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Disease Detection In Tea Leaves Using Computer Vision And Deep Learning Techniques- A Review

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Abstract— Agriculture is the prime factor that controls the significant population of the world. As the large increasing population is directly or indirectly involved in Agriculture fields, it is the foremost and primal source of occupation. Among the agriculture industry Tea plantation agriculture is one of the most essential beverage people used to consume. Likewise in agriculture industry several challenges like crop disease and pest problem widely effect the production. Similarly in Tea plantation agriculture the production is severely affected by diseases. Therefore, automatic detection of disease in tea leaves at early stage has become an important factor. The concept of machine learning based techniques such as Deep Learning techniques diagnose the system for analyzing unhealthy leaves which seems interesting because there is a scarcity of skilled specialist to analyze images and make diagnostic conclusion. Furthermore, the introduction of new sophisticated hardware and software system approach has prompted the development of automated detection system for the early identification of tea leaf disease. This effort will facilitate the researchers those who are new in this field to get a quick introduction towards the trend of Deep Learning and Computer Vision in Tea plant leaves disease detection.

KEY WORDS: Deep Learning, Computer Vision, Tea Leaf Disease.

I. Introduction

In India Tea is one of the most famous beverages among the people. With the increasing world population, the need to improve the quality and quantity of tea plantation has gained significant importance. The use of modern tools especially based on information technology has enable humans to achieve goals to a great extent almost all over the world [1]. But this benefit is achieved at the cost of increased numbers and types of tea leaves disease [2]. The occurrence of Tea leaf disease has negative impact on the Tea plant production. If disease are not discovered in time, plantation insecurity will increase [3]. Early detection is the basis for effective prevention and control of Tea leaf disease and they play an important role in the management and decision making of Tea plantation agriculture production.
Disease infected Tea plants usually shows obvious marks on leaves, stems. Generally, disease and pest conditions presents a unique visible pattern that can be used to uniquely diagnose abnormalities. Usually, the leaves of Tea plant are the primary source for identifying plant disease and most of the symptoms of disease may being appear on the leaves [4].

In most cases agriculture and forestry experts are used to identify disease in Industry or farmers identify disease and pest based on experience. This method is not only subjective but also time consuming, laborious and inefficient. Farmers with less experience may misjudge and may use drugs blindly during the identification process. Quality and quantity will also bring environmental pollution which cause unnecessary economic issue. To counter these challenges research into the use of image processing techniques for Tea plant disease diagnosis has become a wide research topic.

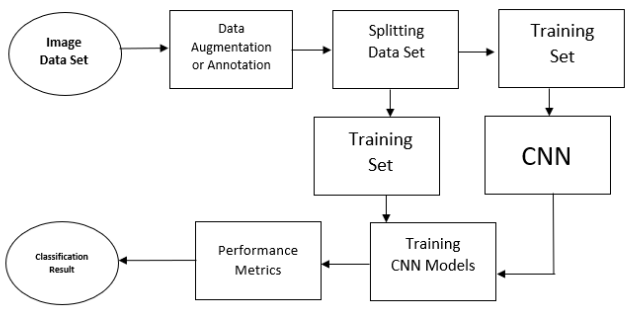

Figure 1: Block Diagram of a Deep Learning based Tea Plant Leaf Disease Recognition Model.

II. Tea leaf disease

The Tea leaves dataset in figure 2 contains images of selected tea leaves disease names as **Blister Blight, Red Scab, Red Lead Spot** & **Leaf Blight**.

A. Brown Blight

Brown blight is a disease that occurs on perennial ryegrass during cool, wet, and cloudy periods in the spring or fall. Brown blight is a "Helminthosporium"™ disease, which is a complex of diseases caused by fungi that produce large, cigar-shaped spores.

B. *Red Rust*

Red rust of tea is one of the major disease in tea cultivation areas of Nepal. It may reduce the fresh yield of about 30-50% if not controlled. We've prepared here about the cause, symptoms and control measure of this algal disease.

C. *Red Spider Mite*

Red spider mite present of the tea crop throughout the year because tea is a perennial crop provides food and shelter due to which Nymphs and adults of RSM lacerate cells, producing minute characteristic reddish brown marks on the upper surface of mature leaves, which turn red in severe cases of infestation.

III. LITERATURE REVIEW

Different types of disease of leaf have been investigated including disease in rice leaf, wheat leaf. Various paper describing the methods suggesting ways to implement the detection of disease will be discussed here in the paper review.
Plants infected with disease usually exhibits visible marks or lesions on either leaf, stems, flowers or in fruits. Generally, each disease or pest condition presents a unique visible

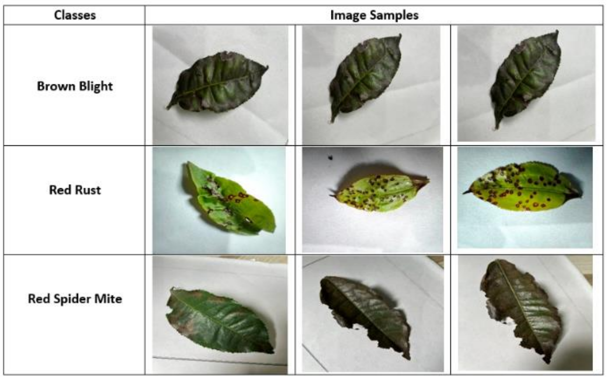

Figure 2: Classification of Disease Types in Tea Plantation

pattern which can be used to uniquely identify or diagnose the anomaly. Extension officer often tries to visualize the control of disease through training themselves to detect and diagnose the disease by some laboratory training test on plants. In context to this, the techniques emerge as a limited boundary.

- The number of extension officer is not that much for performing the test to whole farms. So farmers are not able to get adequate services. [5].
- Training of extension officers becomes costlier to make it possible for farmers [6].
- The farmers and extension officers may not be able to detect the non-familiar pest or disease [7].
- Frequent monitoring of early disease detection is must and stopping it from spreading all over. This process becomes time-consuming, inefficient to perform on ongoing plantation [8], [identification of leaf disease in pepper plant using soft computing techniques][9,10,11].

Computer vision and object recognition in particular has made a successive growth in the field of plantation security system from diseases. The PASCAL VOC Challenge and more recently used Large Scale Visual Recognition Challenge (LSVRC) based on Image Net dataset have been widely used as benchmarks for numerous visualization related problems in computer vision, including object classification. In 2012, a large number of deep convolutional neural network achieved a benchmarks of 16.4% error for the classification of images into 1000 possible categories, while in the following 3 years, various advances in deep convolutional neural network lowered the error rate t only 3.57%. It is being very effective to work by training large neural network, because the trained models can classify the images very efficiently. Use of Deep neural network has given successive results in many diverse domains as example of end-to-end learning. Neural Network works as mapping between an input-such as an image of disease plant-to an output-such as crop disease pair. They are trained by tuning the network parameters in such a way that mapping improves during the training process.
To develop the accuracy in image classification for plant disease diagnosis, a large number of dataset of images are required (diseased image and healthy image), but such datasets does not exist and even smaller datasets are not freely available. To minimize this problem, the Plant Village project has begun to collect thousands of image of healthy and diseased plant and has made them openly and freely available [11-15].

In [16], the authors proposed a model for plant disease detection and classification with the help of healthy leaf images and leaves with diseases. They have taken 25 different types of plants with 87,848 images which include plants diseases, and also healthy plants. Their model performance has been reached up to 99.53% accuracy. Due to the high level of performance, CNN is highly recommended for the detection of plant diseases.
In [17], the authors have done a review on the usage of new techniques in imaging processing and computer vision approaches for plant diseases classification.
In [18], Chen et al. proposed GMDH-Logistic model, which is a self-adaptive classification method used for plant disease detection. In this, the authors introduced a model approach for the automatic detection, recognition, and classification of plant leaf diseases by image process method we perform the feature engineering analysis Plant disease classification through leaf symptoms plays an important role, Zhang, have introduced a novel segmentation method of hybrid clustering to divide the given color image into several pixels to improve the classification accuracy and also to reduce the different segmentation carried out by EM algorithm [19].
In [20], Saradhambal et al. offered a method for building a system that can identify plant diseases automatically. By using the k-means clustering technique and the Otsu s classifier, research was done to predict the infected region of the leaves. Both the form and texture features were retrieved in the suggested study. Shape-oriented features included area, color axis length, eccentricity, solidity, and perimeter, and texture-oriented features included contrast, correlation, energy, homogeneity, and mean.
In [21], Aravind et al. stated for automating the plant disease detection system, research was done on maize crop diseases. Each image was processed to obtain SURF (Speeded up Robust Features) features. The k-means technique was used to cluster the features. Histogram and GLCM were employed as the two feature extraction techniques. These two techniques were used to investigate different textural aspects. Multi-class SVM, based on different kernel functions including linear, polynomial, and radial basis function, etc., was used for classification.
Sabrol, kumar et al. [22] proposed algorithm that begins with the digital image acquisition of contaminated and uncontaminated plants; image pre-processing; segmenting the images to extract features for detection and classification based on feature analysis, neural network, support vector

machine, fuzzy and rule-based classification, and feature extraction from segmented images. Researchers working in the fields of plant pathology and pattern recognition should benefit from this review.

Khirade et al. [23] centered on identifying and classifying plant diseases. To divide the plant's diseased area, the authors employed Otsu's technique and Kmeans clustering. They classified plant illnesses and extracted characteristics of affected leaves using feature extraction and classification algorithms.

Ramakrishnan et al. [24] focused image processing methods to find diseases in groundnut plants. This approach converts RGB photos of the leaves to HSV color images once they have been obtained. In the study of color and texture, co-occurrence matrices and feature extraction analyses are applied. Basically, there are two ways to analyse texture photos. The first approach is a structured one, whereas the second is a statistical one. Back propagation method is used to classify and identify groundnut illness. Back propagation has two stages: phase 1 is propagation and phase 2 is weight updating.

Ananthi et al. [25] outlined a technique for quickly identifying and classifying plant diseases. According to the procedure, a digital camera takes the image first, and then image processing techniques are utilised to extract certain key information. The three bacterial, fungal, and viral plant diseases are the writers' primary focus. To find and categorize the disease, HSI and SGDM approaches were applied. The RGB image was converted using the HSI technique, and color occurrence was done using the SGDM technique.

All the above-named papers are totally studied. These papers gave tons of knowledge regarding the chosen topic. Therefore, the basics foundation construct trends to be discovered from the top of the mentioned papers. Understanding above papers advancement in Deep Learning were revised.

IV. RELATED WORK

When plant are infected by disease it usually exhibits visible marks on either the leaves, stems, flower or fruits. Generally, each disease or pest condition present a unique visible pattern which can be used to uniquely diagnose the anomalies present in it. A large number of officers are trained to diagnose the pest and disease by visual inspection or by conducting test in laboratories on plant leaf or plant fruits samples. These approaches however have several limitations:

1.Unavailability of officers to cover the whole farm. Thus, many farmers may lack extension service t critical times [26-30, 31, 32].

2.Training of extension officers is costly and time consuming [33].

3.Difficulty in finding out the non-native disease and pest for farmers and extension officers [34, 35].

4.A high level of expertise is required to distinguish between anomalies with visually similar characteristics [26, 36-39, 35, 40]. In such a case even a highly trained expert may still arrive at a wrong diagnosis due to fatigue poor illumination or poor eye sight.

5.Continuous monitoring is necessary for early disease detection and prevention of disease from spreading is a tedious work and very time consuming. It is also costly and inefficient.

The use of Image Processing Techniques (IPTs) in crop pest and disease is an active era of research aimed at overcoming these limitations.

In this section, I will present an overview of the work done in the field of leaf disease detection using IPTs. Section 5.1 shows that early works relied on classical image processing procedures and hand-crafted feature extraction from leaf image. These features were then used to train shallow classifier algorithms such as Support Vector Machine (SVM), Principal Components Analysis (PCA), K-Nearest Neighbor (KNN), Decision Tree Classifier (DTC) and Random Forest (RF) [41, 42, 26, 36, 38, 17, 43, 40, 44-49].

V. METHODOLOGY

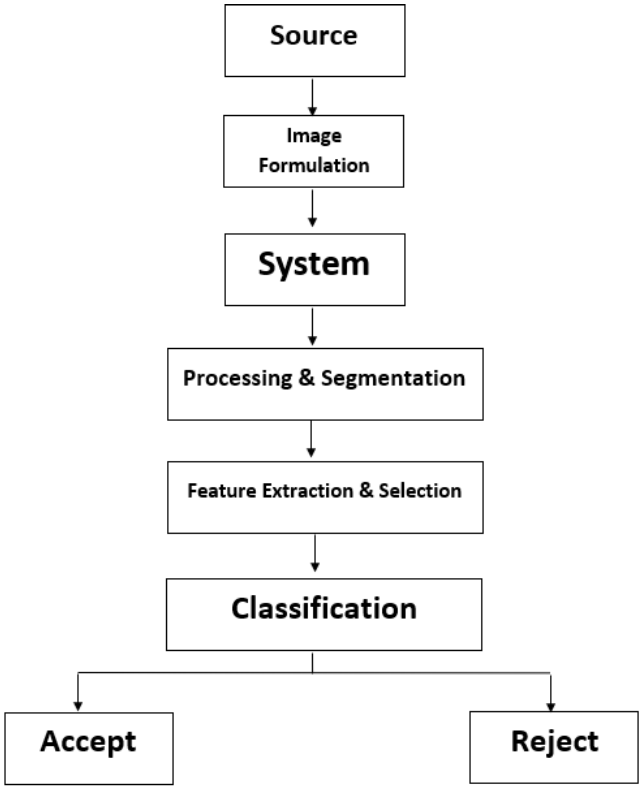

Figure 3: Disease Detection and Classification Model

A. *Identification of Tea Leaf Disease using CNN*

CNNs are a subset of deep neural networks that are frequently used to identify patterns in images. In essence, CNN is a deep learning (DL) algorithm that takes an input image, applies biases and learnable weights to different objects in the image, and can distinguish between them. Convolution, ReLu, Pooling, and Classification (Fully Connected Layer) are the four main operations of CNN. Applications for CNN include the analysis of geographical data, computer vision, and natural language processing, among others. The use of shared weights in convolutional layers, the reduction in pre-processing, the simplicity of classical feature extraction [50], and the capacity to handle both two-dimensional and three-dimensional data are some of the benefits of CNN.

The CNN is mostly employed for picture recognition and classification among the many DL models. To identify and categorize plant diseases, many researchers have employed the existing deep CNNs models, created their own models from scratch or by utilizing transfer learning.

The researchers can employ some of the existing models, such as AlexNet [51], Caffenet, VGG-19 [52], GoogleNet [53], and Inception-Resnet, to create their own models [54]. All of the current models already have their weights pre-trained using datasets like ImageNet [55] and PASCALVOC [56]. Numerous applications, including pedestrian detection [57], gender and smile categorization [58], estimate of heterogeneous face attributes [30], writer identification using CNN [59], biological picture analysis [60], and concrete crack detection [62], among others, use CNN architectures. After AlexNet [51] in 2012, numerous cutting-edge DL models were released. A brief overview of some of the well-known CNN architectures is provided in the section that follows.

The ImageNet Large-Scale Visual Recognition Challenge has been won by AlexNet [51]. Each of the first seven layers in AlexNet receives the Relu activation function, and dropout is used to lessen overfitting [63]. Similar to the GooLeNet [53] which was created in 2014 and has an inception architecture, it employs a parallel combination of 1x1, 3x3, and 5x5 convolutional layers [63] and 3x3 max-pooling layers. It was the winner of the ILSVRC 2014 competition. In order to overcome the degrading issue, another model called ResNet [64] was created in 2015. It is made up of numerous stacked residual units [63]. Another architecture created in 2014 is VGGNet [52]. It has a number of convolutional layers, then pooling layers. It is shaped like a pyramid [65].

The architecture of ZFNet [66], which was established in 2013, is remarkably similar to that of AlexNet [67], however ZFNet has less weights. DenseNet [68] architecture includes fewer parameters and involves dense connections between the layers, which improves accuracy [69]. When compared to AlexNet [69], SqueezeNet [70] has 50 times less parameters, and its primary goal is to shrink the model using deep compression [71]. The first model created for object identification, localisation, and classification was OverFeat [72][69]. MobileNet's [73] CNN design, which has a smaller number of parameters [69], is primarily focused on the depth wise separable convolutional notion.

B. *Common CNN Architecture for Tea Leaf Disease Detection*

The next part provides an overview of the various CNN architectures that were applied to the diagnosis of plant diseases [18] as well as a quick rundown of deep learning meta-architectures that were applied to the identification of plant diseases. CNNs generally adhere to the Lenet-5 design. Fig. 4 displays an illustration of the CNN architecture, which is a common architecture. Convolution layers are the main component used to extract the feature maps from the input pictures. The feature maps are then subjected to pooling techniques like max, min, or average pooling. The output layer for the classification of the disease is the completely linked layer, which is the last layer.

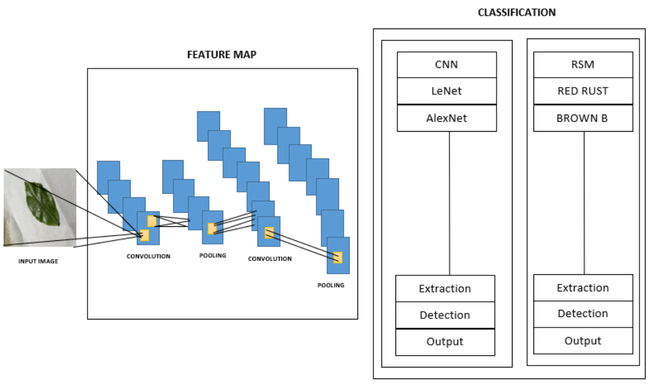

Figure 4: A TYPICAL CNN ARCHITECTURE

Fig. 4 illustrates how CNN-based DL techniques are used to diagnose plant diseases. The image provides a brief summary of the procedures involved in utilising the CNN to diagnose plant diseases. The first step is to gather or use a dataset of high quality. Both public and private datasets are possible. A sizable number of high-quality photos of both healthy and sick leaves should be included in the dataset. The dataset that was obtained may have noise, poor lighting, etc. To lessen these problems, the dataset might be subjected to image pre-processing techniques such scaling, rotation, augmentation, and geometric alterations. After the dataset has been divided into three sections—training, validation, and testing—existing or newly constructed CNN models (AlexNet, VGG, etc.) should be trained using the training data. You have the option of starting from scratch or applying transfer learning [68]. Analysing training accuracy, validation accuracy, training loss, and validation loss will reveal the model's importance. For evaluating the effectiveness of the trained model and classifying plant diseases, deficiencies, and pests, performance metrics like Log-loss, F1 score, Area Under the Curve, Precision, Recall, Specificity, etc. can be utilised. With the aid of visualisation techniques, sickness symptoms can be more clearly understood, and images of plant leaves can be found and located. [74] describes the fine-tuning of DL models for plant disease detection.

VI. CONSLUSION

In this paper, the basic knowledge of Deep Learning techniques has been classified for early detection of disease in tea leaf and presented a comprehensive review of recent research work done in early disease recognition in tea leaf. Provided sufficient data is available for training, Deep learning techniques are capable of recognizing plant leaf disease with high accuracy, data augmentation transfer learning and virtualization of CNN activation maps in improving classification accuracy and the importance of plant leaf disease detection and importance of hyper spectral imaging for early detection of plant disease have been discussed here. Most of the Deep learning frameworks stated in the literature have been a good detection effect on the datasets. But it is very difficult to prepare labelled dataset for early disease detection of tea leaf.

Pests and plant illnesses have a devastating effect on the world's agricultural sector. After a thorough analysis of the literature, it is clear that while AI-based plant disease detection solutions have grown significantly, there are still a number of issues that need to be resolved in order to create high-performing, real-time disease detection systems. This research provides an review on the fields of advancements as well as cutting-edge techniques utilizing DL, ML, and IP.

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