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Deep Convolutional Neural Network and Metaheuristic Optimization for Disease Detection in Plant Leaves

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Abstract

In this research, we employed a deep convolutional neural network, often known as a Deep CNN, to propose a novel approach to the detection of illnesses in the leaves of plants. In order to train the Deep CNN model, a dataset that is already accessible is employed. This dataset contains photographs of the leaves of 39 distinct plant species. Six different methods of data augmentation were utilized, including image inversion, gamma correction, noise injection, principal component analysis (PCA), color enhancement, rotation, and scaling. We came to the conclusion that adding more data to a model can improve its accuracy. The proposed model was trained using many epochs, batch sizes, and dropout percentages over the course of its development. When utilizing validation data, the suggested model performs better than methods of transfer learning that are commonly utilized. Extensive simulations demonstrate that the proposed model is capable of an astounding 83.12% accuracy in data classification. The proposed research is more accurate than the many machine learning technologies that are currently in use. In addition to that, we put the suggested model through our consistency and reliability testing.

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1. Introduction

The use of digital leaf images to diagnose plant diseases is a major topic of research in precision agriculture [1]. Recent advancements in artificial intelligence, image processing, and graphical processing units (GPUs) can expand on and improve upon existing technologies to enable the application of precise plant protection and growth. To guarantee that students are able to spot the distinguishing signs and symptoms of any illness, it is important that learning models display keen observational abilities, as the majority of plant diseases create a wide array of outwardly apparent symptoms [2]. Multiple AI-based tools are currently used for disease diagnosis and classification in the plant world. The most widely used methods include the K-NN algorithm, logistic regression, a decision tree, a support vector machine (SVM) [3, and a deep convolutional neural network (Deep CNN). Combining these methods with a number of different image pre-processing algorithms is a common way to boost feature extraction. The K-NN is a simple classification technique that uses memory to group records into groups according to their similarity. Unlabelled items could be recognized by comparing them to nearby labelled items.

choice trees are used in supervised learning algorithms to represent the choice qualities (the nodes), the outcomes (the branches), and the classes (the leaves). Overfitting the data and overlapping nodes are two more major issues with decision trees. Further, in cases where the output value is categorical and probability distributions are involved, logistic regression can be employed as a special case of linear regression [4]. The SVM is a well-known method for supervised machine learning; it is characterized by a partitioning hyper-plane and can be put to use in statistical learning-based classification and regression applications. Support vector machines have become more popular during the past decade for a wide range of applications, including image and text classification [5].

This study aims to apply a model based on a Deep CNN in order to overcome difficulties in plant leaf disease identification. The Deep CNN is a type of deep learning algorithm. Deep learning is an advancement of traditional machine learning that use hierarchical representations of data to boost the model's complexity. Image classification, object detection, speech recognition, recommender systems, and the processing of natural languages are just some of the many uses for Deep Convolutional Neural Networks [6]. Transfer learning is a knowledge-sharing approach that reduces the time, the data, and the computational costs associated with constructing deep learning models [7]. Through a process known as transfer learning, the knowledge gained by one model can be utilized by another model that has not yet been trained. Plant classification, software fault prediction, activity detection, and emotion classification are just few of the many areas where transfer learning has been put to use. In this study, the proposed Deep CNN model was matched against those of some of the most popular transfer learning methods currently available, including AlexNet, VGG16, Inception-v3, and ResNet.

The Deep CNN algorithm needs a large amount of training data in order to improve its accuracy. When developing a Deep CNN model with insufficient training data, it is often required to enhance images to increase the network's performance. The goal is to produce a Deep CNN Model that is as accurate as feasible. Image augmentation is a method for creating fabricated training images using a variety of processing methods in isolation or in concert. Image inversion, gamma correction, noise injection, principal component analysis (PCA), color enhancement, rotation, and scaling are all examples of these methods [8]. Updates to neural network models typically involve the use of the optimization method known as gradient descent. When applied to the training dataset, this helps to lower the error rate produced by the model. Mini-batch gradient descent is a type of gradient descent algorithm. This method breaks down the training dataset into manageable chunks that may later be used to calculate the model's error and adjust its settings. Mini-batched updates provide a computationally more efficient alternative to the stochastic gradient descent method. The small batch [9] version of the gradient descent method is the most popular choice in the field of deep learning. The proposed Deep CNN model may be trained with the enhanced dataset using mini-batch sizes ranging from 64 to 160.

To overfit means to erroneously learn from the features and sounds in the training data. This hinders the effectiveness of the Deep CNN model when applied to fresh information. The dropout technique was created to address the problem of overfitting in machine learning algorithms. Dropout will randomly reset the state of some number of neurons whenever a forward pass is executed [10]. The suggested model included the use of dropout in the fully linked layer, with the dropout proportion varying from 0.0 to 0.8 at 0.2 increments. Based on our evaluations, it appears that the proposed Deep CNN model can produce competitive results on the dataset, especially when compared to state-of-the-art approaches.

2. Related Work

The purpose of this survey is to provide evidence for the efficacy of a few popular machine learning strategies by illustrating how they may be applied to a range of diverse but related tasks. It also analyses how different AI methods perform the same function of detecting and diagnosing diseases in plant leaves. Leaf disease detection and diagnosis systems are used in this investigation. Some of the more technical aspects of the various learning methods discussed in the reviewed literature are presented here. Using machine learning produces a flexible and powerful framework, perfect for making judgments and incorporating domain experts' insights. These are only a few of the reasons why machine learning algorithms have found extensive use in a variety of fields, with agricultural mechanization being among the most obvious.

In paper [4], the authors propose a model based on decision trees and logistic regressions to recognize hyper spectral images for use in agricultural decision making. Decision trees were determined to be more accurate than logistic regressions by the authors. ANNs, or artificial neural networks, are mathematical models created to process large amounts of unstructured data. Animal neural networks served as inspiration for these models. In order to identify a wide range of leaf-related diseases and pests, the authors of [11] devised and developed the feed forward neural network with back propagation model. The gradient descent values for artificial neural networks can be calculated with the use of the back propagation method. Finding these values using the back propagation method is required for minimizing the error function. Conventional methods are widely regarded as the most distinctive approaches to detecting plant diseases, and the authors of [12] have presented a thorough summary of these methods. In this group of techniques are spectroscopy, imaging, and volatile profiling, all of which can be used to identify plant illnesses. The research compares and contrasts numerous approaches, detailing their respective benefits and drawbacks. Using the SVM's feature extraction capabilities in the context of the Huanglongbing (HLB) or citrus greening disease that strikes lemon plants, the authors of [13,14] devised a further technique. When using multi-band imaging sensor inputs [13], the system is able to achieve an overall accuracy of 85%, while fluorescence imaging increases this to 92.8% [14]. Using SVM classification algorithms and hyper spectral pictures, the authors of [15,16] were able to automate the early identification of plant illnesses. In [17], the author proposed a method for classifying hyperspectral images using the K-NN algorithm and the guided filter technique. In order to detect infected tomato leaves with yellow leaf curl disease, the authors of [18] presented a model. 200 images of damaged and healthy tomato leaf tissue were used to train a support vector machine (SVM) loaded with a range of kernels to create the classification model. On average, the model achieved 90% accuracy in its categorizations.

Similarly, plant genomes related with bacteria can be identified with the use of support vector machines. The outcomes of using this technique to a number of different species are detailed in [19]. In [20], the author suggests an additional method, also based on SVMs, for diagnosing leaf diseases in vine plants. In [1], the author examined the various machine learning approaches taken to the problem of plant disease identification and diagnosis across several fields of study, such as plant gene detection and plant leaf disease categorization. The author of [21] also presented a model for the detection of plant diseases by combining image processing and the Naive-Bayes classification system. Medical image analysis is often offered as a tool for automating disease identification in deep learning-based applications [22]. However, the use of deep learning for disease detection in plant leaves has not been studied thoroughly in the literature. This highlights the importance of novel approaches in this area. Using different datasets and a flexible number of layers, the authors of [23,24] presented deep convolutional neural networks (CNNs) to tackle disease diagnosis tasks for several plant leaf diseases. Using photos of plant leaves and varied amounts of data, the authors of [25,26] developed a similar deep CNN technique for several plant identification tasks. Plants were categorized using this method. Plant diseases and insect pests that feed on plants can be identified with the use of deep convolutional neural networks (CNNs). This method was used to identify pests and diseases in tomato crops [27]. Forty separate research publications were examined by the authors of [28], all of which used deep learning methods to address issues in agriculture.

The authors of [10] propose a model for diagnosing MS in human brains using a 14-layer convolutional neural network equipped with batch normalization, dropout, and stochastic pooling. Models like the one proposed by the authors in [10] use similar strategies. Classification accuracy was typically 98.77% when using this strategy. Using data augmentation techniques and stochastic gradient descent with momentum, a 13-layer convolutional neural network was recently created for the purpose of learning some high-level characteristics in order to identify fruit photos in [8]. Its overall categorization accuracy in the final experiment was 94.94%. It is also possible to use convolutional neural networks to classify multi-temporal crop data. This strategy, outlined in [29], was implemented for commercially significant crops. This approach yielded the highest achievable classification accuracy of 85.54%. In order to create a model for the diagnosis of plant illnesses using a dataset consisting of photographs of plant leaves, we trained and evaluated the K-NN Classifier, Decision Tree, SVM, and Deep CNN. The guiding ideas behind the actual models and the actual datasets used for training and testing will be provided in the next section.

3. Materials and Methods

Additional information on the steps involved in developing, training, and validating the Deep CNN model used for disease detection in plants is provided below. In the sections that follow, we'll outline each step of the technique, beginning with the collection of images to be utilized in the classification.

A. Data acquisition and pre-processing

Images of both diseased and healthy plant tissue were extracted from a dataset about the plant community. A dataset of 54,305 images of the leaves of 13 different plant species was used to train and evaluate the proposed Deep CNN model. There are a total of 38 categories in the database, and each one represents either a healthy plant or one that has been infected. As was said earlier, there is one more category with a total of 1143 images serving as its backdrop. Figure 1 shows a selection of screens from a few of the random classes.

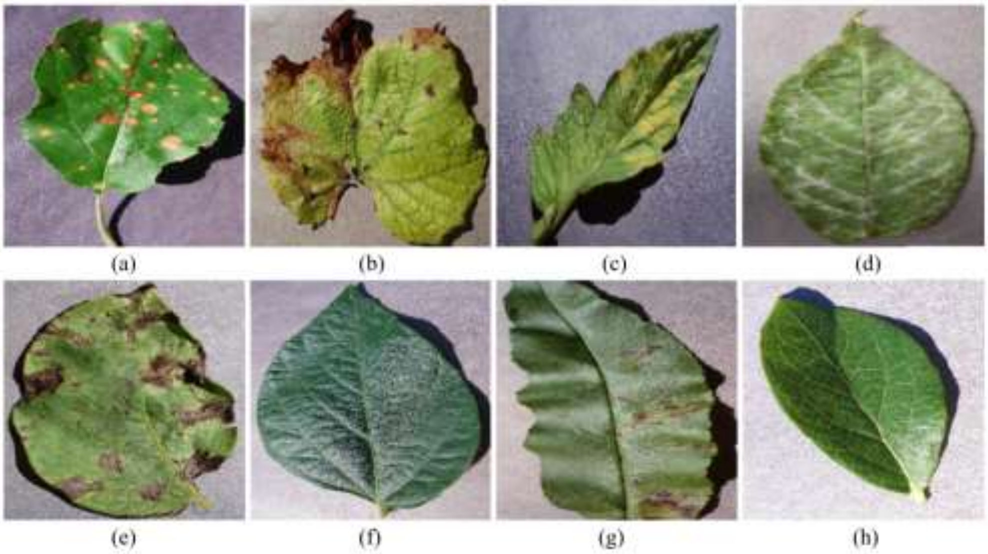

Figure 1: (a) Apple with black rot, (b) grape with leaf blight, (c) tomato with leaf mold, (d) cherry with powdery mildew, (e) potato with early blight, (f) healthy soybean, (g) peach with bacterial spots and (h) healthy blueberry

It is possible to reduce the effects of overfitting by introducing a limited number of purposefully distorted images in the training set. This can be done by applying various image alterations. The augmented images that are utilized in the training set are produced using a number of transformations, such as inversion, Gamma correction, noise addition, PCA color enhancement, rotation, and scaling. These transformations are used to make the enhanced images. Figure 2 provides a visual representation of the augmentation process that was carried out on the example photographs that were included in the training data.

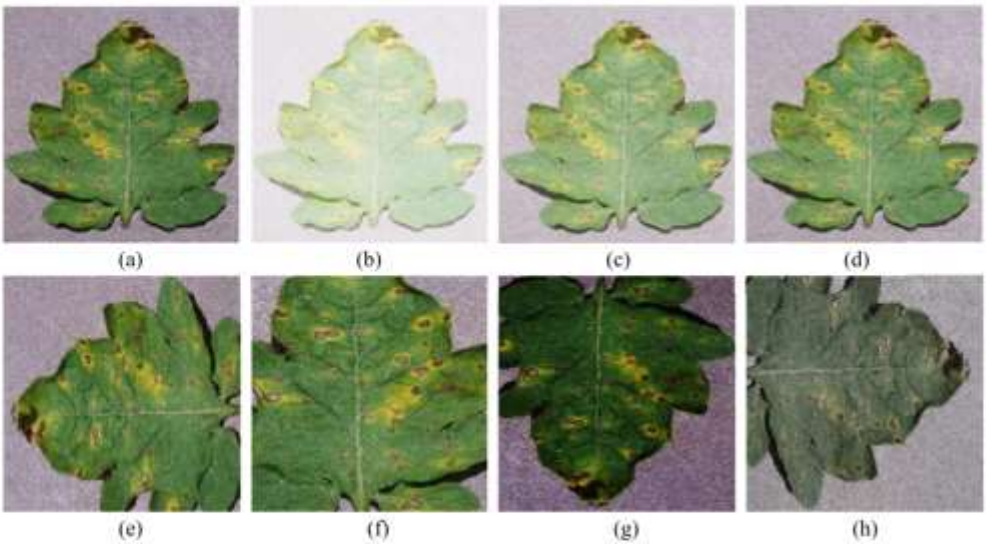

Figure 2: (a) Original image, and (b)–(h) are augmented images.

B. Experimental setup

Scikit-learn, Keras, pillow, and opencv are all written in Python, and this programming language was utilized to implement the training and testing processes for not only this Deep CNN model but also for all other models that are considered to be state-of-the-art. During the training and testing of the models, an NVIDIA DGX-1 V100 with eight Tesla V100 GPUs and a total processing power of one petaFLOP was utilized.

C. Training the Deep CNN network

The Deep CNN, a feed forward artificial neural network from the discipline of deep learning known as feed forward artificial neural networks, is used in several agricultural picture categorization projects [28]. Using Deep CNN can greatly reduce the time and effort needed for feature engineering when it comes to picture classification. During the entire procedure, the model was trained separately on datasets of augmented and unaugmented images. The suggested architecture of the Deep CNN model is depicted in Figure 3.

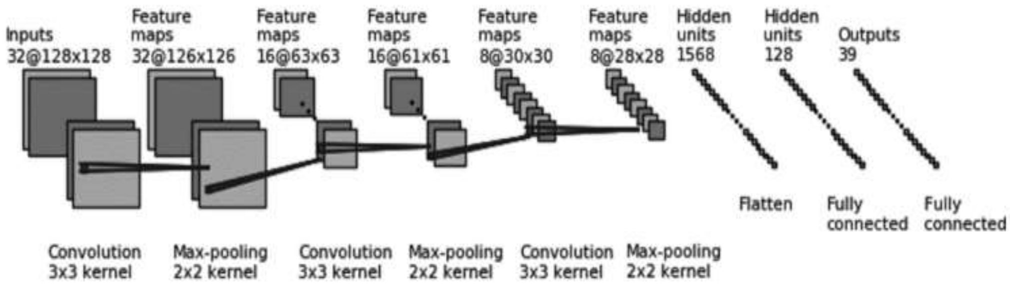

Figure 3: Layered architecture of the proposed Deep CNN model

The Deep Convolutional Neural Network is made up of many layers, each of which executes a different convolution. When it comes to the representations of the training data, the earlier and larger layers produce more universal versions, while the deeper layers provide more particular versions. Before the pooling layers reduce the dimensionality of the input, the convolutional layers serve as feature extractors for the training data [28]. The convolutional layers are responsible for transforming a wide variety of low-level data into higher-level features, which may then be used for classification. Additionally, the Deep Convolutional Neural Network (Deep CNN) relies heavily on its convolutional layers [30].

Deep Learning's specialized Feature Engineering is a quantum leap ahead of more typical Machine Learning approaches when compared to it. Figure 4 is a graphical representation of the layer-specific outputs that the suggested model generates. The pooling layer is in charge of the spatial down-sampling operation that takes place. It contributes to reducing the overall number of configuration options. The pooling layer of the proposed model was given the maximum possible amount of pooling. Maximum pooling performs better than average pooling in the Deep CNN model that was proposed. Another important layer is called dropout, and it refers to the process of deleting nodes from a network. It is a method of regularization that is used to reduce the amount of model overfitting.

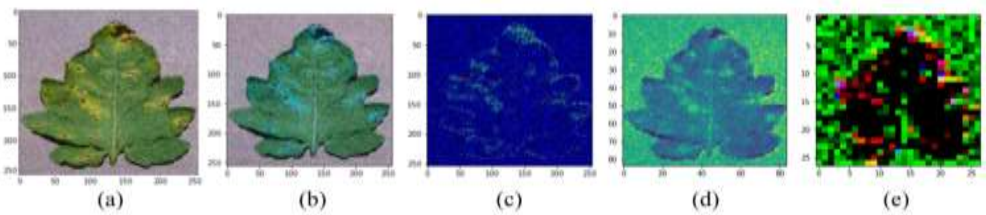

Figure 4: (a) Input image, (b) convolutional layer 1, (c) convolutional layer 2, (d) convolutional layer 3 and (e) flattening layer

4. Results

The created deep CNN model was trained and evaluated on the plant leaf disease dataset. We've done some work on the dataset to get it ready for use, including standardizing the pixel size of the images and splitting it into three parts (80% for training, 10% for testing, and 10% for validating). SVM, logistic regression, decision tree, and K-NN models were compared to the proposed model. Furthermore, the following testing procedures are assessed and contrasted in light of the models' output. In conclusion, the results show that the proposed model is better than the other hypotheses considered. The test's standard deviation will be analysed in the next section. For your convenience, Figure 5 provides a concise overview of the CNN model.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 358, 358, 32)      896

 conv2d_1 (Conv2D)           (None, 356, 356, 32)      9248

 max_pooling2d (MaxPooling2D  (None, 118, 118, 32)     0
 )

 conv2d_2 (Conv2D)           (None, 116, 116, 40)      11560

 conv2d_3 (Conv2D)           (None, 114, 114, 32)      11552

 max_pooling2d_1 (MaxPooling  (None, 38, 38, 32)       0
 2D)

 flatten (Flatten)           (None, 46208)             0

 dense (Dense)               (None, 20)                924180

 dropout (Dropout)           (None, 20)                0

 dense_1 (Dense)             (None, 4)                 84

=================================================================
Total params: 957,520
Trainable params: 957,520
Non-trainable params: 0
_________________________________________________________________
```

Figure 5: CNN model summary

Figure 6 illustrates the level of accuracy achieved by the tests conducted on each model. The percentage of the model's total predictions that were accurate as a proportion of the total number of forecasts is one way to measure the accuracy of the model. With an accuracy of 96.46%, the recommended Deep CNN model exceeds the earlier models, which get prediction accuracies ranging from 50% to 87%. Figure 6 illustrates both the training loss and the validation loss for your reference. Figure 7 is an illustration of the confusion matrix used by the CNN model.

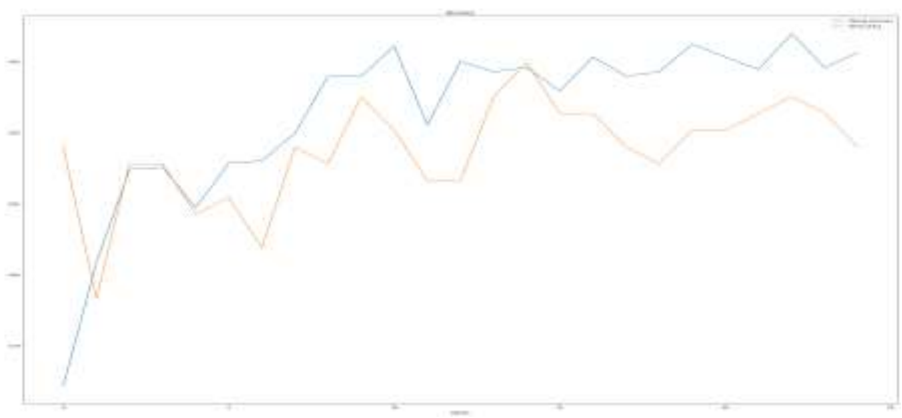

Figure 6: The training accuracy and the validation accuracy

The results that are presented in Table 1 show that all classes of the proposed Deep CNN model achieve better testing accuracy between 92% and 100% when using the leaf image test dataset.

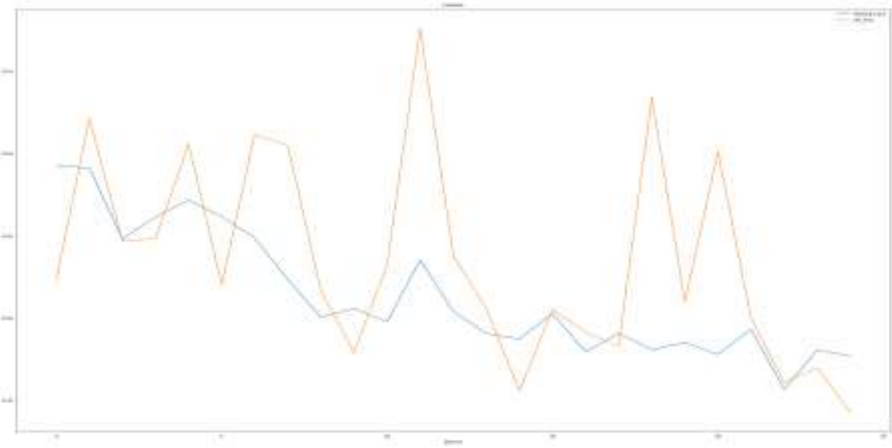

Figure 7: Training loss and validation loss

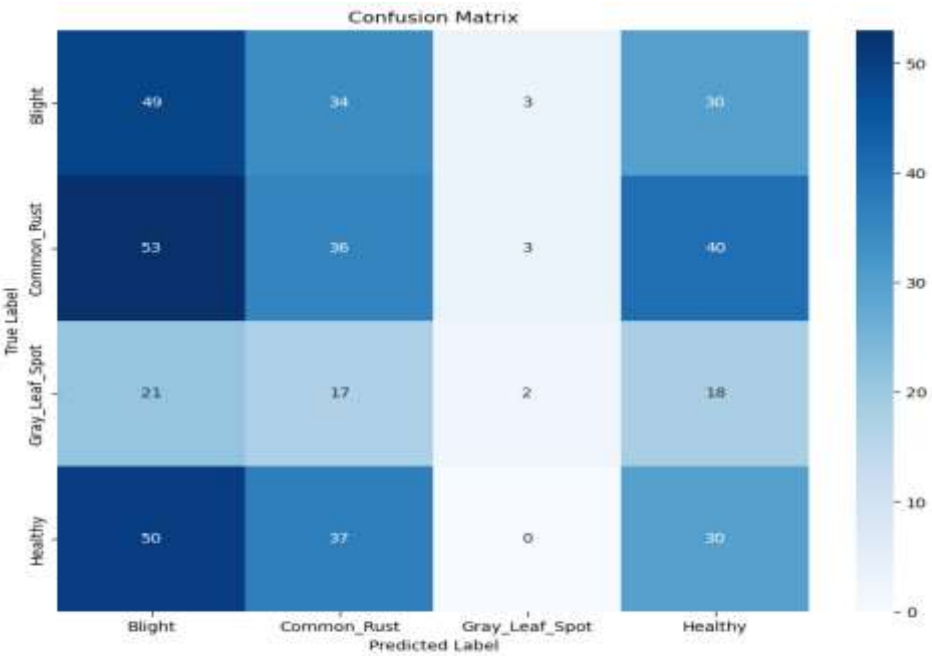

Figure 8: Confusion matrix of CNN model

Table 1: The performance of CNN model

	accuracy	loss	Val_loss	Val accuracy
0	0.784348845	0.492903322	0.423241407	0.817966878
1	0.801672637	0.491136461	0.521465719	0.796690285
2	0.814814806	0.44822982	0.446711838	0.815602839
3	0.815113485	0.461505264	0.448270708	0.815602839
4	0.809438467	0.471757978	0.505971611	0.808510661
5	0.815710843	0.461712688	0.420376003	0.810874701
6	0.816009581	0.448803365	0.511549652	0.803782523
7	0.819892466	0.423478574	0.504834175	0.817966878
8	0.827956975	0.40046066	0.41657263	0.815602839

9	0.827956975	0.405921996	0.379272968	0.825059116
10	0.832138598	0.397592574	0.432289064	0.820330977
11	0.821087241	0.435439706	0.576416254	0.8132388
12	0.830047786	0.404187709	0.438033164	0.8132388
13	0.828554332	0.390618354	0.405649543	0.825059116
14	0.82915175	0.387305558	0.355846107	0.829787254
15	0.825866163	0.402888596	0.405315101	0.822695017
16	0.830645144	0.379558444	0.39128986	0.822695017
17	0.827956975	0.390732437	0.382849365	0.817966878
18	0.828554332	0.380898058	0.534494281	0.815602839
19	0.832437277	0.38508305	0.409802318	0.820330977
20	0.830645144	0.37797451	0.501369953	0.820330977
21	0.828853071	0.393318772	0.39988789	0.822695017
22	0.833930731	0.356647491	0.360830814	0.825059116
23	0.82915175	0.3807244	0.369599283	0.822695017
24	0.831242561	0.37693125	0.342578024	0.817966878

5. Conclusion

In recent years, researchers have been using a technique called deep learning to improve image processing and pattern identification. The difficulties in identifying plant leaf diseases could be more easily overcome with this technique. The suggested Deep CNN model successfully classifies 38 distinct plant varieties as either healthy or diseased based solely on images of their leaves. In addition, from a total of 49,598 training examples before the data augmentation, we now have 55,636. An improved dataset consisting of 61,486 pictures and 3000 training epochs was used to train and evaluate the best Deep CNN model. The model was trained and tested using this dataset. The proposed model classifies images of plant leaves with an average accuracy of 96.46%, ranging from an absolute high of 100% in one class to a low of 0% in another. The results varied greatly depending on the number of training epochs, the size of the batch, and the attrition rate of the participants. The max pooling strategy outperforms the average pooling strategy by a wide margin. When compared to existing machine learning models, the suggested Deep CNN model has been found to have superior prediction ability and performance. Additionally, the AUC - ROC curves, Precisions, recalls, and F1 Scores can be used to assess the stability and reliability of the suggested model. Extending this study will need gathering more photographs from diverse sources exhibiting different plant species, regions, leaf developments, cultivation settings, image qualities, and modes. The expansion's intended effect is to expand both the database's class structure and its overall size. As a result of the improved dataset, the model's performance and accuracy can be enhanced by the application of a number of fine-tuning techniques. Most importantly, the feature study will expand our existing goal of identifying plant illnesses from just referring to plant leaves to also referring to other parts of plants including flowers, fruits, and stems. We may also modify the model such that it can detect diseases in plant leaves. Furthermore, we will conduct a comprehensive examination of the training procedure without employing any labelled images.

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