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A Novel Approach For the Detection of Tea Leaf Disease Using Deep Neural Network

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Abstract

India is among the biggest tea exporter in the world. However, tea leaf diseases caused by persistent pathogen exposure result in considerable crop yield losses around the world. Detection of the disease of tea leaves at early stages can reduce the damage of tea output. Detecting the disease with the naked eye can be inefficient and counterproductive. Convolutional Neural Networks (CNNs) are commonly used to implement an effective method for the image classification. In detection of plant disease, the use of CNN is widespread. Therefore, in the proposed work, a Deep CNN having multiple hidden layers is considered for the classification of diseased tea leaves into different categories. This helps the network in detecting more number of features and thereby improving the accuracy in disease detection. The classification is done consisting of the following categories of leaves; Gray Blight, Algal Spot, Brown Blight, Helopeltis, Healthy Leaves and Red Spot. Further, a labeled dataset consisting of 5867 diseased and healthy tea leaf images have been created and uploaded on Kaggle. The suggested method demonstrates that the model is able to accurately detect the kind of persistent tea leaf disease with a 96.56% accuracy. The accuracy of the following disease classes are as follows, Algal Spot has an accuracy of 98.23%, Brown Blight has an accuracy of 97.98%, Gray Blight has an accuracy of 93.46%, Healthy classes of leaves has an accuracy of 99.10%, the Helopeltis disease class has an accuracy of 98.98% and Red Spot has an accuracy of 92% The model that is proposed in this literature is far superior than the existing methods in terms of accuracy. Furthermore this model can be adopted to work with various IoT devices to deploy in real world applications and the architecture of this model can be used to train different crop images to classify their diseases.

Keywords: Convolutional Neural Network; Tea Leaf Disease Detection; Healthy and Diseased tea leaves;

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1. Introduction

In terms of tea export, India stands fourth after Sri Lanka, Kenya and China. In the Financial year, 2020 India's total export of tea was $826.47 mn, and $755.86 mn in the financial year 2021[1]. Traditionally the identification & analysis of diseases of plants are done with the help of domain experts by going in the tea estate. If the task of disease detection can be automated partially or fully, the time and efficiency of the tea production can be significantly reduced. With automatic disease detection techniques, the crop yield can be increased as well as the dependency of the farmers on the experts for detection of disease will be reduced. With early detection of diseases, one can take preventive measures to stop the spread of the diseases.

Tea produced in India is among the best in the world because of its strong geographic indices, significant investments in tea processing machinery, continual innovation, growing product mix, and strategic market growth. Tea plantations are frequently located in areas having warm weather & lots of rainfall because tea plants can withstand high temperatures and shade. These places, on the other hand, are ideal for the spread and replication of various type of diseases which significantly lowers tea quality as production is increased gradually. Disease symptoms usually be seen on the plants fruits, leaves, and stems. Color shifts from a green hue to different colors are the first indicator that the leaf has been attacked by a disease. A healthy leaf has its own color, whereas a leaf with a disease has a color that is radically different from its original hue.

Microscopic identification, as well as molecular biology and spectroscopic approaches, are the most used ways for identifying plant diseases nowadays. Even the most experienced plant pathologists make mistakes when it comes to microscopic identification, which takes time and can be subjective. Although spectroscopic identification and molecular biology are more precise methods, they are both time- and money-consuming.[2]

Rapid advances in Deep Learning (DL), as well as improvements in device capabilities like memory capacity, processing power, image sensor resolution, consumption of power, and optics, have hastened the development of vision-based applications while also improving performance and cost-effectiveness [3]. DL, in contrast to standard image processing approaches, aids in task accuracy such as object identification, picture categorization, and so on. Since in DL, neural networks are trained rather than hardcoded, applications that employ this method frequently need less fine-tuning and expert analysis. Further, today's system has access to a massive quantity of image data, which helps in efficient training in DL models. While Computer Vision (CV) methods are more domain-specific, DL techniques provide more flexibility since using specific dataset for any application a CNN models and frameworks may be re-trained.

Convolutional neural networks, or ConvNets, were first developed in 1989 by Yann LeCun, a postdoctoral computer science researcher. CNNs may learn to extract information from pictures on their own using numerous layers of convolutional filters. CNNs are fundamentally hierarchical neural networks containing a pooling layer, a fully connected layer, and several convolution layers. Important hierarchical elements of the networks include weight sharing, spatial subsampling, and local receptive fields.

When it comes to translation, shifting, scaling, and other sorts of deformation, CNNs exhibit a high degree of invariance [5]. The main advantage of using CNN is that it can directly take images as input, thus we do not need to extract the features separately to feed into the neural network as well as reconstruction of images. Meanwhile, CNNs' excellent recognition accuracy leads to widespread use in disciplines such as computer vision, where research is accelerating.

The following are the contributions of the proposed work:

1) The proposed work uses a new network architecture for CNN which is able to classify between different tea leaf disease types more accurately than the previous methods proposed in terms of tea leaf disease classification.

2) We have built a new real world dataset which contains 5867 images containing 5 types of diseases as well as healthy tea leaf images.

2. Related Work

In this section, various works in the literature on plant leaf disease detection are studied and reviewed. There are different types of studies in the literature on technological breakthroughs in plant leaf disease detection in recent years, such as advances in technological resources, remote sensing technology, and so on.

Jiang Lu et al. [6] proposed a novel framework that can diagnose wheat disease with the help of deep multiple instance learning, namely DMIL-WDDS. Surprisingly, the suggested approach outperforms the deep traditional CNN model in terms of recognition. (like VGG-CNN-VD16). The image dataset is trained with a batch size of 2 for 20 epochs and 0.00005 as an initial learning rate. Patil et al. [7] developed a technique for the extraction of shape features for detecting disease in sugarcane leaves with an accuracy of 98.60%. The leaf area is calculated using simple threshold segmentation. To segment the lesion region, the triangle approach of thresholding is applied. Davinder Singh et al. [8] proposed a dataset called PlantDoc which consists of entirely new images acquired by the author to detect plant disease. The dataset consists of 27 classes & 13 plant species making a total of 2,598 images across various diseases. They have also done the benchmarking of the collected data in the form of images and showed its usefulness in disease identification in real-world environments. Ramesh et al. [9] developed an algorithm to detect abnormalities that is found on plants in their controlled or outside greenhouse environment. 160 leaf images of papaya tree were used for training the proposed model using the Random Forest classifier. HoG(Histogram of Oriented Gradients) feature extraction was used for producing feature vector for training dataset. The model could classify with approximately 70% accuracy.

Mukhopadhyay et al. [10] developed model for detection of tea leaf disease using computationally sophisticated methods including NSGA-II, PCA, and multi-class SVM. The Silhouette index does the validation for the proposed image clustering technique based on NSGA-II. Then, using PCA, an ideal collection of features is selected, and multi-class SVM-based illness identification is performed. In tea leaves, Five distinct diseases may be detected using the suggested model. The overall accuracy for this model is 83%. Kumari et al. [11] proposed a NN classifier to detect diseases of leaves. The segmentation of the data has been done using the K-means clustering technique. For cotton & tomato diseases, many parameters such as correlation, homogeneity, standard deviation, contrast, energy, variance and mean are retrieved. The classification accuracy for 4 illnesses, leaf mould, target spot septoria leaf spot, and bacterial leaf spot, is 100%, 80%, and 90%, respectively, with an mean accuracy of 92.50 percent. Badage et al. [12] proposed a system that detects leaf diseases in Wheat and Cotton plants. This proposed method uses Canny Edge Detection Algorithm to detect edges of diseased leaves and then apply the machine learning algorithm to classify various diseases. D.Pujari et al. [13] used five plant diseases to test their proposed algorithm. Color and texture features were used in the proposed classifier to classify plant diseases. The study uses 900 images (150 of every type) for the purpose of recognizing and classifying. The key benefit of this suggested method is that it uses minimum number of features to obtain better accuracy for classification and to reduce the time for computing. SVM depicts a considerable improvement in detection accuracy which is better than ANN, with an accuracy of 92.17% versus 87.48% for ANN. SVM showed to be a useful method for automatically classifying the plant diseases studied in this study. Sladojevic et al. [14] proposed a way of employing DL to automatically detect & classify various diseases of plants from diverse images. For distinct class tests, the experimental results attained a precision of 91% to 98%. The trained model's overall accuracy was 96.3% in the end.

The Tea Leaf Diseases Recognizer(TLDR) was proposed by Karmokar et al. [15],which is a project for identifying the various diseases of tea leaves. The tea leaf image is first converted, scaled, cropped, and set to its limiting value in the TLDR image processing technique. Furthermore, they have also used the feature extraction technique. For pattern recognition, the Ensemble Neural Network was employed. The retrieved features, along with the disease kind, are fed into the ANN, which is then trained. Following the testing phase, 91% accuracy was observed. Hossain et al. [16] using a ML method named the Support Vector Machine (SVM) which is having feature in lesser numbers, developed an automated system for detecting three different kinds of tea leaf disease. When compared to previous classifiers and neural networks, the suggested technique can perform the detection of the illness more accurately with an accuracy of 93% when comparison was done with other neural network classifiers that has a detection accuracy of atmost 91%. The suggested approach can process a leaf classification 300 milliseconds faster than earlier research that uses SVM as a classifier.

In Chen et al. [17], the goal of the research was to create a deep CNN that could detect tea leaf disease categories from the photos of the leaf. LeafNet is a CNN model which uses feature extractor filter of different sizes which then automatically extracts the tea leaf disease features from dataset of images. Bag of Visual Words is a model that is created using features from Dense Scale Invariant Feature Transform that are also obtained, that is utilised for identifying diseases using SVM and MLP classifiers. The LeafNet algorithm correctly classified tea leaf illness the most, which has an average accuracy for classification of 90.16 percent, compared to 60.62 percent for the SVM method and 70.77 percent for the MLP algorithm. In order to identify kidney diseases, particularly chronic kidney disease, Singh et al.[18] suggested a deep learning model. One layer for input, five dropout layers, 5 dense layers, and one dense output layer for classification make up the deep neural network's 12 layers. The suggested model surpasses the other four classifiers by obtaining 100% accuracy, beating out SVM, KNN, Naive Bayes, Logistic Regression, and Random Forest classifier. P. Rastogi et al.[19] developed a deep learning model to diagnose leukemia from microscopic blood images.For analysing the effectiveness of the retrieved features using the suggested LeuFeatx model, independent classification tests were carried out using 3 publicly available leukocyte benchmark databases. Deep features were used to construct multi-class classifiers that is superior than other cutting-edge methods in terms of accuracy, sensitivity, and precision for 7 different leukocyte subtypes. These classifiers attained an accuracy of 96.15 percent. By developing a model which is adapted to VGG16 & fine-tuned to extract features, that is crucial for the precise classification of leukocytes, the study proposes a unique 2 step approach for reliable leukocytes classification for the diagnosis of leukaemia. It was discovered that the model can extract significant leukocyte characteristics from tiny single cellular leukocyte pictures. Table 1 summarises different literature that are mentioned above.

Table 1. A Comparison of Methods for the Detection Plant Leaf Disease

Paper	Plants	Method	Result
Jiang Lu et al. [6]	Wheat	DMIL-WDDS	97.95%
Ramesh et al. [9]	Papaya	Random Forest Classifier	70%
Mukhopadhyay et al. [10]	Tea	SVM	83%
Kumari et al.[11]	Cotton and Tomato	K-means clustering	92.5%
Karmokar et al.[15]	Tea	ANN	91%
Hossain et al.[16]	Tea	SVM	93%
Chen et al.[17]	Tea	CNN	90.16%

Existing research shows that detecting and classifying tea leaf illness, as well as discriminating between healthy and diseased tea leaves, requires more precision..In terms of tea leaf disease classification and differentiating between healthy and sick leaves, the proposed CNN model employs a superior network architecture and outperforms all previous techniques described so far.

3. Materials

3.1. Creation of Disease Dataset

All of the images depicting diseases in the tea leaves were taken using a 12-megapixel mobile camera in natural settings. The images were acquired from various tea estates situated in the Unakoti District, Tripura, India. The images were captured having a resolution of $3000px \times 3000px$ at a distance that is approximately 30 cm above the leaves. A total of 2800 tea leaf photos were captured, each displaying signs for one of five diseases as well as healthy leaf images. The tea tree disease identification criteria were based on previously established identification techniques[20, 21]. For identifying the types of diseases, consultation from experts from the tea estate was also taken. All of the photographs in this manuscript have been scaled to $256px \times 256px$. For boosting the generalization capabilities of the classifier, the database size was increased to 5867, which is more beneficial to the network's training. The dataset has been uploaded on Kaggle for reference [22].

The dataset for disease classification used for this work are shown in the Table 2. Various disease type images are shown in the Fig 1. In neural network applications, the 20% of test data 80% of training data ratio is found to be most prevalent. In addition, the dataset was validated using a 10% selection of the test dataset.

3.2. Convolutional Neural Network

CNN can be termed as deep learning technique which takes an input that can be in the form of an image or other data from any dataset and assigns biases and weights to distinct elements in that image to differentiate one

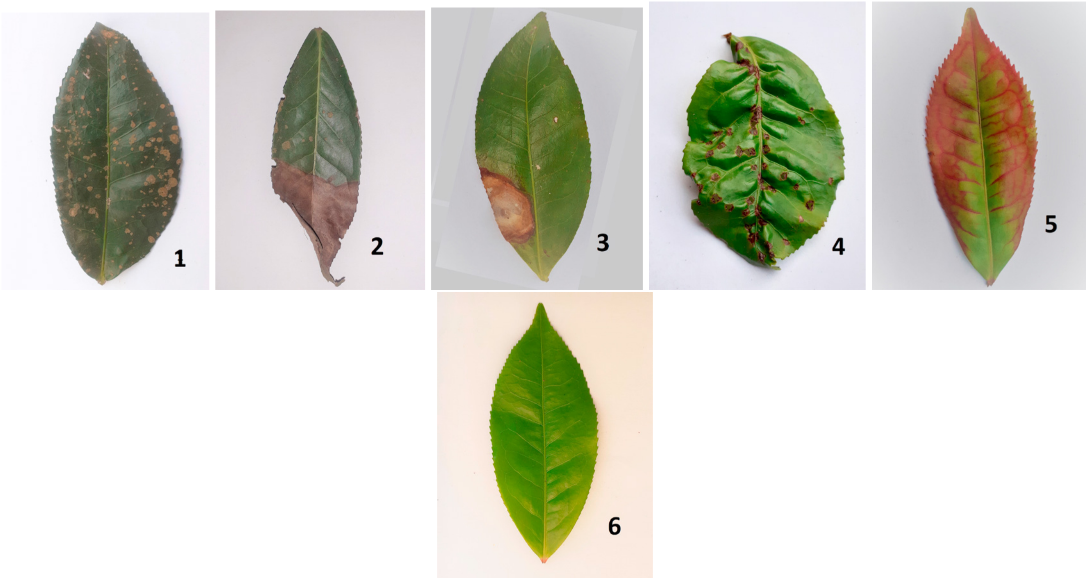

Fig. 1. Example includes images of tea leaf categories used in this study. (a) Algal Spot(Caused by a green parasitic alga Cephaleuros virescens); (b) Brown Blight (Caused by Colletotrichum camelliae Massee.); (c) Gray Blight (Caused by Pestalozzla theae. Sawada); (d)Helopeltis (Caused by Helopeltis theivora); (e)Red Leaf Spot (Caused by Phyllosticta theicola Petch); (f)Healthy Leaf

Table 2. Images From Dataset Consisting Different Classes of Diseases

Disease Class	**Images used for Training**	**Images for Validation**	**Images for Testing**
(1) Algal Spot	800	100	100
(2) Healthy	800	100	100
(3) Helopeltis	800	100	100
(4) Gray Blight	800	100	100
(5) Brown Blight	698	87	86
(6) Red Spot	800	100	100
Total	4694	587	586

from another. First, the input image is transferred to the feature retrieval network, which then sends signals from the retrieved features to the NN to perform the recognition. Afterward, the network generates the output based on the attributes of the image. The feature extraction process in a NN combines layers known as convolution layer and pooling layer pairs. Convolution layer, as its name suggests, uses a technique named convolution to find the features in the image, which is just a set of digital filters. On the other hand, the pooling layer joins the pixels that are adjacent to form a single pixel, due to which pooling layer decreases the size of the image.

Convolution layer creates feature maps, as new images, which emphasises the distinct attributes of the sorce image. The convolution layer operates entirely differently from the other neural network layers, since there are no weighted sum or link weights are present in this layer. Instead, the layer contains filters for converting images, which are referred as convolution filters. The feature map is produced by sending the image through the convolution filters [23]. In the Fig 2, the 2-D convolution method with image dimension M×N and filter size P×Q is shown.

Pooling is another commonly used approach that has been employed in different image processing tasks because it adds neighboring pixels by using some operation in a definite region of the image into a single value, the dimension of the image is reduced by pooling layer. Different types of pooling are Max-pooling, average-pooling etc.

For instance, as shown in Fig. 3, Max Pooling, each coloured box represents a kernel size(2x2) from which the maximum of each colored element is passed as element to the next layer.

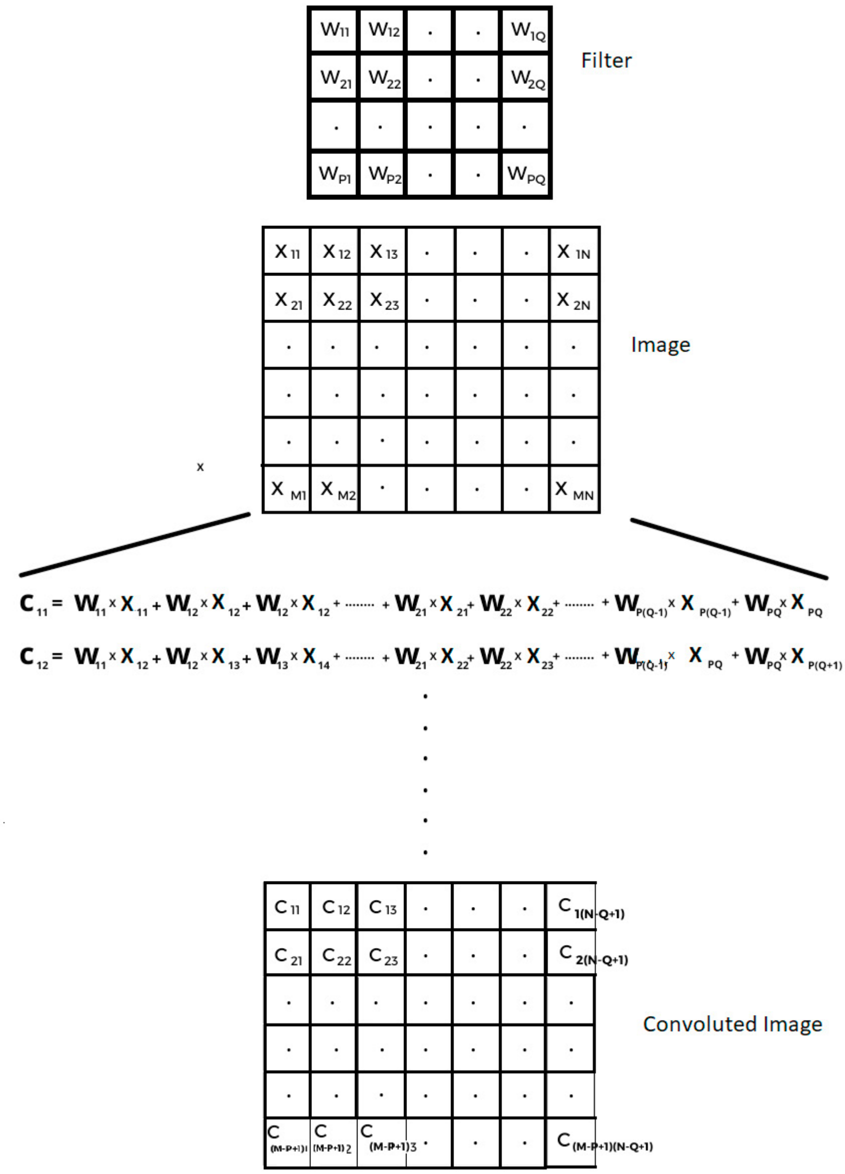

Fig. 2. Convolution Operation in 2D Image.

4. Methodology

As mentioned earlier, the images are collected from various Tea estates in the state of Tripura in India. These images are processed by the data augmentation method that provides the augmented images needed to train the CNN as shown in (Fig 4) in this work. Here the Tea-leaf disease classifier has two primary steps, data preprocessing and using CNN to aid with the categorization of images of diseased tea leaves.[24]

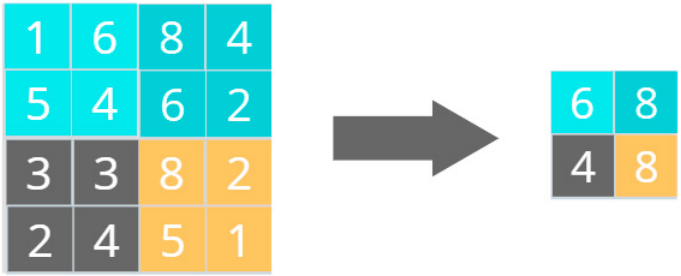

Fig. 3. Max Pooling.

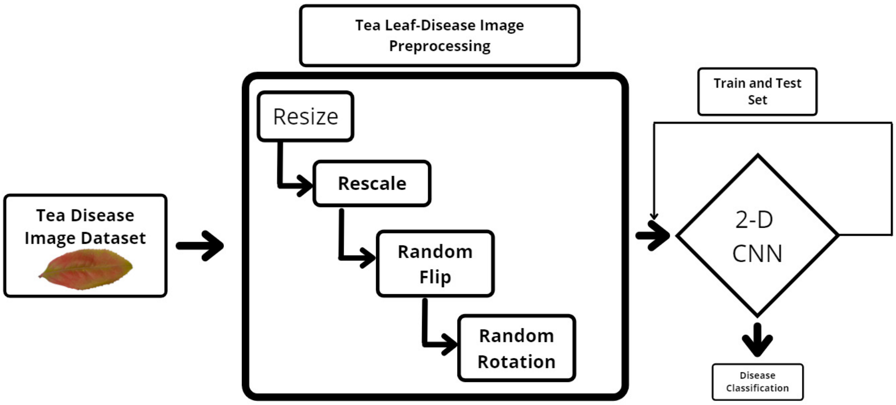

Fig. 4. Model

4.1. Data Augmentation

In the proposed work, different data augmenting methods are used to inflate the amount of images that are present in the dataset, which includes random rotation clockwise, random rotation anticlockwise, random scaling and shearing of the image, applying random contrast in the original image.

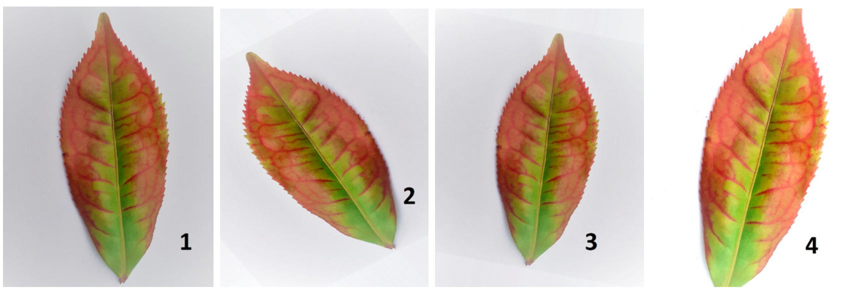

Fig. 5. (a) Original,(b)Skew and Random Left Rotation;(c)Random Right Rotation;(d)Scaling and Rotation with Change in contrast

4.2. Classifier Architecture

In Fig 6. as demonstrated, the proposed Neural Network contains a total of 16 layers. Among the layers 6 are convolutional, 6 layers are pooling, one Soft-Max activation layer and two fully connected layers.

The convolution process is carried out by the 2-D convolution layer as shown in the equation (1) on the output received from previous layer.

$$y[p,q] = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} h[k,l] \, .x[p-k, q-l] \tag{1}$$

where,

y = Output matrix after convolution operation ,**x** = Input image matrix to be convolved, **h** = Kernel matrix, **p,q** = p^{th} and q^{th} indices of Image represented in matrix form and **k,l** = Kernel Size of $k \times l$.

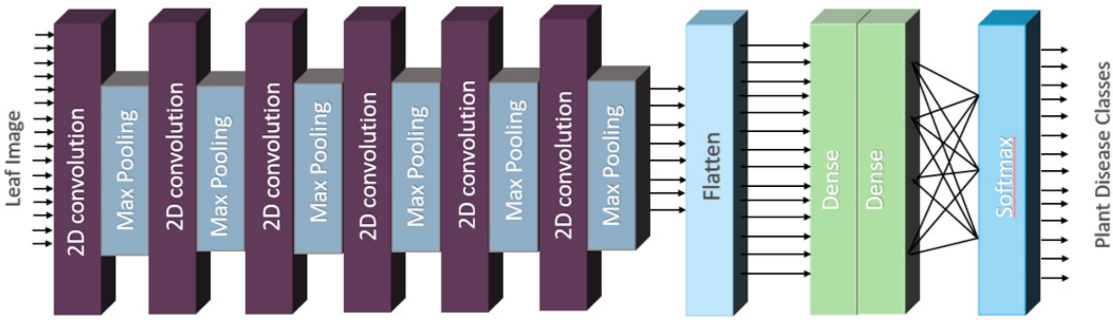

Fig. 6. Architecture of CNN

The 3 colour channels (RGB) were sent to the network directly for processing once the input images were rescaled to 256 x 256 pixels. The following are the definitions for the convolutional and full connection layers:

1. The first convolution layer in the proposed model contains Kernel Size of 3px × 3px pixels and 32 filters. This layer accepts input as 256 × 256 images and 3 channels(RGB). This layer outputs 32 feature maps which is of size 254 × 254. After that, rectified linear unit operation (ReLU) is performed. The activation function ReLU solves vanishing gradients and has better transmission of error when compared to the sigmoid function. The kernel size of the pooling layer is 2px × 2px pixels, with a stride of 1 pixel. Finally we obtained 32 × 127 × 127 feature maps.

2. Next convolution layer consists 64 filters having kernel size of kernel as 3px × 3px. This layer produces 32 x 125 x 125 feature maps. Layer normalization and ReLU processes has been implemented too, as stated earlier. The size of kernel of the pooling layer is 2px × 2px. 32, 62 × 62 feature maps were obtained after the pooling operation was completed.

3. The convolutional layer at third position contains 64 filters and a 3px × 3px kernel size. This layer produces 32, 60 × 60 feature maps, and also 32, 30 × 30 feature maps has been obtained after being undergone through ReLU process.

4. The next convolution layer(Fourth) has 64 no. of filters which has a kernel width of of 3px × 3px and outputs 32 number of, 28 × 28 of feature maps on which ReLU operation is applied. The stride width is 1 pixel, while the pooling layer's kernel is 2px × 2px in size. A total of 32, 14 × 14 feature maps are obtained after pooling.

5. The conv. layer(Fifth) comprises 64 number of filters having kernel widths of 3px × 3px and an output of 32, 12 × 12 feature maps on which ReLU operation is employed. The pooling layer's kernel measures 2px × 2px in size, while the stride is 1 pixel. A total of 32, 6 × 6 feature maps are obtained after pooling.

6. The Sixth and the final convolutional layer produces 32, 4px x 4px feature maps with 64 filters with 3px x 3px kernel widths, on which ReLU operation is applied. The pooling layer's kernel measures 2px x 2px, while the stride is 1 pixel. A total of 32, 2×2 feature maps are obtained after pooling.

7. The first fully connected layer, which has 64 neurons, is followed by a ReLU operation.

8. Six neurons make up the final full connection layer, which represents the 5 disease classes of tea leaf and one healthy class. The output layer receives the output from the last complete connection layer present at the last, which determines input image's disease class. In this case, the softmax activation function is utilised, which ensures that the output values are all between 0 and 1, and confines the individual outputs to these ranges. The suggested model is an excellent match for the softmax function since all outputs' relative values are taken into account by this function.

$$\mathrm{X}_j^k = f\left(\sum_{i=1}^{N} \mathrm{x}_i^{k-1} \times w_{ij} + b_j\right) \tag{2}$$

Where,

N = Total no. of neurons, $\mathbf{X^k}_\mathbf{j}$ = Output received from j^{th} neuron from k^{th} layer and $\mathbf{w_j}$ = Weight kernel for the j^{th} neuron

To enhance the count of operation those are non-linear, a fully connected layer also known as dense layer has been used. It can be seen in equation(2), the dense layer functions . In terms of activation function, with the exception of the last layer, the ReLU is employed in both the Convolutional Layer and Fully Connected Layer. The Softmax activation function is employed at the output layer to provide a output that is categorical from the dataset used for training. The suggested model's layer and parameter breakdown are listed in table 3:

Table 3. Parameters for Proposed Convolutional Neural Network

Layer	Parameter	Activation Function
Input image	256 x 256 x 3	-
Conv. Layer 1	24 Conv. filters (3×3), 1 stride	ReLU
Pooling Layer 1	MaxPooling(2 x 2), 1 stride	-
Conv. Layer 2	64 Conv. filters (3×3), 1 stride	ReLU
Pooling Layer 2	MaxPooling(2 x 2), 1 stride	-
Conv. Layer 3	64 Conv. filters (3×3), 1 stride	ReLU
Pooling Layer 3	MaxPooling(2 x 2), 1 stride	-
Conv. Layer 4	64 Conv. filters (3×3), 1 stride	ReLU
Pooling Layer 4	MaxPooling(2 x 2), 1 stride	-
Conv. Layer 5	64 Conv. filters (3×3), 1 stride	ReLU
Pooling Layer 5	MaxPooling(2 x 2), 1 stride	-
Conv. Layer 6	64 Conv. filters (3×3), 1 stride	ReLU
Pooling Layer 6	MaxPooling(2 x 2), 1 stride	-
Full Conn. Layer 7	64 Nodes, 1 stride	ReLU
Full Conn. Layer 8	6 Nodes, 1 stride	ReLU
Output	1 Node	Softmax

It is crucial to take into account that how changing the bias and weight might reduce the value of defined loss function during the process of training. The Sparse Categorical Cross Entropy function defined in equation (3) can be utilised to reduce loss.

$$J(\mathbf{w}) = -\frac{1}{Z}\sum_{j=1}^{N}\left[b_j log\left(\hat{b_j}\right) + \left(1 - b_j\right) log\left(1 - \hat{b_j}\right)\right] \tag{3}$$

where,

Z = Total Numbers of Neurons present in the layer, **w** = Weights of the Neural Network, $\mathbf{b_j}$ = True Label and $\hat{b_j}$ = Predicted Label

The weights and bias must then be decided and updated, which is done with the help of the Adam Algorithm in this work. The Adam optimization approach is a stochastic gradient descent extension [25], where Adam optimizer employs 0.9 as a beta1 value, 0.999 as beta2 value, an epsilon e of 1e-08 and learning rate as 0.001.

5. Results and Discussion

After preprocessing steps discussed above a total of 5867 images were obtained of both healthy and diseased images. After that the the dataset is divided into two parts. The model is trained on 80% of the dataset's images, with the remaining 10% being utilised for model validation and the remaining 10% is employed as a test dataset. The validation and test dataset images are completely different. So while testing the proposed model is seeing test images for the first time. Further, Tensorflow Keras module for CNN is considered for building the proposed CNN model. For training the model Google Colab pro is used, having 28 Giga-Bytes of RAM and a Tesnor Processing Unit(TPU). The proposed model used the dataset collected from various tea estates having 5 different disease types mentioned earlier as well as healthy leaf images.

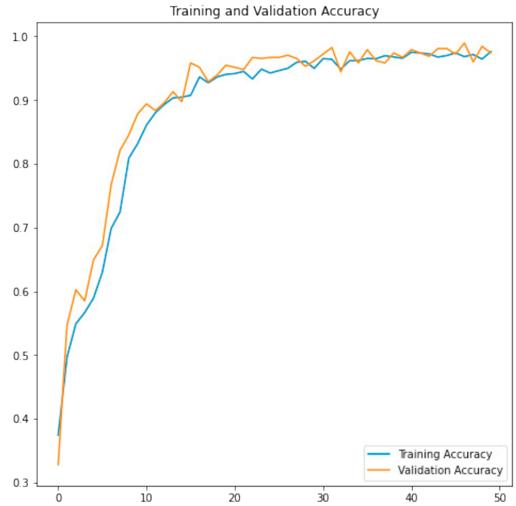

Fig. 7. Validation and Training Accuracy.

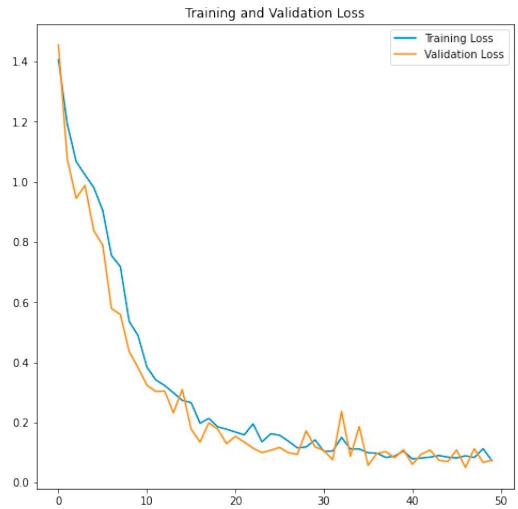

Fig. 8. Validation and Training Loss.

For the training of the model each epoch takes around time varying from 70 seconds to 124 seconds. We ran the training for 50 epochs and the entire training process has taken approximately 59 minutes and 12 seconds. The progress during the training is shown in fig 7.The Orange line is showing validation accuracy and the bluish line is showing accuracy obtained while training. As the training is progressing it can be observed that the training and validation graph converge with one another indicating no presence of overfitting.

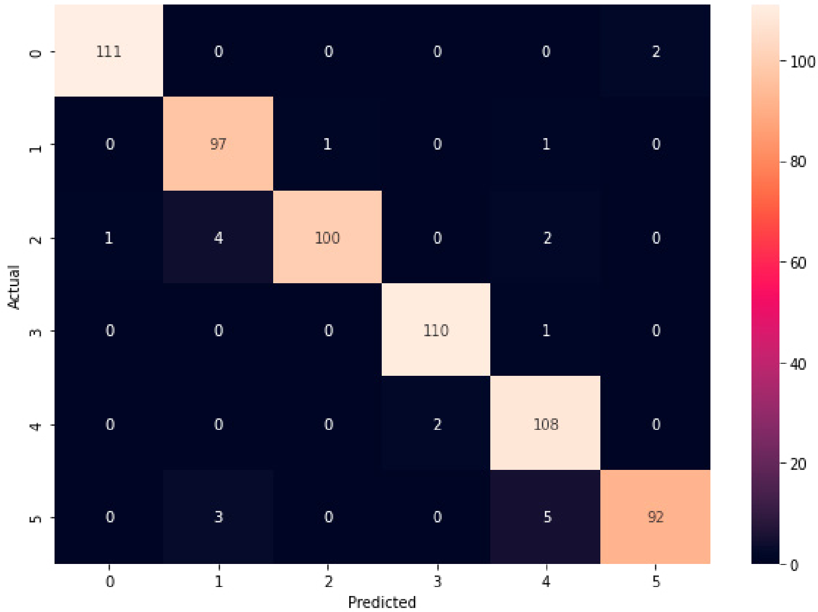

Fig. 9. Confusion matrix for the Proposed Model

Next the different parameters for performance for the model such as F1-Score, Recall, Precision, support and accuracy are analysed and The Table 4 lists the values for various diseases. The different parameters were evaluated using the following equations:

$$Accuracy = \frac{TN + TP}{FP + FN + TP + TN}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

$$Precision = \frac{TP}{TP + FP}$$

Here,

FP = False Positive, FN = False Negative, TP = True Positive and TN = True Negative,

Fig 9 shows the confusion matrix of the test images consists of a total 640 images of leaves which are classified into 5 diseases and healthy categories, out of which 22 images were misclassified. In this figure (9) 0 represents the disease Algal Spot, 1 represents Brown Blight, 2 represents Gray Blight, 3 represents Healthy Leaves, 4 represents Helopeltis and 5 represents Red Spot. The overall accuracy of our model is 96.56%. From this we can reach to the conclusion that the model which is proposed in this literature is performing as intended.

In fig 10, accuracies for different classes of disease are presented. Algal Spot has an accuracy of 98.23%, Brown Blight has an accuracy of 97.98%, Gray Blight has an accuracy of 93.46%, Healthy classes of leaves has an accuracy of 99.10%, the Helopeltis disease class has an accuracy of 98.98% and Red Spot has an accuracy of 92%

Table 4. Performance parameters for five different diseases and healthy leaves used in this study

Class	Precision for Testing	Recall Validation	F1-Score	Support
Healthy	0.9821	0.9910	0.9865	111
Red Spot	0.9787	0.9200	0.9485	100
Helopeltis	0.9231	0.9818	0.9515	110
Gray Blight	0.9901	0.9346	0.9615	107
Brown Blight	0.9327	0.9798	0.9557	99
Algal Spot	0.9911	0.9823	0.9867	113

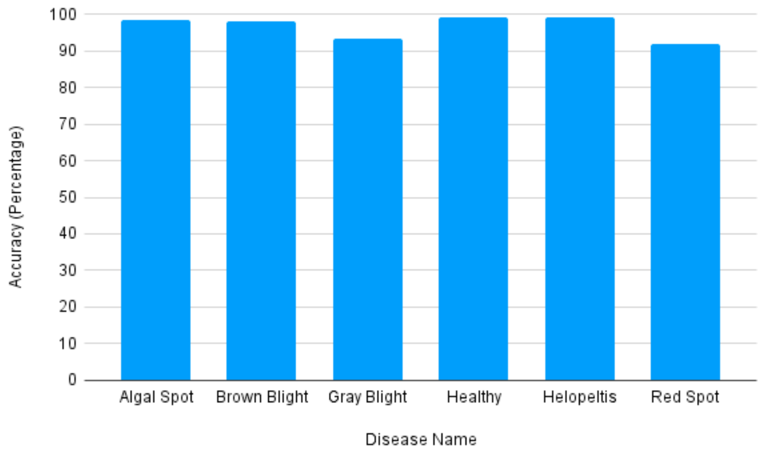

Fig. 10. Accuracy Percentage for Each Class of Disease

Table 5. Comparison between different models in terms overall accuracy

Method	Classes of Leaves	Accuracy(%)
Proposed Model	6	96.56%
Chen et al. [17]	7	90.16%
Karmokar et al. [15]	1	91%
Hossain et al. [16]	2	93%
Mukhopadhyay et al.[10]	5	83%

In fig 11 for each class of the disease graph between True Label vs Predicted Label are presented. It is observed that all of the classes can predict most of the images subjected accurately.

Next this paper compared the proposed model with few of the most recent methodologies in the literature for evaluation purpose. Table 5 contains the results of comparison of the model that is proposed in the paper to those of previously developed models. With a classification accuracy of 96.56 percent, the suggested model outperforms previous techniques in terms of Tea Leaf disease detection.

Further a robust back-end is also developed using RestfulAPI services that can be easily integrated with varoius Mobile Applications, Web applications and IOT devices that are able to send HTTP requests. If an image is sent to the back-end using HTTP request, back-end system has the capability to classify the type of disease and distinguish between diseased & healthy tea leaf and it is also able to send back the response with the prediction accuracy.

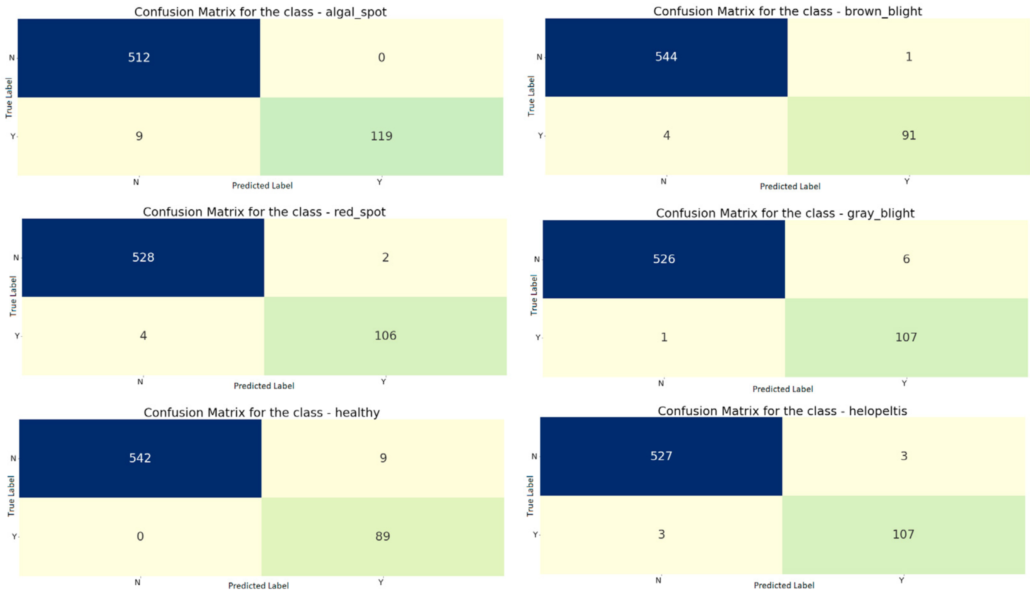

Fig. 11. Confusion matrix for each class of disease

6. Conclusion

Convolutional Neural Networks have become established methods that are used more frequently in image classification. In comparison to other techniques, the complexity required for NN analysis is greatly lowered, and the computing precision is also greatly increased. Additionally, the great fault tolerance of CNNs permits the use of backdrop pictures that are illegible or hazy, significantly improving the accuracy of image identification. Because of all these advantages CNN proves to be more effective than other DL techniques. In this work, a two-dimensional convolutional neural network with RGB images as input is considered and a Tea Leaf disease classification model has been developed. The proposed model can automatically classify tea leaf diseases into five different kinds and distinguish between healthy and diseased leaves. It can be seen that the overall accuracy of the classification is 96.56 percent, while recall and precision are 96.49 percent and 96.63 percent, respectively. The proposed model beats the others in regard to overall precision, accuracy and recall, when comparing with the most recent models reported in the literature. The proposed model does not appear to be overfitted, as evidenced by the results. In future, the accuracy of detecting Gray Blight and Red Spot disease in a leaf, can be improved further. The proposed model can be updated further to identify a larger number of tea leaf diseases. The model can be integrated with IoT devices and can be deployed in real world application. Furthermore the model can be expanded to encompass more crop diseases.

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