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A Novel Approach for Detection of Tea Leaf Disease using Deep Natural Networks

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Abstract: One of the world's largest exporters of tea is India. However, persistent pathogen exposure-related tea leaf diseases cause significant global crop output losses. Early detection of the tea leaf disease can lessen its detrimental effects on tea production. It might be ineffective and harmful to diagnose the illness with the unaided eye. Convolutional Neural Networks (CNNs) are frequently employed to apply an efficient technique for the classification of images. CNN is frequently used in plant disease detection. As a result, the suggested work considers using a Deep CNN with many hidden layers to classify damaged tea leaves into various groups. This aids the network in identifying more characteristics, increasing the precision of illness identification. The following leaf classifications are used for the classification process: Red Spot, Heliopolis, Brown Blight, Algal Spot, Gray Blight, and Healthy Leaves. Additionally, 5867 photos of healthy and diseased tea leaves have been tagged and posted to Kaggle. The proposed approach shows that the model has a 96.56% accuracy rate in identifying the type of persistent tea leaf disease. The following illness classes have the results show that Algal Spot has an accuracy of 98.23%, Brown Blight has an accuracy of 97.98%, Gray Blight has an accuracy of 93.46%, the Heliopolis disease class has an accuracy of 98.98%, and Red Spot has an accuracy of 92% accuracy In terms of accuracy, the model put forward in this literature is significantly better than the current approaches.

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

1. Introduction

India is ranked fourth in the world for tea exports, behind China, Kenya, and Sri Lanka. India exported $826.47 million worth of tea in the fiscal year 2020 and $755.86 million in the fiscal year 2021[1]. Plant diseases are traditionally identified and analyzed on tea estates with the assistance of subject matter experts. The time and efficiency of producing tea can be greatly decreased if the work of illness identification can be automated in part or in full. Crop production can be raised and farmers' reliance on specialists for disease identification can be decreased with the use of automatic disease detection tools. Early disease detection allows for the use of preventative measures to stop the infections' spread. India produces some of the best tea in the world thanks to its robust geographic indices, large investments in tea processing equipment, ongoing innovation, expanding product range, and purposeful market expansion. Because tea plants can tolerate high temperatures and shade, tea plantations are often found in regions with warm temperatures and abundant rainfall. On the other hand, when production is continuously increased, these locations are perfect for the spread and reproduction of different types of diseases, which considerably reduces tea quality. Usually, the fruits, leaves, and stems of the plants exhibit disease symptoms.

The first sign that a leaf has been infected with a disease is when its color changes from a green tint to another color. A robust leaf possesses own color, but a leaf suffering from a disease has a color that is drastically different from what it was before. These days, the most popular methods for diagnosing plant diseases include microscopic identification, molecular biology, and spectroscopic techniques. When it comes to subjective and time-consuming microscopic identification, even the most seasoned plant pathologists make mistakes. Molecular biology and spectroscopic identification are more accurate techniques, but they also need more resources and time[2].Quick developments in Deep Learning (DL) and enhancements in device capabilities such as memory size, processing speed, image sensor resolution, power consumption, and optics have accelerated the creation of vision-based applications and enhanced their performance

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and economics [3]. DL, as opposed to conventional image processing techniques, assists in the accuracy of tasks like classifying pictures, identifying objects, and so forth.

Neural networks in deep learning (DL) are taught instead of hardcoded, hence applications using this technique often require less fine-tuning and expert analysis. Additionally, the system of today has access to a vast amount of visual data, which facilitates effective training of deep learning models. While methods for Computer Vision (CV) are more domain-specific, DL techniques offer greater flexibility because CNN models and frameworks may be re-trained using a specific dataset for any application.

The first convolutional neural networks, or ConvNets, were created in 1989 by postdoctoral computer science researcher Yann LeCun. With many layers of convolutional filters, CNNs can learn to automatically extract information from images. CNNs are neural networks with a hierarchical structure at their core. Numerous convolution layers, a fully connected layer, and a pooling layer. The networks' weight sharing, spatial sub sampling, and local receptive fields are significant hierarchical components.

CNNs show a high degree of invariance with respect to translation, shifting, scaling, and other types of deformation [5]. The primary benefit of employing CNN is that it can accept photos as input directly, saving us the trouble of reconstructing images and separating out the features to send into the neural network. Meanwhile, the high recognition accuracy of CNNs makes them widely used in fields like computer vision, The proposed work makes the following contributions:

1) The suggested method makes use of a novel CNN network design that can distinguish between various types of tea leaf diseases with greater accuracy than the earlier techniques.

2) We have created a brand-new real-world dataset of 5867 photos that include both healthy tea leaf images and photographs of five different illness types.

2. Related Work /Literature Survey

Fawell, J.K. (2016):-"Fluoride in Drinking-water The literature on plant leaf disease detection is examined and reviewed in this part. The literature contains a variety of research on the technological developments in plant leaf disease detection in recent years, including those on advances in remote sensing technology and technological resource management. MIL-WDDS, a novel framework that uses deep multiple instance learning to diagnose wheat disease, was proposed by Jiang Lu et al. [6]. Remarkably, the proposed method achieves better recognition performance than the deep standard CNN model. such as VGG-CNN-VD16. The image dataset is trained for 20 epochs with a batch size of 2 and an initial learning rate of 0.00005. A method for extracting form cues to identify illness in sugarcane leaves with a 98.60% accuracy rate was developed by Patil et al. [7]. The calculation of the leaf area is done by threshold segmentation. The triangle thresholding approach is used to divide the lesion region. PlantDoc, a dataset suggested by Davinder Singh et al. [8], is made up of brand-new photos that were taken by the author to identify diseases of plants.

There are 2,598 photos in all from different diseases in this collection, which is made up of 27 classifications and 13 plant species. Additionally, they bench marked the image-based data they had gathered and demonstrated how effective it was at identifying diseases in actual settings. An algorithm was created by Ramesh et al. [9] to identify anomalies on plants, whether they are in a controlled greenhouse environment or not. The Random Forest classifier was utilized to train the suggested model on 160 papaya tree leaf images. The training dataset's feature vector was created using the HoG (Histogram of Oriented Gradients) feature extraction method. The model's classification accuracy was about 70%.A model for the computational identification of tea leaf disease was created by Mukhopadhyay et al. [10].

complex techniques including multi-class SVM, PCA, and NSGA-II. The suggested picture clustering method based on NSGA-II is validated by the Silhouette index. The best set of characteristics is then chosen using PCA, then multi-class SVM-based sickness identification is carried out. Using the proposed methodology, five different illnesses can be identified in tea leaves. This model's total accuracy is 83%. A NN classifier was proposed by Kumari et al. [11] to identify leaf diseases. The K-means clustering approach has been employed to segment the data. Numerous parameters, including correlation, homogeneity, standard deviation, contrast, energy, variance, and mean, are retrieved for cotton and tomato illnesses. Leaf mould, target spot septoria leaf spot, bacterial leaf spot, and leaf spot have 100%,

90% and 80%, respectively, with a 92.50 percent mean accuracy. A technique for identifying leaf diseases in wheat and cotton plants was presented by Badage et al. [12]. This suggested approach classifies different diseases by first using a machine learning algorithm to identify the edges of damaged leaves using the Canny Edge Detection Algorithm. Five plant diseases were utilized by D. Pujari et al. [13] to evaluate their suggested approach. The suggested classifier employed texture and color cues to categorize plant diseases. To recognize and classify, 900 photos total—150 of each type—are used in the study. This method's main advantage is that it uses the fewest features possible to improve classification accuracy and shorten computation

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times. SVM illustrates a significant increase in detection accuracy that surpasses ANN, with 92.17% accuracy as opposed to 87.48% for ANN.For automatically categorizing the plant diseases examined in this work, SVM proved to be a helpful technique. Sladojevic et al. [14] suggested using deep learning (DL) to automatically identify and categorize different plant diseases from a variety of photos. The experimental results achieved an accuracy of 91% to 98% for different class assessments. The final accuracy of the trained model was 96.3%.

Karmokar et al.'s effort, the Tea Leaf illnesses Recognizer (TLDR), was put forth in order to identify the several illnesses that affect tea leaves [15]. In the TLDR image processing, the tea leaf image is first transformed, scaled, cropped, and set to its limiting value. They have additionally employed the feature extraction method. The Ensemble Neural Network was used to recognize patterns. The illness kind and the recovered features are given into the ANN, which is subsequently trained. Ninety-one percent accuracy was noted after testing. Hossain et al. [16] created an automated system for identifying three distinct types of tea leaf disease by employing a machine learning technique called Support Vector Machine (SVM), which has features in smaller quantities. The recommended technique may detect disease more reliably than prior classifiers and neural networks, with a 93% detection accuracy when compared to other neural network classifiers that have a maximum 91% detection accuracy. The recommended method can handle 300 milliseconds quicker than previous study using SVM as a classifier for a leaf classification.

The objective of Chen et al.'s study [17] was to develop a deep CNN that could identify different types of tea leaf diseases based on leaf pictures. Using feature extractor filters of various sizes, the CNN model LeafNet automatically extracts the features associated with tea leaf disease from an image dataset. Using features from the also-obtained Dense Scale Invariant Feature Transform, the Bag of Visual Words model is constructed and used with SVM and MLP classifiers to diagnose illnesses. The LeafNet system, with an average classification accuracy of 90.16 percent, identified tea leaf sickness the most accurately among the 60.62 percent of the SVM 70.77 percent for the MLP algorithm and the technique. Singh et al.[18] proposed a deep learning model to detect kidney disorders, especially chronic kidney disease.

The 12 layers of the deep neural network consist of one layer for input, five dropout layers, five dense layers, and one dense output layer for classification. The proposed model outperforms SVM, KNN, Naive Bayes, Logistic Regression, and Random Forest classifiers, achieving 100% accuracy superiority. A deep learning algorithm was created by P. Rastogi et al.[19] to diagnose leukemia from microscopic blood pictures.Three publicly available leukocyte benchmark databases were used in separate classification tests to assess the efficacy of the extracted features utilizing the proposed LeuFeatx model. Using deep features, multi-class classifiers were built that is more accurate, sensitive, and precise than other state-of-the-art techniques for seven distinct leukocyte subtypes. The accuracy of these classifiers was 96.15%. The work offers a novel two-step method for the accurate classification of leukocytes for the diagnosis of leukemia by creating a model that is tailored to VGG16 and optimized to extract features that are essential for the precise categorization of leukocytes. Significant leukocyte properties were found to be extracted by the model from microscopic singular leukocyte images. it was found that the model could extract important leukocyte properties. Research currently available indicates that greater accuracy is needed to identify and categorize tea leaf illnesses as well as distinguish between healthy and diseased tea leaves. With regard to classifying tea leaf diseases and distinguishing between healthy and sick leaves, the suggested CNN model works better than any previously documented method since it utilizes an enhanced network design.

3. Experimental Method/Procedure/Design

3.1. Establishing the Illness Database

A 12-megapixel smartphone camera was used to capture all of the photos showing illnesses in the tea leaves in their natural environments. The photos were taken at a number of tea estates in Tripura, India's Unakoti District. The photos were taken at a distance of around 30 cm above the leaves with a resolution of 3000 x 3000 pixels. A total of 2,800 photographs of tea leaves were taken, all of which included images of healthy leaves in addition to evidence of one of five illnesses. The previously developed identification methods served as the foundation for the tea tree disease identification criteria[20, 21].

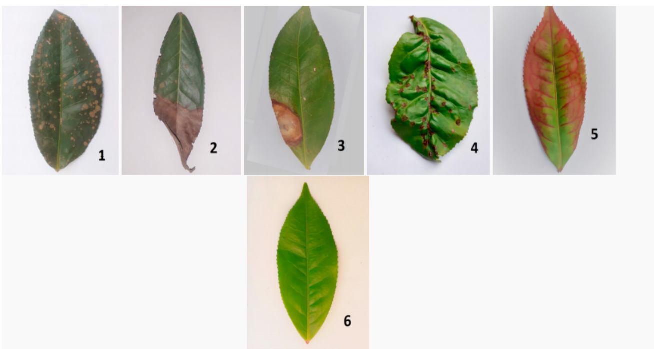

Fig.1 Example includes images of tea leaf categories used in this study. (a) Algal Spot(Caused by a green parasitic alga Cephaleuros virescens); (b) Brown Blight (Caused by Colletotrichum camelliae Massee.); (c) Gray Blight (Caused by Pestalozzla theae. Sawada); (d)Helopeltis (Caused by Helopeltis theivora);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

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Phyllosticta theicola Petch); (f)Healthy Leaf

Experts from the tea estate were also consulted in order to categorize the ailments. Every image in this manuscript has been resized to 256 pixels by 256 pixels. The database size was raised to 5867 in order to improve the classifier's generalization abilities, which is better for the network's training. For reference, the dataset has been posted to Kaggle [22].

Table 2 displays the disease classification dataset utilized in this study. Figure 1 displays illustrations of several illness types. The 20% test data to 80% training data ratio is found to be most common in neural network applications. Furthermore, a 10% sample of the test dataset was used to validate the dataset.

3.2. Convolutional Neural Network

CNN is a deep learning technique that accepts an input, which can be any kind of data from any dataset, including images. gives different components in that image weights and biases to set one apart from the other. The input image is first sent to the feature retrieval network, which subsequently uses the features it has obtained to generate signals to the neural network (NN) for recognition. The output is then produced by the network using the characteristics of the image. Convolution layer and pooling layer pair layers are combined in a neural network (NN) during the feature extraction process. Convolution layer, as its name implies, finds the characteristics in the image by applying a convolutional technique, which is essentially a collection of digital filters. Alternatively, the image size is reduced via the pooling layer, which unites neighboring pixels to form a single pixel. Features maps are produced by the convolution layer as new images, which highlights the unique characteristics of the Score picture.

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

Because it lacks link weights and weighted sums, the convolution layer functions completely differently from the other neural network layers. Rather, the layer has what are known as convolution filters—filters for altering images. The picture is passed through the convolution filters to create the feature map [23]. The 2-D convolution approach with filter size P and picture dimension M×N is shown is shown in Fig. 2.Another widely used strategy that has been used in diff ×Q is pooling. different image processing jobs because it reduces the image's dimension by combining nearby pixels by applying an operation in a specific area of the image into a single value.layer of pooling. There are various forms of pooling, such as average and maximum pooling.As an example, each colored box in Fig. 3 Max Pooling indicates a 2x2 kernel size, from which the maximum of each colored element is sent as an element to the following layer. The output is then produced by the network using the characteristics of the image. Convolution layer and pooling layer pair layers are combined in a neural network (NN) during the feature extraction process. Convolution layer, as its name implies, finds the characteristics in the image by applying a convolutional technique, which is essentially a collection of digital filters. Alternatively, the image size is reduced via the pooling layer, which unites neighboring pixels to form a single pixel.

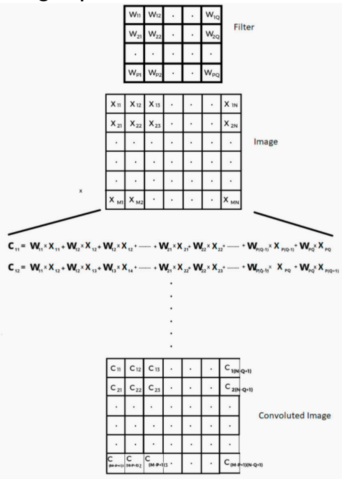

Fig. 2. Convolution Operation in 2D Image.

3.3. Approach

As previously said, the photos were taken at different tea estates in the Indian state of Tripura.

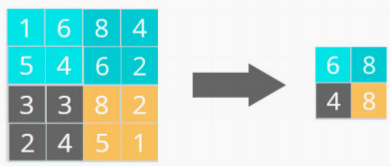

Fig. 3. Max Pooling.

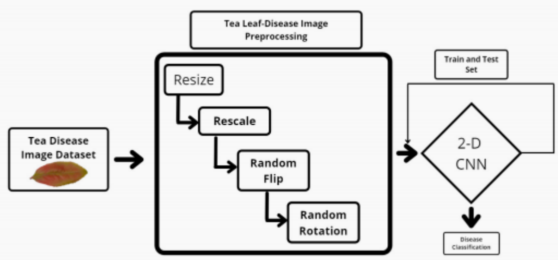

Fig. 4. Model

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As seen in (Fig 4) in this work, these images are processed using the data augmentation method, which yields the augmented images required to train the CNN. Here, there are two main processes in the Tea-leaf disease classifier: preprocessing the data and utilizing CNN to help categorize photos of damaged tea leaves.[24]

3.4. Enhancement of Data

The suggested study uses a variety of data augmenting techniques, such as random rotation in both clockwise and counterclockwise directions, random picture scaling and shearing, and random contrast application, to increase the number of photos in the dataset.

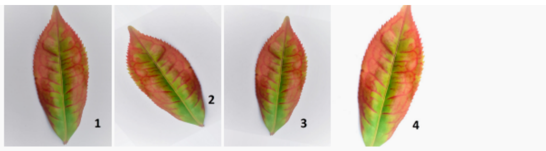
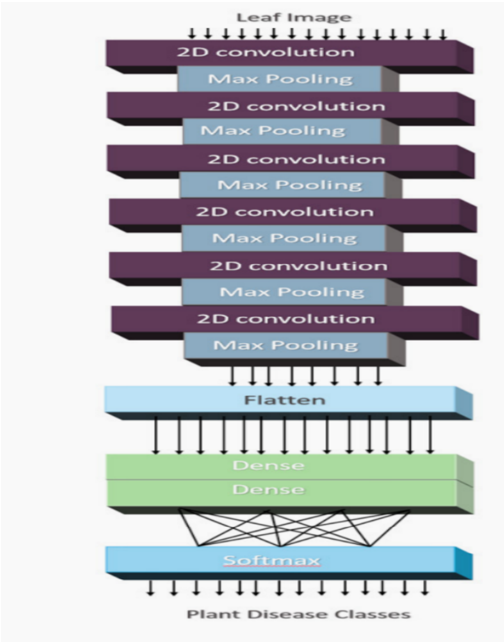


Fig. 5. (a) Original,(b)Skew and Random Left Rotation;(c)Random Right Rotation;(d)Scaling and Rotation with Change in contrast

3.5. Architecture of Classifiers

As shown in Fig. 6, the proposed Neural Network has 16 layers in total. Six of the layers are convolutional, six are pooling, one is a Soft-Max activation layer, and the remaining two are completely connected. Equation (1) illustrates how the 2-D convolution layer applies the convolution process to the output that is obtained from the preceding layer.



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

y = Output matrix after convolution operation ,**x** = Input image matrix to be convolved, **h** = Kernel matrix, **p,q** = pth and qth indices of Image represented in matrix form and **k,l** = Kernel Size of *k* × *l*.

256 by 256 pixels in size. The convolutional and complete connection layers are defined as follows:

(a). The first convolution layer in the suggested model has 32 filters and a kernel size of 3 pixels by 3 pixels. This layer takes three RGB channels and 256 x 256 pictures as input. This layer generates 32 feature maps, each measuring 254 by 254. ReLU, or corrected linear unit operation, is then carried out. Compared to the sigmoid function, the activation function ReLU has superior error transmission and can solve vanishing gradients. The pooling layer's kernel has a size of 2 pixels by 2 pixels and a stride of 1 pixel. Ultimately, 32 × 127 x 127 feature maps were acquired.

(b). The 64 filters in the next convolution layer have kernel sizes of 3 pixels by 3 pixels. 32 x 125 × 125 feature maps are generated by this layer. As previously mentioned, layer normalization and ReLU procedures have also been put into practice. The pooling layer's kernel measures 2 pixels by 2 pixels. 32 and 62 × 62 feature maps were produced following the pooling process.

(c). The third-place convolutional layer has a kernel size of 3 pixels by 3 pixels and 64 filters. This layer generates 32 feature maps measuring 60 by 60, and furthermore, 32 feature maps measuring 30 by 30 are created by the ReLU method.

(d). The fourth convolution layer comprises 64 filters with a kernel width of 3 × 3 pixels. It produces 32 feature maps (28 × 28) that are then subjected to the ReLU process. The step The kernel of the pooling layer measures 2 pixels by 2 pixels in width. After pooling, 32, 14 × 14 feature maps are generated.

(e). The fifth conversion layer consists of 64 filters with 3 × 3 px kernel widths that produce 32, 12 × 12 feature maps that are subjected to the ReLU procedure. The stride is one pixel, and the kernel of the pooling layer is 2 pixels by 2 pixels in size. After pooling, 32, 6 × 6 feature maps are generated.

(f). After applying the ReLU operation, the sixth and final convolutional layer creates 32 feature maps measuring 4 pixels by 4 pixels with 64 filters with kernel widths of 3 pixels by 3 pixels. The stride is one pixel, and the kernel of the pooling layer is two pixels by two pixels. After pooling, 32, 2 × 2 feature maps are generated.

(g). A ReLU operation comes after the 64-neuron initial completely linked layer.

The last full connection layer, which comprises six neurons, reflects the five sickness classes and one healthy class of tea leaves. The output layer determines the illness class of the input image by receiving the output from the last complete connection layer that is present at the end. The softmax activation function in this instance is

$$X_j^k = f\left(\sum_{i=1}^{N} x_i^{k-1} \times w_{ij} + b_j\right)$$

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N = Total no. of neurons, **X k j** = Output received from jth neuron from kth layer and **wj** = Weight kernel for the jth Neuron employed, limiting the ranges of each output and guaranteeing that all output values fall between 0 and 1. Given that the softmax function considers the relative values of all outputs, the proposed model is a perfect fit for it.

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

During the training phase, it is important to consider how adjusting the bias and weight might lower the value of the established loss function. To reduce loss, one useful tool is the Sparse Categorical Cross Entropy function, which is defined in equation (3).

Next, the weights and bias need to be determined and updated, and the Adam Algorithm in this study helps with that. The Adam optimization method is an extension of stochastic gradient descent [25]. The Adam optimizer uses an epsilon e of 1e-08, a learning rate of 0.001, 0.9 as a beta1 value, and 0.999 as a beta2 value.

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

where,

Z = Total Numbers of Neurons present in the layer, **w** = Weights of the Neural Network, **bj** =True Label and *b*ˆ *j* = Predicted label

4. Results

Following the previously mentioned preprocessing procedures, 5867 pictures, including both healthy and sick photographs, were obtained. The dataset is then split into two halves. Eighty percent of the dataset's photos are used to train the model, while the remaining ten percent are used as a test dataset and model validation. The photos from the test and validation datasets are entirely different. Thus, test images are being seen for the first time while the suggested model is being tested. Moreover, the CNN Tensorflow Keras module is taken into consideration when developing the suggested CNN model.

Google Colab Pro, which has a Tesnor Processing Unit (TPU) and 28 Gigabytes of RAM, is utilized to train the model. The suggested model made use of data gathered from several tea estates using Earlier, five distinct disease categories were discussed, along with pictures of healthy leaves.

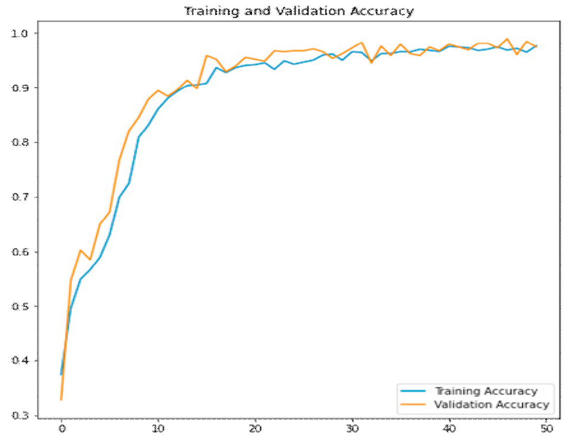

Fig.7 Validation and Training Accuracy

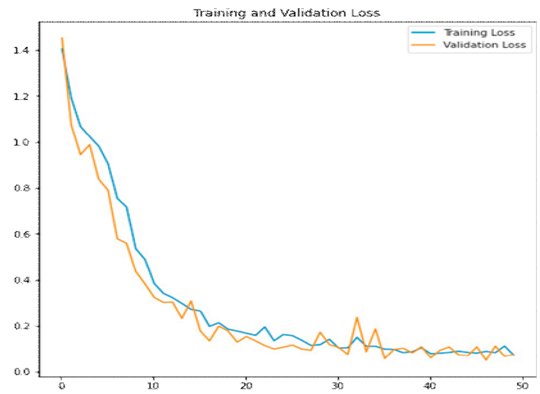

Fig.8 Validation and Training Loss

Each epoch of the model's training takes roughly varied amounts of time, from 70 to 124 seconds. The training process took about 59 minutes and 12 seconds to complete after 50 epochs were run.

Figure 7 illustrates the training progress. Validation accuracy is indicated by the orange line and the bluish line is displaying the accuracy learned throughout training. The training and validation graphs converge with each other as the training goes on, showing that overfitting is not present.

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

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

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

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

Here,

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

The model's performance metrics, including F1-Score,

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recall, precision, accuracy, and support, are then examined.

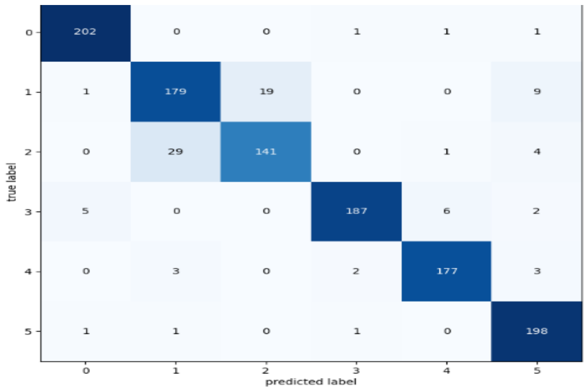

Fig.9 Confusion Matrix for Proposed model

The values for these metrics are listed in Table 4 for a variety of diseases. The following formulas were used to assess the various parameters:

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

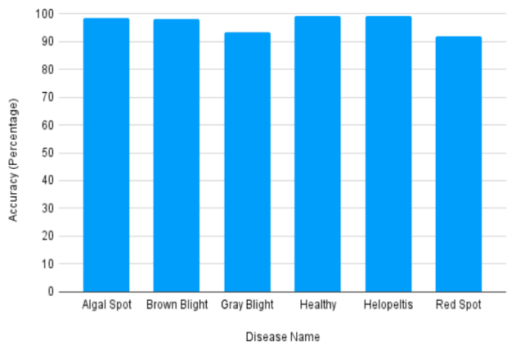

Fig. 10 Accuracy Percentage for Each Class of Disease

Table 5.2 Comparison between different models in tterms of overall accuracy

Method	Classes of Leaves	Accuracy (%)
Proposed Model	6	96.56%
Chen	7	90.16%
Karmokar	1	91%
Hossain	2	93%
Mukhopadhyay	5	83%

640 photos of leaves overall, divided into 5 categories for diseases and 5 categories for health, make up the confusion matrix of the test images, as shown in Fig. 9. Of these, 22 photos were incorrectly identified. The diseases Algal Spot (0), Brown Blight (II), Gray Blight (II), Healthy Leaves (III), Heliopolis (IV), and Red Spot (V) are represented in this figure (9). Our model's total accuracy is 96.56%. This leads us to the conclusion that the model put forth in this body of research is operating as planned. Figure 10 displays the accuracy values for several illness types. With an accuracy of 98.23% for Algal Spot, 97.98% for Brown Blight, and 93.46% for Gray Blight, Red Spot has an accuracy of 92%, the Helopeltis disease class has a 99.98% accuracy, and the healthy classes of leaves have a 99.10% accuracy.

It has been noted that every class is able to correctly guess the majority of the images that are presented. Subsequently, this paper conducted an evaluation by contrasting the suggested model with a couple of the most recent approaches found in the literature. The results of comparing the model suggested in the research with earlier models' development are shown in Table 5. In terms of Tea Leaf disease identification, the proposed model performs better than prior methods, with a classification accuracy of 96.56 percent. Additionally, a strong back-end is created utilizing Restful API services, which are simple to integrate with a variety of Web, mobile, and IOT apps that can send queries using HTTP. The back-end system can diagnose the type of disease and distinguish between diseased and healthy tea leaves if an image is supplied to it via an HTTP request. It can also return a response with an accuracy forecast.

5. Conclusion

In image classification, convolutional neural networks have emerged as a reliable technique that is increasingly utilized. NN analysis requires a huge deal less complexity than other methods, yet it also requires a great deal more computing precision. Furthermore, because CNNs have a high fault tolerance, it is possible to employ blurry or unreadable background images, which greatly increases image recognition accuracy. With all these benefits, CNN turns out to be more efficient than other DL methods. This work considers a two-dimensional convolutional neural network that receives RGB photos as input and develops a model for the categorization of Tea Leaf illness.

The suggested approach is capable of automatically identifying healthy and diseased leaves and classifying tea leaf illnesses into five categories. It is evident that the classification's overall accuracy is 96.56%, whilst recall and precision are 96.49% and 96.63%, respectively. When compared to the most recent models published in the literature, the suggested model performs better than the others in terms of overall precision, accuracy, and recall. The findings support the notion that the suggested model is not overfitted.

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