested DNN is distributed over the GPU for speeding up the training phase. The required time needs to be calculated for the training phase, which is nearly equal to 1248.5 (s) for the iteration. It is essential to consider how much time is required for training the suggested deep neural network. The required time in the training phase may be more significant when the CPU utilization is done in the training phase. The additional experiment needs to be performed, and the time required to train the network must be calculated to mention the training question of whether the used unit is the CPU. The used machine has the specifications such as 16 GB memory RAM and Intel Core i7, CPU of 4GHz speed. It needs huge time to train the system. The required time is different from the essential along with GPU. It is necessary for training the model to have the CPU in this scenario of the GPU loss.

Over-fitting is one of the significant problems presented in section 4. Hence, this problem is investigated to analyse the performance of the proposed system. First, the dataset is classified into five image groups (A to E). Every group has the natural vegetation of the original dataset. In addition, group A is concerned with the testing data and the other groups have the training dataset of 800 images. The complete testing and training phases are performed to obtain the best accuracy. Group *B* is the testing dataset for the experiment's next step, and other groups have the training dataset. Also, the new training and testing datasets are utilized to train and test the suggested model and the accuracy is calculated. This process has to be continued. Every group is considered as the testing dataset; the remaining is considered the training dataset. The accuracy is compared which is obtained consecutively to prove that there is no over-fitting. However, the over-fitting problem is considered when the architecture design and the model implementation prevent over-fitting concerning the parameter known as weight decay. The weight decay and the dropout layer are explained before.

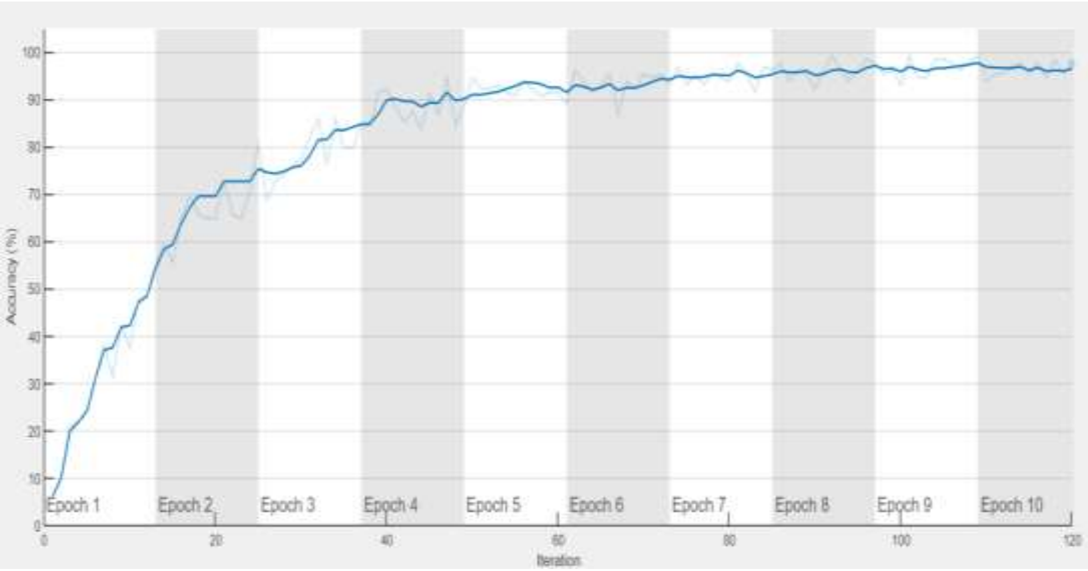

Fig 2 Accuracy computation

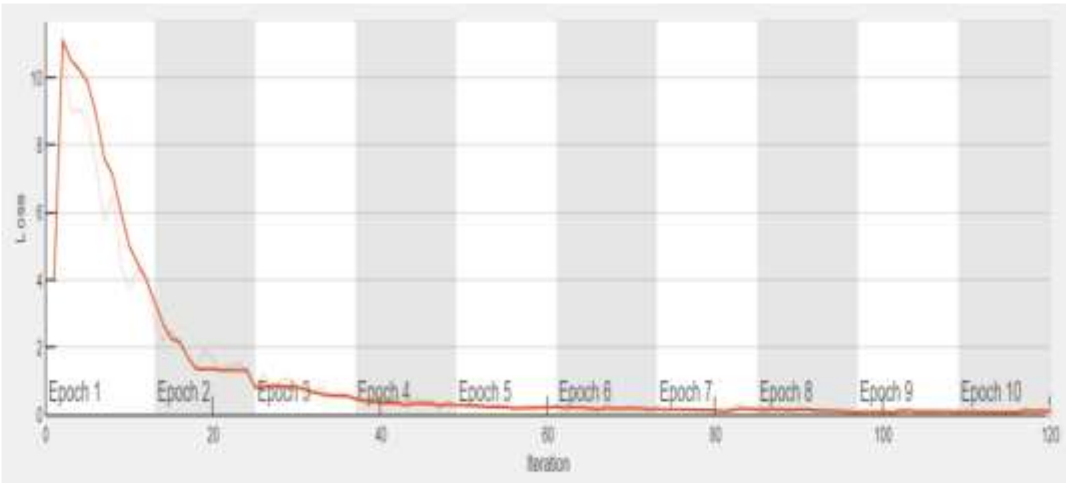

Fig 3 Loss computation

The confusion matrix is implemented to visualize and evaluate the system performance to recognize the natural vegetation. The confusion matrix is 36 × 36 matrices with information regarding the exact classification outcomes and various category labels in the rows and columns via the classification in the classification task for the natural species of plant. The confusion matrix attained for the classification experiment is presented. One misclassification is identified for one of the classes during the classification investigation, and the name of the plant species is Cornus. Cornus sample is predicted wrongly as Amelanchier Canadensis. 99.5% accuracy is obtained using the deep network implementation. A higher accuracy is obtained over all the six systems used in the combined modern methodologies. The number of accurate classifications for every species of plant is presented in Fig 2.

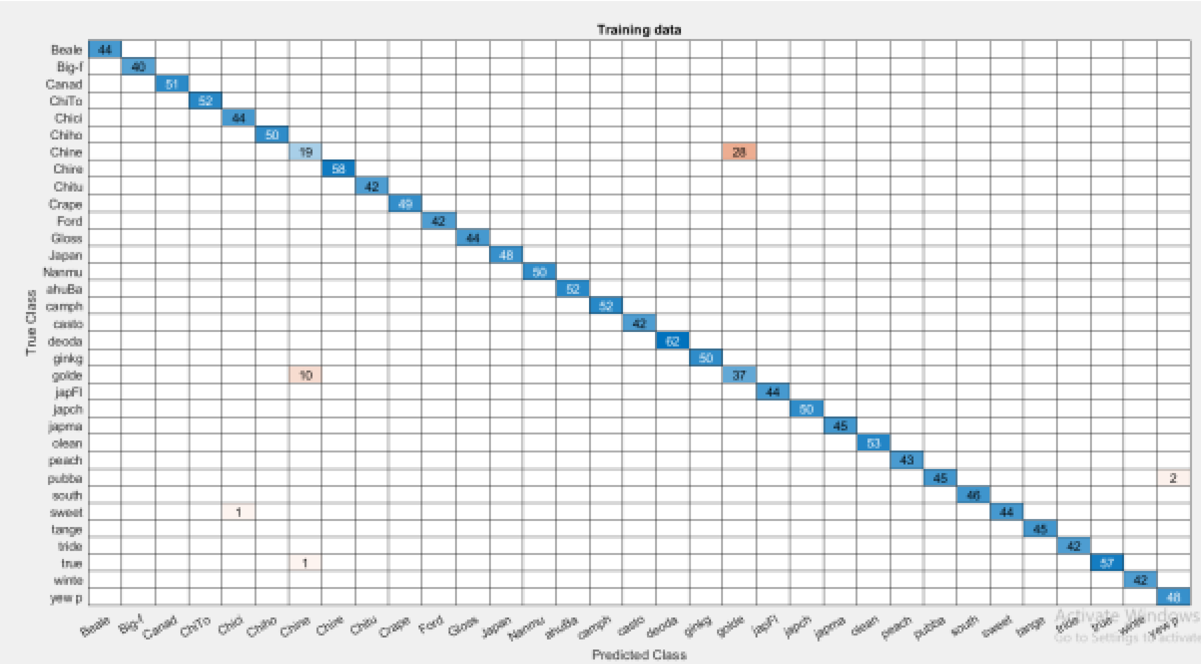

Fig 4 Confusion matrix of training data

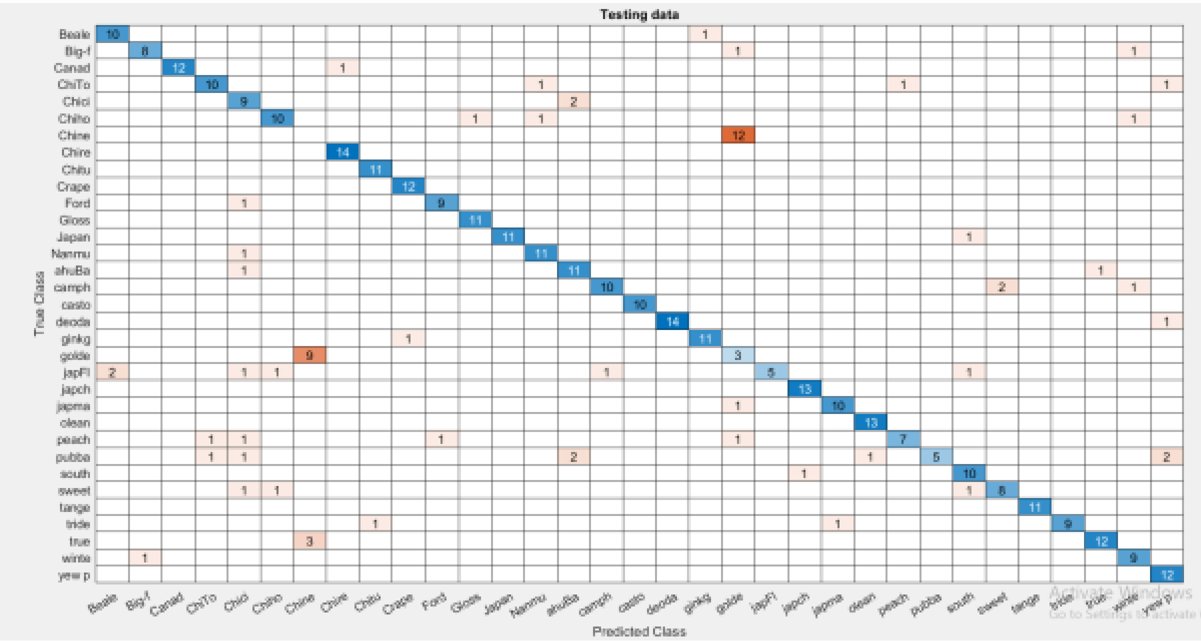

Fig 5 Confusion matrix of testing data

Various modern description and detection approaches are presented [9] which are used for creating plant recognition systems. The system utilizes SIFT algorithm and attains an accuracy of 94.94% with the three constructed systems. The systems are impacted by the distance factor. One vocabulary is implemented for every distance when the proposed model concerns the implemented system having FAST-SIFT. Hence, the dependence exist even now on the distance between the camera and the image. It is essential to measure the distance among the sample plant and camera like the pre-information, when the intention is to find the plant type from the image of a new sample. There are three new systems to be constructed when the description and the detection algorithms are SURF, modern combined methodologies, FAST-SURF, and HARRIS-SURF. The dependency is available on the distance for the automated systems of plant recognition, and every system contains its vocabulary at mentioned distances. SURF obtains the most remarkable accuracy with the implemented system, which is 93.9575%. The prediction process obtains the least accuracy of 97% where the accuracy is accepted because of the system's nature and characteristics.

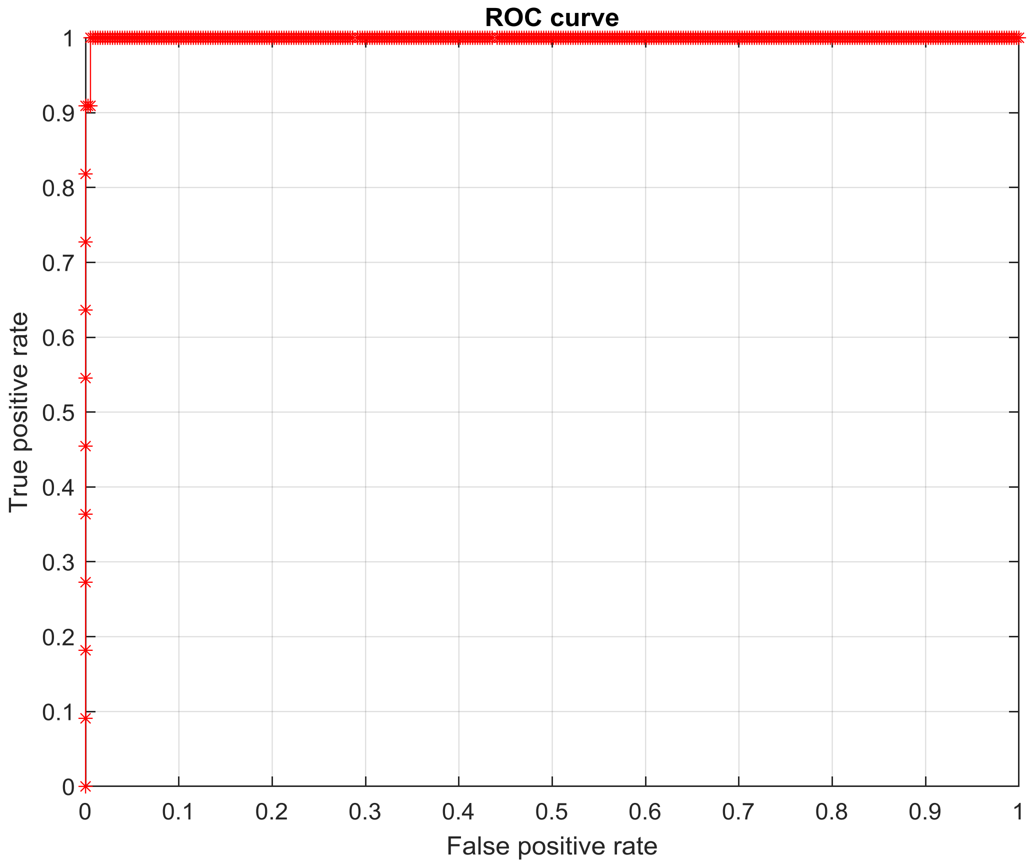

Fig 6 ROC curve

Three determination measures are obtained: recall, F-score, and precision for the complete assessment of the confusion matrix. The measures give essential information about the developed recognition system of the natural plant. The recall and the precision have the greater values for the mean of plant species and obtains the best performance for the species of plant in the model. Consider an instance that the value of recall is less than 1 for Cornus, which is equal to 0.98. On the other hand, the recall value is exactly 1 for the Hydrangea, which is the better value of recall. When all the test images are classified and predicted correctly, the area is lesser than the greatest value, and this is the greatest possible value when considering the one classification, which is wrong. This area's significance is equal to 2.98039 as there is only one incorrect prediction (testing).

The areas under the recall measurements are equivalent to 97% when no incorrect prediction is considered (testing). It is the greatest possible value if one incorrect classification happens.

$$Precision = \frac{No. of\ positive\ predictions}{Total\ no. of\ positive\ predictions} \tag{5}$$

$$Recall = \frac{No. of\ appropriate\ positive\ predictions}{actual\ class} \tag{6}$$

Figure 9 shows both the measurements of precision and recall that helps for the comparison, which happened simultaneously in one image and the behaviour needs to be investigated for the measure at a similar time. The F-score is the last measure measured using the two other criteria called recall and precision, and this is the harmonic mean for the recall and precision measurements. 1 and 0 are the most significant and smallest possible values, and the measurements are concerned with both recall and precision. F-Score measurements are shown in figure 10 for every species of plant. Amelanchier Canadensis, Hydrangea, Cornus and Acer Pseudoplatanus are considered.

Acer Pseudoplatanus and Hydrangea are two classes with least value related to Cornus. Here the value is the same as 0.97. Amelanchier Canadensis pose an F-score and the value is lesser than 1 due to the Cornus sample using the plant recognition system, which is recognized as Amelanchier Canadensis. The Hydrangea and Acer Pseudoplatanus are the species of plant which are more robust when evaluated with other species of plant dataset such as Amelanchier Canadensis and Cornus. This measurement has the benefit of concern regarding the false negative and false positive predictions. At the same time it provides the novel sense to the obtained measures using the confusion matrix as expressed in Eq. (7).

$$F - score = \frac{2 * precision * recall}{Precision + recall} \tag{7}$$

A new graph is plotted for the ROC curve (Receiver Operator Characteristic) to determine the natural vegetation system performance. The graph is planned based on the relationship between the false and true positive rates. The trade-off is shown among the false positives and true positive rates. In addition, less accuracy is obtained when the curve is closer to the 45^0 diagonal of ROC space. The test has the ROC curve presented in Fig 6, nearer to the ideal classifier that can differentiate among the classes. Fig 6 shows the 45-degree diagonal of the ROC space.

The experiment must be conducted for the layers and output visualization. A visualization tool is designed to help in the trained neural network interpretation. The layers are visualized using this tool in the implemented deep network, and the outcome is shown in the visual format. In addition, this presents a comparison of different test images. The focus is to create the complete procedure, which is automated fully to use the mentioned tool. The outcomes of four samples are represented in Fig 7 to Fig 16.

Fig 7 Input sample

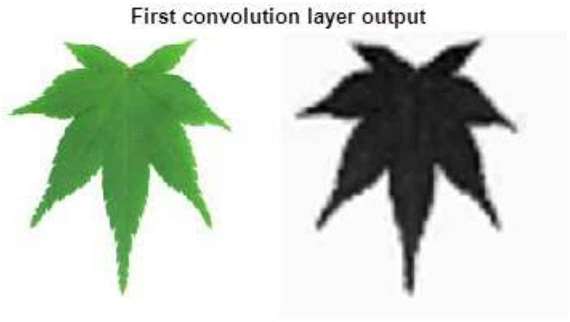

Fig 8a First convolutional layer output

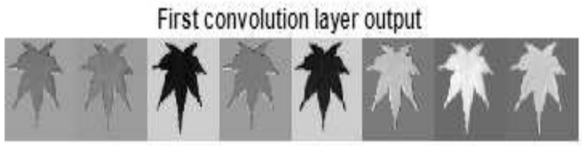

Fig 8b First convolutional layer output

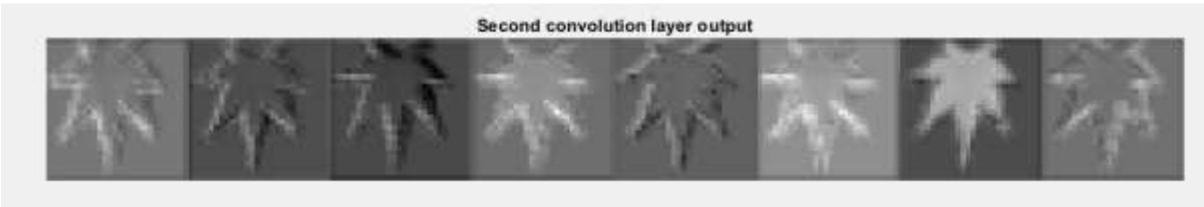

Fig 9a Second convolutional layer output

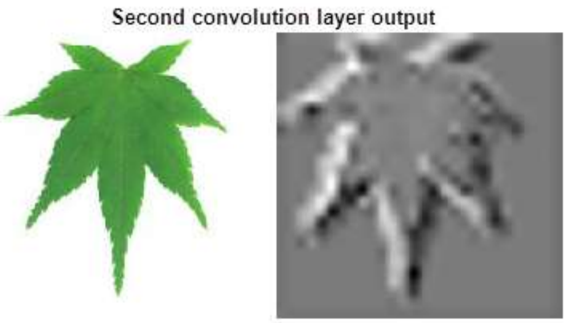

Fig 9b Second convolutional layer output

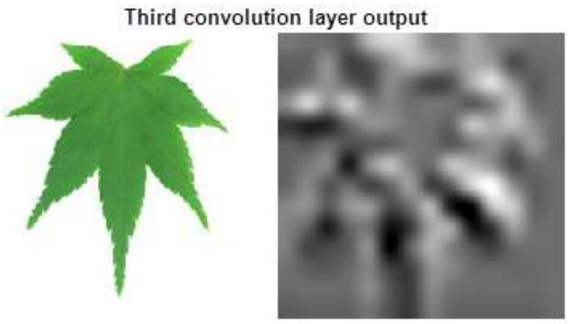

Fig 10a Third convolutional layer output

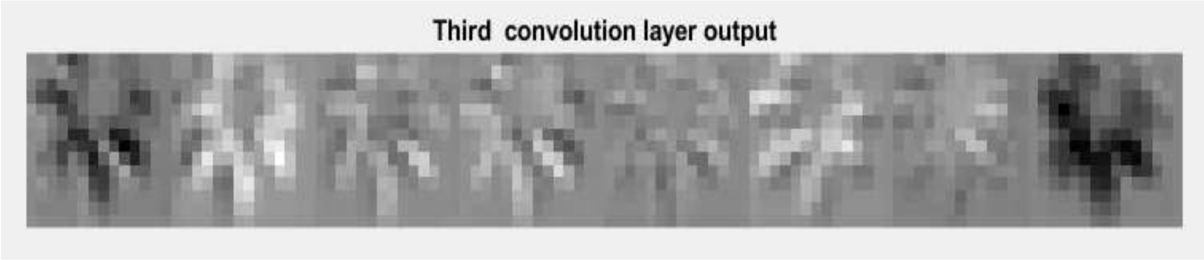

Fig 10b Third convolutional layer output

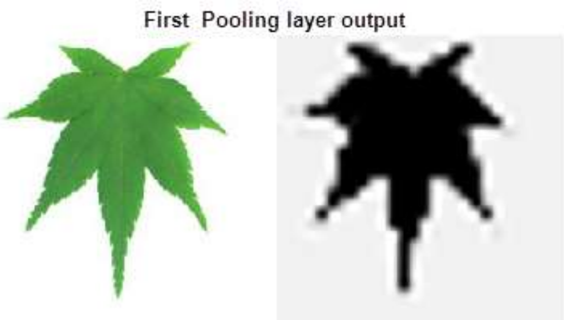

Fig 11a First pooling layer output

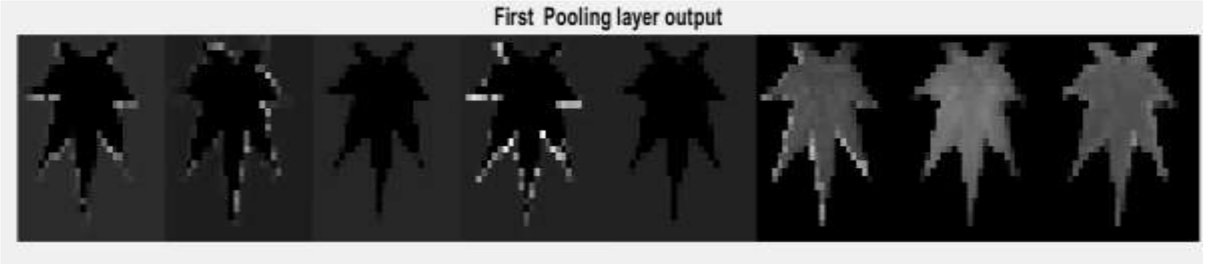

Fig 11b First pooling layer output

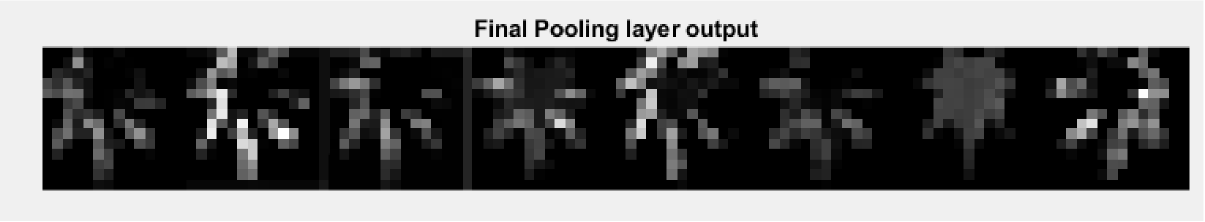

Fig 12 Final pooling layer output

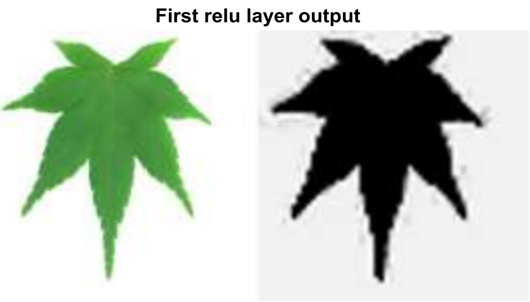

Fig 13a First RELU layer output

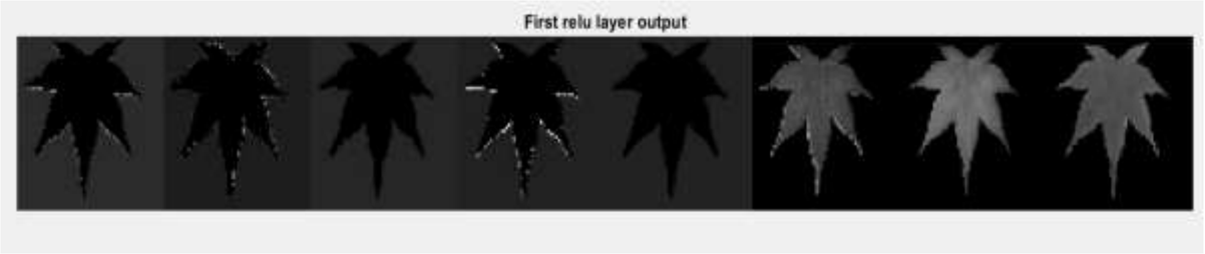

Fig 13b First RELU layer output

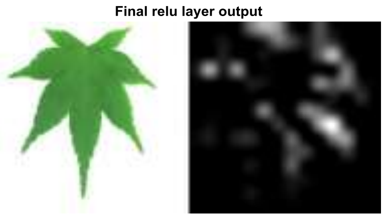

Fig 14a Final RELU layer output

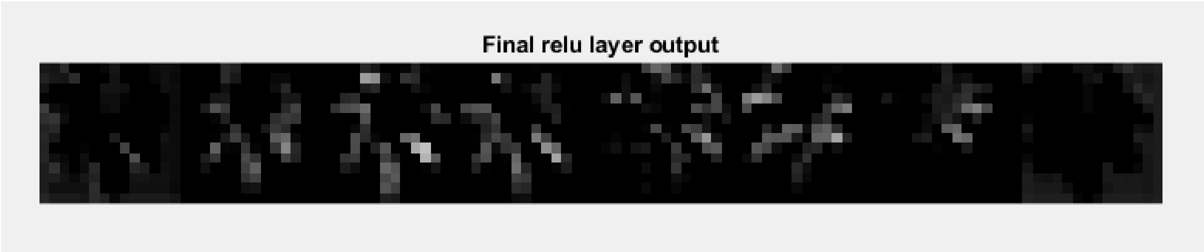

Fig 14b Final RELU layer output

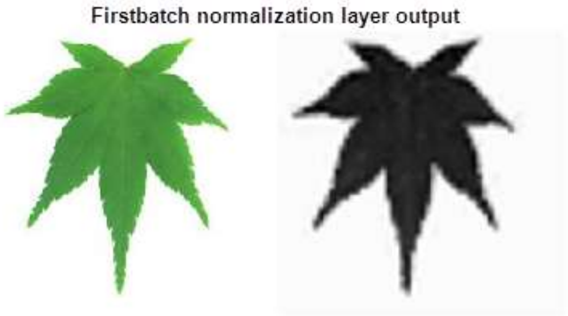

Fig 15a First batch normalization layer output

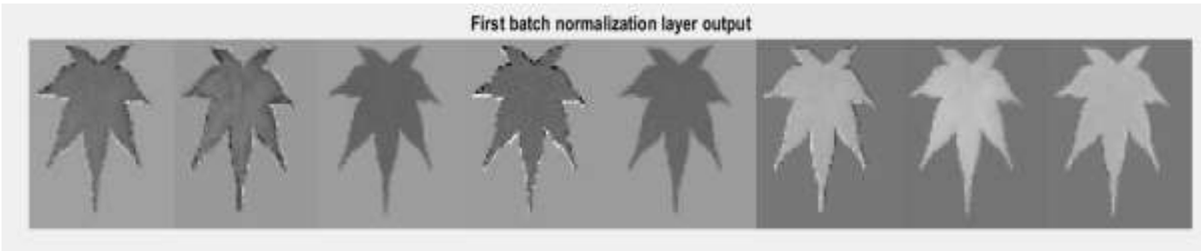

Fig 15b First batch normalization layer output

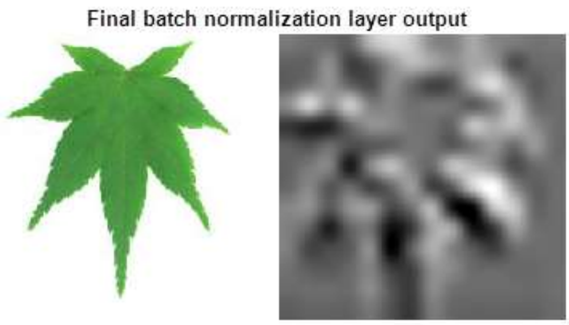

Fig 16a Final batch normalization layer output

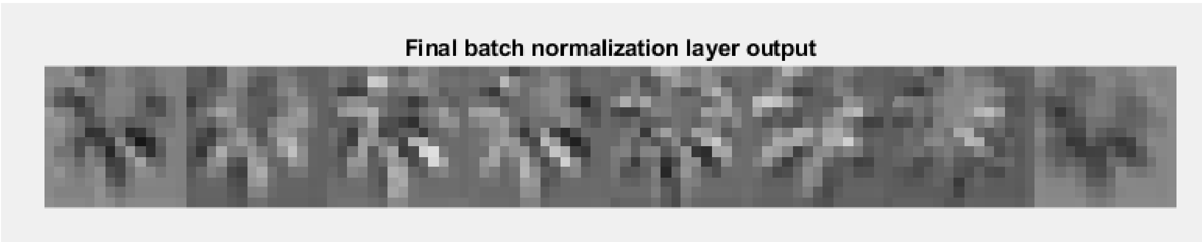

Fig 16b Final batch normalization layer output

Cornus is the first name and the value is mentioned as 0.97. About 97% is obtained using the value related to Cornus's probability. Amelanchier Canadensis is the second option and the left side has a value of 0.02. It mentions the likelihood of Amelanchier Canadensis as 2% of the input test image. The following options are the two other species of plant names, with a value of zero. The input test image can be predicted and visualized, as mentioned.

5. Conclusion

Classification of different plant species is a challenging task, which is implemented efficiently using Deep Neural Network (DNN) in the proposed system. Based on the properties and the characteristics of the images in the dataset, the classification of images is performed. . The implemented system has one of the essential properties: generality is unique and relatable to various natural conditions. There are four species of plant which are classified by the deep network classifier having a greater accuracy that is close to 85.17% for testing data and 97.33% for training data, 90.9% recall for testing data and 100% recall for training data and 58.8% precision for testing data and 100% for training data. The model shows a lesser error rate of 1.482554e+01 for testing data and 2.668361e-02 for training data. The deep-learning-based system achieves greater accuracy having a satisfactory performance when compared to the modern methodologies and the conventional techniques for analysing natural vegetation. It is effective in various factors like generality, flexibility and compatibility. This system can be used to challenge the performance in the natural outdoor environment and real-time conditions These systems are helpful in multiple situations. The suggested system has robust and distance independent in uncontrolled natural circumstance, which is influenced using different natural factors such as weather, complicated backgrounds, photographing time, changes in more significant viewpoint, change in light intensity and so on. In contrast with the previous model, the suggested model handles the gap in the real-time applications and the previously suggested systems by determining new factors such as weather conditions, time and distance. The proposed fully automated system can be utilized in various domains like drugs, medicine, agriculture, etc. The potential use of histogram equalization and NNs are the future research areas, and the efficient techniques of data augmentation and the approaches are used to enhance both the diversity and number of natural images.

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