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Cascade Region Proposal Network (CRPN) Based Segmentation And Convolutional Deep Belief Network (CDBN) For Turmeric Plant Disease Detection

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ABSTRACT

Agriculture is one of the fundamental elements of human civilization. Crops and plant leaves are susceptible to many illnesses when grown for agricultural purposes. There may be less possibility of further harm to the plants if the illnesses are identified and classified accurately and early on. Early detection and recognition of plant disease is a prerequisite for controlling plant disease, and one of the key steps is to segment plant diseased leaf images. In this paper, Cascade Region Proposal Network (CRPN) is introduced which adopts multiple stages to mine hard samples while extracting region proposals and learn stronger classifiers. Meanwhile, a feature chain and a score chain are proposed to help learning more discriminative representations for proposals. Moreover, a loss function of cascade stages is designed to train cascade classifiers through backpropagation. Once the diseases are segmented and then it is classified using Convolutional Deep Belief Network (CDBN) is a network model that consists of a CRBM. Experimental results show the effectiveness of the proposed model in terms of precision (P), recall (R), accuracy (A) and f-measure (F1).

Keywords: *Cascade Region Proposal Network (CRPN), Convolutional Deep Belief Network (CDBN), Gray Level Co-Occurrence Matrix (GLCM), Convolutional Restricted Boltzmann Machines (CRBMs), Convolutional Neural Network (CNN), Artificial Intelligence (AI), turmeric leaf disease detection, Median Filtering (MF) and classification.*

1. INTRODUCTION

Agricultural is the backbone of country and which the basic term of food production for human. This agricultural research is aimed towards an increase in productivity and food quality with increased profit and less expenditure. The world will need 50 percent more food by 2050. Agriculture is a five trillion-dollar global industry and now the industry is switching to Artificial Intelligence (AI) technologies. With the help of AI, analyzing real-time data such as temperature, soil conditions or weather conditions is much easier for farmers to increase the productivity of their farms. Sensors with AI technology can detect weeds and decide the herbicides for applying in the field [1]. AI is also used in creating seasonal forecasting models to increase agricultural productivity. From drones, AI-enabled cameras can capture images from farms and analyze the data for problem identification, suggesting potential improvements [2]. The production of agricultural land decreases yearly due to different type's disease affection.

Turmeric herb is common in South and East India, but it is cultivated mostly in Malaysia and India as an annual crop [3]. Turmeric (Curcuma longa) is a crop of economic and medicinal importance. Like other crops, it is susceptible to a variety of diseases that seriously affect its productivity and quality. For the effective management of these diseases, detection, and identification should be done as early as possible to minimize the loss in agriculture and to preserve farming on a sustainable basis [4]. The crop productivity may be affected due to various diseases like leaf spot, leaf blotch, and rhizome rot. Appropriate detection and prevention methods must be identified to increase the production rate. Early detection of diseases and control measures will reduce the usage of pesticides and safeguard environmental conditions. The infection of such diseases causes the change in the color and appearance of the turmeric leaves. The existing methods for plant disease detection simply by naked eye observation or laboratory based techniques by experts is time consuming and requires continuous monitoring of plant. Therefore, if the plant monitoring methods can be stored by using some programming language into an automatic module then the process can be error tolerant. Hence image processing plays a vital role in disease detection and analysis [5]. Machine Learning (ML) and image processing technology provide tremendous advantages over traditional recognition methods and manual diagnosis.

Image processing is used to improve the quality of images to extract valuable information from them; as a result of this feature, image processing techniques are used in many areas of the medical and agricultural fields, such as color processing, remote sensing, and pattern recognition. Image processing techniques that are acceptable, effective, and dependable can be used to discover disease in plant leaves. Image processing can be used in a variety of fields, including biology, agriculture, medicine, engineering, computing, etc. The images are processing at hidden layer which contains different image processing layers like convolutional, padding, pooling etc., are used for training the model. Computerized image processing techniques are critical for detecting and classifying plant diseases early before they cause widespread damage to entire crops [6]. To address this, several DL, image processing, and ML techniques were being developed to detect and classify disease in plants using images of plant leaves. DL technologies can help agricultural firms succeed.

In the recent works several image processing methods and algorithms are used for the detection of turmeric plant diseases. Kuricheti and Supriya used a k-means algorithm for image segmentation and a support vector machine (SVM) classifier for feature extraction to develop a GUI system for detecting turmeric diseases and controlling their spread. Visual Geometry Group 16 (VGG 16) is an architecture used in Convolutional Neural Network (CNN) for turmeric diseased image classification and detection. Kannan and Thangavel used Linear Discriminant Analysis (LDA) and Adaptive Network Based Fuzzy Inference System (ANFIS) classifier is used for classification method and it helps to improve the detection rate and reduce the entropy loss.

AI is a faster booming technology in now-a-days, these technology involved in all sector of human life form as well as agriculture for better efficiency improvement and sophisticated purpose [7]. However these methods do not produce the sufficient accuracy results. Existing method Improved YOLOV4 (IYOLOV4) potential for lower accuracy when dealing with small objects, then might struggle to precisely locate small objects within an image. To avoid these problems in existing work to enhance the detection accuracy of turmeric diseases, a deep learning-based technique called the CDBN is proposed.

The objective of the research is to introduce a new technique called Cascade Region Proposal Network (CRPN). Proposed work steps are initially, image augmentation using methods such as image rotation, image colour, image brightness transformation, motion blur transformation and Cycle-Generative Adversarial Network (Cycle-GAN) deep learning model. Secondly, image preprocessing is computed using Median Filtering (MF) based noise removal. Then image segmentation, segment plant diseased leaf images Cascade Region Proposal Network (CRPN) which adopts multiple stages to mine hard samples while extracting region proposals and learn stronger classifiers. After that feature extraction, features are extracted using Gray Level Co-Occurrence Matrix (GLCM) method. Finally classification, classified using Convolutional Deep Belief Network (CDBN) is a network model that consists of a CRBM. Multiple Convolutional Restricted Boltzmann Machines (CRBMs) are connected to form a CDBN. The objective function of a CDBN is to maximize the log-likelihood function to get the optimal parameters, and reconstruction error is used to evaluate the model. The reconstruction error refers to the difference between the original data after Gibbs sampling with the training sample as the initial state and the distribution of the RBM model.

The rest of the paper is structured in the following way: In Section 2, provide an overview of traditional turmeric plant disease detection and classification models. The proposed methodology discussed in Section 3. In Section 4, discuss the performance of proposed framework using specific metrics. Finally, conclude the paper in Section 5 and suggest directions for future research

2. LITERATURE REVIEW

The different turmeric plant disease detection models using Deep Learning (DL) models are analyzed and listed in this section. Based on the analysis, the fundamental issues in turmeric plant disease detection and classification are found to design a new framework.

Rajasekaran et al [8] proposed a Visual Geometry Group and 16 refer to that the architecture contains different convolution layers (VGG 16) for turmeric leaf diseases detection and classification. VGG 16 is an architecture used in Convolutional Neural Network (CNN) for diseased image classification and detection. The images are processing at hidden layer which contains different image processing layers like convolutional, padding, pooling etc., are used for training the model. The proposed model consists of Internet Protocol camera (IP), Raspberry pi 4, Router and Field monitor. From the agricultural land, the IP Camera captures the real time images of Turmeric plant. The IP which connected to internet through router and it collects data by capturing images from agricultural land. The Raspberry pi 4 contains the necessary software tools analysis data based on Deep Learning (DL) algorithm contains. The performance assessments are accuracy and loss. CNN helps to identify the infected and non infected leaf images based on model trained accuracy level at early. The overall accuracy obtained by VGG-16 was 0.9624 and loss was 0.8719 which was better accuracy value as compared to Alex-net, so thus VGG-16 is proposed to this model.

Selvaraj et al [9] suggested a Gazelle Optimization Algorithm (GOA) is combined with deep learning MobileNetV3 for turmeric plant diseases detection and classification. GOA is combined with deep learning MobileNetV3 network to attain enhanced disease detection performance. The performance evaluation metrics are accuracy and precision. Experimentation on dataset with 5000 samples, including leaf spot, leaf blight, leaf rot, and curl disease-affected leaves, the proposed model performance is evaluated and observed with a maximum accuracy of 96.8%, a precision of 97.1% over conventional disease detection models.

Chathurya et al [10] enhanced an InceptionV3 and VGG16 for real-time turmeric leaf disease identification and classification. The dataset consists of turmeric plant leave collected from one of the fields located in Andhra Pradesh, India. Many image classification models as well as transfer learning models are applied. A plant disease hindering normal growth constitutes a significant factor contributing to reduced agricultural yields and accompanying financial losses. Early disease identification contributes to the advancement of medicines capable of healing plant diseases. Leaf examination is one of the best techniques for detecting plant diseases. Learning models CNN and transfer learning models like InceptionV3 and VGG16 are applied with and without data augmentation. The most successful model was found to be CNN with data augmentation which showed a highest accuracy, and it also predicted almost all the testing images correctly. Enhancing the model's accuracy can be achieved by augmenting the size of the dataset.

Banerjee et al [11] presented a hybrid Convolutional Neural Network with Random Forest (CNN-RF) for turmeric leaf disease diagnosis. This research helps considerably to contribute to the advancement of efficient pest and disease control techniques by providing exact disease detection and classification, consequently improving crop protection and supporting sustainable turmeric production procedures. The life-altering effects of advanced Artificial Intelligence (AI) techniques in tackling important agricultural difficulties, resulting in greater yields and improved health of turmeric crops. The performance assessments are Precision, Recall, F1-Score and accuracy for a variety of diseases, including Leaf Spot, Bacterial Diseases, Fungal Diseases, Viral Diseases, Rust Diseases, Leaf Curling Diseases, or Wilting Diseases. These data highlight the model's outstanding ability to classify and diagnose turmeric leaf illnesses. Furthermore, the proposed model's high accuracy rate emphasizes the model's suitability for real world agricultural use.

Siam et al [12] developed an Inception-v3 for turmeric leaf disease detection. A new dataset consisting of 1037 originals and 4628 augmented images of turmeric plants representing five classes: healthy leaf, dry leaf, leaf blotch, rhizome disease roots, and rhizome healthy roots. The dataset was pre-processed to enhance its applicability to deep learning applications by resizing, cleaning, and augmenting the data through flipping, rotation, and brightness adjustment. The turmeric plant disease classification was conducted using the Inception-v3 model, attaining an accuracy of 97.36% with data augmentation, compared to 95.71% without augmentation. Some of the major key performance metrics are precision, recall, and F1-score, which establish the efficacy and robustness of the model. The dataset collected from different fields of Charpolisha in Jamalpur, from August 2024 to Janurary 2025. The publicly available dataset and the results obtained are expected to attract more research interest for innovations in AI-driven agriculture.

Kannan and Thangavel [13] introduced a Spatial Fuzzy C-Means clustering (SFCM), Gray Level Co-Occurrence Matrix (GLCM), Linear Discriminant Analysis (LDA) and Adaptive Network Based Fuzzy Inference System (ANFIS) for identification and classification of turmeric plant leaf diseases. The proposed work steps are pre-processing, segmentation, feature extraction, and classification. Initially, for pre-processing state, the input images are to be converted from one color space which is Red Green Blue (RGB) to Hue Saturation Intensity (HSI) color space. Secondly segmentation, the data base of different leaf images was created and processed using SFCM segmentation, and then leaf images textural analysis was carried out using GLCM. Finally, LDA-ANFIS classifier is used for classification method and it helps to improve the detection rate and reduce the entropy loss. It is highly efficient and accurate to detect the disease image with different number of categories (Leaf Spot, Leaf Blotch Disease and Bacterial Wilt Disease etc.). Experimental analysis is done to calculate the performance metric like as Accuracy, Precision, F-measure, Recall, Sensitivity and Specificity. Then, the comparative analysis of the existing parameters is compared to the proposed algorithm parameters. The proposed system LDA-ANFIS algorithm is achieved higher accuracy.

Albattah et al [14] formulated an EfficientNetV2-B4 for multiclass plant disease detection. An improved EfficientNetV2-B4 with additional added dense layers at the end of the architecture. The customized EfficientNetV2-B4 calculates the deep key points and classifies them in their related classes by utilizing an end-to-end training architecture. The PlantVillage dataset is a large and online accessible standard database of crop leaf disease classification. For performance evaluation, a standard dataset, namely, the PlantVillage, Kaggle along with the samples captured using a drone is used which is complicated in the aspect of varying image samples with diverse image capturing conditions. The evaluation metrics, namely, precision, recall, F1-score, and accuracy. The obtained results confirm the robustness of proposed approach in comparison to other recent techniques and also show less time complexity.

Based on the analysis, identification and classification of turmeric plant leaf diseases model is needed to increase the efficiency and accuracy of detecting plant leaf disease. A Convolutional Deep Belief Network (CDBN) is designed in this research to detect and classify the severity of the disease. The motivation is to address the challenges of accurately identifying and diagnosing turmeric plant leaf disease.

3. PROPOSED METHODOLOGY

The proposed model is discussed detail in this section. The proposed work five major steps are image augmentation, image pre-processing, image segmentation, feature extraction, and classification. Firstly, image augmentation using image rotation, image colour, image brightness transformation, motion blur transformation and Cycle-Generative Adversarial Network (Cycle-GAN) deep learning model. Secondly, image pre-processing using Median Filtering (MF). Thirdly image segmentation, Cascade Region Proposal Network (CRPN) is introduced which adopts multiple stages to mine hard samples while extracting region proposals and learn stronger classifiers. Moreover, a loss function of cascade stages is designed to train cascade classifiers through backpropagation. Then feature extraction, features are extracted using Gray Level Co-Occurrence Matrix (GLCM) method. Finally classification, once the diseases are segmented and then it is classified using Convolutional Deep Belief Network (CDBN) is a network model that consists of a CRBM. The objective function of a CDBN is to maximize the log-likelihood function to get the optimal parameters, and reconstruction error is used to evaluate the model. The overall process of the proposed work is shown in figure 1.

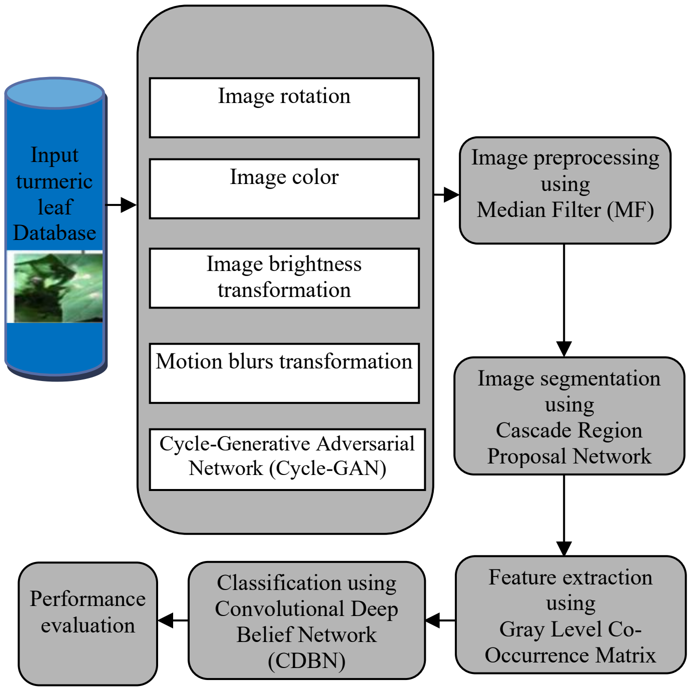

Figure 1. The Overall Process Of The Proposed Work

3.1 Image Augmentation

Image augmentation is a technique that creates more training data by altering existing images. It's used to improve the performance of Deep learning (DL) models [15]. DL methods need more datasets for accurate object detection. Huge dataset could improve the object detection accuracy rate and increase performance. The dataset 1,600 images are taken from a real-time environment. In order to expand the training image dataset, data augmentation is applied to artificially enlarge the dataset. Traditional augmentation techniques like image rotation, image colour, image brightness transformation, and motion blur transformation are used. CycleGAN, the DL model for image augmentation is also used for finding better detection accuracy. The various image augmentation methods are discussed as follows:

3.1.1 Image Rotation

This technique to increase the size of training data by creating multiple images rotated at different angles. Actual pictures are rotated 90 and 180 to expand the dataset. The neural network performance can be improved by using a larger dataset with image rotation.

3.1.2 Image Color

The human vision ability to detect the color invariance of the leaves under changing light conditions, but imaging technology lacks this capability. It is based on the gray-world hypothesis, which states that an image with a significant number of color changes will have the same grey value if the average value of the components R, G, and B is the same. The grey world method implies that the average light reflection from objects is normally a fixed value, similar to grey. In the training set for color invariance, this color balance algorithm is applied to images.

3.1.3 Image Brightness Transformation

The brightness transformation is a typical way of data augmentation used to improve the robustness of a network. Multiplying the proportionate coefficient near 1.0 with the original RGB image can result in increased or decreased image brightness.

3.1.4 Motion Blurs Transformation

The distanced camera can make incorrect focusing and movement of the camera may lead to blur image. To obtain the blur image transformation in equations (1) and (2). Parameters L (length reflects the linear motion of the camera pixels) and q (theta is the angle between horizontal line and direction of the motion of the camera) are set based on the application type.

$$g(x, y) = h(x, y) * f(x, y) \tag{1}$$

$$h(x, y) = \{\frac{1}{L}, \sqrt{x^2 + y^2} \leq L \; and \; \frac{y}{x} = tan\theta \; 0, otherwise \tag{2}$$

where: $g(x, y)$ is a motion-blurred image, $h(x, y)$ is a degenerate function, $f(x, y)$ is the original image.

3.1.5 Image Augmentation using Cycle-Generative Adversarial Network (Cycle-GAN) Deep Learning (DL) Model

GANs are a widely used data augmentation approach to detect patterns and variances in image samples from the training dataset. GANs are reliant on two main components, namely, generator and discriminator. The generative model aims to generate samples that get closer and closer to the true samples. By capturing the distribution of the genuine sample data, the generator (G) can produce a sample that is comparable to the original training data with a noise z that follows a predefined distribution such as uniform or Gaussian distribution. The discriminator (D) is a binary classifier that determines how likely a sample is drawn from training data rather than generated data. The discriminator will output a high probability if the sample belongs to the true training data, and a low probability if it does not. The generator and discriminator alternately enhance their networks during training until Nash equilibrium is obtained [16]. Cycle-GAN can learn the features of diseased turmeric leaf plants and healthy turmeric plants by training process and generating diseased spots on the surface of healthy turmeric leaves.

3.2 Pre-processing

After image augmentation input data needs to preprocess to remove the noise. Image pre-processing is the process of manipulating raw image data into a usable and meaningful format. It allows you to eliminate unwanted distortions and enhance specific qualities essential for computer vision applications. Smoothing, blurring, and filtering techniques can be applied to remove unwanted noise from images.

3.2.1Median Filter (MF)

Median Filter (MF) method is used for noise reduction. MF is a nonlinear operation [17]. This work utilized this as a part of picture handling to decrease salt and pepper and spot noise. MF the neighboring pixels are ranked according to brightness and middle esteem turn into the new incentive for the focal pixel. The length of the filtering window is describe as n where signal length is N. The output of the MF is given by the function as follows equation (3),

$$med(a_i) = \left\{ a_{k+1} n = 2k + 1(odd) \; \frac{[a_k + a_{k+1}]}{2} n = 2k(even) \right\} \tag{3}$$

Here a_k is the k-th maximum observed data and $a_1, a_2, a_3 \ldots a_k$ are the observed data. It is the highlighting characteristic of the MF that it eliminates the pulse noise, and local details remain intact. After this technique, the resulting image is then provided to the image segmentation block, where the CRPN is applied to the images to extracting region proposals.

3.3 Segmentation

Image segmentation is one of the key computer vision tasks, it separates objects, boundaries, or structures within the image. It involves partitioning a digital image into multiple segments (regions or objects) to simplify and analyze an image by separating it into meaningful components, which makes the image processing more efficient by focusing on specific regions of interest. A typical image segmentation task goes through the following steps:

1. Groups pixels in an image based on shared characteristics like colour, intensity, or texture.
2. Assigns a label to each pixel, indicating its belonging to a specific segment or object.
3. The resulting output is a segmented image, often visualized as a mask or overlay highlighting the different segments.

Cascade Region Proposal Network (CRPN) to efficiently segment images. This model is very efficient in working with small amount of data and provides precise segmentation.

3.3.1 Cascade Region Proposal Network (CRPN)

Based on RPN, several strategies to further improve proposal quality, including pretraining RPN, cascade RPN.

Pretraining RPN

RPN generate these so called "proposals" for the region where the object lies, a small network is slide over a convolutional feature map that is the output by the last convolutional layer. RPN generate the proposal for the objects. RPN sub-network is connected to an intermediate layer, e.g. the last layer of conv4_x block for ResNets. And normally an extra 3 ×3 convolution layer is added, which acts as a buffer to prevent direct back-propagation of gradients from the RPN branch. In Faster R-CNN baseline, this layer is randomly initialized and trained from scratch during fine-tuning. When fine-tuning RPN, the linear classifier is replaced with RPN's classification and Bounding box regression (Bbox regression) layers.

Cascade Region Proposal Network (CRPN)

Cascade architecture to refine score and location of RPN proposals. Figure 2 shows the Cascade Region Proposal Network (CRPN) pipeline. The upper part is a standard RPN (RPN 1), which utilizes sliding window proposals as anchors and produces Bbox regression proposals [18]. Besides RPN 1 add another RPN sub-network (RPN 2), which takes output proposals of RPN 1 as input. Note that the input proposals of RPN 2 refer to those right after bounding box regression without any post-processing (e.g. sorting, non-maximum suppression and truncating in number). When training RPN 2, the sliding window anchors are used to locate the pixel position in the feature map, while their corresponding proposals are used to compute classification and Bbox regression targets. During inference, find that RPN 2 improves recall of medium and large images while hurts recall of segment into small images. Compared with other cascade region proposal methods, proposed CRPN approach has the following advantages:

1. Easy to implement: The logic of RPN 2 is very similar to standard RPN.
2. Computationally efficient: The fully convolutional nature makes it very efficient in terms of both computational and memory cost.

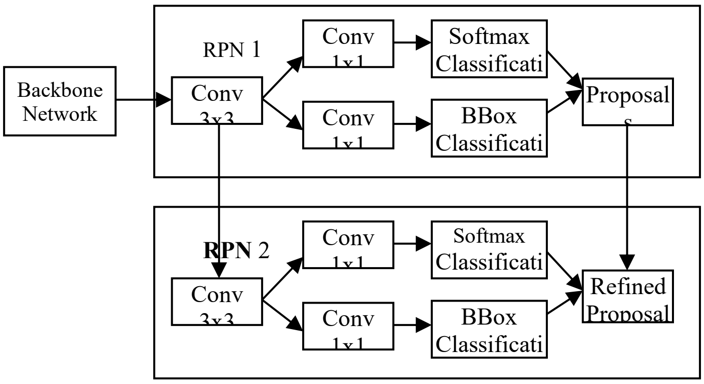

Figure 2. Cascade Region Proposal Network (Crpn) Pipeline

3.4 Feature Extraction

Image feature extraction involves identifying and representing distinctive structures within an image. Features are characteristics of an image that help distinguish one image from another. These can range from simple edges and corners to more complex textures and shapes. Texture analysis is a vital aspect of image processing and computer vision that focuses on quantifying and characterizing the spatial arrangement of pixel intensities within an image. Understanding the texture of an image can be crucial for tasks like classification, segmentation, and recognition, particularly when dealing with images containing repetitive patterns or complex structures. Gray-Level Co-occurrence Matrix (GLCM) algorithm is used for feature extraction.

3.4.1 Gray-Level Co-occurrence Matrix (GLCM)

Once the turmeric leaf disease images are get segmented it send to the feature extraction. Gray-Level Co-occurrence Matrix (GLCM) is used in this work for feature extraction. GLCM is a statistical method used to capture the spatial relationships between pixels in an image. It measures the frequency of occurrence of pairs of pixel values at specified distances and orientations within a segmented image. GLCM can extract texture features such as contrast, correlation, energy, homogeneity, and entropy which provide information about the texture properties of the image. GLCM is particularly effective for analyzing textures with well-defined patterns and structures [19].

Energy: Energy indicates the uniformity observed in the mammographic image. Generally, energy is computed from the value of the mean squared signal. It is computed as equation (4),

$$Energy = \sum_{i,j=0}^{n-1} p(i,j)^2 \tag{4}$$

Contrast: The contrast provides the measure of the difference between the least and the highest values of a set of pixels present in vicinity. It computes as equation (5) amount of the local differences that exist in the image,

$$contrast = \sum_{i,j=0}^{n-1} (i-j)^2 p(i,j) \tag{5}$$

Correlation: The correlation provides a measure of the correlation of a pixel with its neighbour over the entire image. It computes as equation (6),

$$correlation = \sum_{i,j=0}^{n-I} \frac{(i \times j)p(i,j) - u_i u_j}{\sigma_i \sigma_j} \tag{6}$$

$\sigma 2$ = the difference of the intensities of all the reference pixels in the associations, which made their contribution to the GLCM, computes as equation (7),

$$\theta^2 = \sum_{i,j=0}^{N-I} p_{i,j}(i-u) \tag{7}$$

Homogeneity, Angular Second Moment (ASM): ASM utilized for measuring the homogeneity of the image. It computes as equation (8),

$$homogeneity = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \{p(i,j)\}^2 \tag{8}$$

Entropy: Entropy specifies the measure of the irregularity or complexity existing in the image. Entropy achieves the highest value if the values of $p(i,j)$ are assigned quite evenly throughout the entire matrix. Entropy has ahigh but inverse correlation with Energy. It computes as equation (9),

$$Entropy = -\sum_{i,j=0}^{n-1} p(i,j) \log \log p(i,j) \tag{9}$$

Where $'i'$specifies the rows of the GLCM matrix, $'j'$ refers to the columns of the GLCM matrix, $'n'$ specifies the number of gray levels and $p(i,j)$ refers to the cell represented by the row and the column of the GLCM matrix. Depending on these assessments, the extractions of the texture features are obtained.

3.5 Classification

After feature extraction need the extracted features are classified to detect the turmeric leaf diseases. Image classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules. The categorization law can be devised using one or more spectral or textural characteristics. Two general methods of classification are 'supervised' and 'unsupervised'. Convolutional Deep Belief Network (CDBN) used for classification of turmeric leaf disease.

3.5.1 Convolutional Deep Belief Network (CDBN)

Convolutional Restricted Boltzmann Machine (CRBM)

Convolutional Restricted Boltzmann Machine (CRBM) is an improvement on the basis of the original RBM, and the structure of CRBM is similar to that of RBM. CRBM is an improved model composed of two random variable matrix layers, namely, the visible and hidden layers. An image with extracted features of the local receptive field and weight sharing is regarded as the input layer of CRBM. The hidden layers are locally connected with visible layers, and their weights are shared by convolution [20]. CRBM model, as shown in Figure 3, comprises the view layer V, the hidden layer H, and the pooling layer P, for a total of three layers. The size of the input layer matrix is $N_v \times N_v$, the number of groups of matrices in the hidden layer is k, each group is a binary array with the size of $N_H \times N_H$, and $N_H^2 K$ hidden layer units are present. Each group of hidden layers is associated with an $N_w \times N_w$ size filter. Figure 4 shows the process of obtaining the hidden layer from the visible layer. The size of the convolution kernel is 3×3, and the hidden layer units are divided into k sub-matrices. $W_1, W_2, \dots, W_K$ connects the visible and hidden layers. Moreover, b_k indicates the value of each hidden layer unit bias, and

C is the bias globally shared by all visible units. We obtain the energy number of CRBM as Equation (10),

$$E(v,h) = -\sum_{k=1}^{k} h^k(w^k * v) - \sum_{k=1}^{k} b^k \sum_{i,j} h_i j^k - c \sum_{i,j} v_{ij} \tag{10}$$

where $*$ indicates convolution, v_{ij} denotes the input values of the ith visible layer unit and the jth hidden layer unit, h^k denotes the kth hidden layer, $h_i j^k$ denotes the values of the ith visible layer unit and the jth unit of the kth hidden layer, and w^k denotes the convolution kernel of the kth hidden unit. As with standard RBM, the conditional probability distribution is given as equations (11-12),

$$p(v) = \sigma\left(\left(\widetilde{W}^k * v\right)_j + b_k\right) \tag{11}$$

$$p(h) = \sigma((W^k * h^k)_i + c) \tag{12}$$

Where $\sigma = \frac{1}{(1+e^{-x})}, \widetilde{W}_J^k \triangleq W^k_{N_{w-j+1}}$.

A CRBM is a single-layered network. It can be considered as the basics of a CDBN. Stacking multiple CRBMs, with the hidden layer of the previous RBM as the visible layer of the next CRBM, constitutes a CDBN. In the each training, the RBM of the lowest layer is trained, one layer at a time, until the top layer.

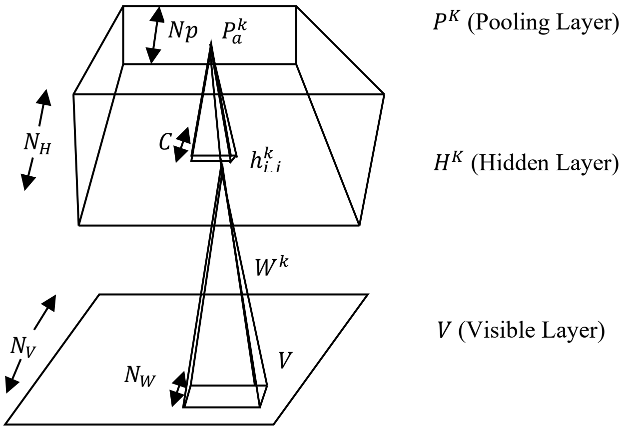

Figure 3. Structure of a convolutional restricted boltzmann machine (crbm)

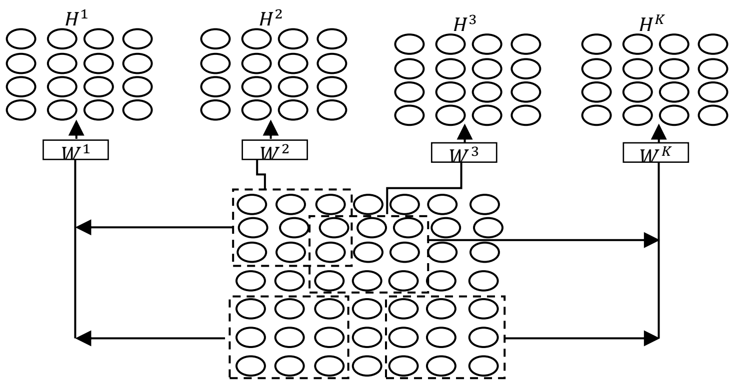

Figure 4. The process of obtaining hidden layers from the visible layer based on crbm

Convolutional Deep Belief Network (CDBN)

CDBN is a network model that consists of a CRBM. Multiple CRBMs are connected to form a CDBN. The outcome of the previous CRBM layer is regarded as the input of its subsequent layer. The model fitting ability is further improved by multi-layer linking. The objective function of a CDBN is to maximize the log-likelihood function θ (.) in order to get the optimal parameters, and reconstruction error is used to evaluate the model. The reconstruction error refers to the difference between the original data after Gibbs sampling with the training sample as the initial state and the distribution of the RBM model

[21]. A smaller reconstruction error indicates better training. Reconstruction error is given by Equation (13), with $\hat{X}_i$ and X_i indicating the real output and ideal output,

$$Error = \frac{1}{N}\sum_{i=1}^{N} (\hat{X}_i(W^k, b^k) - X_i)^2 \tag{13}$$

The standard CDBN uses only single-layer output features but ignores the comprehensive utilization of the features of each layer. As a consequence, the classification results are not representative. An improvement of the model connection mode is proposed. The outputs of a two-layer CRBM are combined into a vector and input to the softmax classifier by multi-level feature fusion to utilize features, further improving classification accuracy. Model training can be summarized according to the following steps:

1. Forward propagation:

a. Use Contrast Divergence (CD) algorithm to pre-train W and b and determine the opening and closing of the corresponding hidden element.

b. Propagate upward layer by layer, calculate the excitation value of each hidden element, and use the sigmoid function to complete the standardization.

2. Back propagation:

a. Use the minimum mean square error criterion for the backward error propagation algorithm and update the parameters of the network.

b. Update the weight and bias of the network with Adam optimizer.

4. RESULTS AND DISCUSSION

This section displays the outcomes of the classifier analysis of the turmeric leaf dataset. The dataset 1,600 images are taken from a real-time environment. The suggested CDBN classification algorithm for lung turmeric leaf disease detection has been evaluated in this research using images acquired from the turmeric plant. Then, various existing techniques are LDA-ANFIS [13], YOLOV3-tiny, and IYOLOV4 have been suggested for results comparison of proposed CDBN.

Performance measures: The performance of the model is evaluated by Precision (P), Recall (R) or Sensitivity, F-Score (or) F-measure (F1), and Accuracy (A) has been used to evaluate the classifiers in this study. The outline of the confusion matrix is revealed in Table 1. For binary classification problems, samples can be split into True Positive (Tp), False Positive (Fp), True Negative (Tn), and False Negative (Fn) based on the combinations of actual class and predicted class.

Table 1. Confusion Matrix

Actual Class	**Prediction Class**	
	P	**N**
P	Tp	Fn
N	Fp	Tn

The performance of classifiers was assessed using the following metrics: Precision (P), Recall (R) or Sensitivity, F-Score (or) F-measure (F1), and Accuracy (A). With the direction of the following equations (14-17).

Precision (P) measures the predicted positive instances that are real positives. Mathematically, it is given by Equation (14),

$$Precision(P) = \frac{Tp}{Tp + Fp} \tag{14}$$

Recall (R) or Sensitivity evaluates the analysis of the total relevant results correctly classified by the proposed algorithm. Mathematically, it is given by Equation (15),

$$Recall(R)/Sensitivity = \frac{Tp}{Tp + Fn} \tag{15}$$

F-Score (or) F-measure (F1) is a harmonic mean of precision and recall. It takes the equilibrium between precision and recall. Mathematically, it is given by Equation (16).

$$F - Score/F - measure(F1) = 2.\frac{Precision(P) * Recall(R)}{Precision(P) + Recall(R)} \quad (16)$$

Accuracy (A) assesses the precision or correctness of a machine learning or classifier models predictions. Mathematically, it is given by Equation (17)

$$Accuracy(A) = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \quad (17)$$

Tp, Fp, Fn and Tn refer to the number of plant diseases correctly identified, the number of plant diseases wrongly identified, the number of plant diseases missed, non-positive samples diagnoses were accurate. The comparative analysis of the proposed classifier with existing methods is discussed in table 2.

Table 2. Comparative Performance Of The Proposed Classifiers With Existing Methods

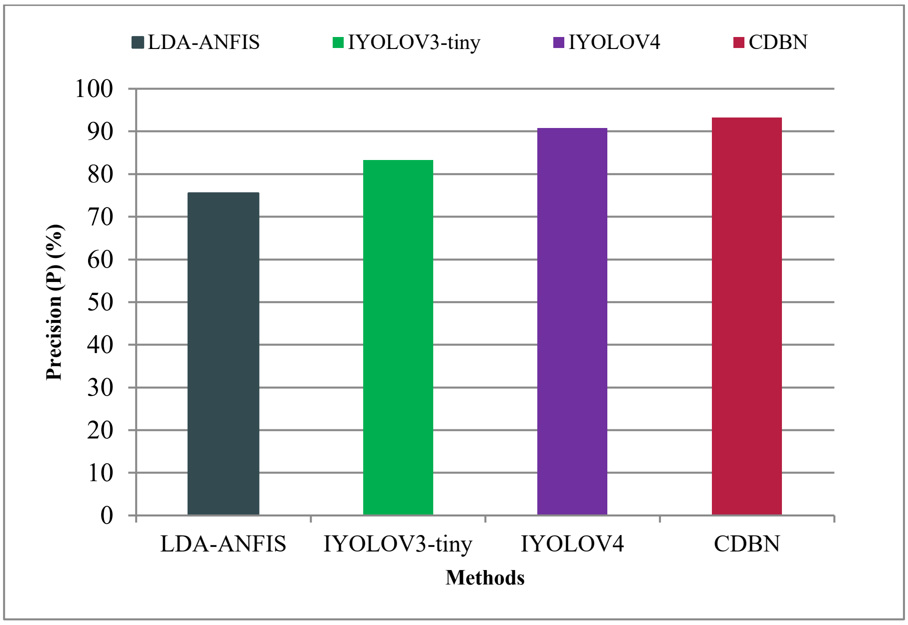

Figure 5. Precision (P) Comparison Vs. Classifiers

Figure 5 shows the precision (P) performance metric comparison between existing classifiers like LDA-ANFIS, IYOLOV3-tiny, IYOLOV4 and proposed CDBN for turmeric plant diseases detection. In the above figure X-axis represents the methods and the y-axis represents the precision (P) results. Proposed work using MF for noise removal and it increases the precision results. From the results it is concluded that the proposed CDBN classifier has produces highest precision results of 93.2% while the existing LDA-ANFIS, IYOLOV3-tiny, and IYOLOV4 has lowest precision of 75.5%, 83.2% and 90.8% (Refer Table 2).

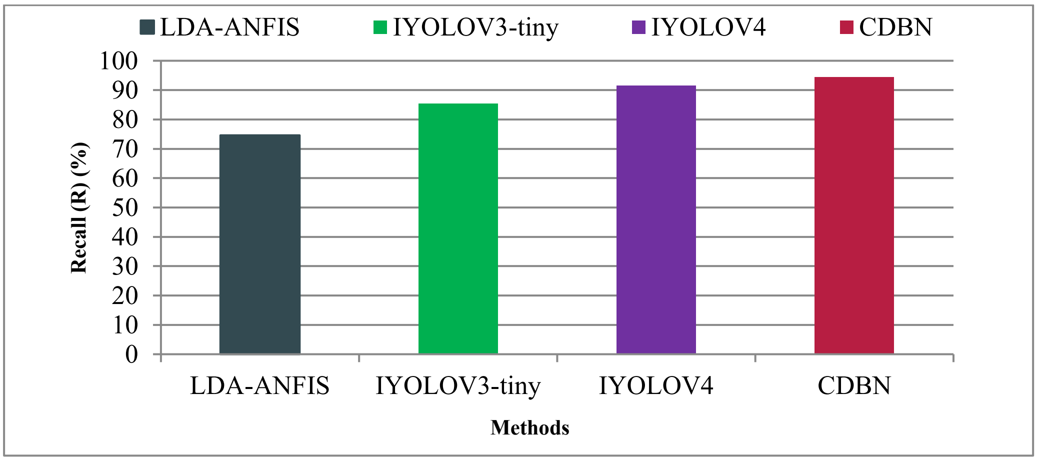

Figure 6. Recall (R) Comparison Vs. Classifiers

Figure 6 shows the performance comparison results for the existing classifiers like LDA-ANFIS, IYOLOV3-tiny, IYOLOV4 and proposed CDBN for turmeric plant diseases detection interms of recall (R). In the above figure X-axis represents the methods and the y-axis represents the recall (R) results. From the results it is concluded that the proposed CDBN classifier

Evaluation Metrics/Classifiers	LDA-ANFIS	IYOLOV3-tiny	IYOLOV4	CDBN
Precision (P)	75.5	83.2	90.8	93.2
Recall (R)	74.6	85.5	91.6	94.4
F –Measure (F1)	75.1	84.4	91.2	93.8
Accuracy (A)	78.7	87.2	95.2	96.5

has produces highest recall results of 94.4% while the existing LDA-ANFIS, IYOLOV3-tiny, and IYOLOV4 has lowest recall of 74.6%, 85.5%, and 91.6% (Refer Table 2).

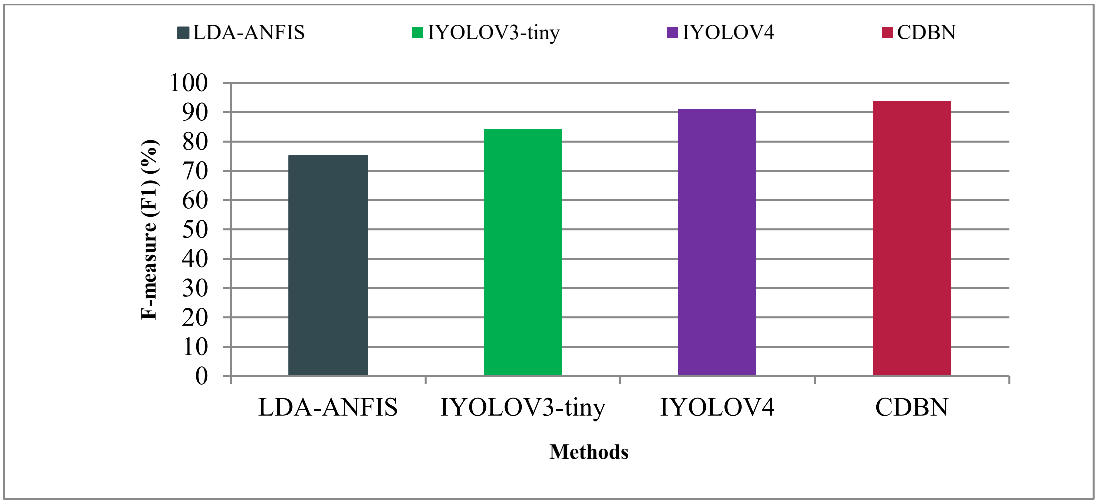

Figure 7. F-Measure (F1) Comparison Vs. Classifiers

F-measure (F1) performance metric comparison between existing classifiers like LDA-ANFIS, IYOLOV3-tiny, IYOLOV4 and proposed CDBN for turmeric plant diseases detection are shown in figure 7. In the above figure X-axis represents the methods and the y-axis represents the f-measure (F1) results. From the results it is concluded that the CDBN classifier has produced highest F-measure results of 93.8% while the existing LDA-ANFIS, IYOLOV3-tiny, and IYOLOV4 has lowest F-measure of 75.1%, 84.4%, and 91.2% (Refer Table 2).

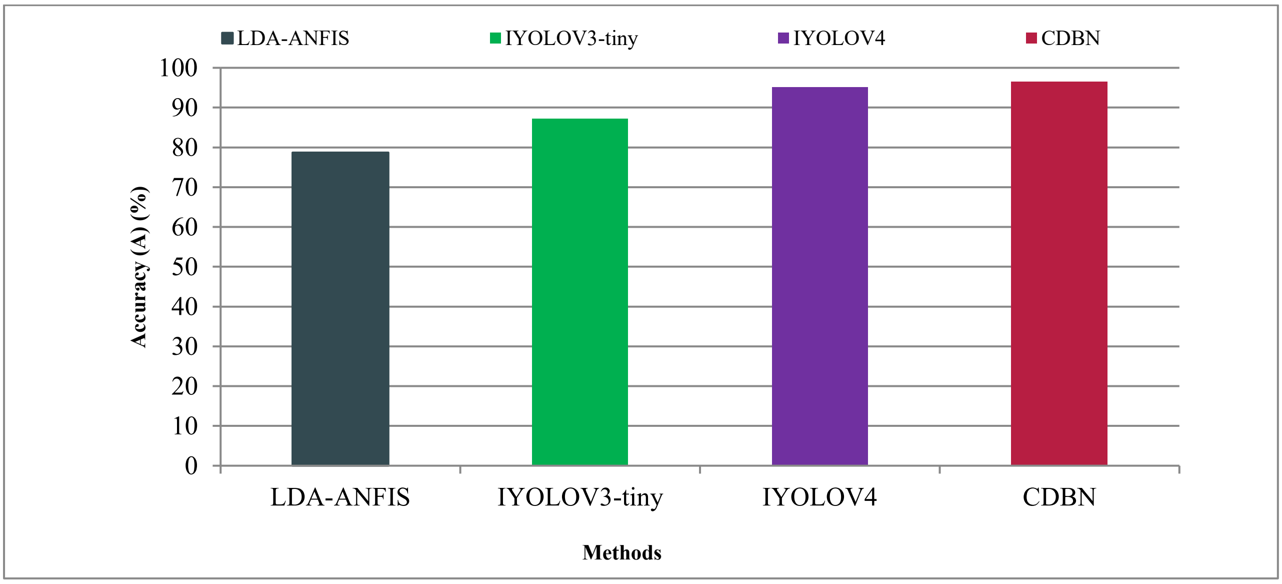

FIGURE 8. ACCURACY (A) COMPARISON VS. CLASSIFIERS

Figure 8 shows the Accuracy (A) performance metric comparison between existing classifiers like LDA-ANFIS, IYOLOV3-tiny, IYOLOV4 and proposed CDBN for turmeric plant diseases classification. In the above figure X-axis represents the methods and the y-axis represents the accuracy (A) results. This work using data augmentation by which accuracy increases. From the results it is concluded that the proposed classifier CDBN has produces highest accuracy results of 96.5% while the existing LDA-ANFIS, IYOLOV3-tiny, and IYOLOV4 has lowest accuracy of 78.7%, 87.2%, and 95.2% (Refer Table 2).

5. CONCLUSION AND FUTURE WORK

Disease identification plays a vital role in agricultural sector. Turmeric being a rhizomatous crop and well known for its therapeutic effects, monitoring such crops is crucial. The turmeric leaves are mainly exposed to diseases like Leaf Spot and Leaf Blotch. This work aimed to provide a deep learning model for automatic detection of turmeric plant leaf diseases. The CDBN framework for turmeric plant images in real-world environment, integrating advanced techniques for image augmentation, image pre-processing, image segmentation, feature extraction, and classification. Firstly, image augmentation using image rotation, image colour, image brightness transformation, motion blur transformation and Cycle-GAN deep learning model. Secondly, image pre-processing using MF. Thirdly image segmentation, CRPN which adopts multiple stages to mine hard samples while extracting region proposals and learn stronger classifiers. Then, features are extracted using GLCM method. Finally, classification using CDBN deep learning algorithm. Results show the effectiveness of the proposed CRBM model in terms of precision (P), recall (R), accuracy (A) and f-measure (F1). Results show that the proposed model achieves 96.5% accuracy which is better than other existing models. Overall, the experimental results state that the CRBM model performs much better than other models for turmeric leaf diseases. In the future, the work can be extended for other vital diseases in turmeric leaf and other important crops.

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