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DEEPLEAF: HARNESSING DEEP LEARNING FOR TEA PLANT HEALTH

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Abstract

Tea, also sometimes referred as Chai is one of the popular aromatic beverages consumed across the world, and it is consumed in various forms & flavours. Tea plants are generally cultivated in tropical and subtropical climatic conditions. China, India, Kenya & Sri Lanka together contributes to more than 75% of the world tea production, with India ranks only next to China with 1.2 million tonnes of tea production in 2020 [10]. Timely identification of the presence of disease in tea leaves is a crucial task during the cultivation processes & prevent rapid spread of the same. The manual identification of the disease is more linked to the skill set, knowledge & expertise of the particular individual. Image processing technique through Convolution Neural Network (CNN) is being utilized in this paper for Disease identification & classification with prime focus on Tea leaves. The objective is to have a automated system for classification of diseases present in the tea leaves images with the help of dataset, and produce the results along with its cause, symptoms & precautions. This non-manual oriented & non-destructive disease identification & classification system is expected to be of high assistance to the tea cultivation & processing industries to have improved monitoring process. This deep-learning model uses CNN technique for feature extraction and classification processes and reached the overall accuracy of 88% (training accuracy 92% and validation accuracy 80%). The output of the system is shown through Streamlit framework for a user-friendly illustration.

Keywords:

CNN, Deep-learning, Feature Extraction, Stream Lit, Tea leaves Disease

1. INTRODUCTION

In the current era of digitalization, advancement in the field of agriculture is of prime importance to have food security, loss due to spread of diseases etc., Deep-learning and Image processing technologies have helped in various forms in agriculture sector. A non-destructive method is always preferred, which helps in classification of larger set of data. The deep-learning based identification is cost effective and non-demandable approach in categorizing images with larger set of data with more accuracy rate. It also stands ahead due to its faster feature extraction and classification processes which outfits its better algorithm.

In agriculture sector, spread of diseases in the plants results in huge loss of value to the farmers and industries, and it also affects the food chain and security. In country like India, where major part of the population is depending on agriculture related source of income – preventive measures for spread of diseases should be in faster pace and easier process since visual inspections will not yield accurate results at all stages. Laboratory inspection is also lengthy process due to the geographical location of the laboratories and the waiting time due to demand levels, While the advanced AI and ML techniques enables for a faster, accurate results on the spot - will assist for technological growth of agriculture sector.

In particular to Tea, which is also colloquially called as "chai" or similar terms – is one of the largest consuming common beverages in the world. Cultivation of tea plant requires specific climatic conditions, moisture and soil conditions. Disease in tea plant occurs in its different parts like stem, roots but most of its diseases are happen to be occurring in its leaves. All these diseases are difficult to identify through normal visual inspection because of its various state of nature and maturity of the disease. So there arises the necessity of advanced disease identification and classification technique to increase the efficiency and productivity of the tea industry.

There are various and different kinds of Machine learning techniques are available such as Visual Geometry group (VGG), AlexNet, Inspection-V4, ResNet, however CNN takes a lead in classification and identification of the disease with fast and easy way of approach. The CNN with usage of Max pooling and average Pooling techniques to get the results with detailed description. YOLO (You Look Only Once) techniques are used to segregate the affected parts clearly. The paper describes about the name identification of diseases along with the cause, symptoms and its effects. Using streamlit framework to get the detailed overview of the diseases at one stretch, and with user friendly output illustration.

2. RELATED WORKS

In this section, a short summary of a few earlier works in this domain and brief their key points and findings.

Krizhevsky et al. [1], an attempt has been made to train about 1.2 million high resolution images where they found the results with top-1 and top-5 error upto 35% and 17.0% respectively. Neural networks were trained with 60 million of parameters and achieved a reduced error rate from 26.2~ from older measures to around 15%. The research is on a extended phases where the authors planned to make out the experiments with unsupervised models and video stream to grab more insights and produce results.

Simonyan et al. [2] is based on two visualisation technique that computes the gradient of class sore with respect to input image where the first one generates image and second generates saliency map. The results are established with comparison basis between gradient-based convnet and deconvolution methods. The future scope states with the incorporation of saliency maps with leaning principles with more formulation techniques.

Bao et al. [3] proposes improved model of Retina Net Target detection with more focused-on target detection. The issue of insufficient samples is resolved using data augmentation techniques. The results show accuracy rate with the mAP value of around 93.84%. Compared to the original network value the accuracy rate has increased by 4% of recall value and 1.5% of

identification rate. Ax-RetinaNet adapts X-modules to fuse and manipulate multiple images to achieve detailed information about targeted position and number of training images were expanded to avoid overfitting. The results show comparatively high results than existing works.

John [4] discusses about the problem and difficulties faced while identifying diseases in plants using visual inspection. This paper proposes various machine learning techniques and their advantages and disadvantages with their accuracy rate. This paper also discusses about the rate of diseases that affect both the leaves and root and their major cause. It detail about the main aim to identify the root cause of the diseases by automatic inspection. The system compares very old methods with deep learning methods and provides their accuracy rate which shows that CNN rates with high accuracy compared to other methods like SVM. K-means clustering etc,.

As a summary, most of the earlier works has focused on the disease identification and classification using various techniques. But the inferences and way forward with the disease identification is not been made as a part of the system. Also, the earlier works are generic with common vegetables and fruits, while this paper focusses particularly on the tea leaves with indepth analysis with number of diseases, its cause, symptoms and precautions. In general - comparing the accuracy levels of various systems available – CNN based models have resulted with higher accuracy levels.

3. PROPOSED SYSTEM

3.1 INTRODUCTION TO CNN

Convolution Neural Network (CNN) is first proposed by a Japanese research scholar Mr. Fukushima to understand the biological vision mechanism. The word “convolution” can be shortly described as product of two function say as (x and y) convolute to produce the new function say (z) to show how the form of one is modified by other. Thus, it combines two signals as one. It can also be described as converting all pixels in receptive fields to a single value. CNN is mainly working fine for automatic detection and identification where it highly useful for deep learning models in computer Vision. Deep learning uses CNN to recognize the objects or entity present in the image. Thus, the need of CNN extends by scalable approach mainly for pattern recognition where it follows principles from matrix multiplication from linear algebra which is complicated task made easy by its futuristic approach. It reads information directly from data. CNN Includes 7 layers which are as follows. The two main types of Convolutions are continuous and discrete.

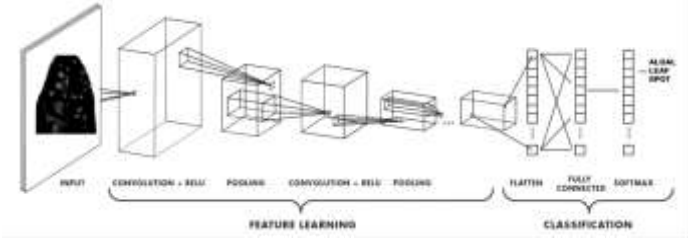

Fig.1. CNN Architecture

3.2 ESSENTIALS BEFORE CNN

3.2.1 Image Representation:

Images are represented in RGB format where each channel intensity is measured with height and width of the image which is noted in matrix form

3.2.2 Edge Detection:

Every single image includes vertical and horizontal edges combines to form an image where convolution uses filter to detect edges. For example: Image 6*6 convolute with 3*3 filter to produce 4*4 image which provide prescribed form of details required. If we have M x M image size and D x D filter size then after convolution result will be

$$(M \text{ x } M) * (D \text{ x } D) = (M\text{-}D\text{+}1) \text{ x } (M\text{-}D\text{+}1)$$

3.2.3 Stride and Padding:

Each step moved is denoted by stride and by default it is set as 1. Inorder to maintain same dimension between input and output – a process called as padding, which adds zero to the input matrix in a symmetrical manner.

3.3 LAYERS OF CNN

3.3.1 Input Layer:

Input is taken as image where it is mentioned as three-dimensional matrix where there is a need to convert column dimension as 1. Say for an instance if the size of the image is 28*28=784 which is converted as 784*1 before feeding in.

3.3.2 Convo Layer:

This is often referred as feature extractor layer which extracts features of the image that is most required. This is a combined form of (Convo+ReLU) where Relu is the activation function used. ReLU makes all negative value as zero. Convolution operation takes place from part of the image and process repeats until the process covers the entire image. This output is fed as an input to the subsequent layer.

3.3.3 Pooling Layer:

Subsequent to the convolution process - as there is a need to minimize the spatial volume of the input image there includes a pooling layer which is mostly used between two convolution layers. Pooling layer includes two Hyperparameter functions as Filter (X) and stride (Y). In general, if we have input dimension W_i x H_i x D_i, then $W_o = (W_i - X)/Y+1$

$$H_o = (H_i - X)/Y+1$$

$$D_o = D_i$$

where W_o, H_o and D_o are the width, height, and depth of output.

3.3.4 Fully connected Layers:

Weights, biases, and neurons are parts of Fully connected layers which connects the neurons layer to layer.

3.3.5 SoftMax Layer:

The other name of logistic layer is SoftMax which relies at the end of Fully connected layer. Binary classification is done using logistic layer and multi classification is done by SoftMax layer which is the last layer of CNN.

3.4 EXPERIMENTAL SETUP

3.4.1 Anaconda Navigator

Anaconda Navigator is used which helps to use the python distribution for easy computation. It is an Open-source software which helps in easy installation and are supported by all environments like Linux, Mac and windows system with less dependencies. This helps to initiate the process with less cost. TensorFlow is used as both interface and framework for understanding machine learning models.

3.4.1 Data augmentation and Drop-out Technique:

Data augmentation is a technique to enhance the feature extraction process through 360-degree rotation of the image. Example shown in Fig.2.

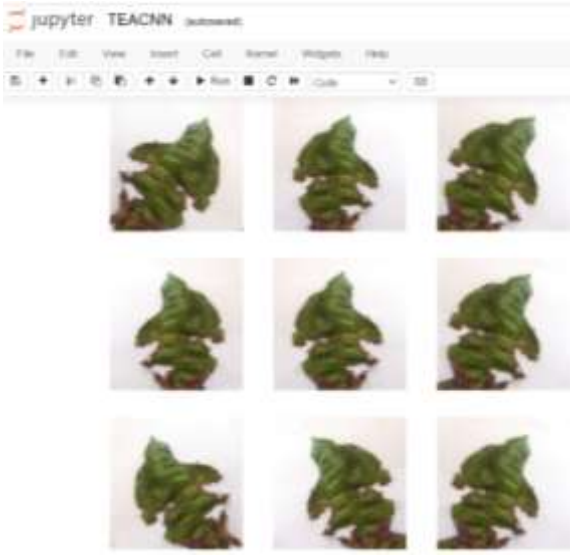

Fig.2. Data Augmentation - Example

When an image is rotated 360 degrees, there arises a chance of losing a pixel data from the image. In order to prevent the same, a regularization technique called Dropout is being used. Overfitting is a common issue faced during image processing, and it can lead to issues like inconsistent / poor performances outside of using the training data which affects the overall performance of the CNN with a smaller dataset of training data. Dropout regularization is one of the techniques to prevent the overfitting problem [1].

3.4.2 Epochs Conducted:

Several Epochs were conducted to obtain the best possible accuracy at around 92.7%. With the support of Adam optimizer, this level of accuracy values was able to obtain and the type of entropy used is Sparse Categorical Cross entropy. The Fig.3 illustrates the computational speed, number of epochs and the training and validation accuracy details.

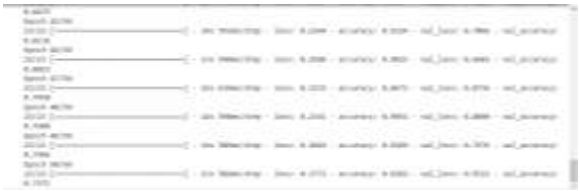

Fig.3. Epochs performed

3.4.3 Streamlit Framework:

Streamlit is an open-source framework which enhances the user-friendliness of the system. Streamlit software has further advantages since Streamlit consumes comparatively reduced storage space than other available frameworks. In the proposed model – Streamlit framework is used to display the name, type cause, symptoms and precautions of the disease.

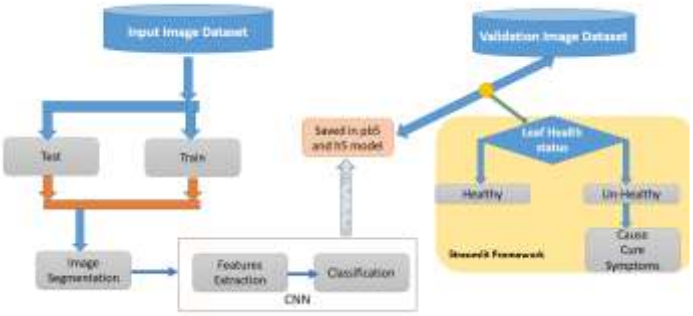

Fig.4. Flow diagram

4. RESULTS AND DISCUSSION

4.1 IDENTIFICATION AND CLASSIFICATION OF DISEASE

In this proposed model for analysing tea leaves, for the presence of any diseases and classifying the same - a non-destructive method based on computer vision is being developed through CNN technique. Deep learning-based convolution neural network technique is used to classify whether the leaf is infected with any disease, and specify the name of the disease, where the details of the infected area are keenly noted using YOLO. Few examples of Identification and classification of disease in tea leaves are illustrated in Fig.5 to Fig.8.

Fig.5. Healthy Tea Leaf

Fig.6. Disease – Anthracnose

Fig.7. Disease – Graylight

Fig.8. Disease – Red Leaf spot

4.2 STREAMLIT FRAMEWORK (CAUSE, SYMPTOMS AND PRECAUTIONS)

In order to have a user-friendly output, the proposed system makes use of Streamlit framework to display results in the required design and colours in a cost-effective approach. By making use of the Streamlit framework, the system outputs the disease name along with the cause, symptoms and precautions for the disease in a single page display. The experimental result examples are illustrated below in Fig.9 and Fig.10.

Fig.9. Streamlit Result – Brownblight disease

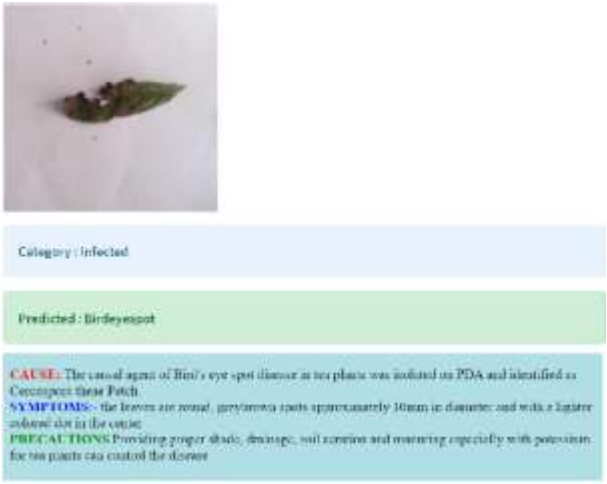

Fig.10. Streamlit Result – Birdeye spot disease

4.3 MEASUREMENT OF PERFORMANCE

The Fig.11 illustrates the training and validation accuracy, and Training and validation loss achieved. Further better accuracy percentage can be achieved with increased number of epochs. The Fig.12 shows the output of overall loss of 26.58% and overall accuracy of 88.28%.

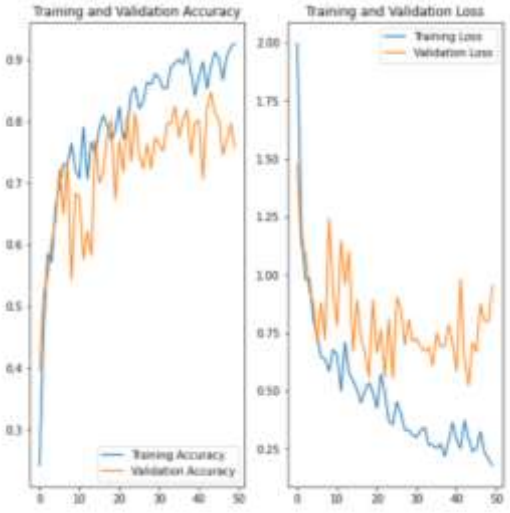

Fig.11. Training and Validation – Accuracy and Loss graph

Fig.12. Overall Loss and Accuracy

Upon the review of the other researched models in the recent years, the accuracy level obtained in this presented paper based on Convolution neural network is at-par (or) better than the previous discussed models based on alternative techniques such as Support vector machine (SVM) or Artificial neural network (ANN). The Table.1 compares the current proposed model with various other models discussed by the researchers in the past.

Table.1. Comparison of existing work

Author (s)	Input Image	Classifier	Accuracy
Arivazhagan et al. [5]	-	Min. distance classifier	86.00%
Zhang et al. [6]	Any	BBO + FNN	89.11%
Sendin et al. [7]	Maize	PLS-DA	83-100%
Nandi et al. [8]	Mango	SVR	87.00%
Krizhevsky et al. [1]	Any	ImageNet classification	84.70%

5. CONCLUSION

This computer-vision based system is intended to address the on-going inspection constraints faced by tea industries in identifying the disease without any human expertise dependency. Moreover, a Non-destructive method of inspection is highly preferred as that leads in testing of multiple leaves at a time. So, the proposed model is designed with CNN- Deep learning-based techniques through which multiple images can be categorized at a time without any manual intervention or destruction of leaves. Also, adjustment of learning rate is considered as one of the major shortcoming which was attempted to overcome in this system by increasing number of epochs thus results in increasing the accuracy rate. Moreover, imbalance of dataset was also considered to be a point of concern in the earlier works where we try to overcome by increasing the number of images for training and testing purpose. In addition to the system enhancement techniques- most of the existing works only deals with identification of the name of the diseases where in the proposed model is designed for industrial purpose and designed to be user friendly using Streamlit framework. The proposal processes the input data and classifies whether the leaves are healthy or not and displays the cause, symptoms, and precautions to be taken. Future scope of work will be based on increasing the efficiency % by developing further more balanced dataset.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/code/rizqyad/tea-leaves-disease-classification, reference number [12].

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