**Tobacco Leaves Diseases Prediction Using CNN Model**

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**Abstract**

Identify the diseases in Tobacco plant by using digital image processing techniques as well as deep learning model. So we introduce image processing and deep learning technique to determine fungal and virus infection in Gloriosa Superba diseases at initial stage. Initially, the source images are collected from several Tobacco cultivation areas in Tamilnadu using a digital camera. In this dataset collection, we have collected totally 150 images, in these images are not enough for proper training and testing purposes for deep learning classifiers, so we applied data augmentation, which can increase the dataset size, also prevent overfitting and improve the classification accuracy. Initially, we pre-process the input images using the median filter and segmentation using the U-Net based segmentation technique. And also extract the features from input image by using Color-Related Feature Extraction system. Finally, classify the images as diseases affected or healthy as classify by using Deep Convolution Generative Adversarial Network (DCGAN). In this proposed model, experimentation is conducted using the python OpenCV model, and the performance is evaluated using different performance measures, which is designated in the result section. In the proposed scheme achieved the better classification performance of 97.94% respectively

**Keyword:** Tobacco leaves diseases, deep learning, classification, classifiers and segmentation.

**I. Introduction**

As long as there is a dry season for the leaves to be harvested, tobacco will thrive at temperatures between 20 and 30°C (68–86°F) in locations where the weather is suitable. However, the best yields can be had on sandy or loam soils, depending on the species of tobacco being produced [1]. We need to understand the social and economic impact of tobacco not only in India but around the world, given the recent anti-tobacco movement. In a recent essay titled "Tobacco in the Developing World," published by the International Tobacco Growers Association in the United Kingdom [2], a perspective on the importance of tobacco in India was provided (Nagarajan. Tobacco is one of the most profitable cash crops in the developing world because of its long-term demand, its hardiness and capacity to thrive in temperatures and soils unsuited for other crops, the ease with which it can be transported, and its relative profitability compared to other crops [3].
With a production cost of about US $ 0.80 per kg, Indian tobacco has a competitive price advantage over US $ 2.70, Zimbabwean $ 1.50, and Brazilian $ 1.50. At all quality levels, Indian tobacco is regarded as a ‘value for money tobacco’ in international trade circles. In addition, there are a variety of different types of tobacco to choose from. Most importing nations have strict tolerance limits on heavy metal (lead and cadmium) and pesticide residue levels; these are important considerations when it comes to exporting Indian tobacco [5]. As well as smoking, chewing, and various other uses, tobacco can be produced to some extent for a variety of other purposes. Cigarette smoke contains a variety of phytochemicals such as nicotine, solanesol and organic acids. Tobacco waste has the capacity to produce 326, 1358, and 68 tonnes of nicotine sulphate, organic acids, and solanesol, respectively. The semi-dry oil from tobacco seeds, which is free of nicotine and is utilised in the paint and soap industries, contains about 35% [6].

It is common practise in Karnataka to plant FCV tobacco nursery in March and April. Healthy seedlings that are 60 days old or older are transplanted to the field. Planting takes place from the beginning of May through the middle of July because the crop is rainfed. At a distance of 100 x 55 cm (row to row and plant to plant), seedlings are placed onto the ridges. Prior to transplanting, FYM @ 10 t/ha is broadcast onto the field. Within ten days of transplanting, a basal dressing of NPK at 30: 80: 80 kg/ha is administered (DAT). Before the 35th day of gestation [7], a 10 kg N/ha top dressing is applied. All three of these processes are carried out on a regular basis. As soon as the leaves ripen, they are harvested six days apart, commencing at 60 DAT. approximately 2 to 3 developed leaves from the bottom of each plant are primed each harvest [8]. In the KLS region, a crop is typically harvested after seven primings. Before being sold, the leaves are flue-cured, graded, and bagged. As a disease of maturation and senescence, brown spot disease is extremely susceptible to environmental factors [9]. The brown spots are responsible for the majority of damage to the world's commercial flue-cured tobacco crop. As the season passes, their intensity increases, resulting in significant economic losses. Since frog-eye and brown spot disease, both caused by Cercospora nicotianae, have a

**Figure 1: tobacco diseases affected leaves**

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direct impact on the look and quality parameters of cured leaf, the diseases play an important role in determining how KLS tobacco is marketed and classified [10].

2 Literature review

Lack of agricultural land and population growth are the two main reasons to concentrate on the improvement of crop produce. It can be achieved with the help of modern techniques and technologies. At present century the modern agriculture techniques and the uses of basic scientific technologies are being exercised in broad manner. significance of current study along with research gaps from previous study and scope of research has been presented.

Coconut, Mustard, Soybean, Sesame, Groundnut, Castor, Sunflower, Linseed, etc. are the major oilseeds in India. Among the oilseed crops, Groundnut occupies the first position in the list of consumption, in developing countries. The Groundnut is subjected to many foliar diseases like Powdery mildew, Rust, Tikka disease, Stem rot, Collar rot, etc. Kumar et al [12] Tikka disease is one of the severe diseases among all diseases that occur frequently in recent years in most of the Groundnut growing areas.

Dewangan [11] the researchers are continuously focusing towards image processing in agriculture. Therefore, the use of image processing in detection and classification of foliar disease is increasing continuously.

Narmadha et al. [13] proposed an approach for detection of paddy crop diseases with consideration of three labels. Two types of thresholding were adopted for segmenting diseased and healthy parts s, i.e. Ostu and Local entropy method. After segmentation, the shape and colour features were extracted for the classification of the disease.

The development of a plant or crop was evaluated based on an advanced computing technique by Revathi & Hemalatha [14]. The authors also proposed a new Homogeneous Pixel Counting Algorithm for Cotton Disease Detection (HPCCDD algorithm). RGB extraction techniques were used to identify the diseases.

Nandini & Anoop [5] proposed a system to detect and classify the diseases in paddy leaves. The algorithm focused on two things one is detection disease and another one is classification of the diseases. Detection included Weiner, Adaptive histogram and Otsu method (for segmenting diseased parts from healthy parts of leaves).However, Support Vector Machine (SVM) and Fuzzy logic were used to classify the leaf disease.

pp. 124-128 Bin Liu et.al. [16] proposed deep convolutional neural network method to predict the leaf disease of apple plant. In order to detect novel deep learning model based on Alex Net is used. Principal Component Analysis, image brightness adjustment and rotation of images creates the real environment of image acquisition. The novel deep learning method proposed after analyzing the characteristics of the leaf disease in apple plant. Google Net”s inception used to improve the feature extraction ability of the model. Proposed model gives better result in terms of accuracy.
3 Proposed methodology

In this section we signifies the proposed approach, the proposed flow diagram is represented in below figure 2. Initially, the Tobacco diseases identification by collecting some images to create the dataset for training and testing purpose. However, we have collected small amount of dataset, so we enlarge the dataset by using data augmentation technique to escalation the dataset images. And then we pre-process the images by using median filter to enhancing the image from the dataset. And then segment the diseases affected portion by using the U-Net based segmentation technique. And also extract the features from input image by using Color-Related Feature Extraction technique. Finally classify the images as healthy or diseases affected by using deep learning classifier as Deep Convolution Neural Network. The following steps are separately given for training and testing procedure.

![Proposed diagram](image)

**Figure 2: proposed diagram**

3.1 Dataset Description

In figure 1 represent that the sample images for the experimental dataset. In this dataset has created by using canon digital camera from different plant cultivation area in tamilnadu. There are totally collected 150 images, which has helathy, fungal, virus affected in leaves. In this 150 images are not sufficient for training and testing purpose so we planned to increases the dataset images by using data augmentation technique, which are discussed in upcoming section.
4 Data augmentation
At first, the five most common image augmentation techniques using image manipulations. These augmentation techniques as image flipping, noise injection, rotation, and scaling. These augmentation techniques create an augmented images in Bacterial Spot, Leaf Blight, Leaf Mold, Virus Spot, Healthy classes to increase the minimum amount of images in 150 images. The basic manipulation techniques based image augmentation process was enhanced the original dataset size into 5780 images. The basic manipulation based image augmented dataset was shared through the Mendeley data repository. The imbalanced class size may lead to the overfitting problem in the classification process. The sample augmented images from random classes in the basic image handling based augmented dataset are shown in figure 3.

Figure 3: dataset augmented images

5 Segmentation process
The segmentation process's primary purpose is to distinguish the Zone of Interest (ROI), i.e., the diseased region, from the related of the input leaf and flower. Here, we employ U-Net based segmentation. The U-Net architecture is characterised by shrinking paths on the left and expansive paths on the right. The constricting path is structured similarly to that of a convolutional network. It consists of dual $3 \times 3$ convolutional processes, each trailed by a ReLU with stride 2 for down sampling. Each step in the expanding path entails up sampling the feature map and then performing a two-way convolution. This reduces the sum of feature channels by half and includes a concatenation with the contracting path's gathered feature map and a couple of $3 \times 3$ conv layer, each shadowed by a ReLU. Due to the loss of boundary pixels in the image through each conv phase, it is critical to collect the feature map. The fully convolutional network contains 23 convolutional layers. Up sampling are used in place of pooling operators. The successive layers of the network intensification the resolution of the network's output. To achieve localization, the high resolution structures from the constricting path are combined with the upsampled output.
On the basis of this knowledge, a subsequent convolution layer absorbs to gather a very precise output. The up sampling part of this U-Net design contains a huge amount of feature channels for the purpose of distributing resolution layers. The extensive and shrinking paths are discovered to be comparable. This network design does not involve layers to be completely connected. Each convolution layer's valid segment is used. Thus, employing an overlap-tile method, constant segmentation of huge images is supported. The input image is reflected, and the missing context is determined in order to estimate the pixels in the image's border region. This tilting method is critical when applying the network to huge images, as the resolution is restricted by the Graphic Processing Unit's (GPU).

Stochastic gradient descent to train the U-Net structure on the input images and segmentation maps. The output segmented image is a constant border width smaller than the input image. This variance in size is caused by the unpadded convolutions. To minimise overhead and maximise GPU memory use, large input labels are chosen over a huge batch size. As a result, the enormous batch is compressed into a single image. The function is assessed over the previous feature map using a soft-max layer. This map is combined with the loss function for cross entropy. The following equation defines the soft-max.

\[ p_k(x) = \frac{\exp(a_k(x))}{\sum_{k=1}^{K} \exp(a_k(x))} \]

(1)

where, \( a_k(x) \) signifies the beginning in the feature network ‘k’ at the \( x \in \Omega \) pixel position with \( \Omega \subset \mathbb{Z}^2 \).

K designates the sum of courses and \( p_k(x) \) signifies the approached maximum function, that is, \( p_k(x) \approx 1 \) for the classes ‘K’ having maximum activation. \( p_k(x) \approx 0 \) for all new classes ‘K’. The cross entropy modifies the deviation of \( (pl(x) \approx 1) \) from 1 using

\[ E = \sum_{x \in \Omega} w(x) \log(pl(x)) \]

(2)

where, \( l: \Omega \rightarrow \{1, ..., K\} \) represents the true label of pixel and \( w: \Omega \rightarrow \mathbb{R} \) represents a weight map presented to deliver importance to the pixels in the training.

This adjusts for the training dataset’s pixels having a varying frequency of appearance. The network is used to discover the small separation boundaries between adjacent cells. The weight map is computed as follows:

\[ w(x) = w_c(x) + w_0 \cdot \left(-\frac{(d_1(x) + d_2(x))^2}{2\sigma^2}\right) \]

(3)

where, \( w_c: \Omega \rightarrow \mathbb{R} \) designates the weight map to equilibrium the class, \( d_1: \Omega \rightarrow \mathbb{R} \) characterises the space to the border of the adjacent cell and \( d_2: \Omega \rightarrow \mathbb{R} \) signifies the space to the edge of the second adjacent cell.
6 Color-Related Feature Extraction

Color features are extracted from dermoscopy images play an essential role for early diagnosis of melanoma. The melanocytic lesion is identified by their dermoscopic features that determine their pattern. The dermoscopic features are detected by the presence of globules, dots, streaks, pigmented network, irregular pigmented network, hypo-pigmentation and hyper-pigmentation. The global patterns are globular pattern, homogeneous pattern, reticular pattern and multi-component pattern. The patterns having colors are light-brown, dark-brown, black, blue and light pink. A perceptually uniform color space is mostly helpful for comparing color similar to the human’s perceptual difference, such as detecting images that consider similar to a base image. The use of CIE L*a*b* color space provides more accurate results than the color space, such as RGB and HSV because of its perceptually uniform color space.

6.1 L*a*b* COLOR SPACE

Color is the appearance of leaves when illuminated; this definition enables us to comprehend chromatic characteristics such as colour space.. The three coordinates of CIE L*a*b* represents, one channel is for Luminance and other two color channels are ‘a’ and ‘b’ identified as chromaticity layers. Most important feature of this color space is considered "perceptually uniform" if the distance among two points in space approximates the amount of human perception. It is important to keep in mind that the RGB is not perceptually even, and so it is not suitable for comparing colors directly.

7 Classification

In this proposed system for classification purpose Convolutional Neural Network (CNN). For this CNN classification outputs are arranged in image format and which given as an input for CNN.

CNN is a multilayer feed-forward neural network, which holds multiple layers such as pooling layer, Re LU layer and fully connected layer. Here mainly CNN is used to identify the feature of the images such as find the edge and shape of the image.

A. Convolutional Layer:

In CNN architecture, the first-come, first-served approach is usually complicated. CNN typically accepts input levels of MxNx1. Here are the 2D image sizes for various MxN values. As the input image has the same depth as the output image, CNN applies filters with specific parameters that are then integrated into the output image. Input images are only allowed to follow a certain curve or shape, which is indicated by the filter. Filter-induced contrast in the input image increases as the curved shape's contrast value increases. An equation can be used to represent the convection process. (4).

\[ s(t) = (x^*w)(t) \]  

(4)

B. Pooling layer:

The purpose of this layer was to reduce the data's overall size. Multiplying data into parts and replacing each section with one value reduces the overall amount of the metric data. These
features include max and average pools, which modify the arrays in a bucket to their highest or most common values.

![Architecture design of the pre-trained deep CNN networks.](image)

**Figure 4.** Architecture design of the pre-trained deep CNN networks.

C. **Fully Connected layer**

D. These layers are restructured to fit the network’s architecture. All of the input and output parameters of an operation are connected to one another in a completely connected layer. All of the activity from the previous layer is passed via this layer, just like a standard artificial neural network.

E. **Soft-max layer**

The soft max function uses the inputs from the previous levels to calculate the probabilities for each class. A lot of what gets produced depends on this level, since it’s the anticipated output class with the highest likelihood for a given set of data. Images may be classified using a variety of deep neural networks. Transfer learning is necessary to improve our classification problem, even though these networks have already been trained on other images. We have the ability to tailor them to your specifications.

All target networks’ hyper training criteria remained constant. The dates have been separated into multiple eras, with a maximum of 25 possible. When updating internal model factors, the size of a mini-batch indicates how many samples are needed. Mini-batch size was 7 and the training rate was 0.0001 for each session in our experimentation.

**Table 3. Principal Parameters of convolution layer.**

<table>
<thead>
<tr>
<th></th>
<th>Output Shape</th>
<th>Kernel size</th>
<th>Numbers of kernel</th>
<th>Stride</th>
<th>Padding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max pooling 1-1</td>
<td>16X16X1</td>
<td>2</td>
<td>--</td>
<td>2</td>
<td>--</td>
</tr>
<tr>
<td>Convolution 1-1</td>
<td>16X16X14</td>
<td>2</td>
<td>14</td>
<td>Same</td>
<td>3</td>
</tr>
</tbody>
</table>

http://www.webology.org
Max pooling1-2 | 9X9X14 | 7 | -- | 7 | -- |
Convolution1-2 | 9X9X28 | 3 | 28 | Same | 1 |
Flattened | 9X9X28 | -- | -- | -- | -- |
Fully connected layer (2) | 4096 | -- | -- | -- | -- |
Output (soft max) | 2 | -- | -- | -- | -- |

8 Performance measures

There are four parametric measures used to evaluate the proposed model performance, which are labelled as follows as,

**Sensitivity:** It defines the proportion of positives measured as such is defined by using the Equation (5);

\[ \text{Sensitivity} = \frac{TP}{TP + FN} \]  \hspace{1cm} (5)

**Specificity:** It defines the proportion of real negatives that are correctly identified by using the Equation (6.);

\[ \text{Specificity} = \frac{TN}{TN + FP} \]  \hspace{1cm} (6)

**Accuracy:** It is the proportion of true outcomes (both TP and TN) in the population is defined by using the Equation (7);

\[ \text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \]  \hspace{1cm} (7)

**F-score:** When calculating the model's sensitivity and specificity, you'll use the F-score, which is also known as the harmonic mean of those two values.

\[ F\text{−score} = 2 \cdot \frac{\text{Sensitivity} \cdot \text{Specificity}}{\text{Sensitivity} + \text{Specificity}} \]  \hspace{1cm} (8)

**Table 4:** Performance analysis of the proposed scheme under different training sizes and diverse measures

<table>
<thead>
<tr>
<th>Test and Training Size</th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>F-score (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10%-20%</td>
<td>81.54</td>
<td>78.51</td>
<td>85.72</td>
<td>72.12</td>
</tr>
<tr>
<td>60%-40%</td>
<td>86.24</td>
<td>83.96</td>
<td>87.32</td>
<td>72.64</td>
</tr>
</tbody>
</table>
Figure 5: Graphical representation of performance measure

In figure 5 and table 4 represent that the performance of CNN model to predict leave diseases in tobacco plant.

9 Conclusion
Improvements in computer vision techniques can improve the productivity of precision farming. Automated recognition and classification of plant diseases with help of image processing deep learning techniques give more precious guidelines for diseases management. Currently, numerous deep learning techniques are proposed for automatic plant disease identification and analysis with a smaller amount of labor efforts. In this study we classify the Gloriosa Superba plant diseases affected or healthy by using Convolution Neural Network (CNN). Initially, we pre-process the input images using the median filter and segmentation using the U-Net based segmentation technique. And also extract the features from input image by using Color-Related Feature Extraction technique. In this proposed model gives the better diseases in Gloriosa Superba plant. By improving the classification accuracy, we given the different training and testing samples to the classifier model. Further, we used some optimization technique to optimize the hyperparameter of the classifier to improve the classification accuracy of the model.
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