International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys.14, No.1 (Oct-23)

http://dx.doi.org/10.12785/ijcds/140199

Real-Time Disease Detection System for Maize Plants Using Deep Convolutional Neural Networks

Prabhnoor Bachhal[1], Vinay Kukreja[1] and Sachin Ahuja[2]

[1]*Chitkara University Institute of Engineering & Technology, Chitkara University, Punjab, India*
[2]*University Institute of Engineering Chandigarh University Punjab, India*

Received 15 Dec. 2022, Revised 16 Sep. 2023, Accepted 21 Sep. 2023, Published 1 Oct. 2023

Abstract: In agriculture diseases, living and non-living creatures account for about 22% of crop production loss. For farmers, it's crucial to identify these pressures in their early stages using only their eyes. Early disease patterns and clusters can be identified using computer vision technologies. But in recent years, image processing-based deep learning technology has shown useful for identifying stress in Maize plant leaves. This work has used Primary and secondary datasets. The Plant Village dataset is compiled in this study for the segmentation of object detection. Furthermore, the data set included a total of 100 pictures for Common Rust, 50 for Southern Rust, 70 for Gray Leaf Spot, 30 for MLB, and the final 30 for Turcicum leaf blight diseases. The 90 images were all taken of healthy leaves. The model has been trained using the labelled, improved, and supplemented data. The maize plant's sick objects have been divided up using the P-CNN (PSPNet + CNN) model that has been suggested. The PSPNet and Basic CNN model are used for used together within semantic segmentation to improve object detection. In terms of Recall, Precision, Intersection over Union (IoU), Accuracy, and Mean Intersection Over Union (mIoU), the suggested YOLO+CNN and VGG16+CNN models outputs are contrasted based on mIoU parameters. The suggested model performed 14803 images, and image processing operations in 30ns, which is faster than other comparable models. The proposed model (P-CNN) has achieved an accuracy of 99.85% which is significantly higher than that of other modified segmentation methods. The single and multiple-leaf diseases have been detected for identification and classification in this work using the semantic segmentation data.

Keywords: Maize leaf disease; Convolutional Neural Network; Pyramid Scene Parsing Network; Deep Learning; Semantic Segmentation.

1. Introduction

Agriculture employs more than 58% of the workforce and generates more than 20% of India's GDP. Over 70% of rural small households in India depend on agriculture [1]. India's population is continuing to rise, which has raised the demand for food, leading to a situation where agricultural output cannot keep up with the demand. Climate change, plant diseases, weeds, and other issues are the main causes of decreased food supply. Because they constitute a severe threat to food supply and the viability of small-scale farmers, our research focuses on plant diseases. One of the developing crops, maize, also known as corn, is particularly adaptable to a variety of environmental situations. This is one of the significant global industrial food crops. Due to its superior output compared to other cereal crops, it is also known as the queen of cereals. In contrast to other cereal crops, it is cultivated in almost every nation aside from Antarctica and in a wide range of agro-climates. Its plant area and overall yield are the greatest in the world, excluding rice and wheat [2]. However, recent changes in agricultural methods, a wide range of pathogen species, and poor plant protection techniques have led to an increase in the number of maize disease species and the severity of the harm they inflict. Curvularia leaf spot, Dwarf mosaic, Gray leaf spot, Northern corn leaf blight or Turcicum leaf blight (TLB), Brown spot, Common rust, and southern corn leaf blight or Maydis leaf blight (MLB) are the most common forms of common maize leaf diseases.

The productivity of maize is severely impacted by maize diseases. The diseases can be seen in a variety of crop sections, including the leaf, stem, or panicle. The diseases cannot be accurately detected by looking at the plant with the naked eye. This results in improper pesticide application, which, as a result of bio-magnification, causes serious chronic diseases in humans and also lowers the quality and output of maize. Therefore, it is crucial to identify maize diseases to protect the good quality and

E-mail address: prabhnoor.bachhal@chitkara.edu.in, vinay.kukreja@chitkara.edu.in, ed.engineering@cumail.in

high production of maize. This study suggests a method for automatically classifying the diseases in maize leaves Compared to skilled plant pathologists, novice farmers may have a tougher time recognizing diseases [3]. Farmers could benefit greatly from an automated system that is created to identify plant diseases by the way the plant looks and by visual symptoms as a verification system in disease diagnostics. Numerous initiatives have been launched to swiftly and accurately identify leaf diseases.

Primary agricultural disease identification in poor nations like India is done by the farmer through visual inspection, and accurate disease diagnosis typically depends on the farmer's skill, experience, and aptitude. As it turns into a matter of subjective analysis, there is always a possibility of inaccurate disease identification. Sometimes the agronomists or plant pathologists may even misidentify the diseases, resulting in poor countermeasures [4]. This poses a serious issue in terms of effectively diagnosing agricultural disease, providing quick treatment, and avoiding crop damage. Machine learning (ML) and deep learning (DL), both of which make it very simple for machines to learn a large number of patterns and subsequently act, have recently been introduced in response to the numerous uses of AI in daily life. Without being specifically created to do so, ML and DL enable applications to increase their prediction accuracy Artificial Algorithms that analyze and identify patterns or images more correctly than humans have arisen because of the relationship between DL technology and computer vision [5]. While computer vision focuses on teaching computers to think and behave with less human interaction, DL focuses on teaching machines to think with the given description inspired by the nervous system.

Almost every subject is benefiting from machine learning and computer vision since they can produce more promising results at a lesser cost. More research is being done on the uses of these technologies as time goes on. The use of Deep Learning-based approaches in the agriculture sector is starting to increase [6]. DL has revolutionized the study of computer vision and can now handle a variety of tasks, such as maintaining soil fertility, automating crop lesion detection, forecasting rainfall, predicting agricultural production, etc. To assist farmers and boost plant yield, some Deep Learning-based solutions have been created for the autonomous diagnosis of plant diseases [6], [7]. Numerous studies have suggested that Convolutional Neural Networks (CNNs) can be used to recognize leaf diseases. The latest approach has worked with some accurate classifiers as compared to basic ML techniques that concentrated on unique characteristics. High precision alone is insufficient for the classification of plant diseases. Users must be informed about the diagnosing process and the symptoms present in the specific crop. This can be done by using image processing methods to highlight only the afflicted areas of a leaf [8].

Plant diseases can do a tremendous deal of harm to crops by drastically lowering their yield because they impede crop growth and result in subpar goods. The world's population is expanding quickly, and biofuel crops struggle to keep up because of their lower yield and high fibre content. Plant leaf ailments are visible to the naked eye [9], which is an established method for their detection and diagnosis. However, when the symptoms are assessed based on personal experiences, manual recognition can have negative effects because it can lead to misdiagnosis [10]. The complete flow of work is given in Figure 1.

Input maize image from plant village. Furthermore, the data is pre-processed using different techniques such as cropping and resizing. The dataset is augmented using flipping and rotation operations. Set the semantic segmentation of the diseased part of a leaf and implement histogram equalization. Set the bounding box in the diseased part of the leaf to discriminate the background and Foreground features. Implement the proposed model name P-CNN, where CNN works as a classifier for classifying diseases. The performance of the suggested model is computed and evaluated against VGG19+CNN [11] and YOLO+CNN [12] with the Convo blocks of CNN changed.

This study suggests a useful proposed model for the detection, localization, and classification of various maize leaf diseases. The Pyramid Scene Parsing Network (PSPNet) and Convolutional Neural Networks (CNN) have been combined that make up the created system for better classification of disease. The CNN model is linked to PSPNet, which will improve prediction performance, instead of using network layers that are fully connected. Eventually, the feature extraction function is processed using the PSPNet. Comparing the suggested prototype to recently developed techniques; it obtains effective classification accuracy. This work's primary contribution is listed as follows:

1) Examining and assessing the classification and detection methods for recently discovered maize leaf diseases with PSPNet with CNN in the proposed P-CNN model.
2) Creating an effective system for classifying and identifying plant leaf diseases using the change of Convo blocks of the CNN model, Adam optimizer and a learning rate of 0.0001.
3) Employ a dataset of maize leaves to confirm the effectiveness of the suggested hybrid method and compare the results with other state-of-the-art models.

The rest of the paper is structured as follows: In section 2, a quick summary of the research for identifying plant diseases using various ML and DL techniques is presented. The architecture of the suggested model for identifying maize leaf diseases from infected leaves is discussed in section 3 with data pre-processing techniques. Section 4 presents the result of the P-CNN model, and Section 5 provides a discussion of the proposed model with some of the existing

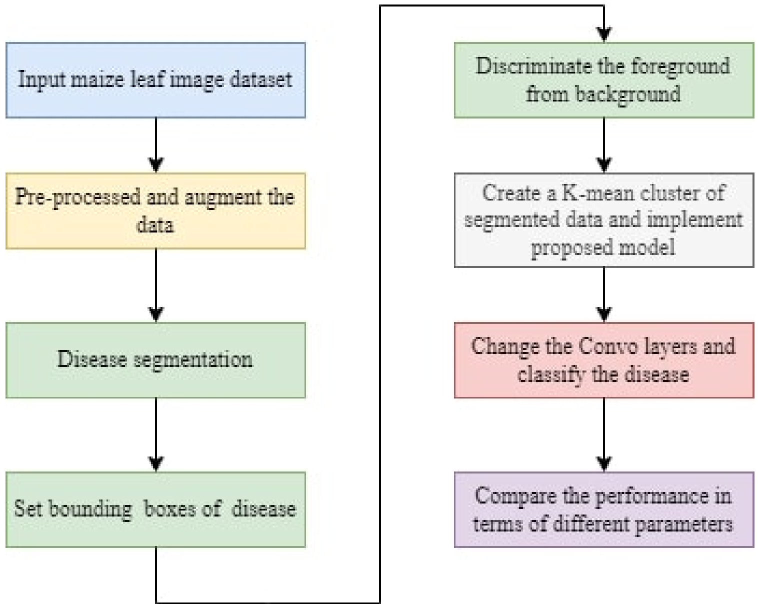

Figure 1. Dataflow of the model

models. Section 6 summarises the effort and talks about the results in the future.

2. Related Work

The literature on various forms of leaf disease identification, detection, and classification using Machine and Deep Learning approaches has been covered in this area. A small body of literature also discusses many plant diseases and their diverse forms.

An approach for identifying maize leaf diseases that Chen and Wang [9] presented uses probabilistic neural networks and image processing technology (PNN). The method's highest recognition accuracy was 90.4%. However, the PNN classifier's recognition rate and efficiency decline as more training instances are added. Xu et al. [10] developed a technique for diagnosing maize leaf disease based on adaptive weighting multi-classier fusion. This method was used to analyse seven common types of maize leaf diseases. The average recognition rate was 94.71%.

Goram et al. [11] collected 80,000 images from reliable sources that were used to access and gather X-ray images of pneumonia, TB, lung cancer, lung opacity, and most recently Covid-19. The model was tested using Google Colab Pro. Results showed that the suggested VGG19-CNN attained the best performance with 93.76% accuracy. Gangadevi et al. [12] used hybrid (YOLO + CNN) deep learning methods to build a novel approach for identifying paddy leaf disease. By using "adaptive K-means clustering," the unusual region of the paddy leaf is segmented. To determine performance metrics and accuracy, experimental analysis is carried out. The accuracy of the suggested model was 96.68%. Wang et al. [13], Qi et al. [14], and Zhang [15] presented various approaches utilizing digital image processing techniques based on fisher discriminant, Retinex algorithm coupled with PCA and SVM, and Quantum Neural Network (QNN) and combination features to identify maize leaf disease. The highest classification accuracy in the research was 95.3%, however, these methods involved fewer maize diseases. Different techniques are used to detect diseases in maize. The highest recognition accuracy reported was 95.3%, which is below the standard for good recognition accuracy. Further research must concentrate on ways to increase classification efficiency.

The artificial neural network (ANN) has been employed by Jafari et al. [16] to scale the imbibition recovery curve. Recent developments show that deep-trained neural networks are a useful method in pattern recognition and computer vision. The LeNet Architecture for digit recognition was developed in 1998 by LeCun et al. [17]. Over the past 20 years, the LeNet architecture has been used for a variety of applications. Badea et al. [18] employed LeNet and Network in Network Topologies for a range of applications, such as diagnosing burn wounds from pediatric patients, detecting art movement, and identifying facial critical areas. To recognize 3D objects using volumetric representation, Xu et al. [19] employed LeNet. For the categorization of plant leaf diseases, such as tomato [20] and rice [21], convolutional neural networks (CNNs) are increasingly extensively used. Albattah et al. [22] enhanced CenterNet by removing deep-seated critical spots based on DenseNet-77 and categorising and identifying 26 different plant disease types in 14 different plants, including tomatoes, apples, grapes, etc. However, the detection effect of tiny diseases in plants was not optimal.

Ferreria et al. [23] have applied CNNs to the identification of weeds in soybean crops. Deep neural networks have not yet been used in research studies to classify diseases in maize leaves. Using various pooling techniques, filter sizes, and algorithms, Lu et al. [24] were able to pinpoint 10 prevalent rice diseases. The accuracy of the suggested model, which is based on convolutional neural networks, was 95.48%. Nanehkaran et al. [25] developed a new model for the identification of plant diseases, which included phases for image segmentation and image classification. In the picture segmentation stage, they suggested a hybrid segmentation technique based on hue, saturation, and intensity as well as LAB, and employed CNN models in the classification stage.

The problem of sparse information as well as the various abnormalities shown in photos of field-grown plants was solved by this method. The accuracy percentage of the identification method was 96.7%. Some studies have been able to improve the detection accuracy of plant diseases to some extent by using different convolutional neural network models and altering the ratio of training set size to testing set size. To achieve a high level of detection accuracy of sickness in maize leaves, a recognition model with fewer characteristics must be created. According to the datasets each study utilized, Table 1 displays the results from several authors that employed pre-trained DL prototypes to identify and categorize various plant leaf problems.

TABLE I. Table 1: Literature study result of different state-of-art models

Ref. No.	Method	Accuracy	Plant Name
[26]	EfficientNet - CNN	96.18%	Plant Leaf
[27]	United Model	98.2%	Grape Leaf
[28]	F-CNN & S-CNN	98.3%	Tomato Leaf
[29]	Proposed FCNN & SCNN	92.01%	Crop Leaf
[30]	Hybrid Principal Component Analysis	95.1%	Plant Leaf
[31]	Deep Transfer EfficientNet B7 model	98.7%	Grape Leaf
[32]	CNN	95.1%	Corn Leaf
[33]	AlexNet Model	99.15%	Maize Leaf
[34]	AlexNet, GoogleNet, VGG16, and VGG19	99.14%	Maize Leaf
[35]	SegNet, UNet, and DeepLabV3+	97%	Maize Leaf

It is also being done to compare various modern deep-learning technologies. These works mainly focused on computing time and overfitting problems. To do this, they employed a variety of strategies, including the selection of essential features for precise classification. Additionally, they concentrated on one classifier for feature categorization rather than employing a variety of classifiers for a fair comparison. According to many of the works mentioned, the use of structures in horticulture plant leaf disease prediction has certain study work gaps that need to be addressed. These include the number of categories and optimization trade-offs, the recognized sicknesses, the enhancement of epochs, increased productivity, etc. Classification efficiency is mostly derived from class effectiveness and the accuracy of deep learning architectures.

Diseases caused by bacteria and fungi harm the maize leaf. While northern leaf blight and grey leaf spot are bacterial infections, common rust is a fungal disease. To help farmers properly and successfully identify the sickness using digital cameras at an early stage, the deep network prototype for diseases in maize leaf was developed. It is important and difficult to extract information from photos of maize leaves that can be used to identify diseases. However, deep networks proposed model names from the raw data, and P-CNN can systematically and intelligently collect the characteristics. The learned attributes are regarded as the higher-level intellectual representation of the lower-level images of raw, healthy, and diseased maize leaves. Additionally, a prototype based on deep learning is regarded among the finest categories for pattern identification jobs to enhance the outcomes of investigative work. To categorize the maize leaf diseases, the proposed deep network model P-CNN is used.

3. Material and Method

The suggested cutting-edge hybrid strategy, which uses a CNN model that is trained on different images of maize leaf to categorize the disease, is discussed. Figure 2 depicts the suggested recognition systems steps.

A. Data Collection and Pre-Processing

Images of plant leave taken from Plant Village are used to evaluate the performances [36]. The number of image datasets gathered for the identification and detection of lesions is summarized in figure 3 and a few sample images are shown in figure 3. The 370 images were taken in a field of corn crops. The Intel Real Sense LiDAR digital camera L515, the Canon digital SLR DIGICAM EOS 850 D 18-55IS STM, and the Sony w 800 (up to 1024 × 768 depth resolution) have all been employed as the three RGB virtual cameras for photo capture. The stress images were captured at Mullana at coordinates 30.2753° N and 77.0476° E. (Haryana) Verification images were obtained in August 2022 at two commercial corn fields (located at 24.84° N and 24.84° E, respectively). The Common Rust, Southern Rust, Gray Leaf Spot, Maydis leaf blight (MLB), and 90 healthy Leaf pictures are among them. During the process of taking

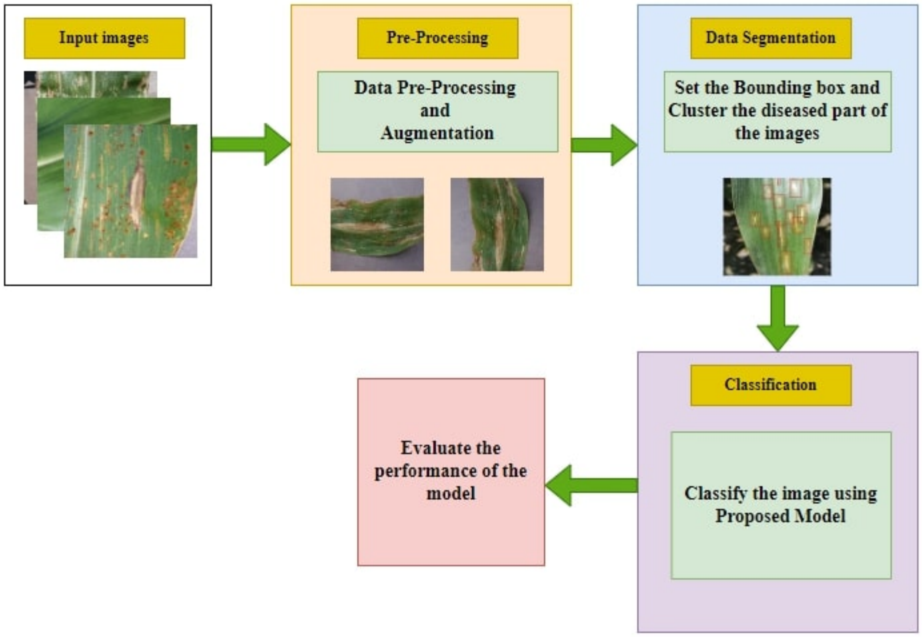

Figure 2. The architecture of the proposed hybrid CNN

a picture, the ground-sampling distance for digital cameras was adjusted at 0.05 cm pixel-1. Between the hours of 9:00 am and 5:00 pm, images were taken throughout various sunshine conditions, such as clear, partly cloudy, or overcast skies. The data set included a total of 100 pictures for Common Rust, 50 for Southern Rust, 70 for Gray Leaf Spot, 30 for MLB, and the final 30 for Turcicum leaf blight (TLB) leaf disease. The 90 images were all taken of healthy leaves. The diseases are occurred due to some common stress which is: bacteria, viruses, fungi, temperature, nutrients, and water access.

The data collection technique is important in real-time operations because inaccurate information in a data set can undermine the investigational result. Therefore, a common norm should be expressed and followed during the data collection process.

The entire dataset has been divided among two separate datasets, having a proportion of training to testing being 80:20. The data is divided into six separate classes, of which one class represents the healthy leaf images and the other five indicate various maize leaf diseases. The information consists of a set of 256x256 pixel RGB photos of leaves. Based on their picture classes, healthy and sick leaves can be distinguished. It was made sure that each shot had a single centroid leaf during the photo shoot. Additionally, similar lighting and shooting conditions are maintained. It is only normal to wonder how to use the data effectively after studying a variety of data. As is common knowledge, a variety of factors, including noise and human error, can taint data obtained from any location. The algorithm may produce inaccurate results using such data directly. Pre-processing [37] input data is therefore the next step.

$$M_{RGB}(C_r) = \frac{W'}{h'}(224 \times 224 \times 3) \quad (1)$$

$$R = ((x + o_r)\,x,\ (y + o_r)\,y) \quad (2)$$

Data pre-processing is a strategy to enhance picture quality, which can enhance model accuracy. It has also reduced or eliminated noise that was present in the original input data, etc. Color Space Transformation (CST) is shown in equation 1 and scaling, and resizing is shown in equation 2 which are some of the pre-processing techniques. In this work, the leaf image is resized $224 \times 224 \times 3$, which is then used to evaluate the performance of the proposed model.

B. *Data Augmentation*

To enhance the picture count and decrease overfitting, data augmentation is essential for data preparation. By using the following data augmentation approaches, the data would be able to multiply 10 times while producing more photos for each class.

a) **Horizontal Shift:** To create a new picture in which the leaf is not located in the centre, the arbitrary movement horizontally shifts the picture out of the centre, to strengthen the structure, and to make it less vulnerable to overfitting.

b) **Vertical Shift:** Similar to a horizontal shift, a vertical shift shifts the picture farther from the centre. Within the range of 1% picture magnitude, both filters generate arbitrary fluctuations.

c) **Flips:** This filter creates a vertically or horizontally

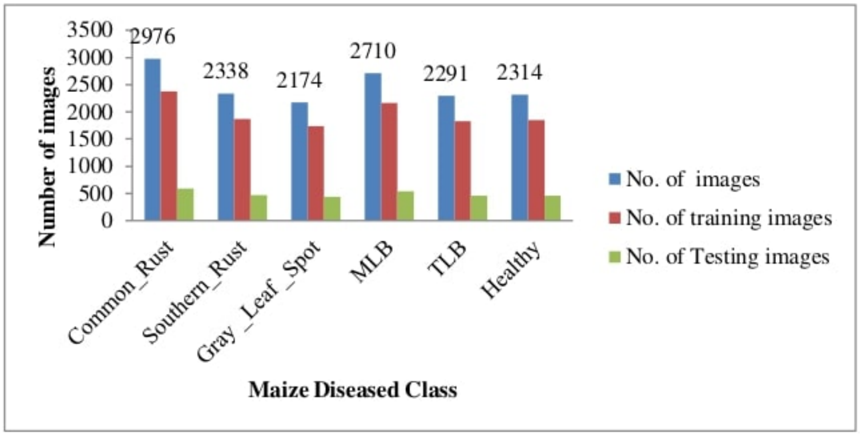

Figure 3. Per/class number of maize leaf dataset

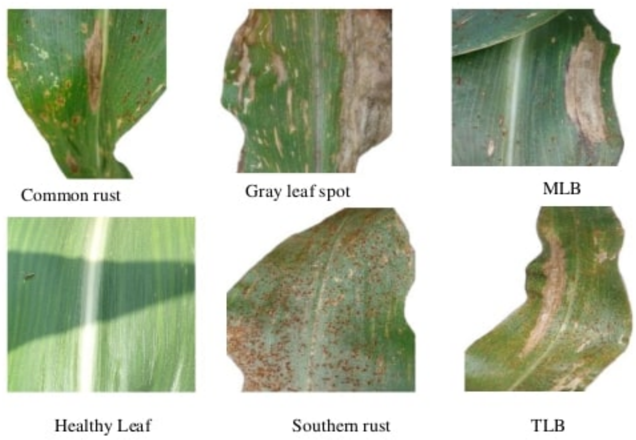

Figure 4. Sample input of maize leaf disease dataset

flipped image that is a replica of the original.

d) **Zoom:** Every image is randomly zoomed by up to 15% in this method.

Figure 5 shows the steps followed for the augmentation and pre-processing of leaf disease images.

C. Disease data segmentation and classification

The proposed model name Pyramid Scene Parsing Network using Convolutional Neural Network (P-CNN) is used for the detection and classification of maize leaf disease. The functionality of the PSP-Net and CNN models is incorporated in the proposed model. It includes 67 Convo layers in total, of which 30 Convo layers are from PSP-Net, 15 Convo layers for up-sampling, and 15 Convo layers for down-sampling. The softmax layer and max pool layer are all incorporated in the suggested model with CNN. Substituting three of the maximum pool layers from the pyramid's five layers of up-sampling. Softmax layers will ultimately produce the picture classification output. The proposed model receives input from the pre-processed dataset. The suggested approach has successfully generated a morphological feature map of maize from a given dataset. Max's pooling layer and up-sampling technique have been used to minimize the specific scale of the picture feature map. After the creation of pixel-wise data depiction for every category and the processing of the soft-max layer, the outcome was displayed. The proposed P- CNN model has shown in Figure 6.

The proposed model is used for two key reasons. First, it may use convolution layers to extract thorough characteristics from local information. Second, it will offer the most accuracy for the few samples. A proposed prototype having a skip connection mechanism and a consolidated convolution layer constraint (kernel size, 3×3) has been suggested. Kernel size, padding, and activation functions have all been utilized in this study. There are 3×3 is the kernel size, and 0 is utilized as padding around the outside of the picture. Conv 64, and the kernel size of the outer layer have all been utilized in the ReLu activation function.

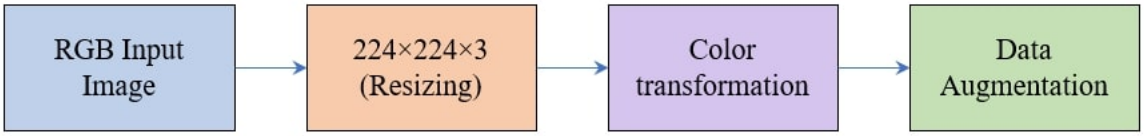

Figure 5. Pre-processing and augmentation technique

Furthermore, the binary (0, 1) picture segmentation problem is handled by the sigmoid function. Figure 6 outlines all the steps in the proposed model. The cascade representation of object detection was employed in this study. It will also show how well major semantic segmentation and object identification work. The proposed model, which has altered three of the five max-pool layers, has been used in this study to create a novel framework for semantic segmentation. Before moving on to the next step and, lastly, before semantically segmenting the maize component to look at the pertinent data, the max-pool information is analyzed. The overall modifications are enhancing the flow and precisely attain the image's goal. The algorithm (EMDMP) presented in table 2 uses a few abbreviations.

TABLE II. Abbreviations used in algorithm 1 (EMDMP)

Notation	Meaning
M_{RGB}	Maize RGB image
$M_{RGB}(C_r)$	Cropped and resized image
R	Resized image
w', h$'$	Resized width and height of an image
w, h	Original width and height of image
x$_{R,}$ v$_{r,\ and}$ Or	Degree of axis and origin
$T(x_{r,} y_r)_c$	Enhanced image
B_x	Bounding Box
FC	Fully Connected layer
$C_L(RGB)$	Classified image
IoU, mIoU	Intersection Over Union and Mean Intersection Over Union
F_i	Fragmented image
$a, b,\ c$	a and b is the axis, and c is the confidence
$I_{max}\ and\ I_{min}$	Pixel value maximum, and pixel value minimum
TP and TN	True Positive and True Negative
FP and FN	False Positive and False Negative

The steps of the proposed model algorithm are given in Algorithm 1.

Algorithm 1: Estimation of Multiclass Leaf Disease in Maize Plant (EMDMP)

Input: Take M_{RGB} the field acquired from the plant village dataset.

Output: Multi-class classified disease object

1. Take M_{RGB} as 255 × 255 × 3 and set as a $M_{RGB}\left(C_r = \frac{W'}{h'}(224 \times 224 \times 3\right) = R$
Set the pixel coordination (x, y) in R and $R = ((x + o_r)\,x,\ (y + o_r)\,y)$ in the old image with $(0-90,\ 90-180\ degree)$
2. Rotate the $M_{RGB}(C_r)$ as
$x_R = x + cos(Ang) - y \times sin(Ang) and\ y_R = x + sin(Ang) + y \times cos(Ang)$
Set $T(x_{r,} y_r)_c = I_{max} - I_{min}$ where value very $0 - 255$
3. Implement the proposed model as B_x with (a,b, w,h, c with (n× m stride
   - $If\ (B_x > F_i)$
   Then → Go to step 6
   else
   print → select B_x
4. Implement CNN with reduce convo block ;(5 x 5 x 16 filter size 6 x 6
5. Print → highest accuracy, IoU, MIoU and Return $C_L(RGB)$

Take 255 × 255 × 3 and set $M_{RGB}(C_r)$, $\frac{W'}{h'}(224 \times 224 \times 3)\ as\ (x, y)$ in R. Furthermore, Rotate the $M_{RGB}(C_r)$ using the methodx_R and y_R and finally get the enhanced greyscale image as $T(x_{r,} y_r)_c = I_{max} - I_{min}$with value range from 0-255. Further, implement the proposed model B_x w$(a, b,\ \ w, h,\ \ c)$ with $(n \times m)$ stride and check the condition of bounding boxes in comparison with background(F_i)T$convo\ \ block$ $(5 \times 5 \times 16)$ filter size 6×6 and based on the parameters such as accuracy,Mean Intersection Over Union(mIoU), Intersection Over Union(IoU) a Return $C_L(RGB)$.of the traditional YOLO and VGGextremely comparable to the VGGThe suggested model's skeleton is the traditional VGG19+CNN model. The fundamental VGG19+CNN concept requires additional time for pooling. Therefore, it is essential to first limit the number of pooling layers. The VGG19+CNN CNN model'In the last phase of the convolutional layer, Batch Normalization (BN) has been introduced to ensure data stability [31].

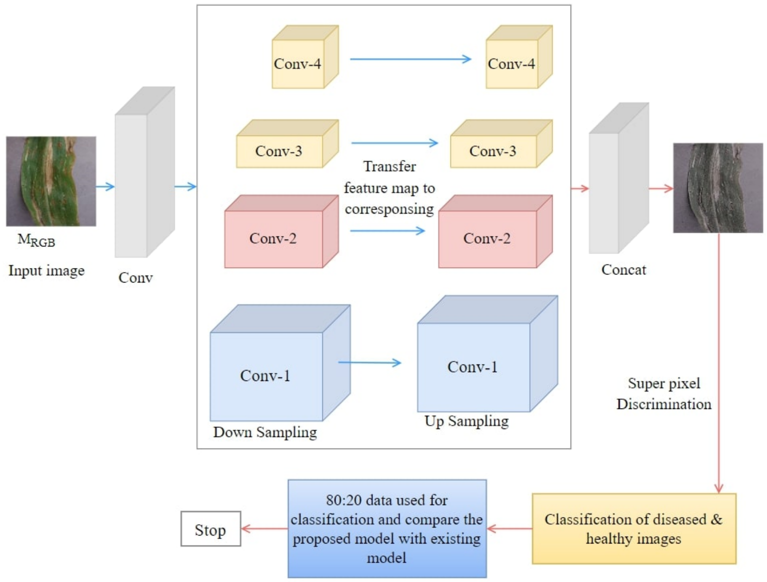

Figure 6. Proposed P-CNN model

4. Result and discussion

The 14803 images used in this study were divided into 80:20 which include 6 different classes of datasets. Table 3 displays the dataset's overall distribution.

TABLE III. Dataset distribution

Dataset Class Name	No. of images	No. of training images	No. of testing images
Common rust	2976	2381	595
Southern rust	2338	1870	468
Gray leaf spot	2174	1739	435
MLB	2710	2168	542
TLB	2291	1833	458
Healthy	2314	1851	463
Total	14803	11842	2961

The 11842 images that were pre-processed before being fed to the algorithm used in the remaining portion of the studies. The 14803 images that were used along with 370 primary datasets. This work has used 11842 images for training and the remaining 2961 images for testing the model.

A. Experimental Setup

This work developed a classification model for leaf disease using Python 3 and the Keras framework. The model was tested using a Google Colab Pro version with 15GB of storage, 8 GB of RAM, and a P100 processor. The pre-processing phase comprised scaling, normalization, and conversion to an array of data using the Image Data Generator class in Keras.

B. Evaluation of model

The outcome of segmenting vegetation from a small number of input photos was drawn from three separate datasets. It can be shown that PSP-Net + CNN performed better than the alternative model. Prepares a homogenous color object prototype using the similar object's pixel intensity after object classification using semantic segmentation. The Plant Village dataset has enabled more accurate item recognition during observation. The segmentation of the backdrop and vegetation can reveal more precise details of the object's vegetation.

The output of the pre-processing stage was used to construct the proposed input for the multi-class DL models to categorize the leaf diseases. The prototype has been trained as well as validated using an optimizer and the relevant fit techniques across 200 epochs. Each epoch used eight iterations and 32 different batch sizes. The efficacy measure formulas have been input into the outputs of the authentication figures with the utmost accuracy. Utilized was the Adam optimizer, with a learning rate of 0.0001. When evaluating the model's performance, Recall, the IoU, mIoU, loss, Accuracy, Precision, and F1-Score were used. The percentage of occurrences with accurate predictions out of all instances was used to calculate accuracy. The precision was indicated by the positive predictive value. Accuracy was determined by dividing the number of positive samples by the number that was anticipated to be positive.

C. Semantic Data Analysis of Disease

To identify the regions of vegetation in the images that include maize leaves, the vegetation segmentation M_{RGB} was employed. The result includes segmented disease objects. Each segmentation and classification of the data is compared using a pre-trained YOLO+CNN and VGG-16+CNN classifier. Figure 7 compares the performance of several classifiers in detecting phrases like healthy or diseases using these properties. Pay attention to the improvement in classifier performance brought about by weighted training using different techniques. This work confirms earlier findings by demonstrating how sampling tactics (random sampling) can help to improve the classifier performance for an unbalanced dataset. Efficiency and recall calculated for the disease category upon that testing set are used to evaluate performance. While accuracy and recall numbers are somewhat improved by sampling techniques that take into consideration class imbalance, the absolute values still fall short of the appropriate cut-off. According to Figure 7, the proposed model data accuracy and recall are 99.85% and 98.7% respectively. However, to support the selection of the bounding box size, the results from areas of various sizes were analysed. In this work, we retrained the classification models using both side length increases and reductions. When accuracy and recall values are considered, classifiers trained with side-length masks outperform those trained with the mask on average. Figure 6 displays the bounding box representation of the maize dataset.

This work has used the Plant Village dataset and used three different classifier models named YOLO+CNN, VGG19+CNN, and the proposed model (P-CNN). The existing model as YOLO and VGG 19 has updated with 3x3 convo layer with basic CNN model. Comparing the suggested model to the other two classifiers, it has a superior accuracy score of 99.85%. For classifying maize leaf disease, the YOLO+CNN model had an accuracy of 96.68% while the VGG19+CNN model had an accuracy of 93.76%. The result evaluation of the proposed model in comparison with other models is given in table 4.

Accuracy is one of the parameters for evaluating classification models is accuracy. Informally, Accuracy is the degree of the way the model changed into positive detection and the way by which it becomes calculated. The accuracy of the formula is given in equation 1 [21].

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

Another is precision which is the degree to which two or more measurements are close to each other. The formula of precision is given in equation 2.

$$Precision = \frac{\sum TP}{\sum TP + \sum FN} \times 100$$

Furthermore, recall (also known as Positive Predictive value) is the percentage of relevant examples found among the recovered instances, whereas recall (also known as sensitivity) is the percentage of relevant instances found. As a result, relevance lies at the heart of both precision and memory [30]. The formula of Recall is given in equation 3.

$$Recall = \frac{\sum TP}{\sum TP + \sum FP} \times 100$$

The F1-Score is the measure of a model's accuracy on a certain dataset is its F1 score. It is employed to evaluate binary classification schemes [31] that categorise examples into positive and negative groups. The harmonic mean of the model's precision and recall, which is a method of combining the two, is what is meant by the F1-score stated in equation 4.

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

The Recall and F1-Score achieved by the proposed model are 99.45% and 98.97% respectively. In comparison with the proposed model, the YOLO+CNN have achieved Recall 98.54% and F1-Score 98.9%, and VGG19+CNN have achieved Recall 93.09% and F1-Score 92.56%. The bounding box is accurately estimated based on two parameters as IoU and mIoU which have achieved 99.97% and 98.96% which has greater the 0.5%.

5. Discussion

The most common maize disease is classified using multiclass supervised deep learning in this study. We employed the fully connected CNN feature extraction model for classification together with the pre-trained VGG19 model for feature extraction. The usage of a VGG-19 model followed by a CNN model is used to illustrate the utilization of maize images to detect particular types of disease class diseases. For our model, input data consisting of the disease portion of a picture with dimensions of $224 \times 224 \times 3$ were used. During the feature extraction stage, the VGG19 pre-trained model is followed by three CNN blocks. Large-scale picture applications benefit greatly from the better accuracy that VGG19+CNN is designed to provide.

The VGG19 was combined with several deep-learning models to increase the accuracy of picture categorization. A convolution layer with a ReLU as the activation function makes up each CNN block. After these three CNN blocks, a batch normalization layer, a max-pooling layer, and a dropout layer were added, as seen in figure 5. A one-dimensional data vector was created from the result of the feature extraction stage, which was then modified by the flattening layer and utilized as an input in the classification stage. The remaining categorization step components are made up of three thick layers with 512, 256, and 128 bits apiece. We argue that the proposed strategy emphasizes the precise identification of the treatment zones rather than the precise identification of such pixels. Additionally, the recommended method's massive data requirements are far smaller than those of an end-to-end segmentation network, which improves generalization and scalability.

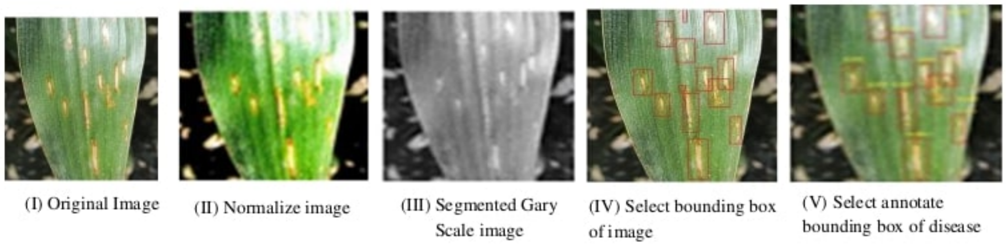

Figure 7. Maize plant semantic data analysis (left to right): (I) Original Image, (II) Normalize image, (III) Segmented Gary Scale image (IV) Bounding box, (V) Select annotate bounding box of disease .

TABLE IV. Result evaluation of the proposed model in comparison with other models.

Dataset	Classifier	Accuracy	Recall	F1-Score	Precision	IoU	MIoU
Plant Village	PSP-Net +CNN	99.85	99.45	98.97	98.93	99	98
	YOLO+CNN	96.68	98.54	98.9	90.98	92	92
	VGG19+CNN	93.76	93.09	92.56	91.9	97	96.4

The recommended approach does not need the development of specific characteristics. Therefore, it may be used with any combined stress in leaves.

Binary cross entropy is used to compare each of the predicted probabilities to the actual class output, which can only be either 0 or 1. The probabilities are then given a score that penalizes them according to how far off the projected value they are. How near or far the value is from the real value is shown by this.

For a single data point, the category cross-entropy loss function is where p is the probability for the positive class, weightage (w1) and weightage(w0) are the class weights for the positive class and y=1,0 for the labels that are positive and negative. The soft-max layer of the proposed PSPNet+CNN model has been used to evaluate the cross-entropy and weight-cross entropy loss of images. The Plant Village dataset, which has a maximum precision of 0.97 and a minimum precision of 0.57, was used in this investigation. The categorized item may overlap, allowing for the partial or whole object to be discovered. The error rate, which is shown in figure 8, is used to estimate the identified object.

The error rate based on the MA, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) of the Plant Village dataset are reported in Figure 8. Following the observation, the accuracy of the plant village dataset is 99.85% and 1.62, whereas 2.06 has an error rate of MAE and RMSE. Precision, recall, and F1-score for the suggested model were 97.8%, 98.7%, and 97.8%, respectively. The current model classifier has attained data accuracy of 89.93%, 90.90%, and 84.23%.

6. Conclusion

The segmentation and detection of single-biotic and multi-biotic lesion areas on maize leaves is a very difficult task because of several interconnected factors, including ambient lighting, a complex background, a diversity of symptoms, and more. This work has used 14803 images using primary and secondary dataset for classification of images. To handle the complexity of the backgrounds in real-world photos, this research introduced a P-CNN model with the inclusion of an instance segmentation step. To address the challenges of data labelling and the lack of training data, a data augmentation technique was developed. The results of the experiment's analysis revealed that:

1) The P-CNN model had an accuracy of 99.85%, which is significantly higher than that of other modified segmentation models. The lesion items can be divided up using the hybrid model. With a time, consumption of 51.71ms, the segmentation parameter IoU was lower than that of other models at 99.91%.
2) Merging the background and foreground data sets may greatly improve the data collection. It can lessen overfitting brought on by insufficient training data.
3) In every environmental circumstance, the proposed approach could precisely separate the multiple and single items.
4) The P-CNN model accurately segments higher pixel ranges; however, it fails to accurately segment lower pixel ranges. The current method's inability to identify regions when lesions overlap is one of its semantic segmentation shortcomings. The current method's inability to identify regions when lesions overlap is one of its semantic segmentation shortcomings. The other decision element in this hybrid model is the small number of picture datasets.

In the future, more picture segmentation methods can be researched to more accurately identify, classify, and detect minute biotic and abiotic lesions. For greater accuracy, different size datasets with various morphological characteristics can be used.

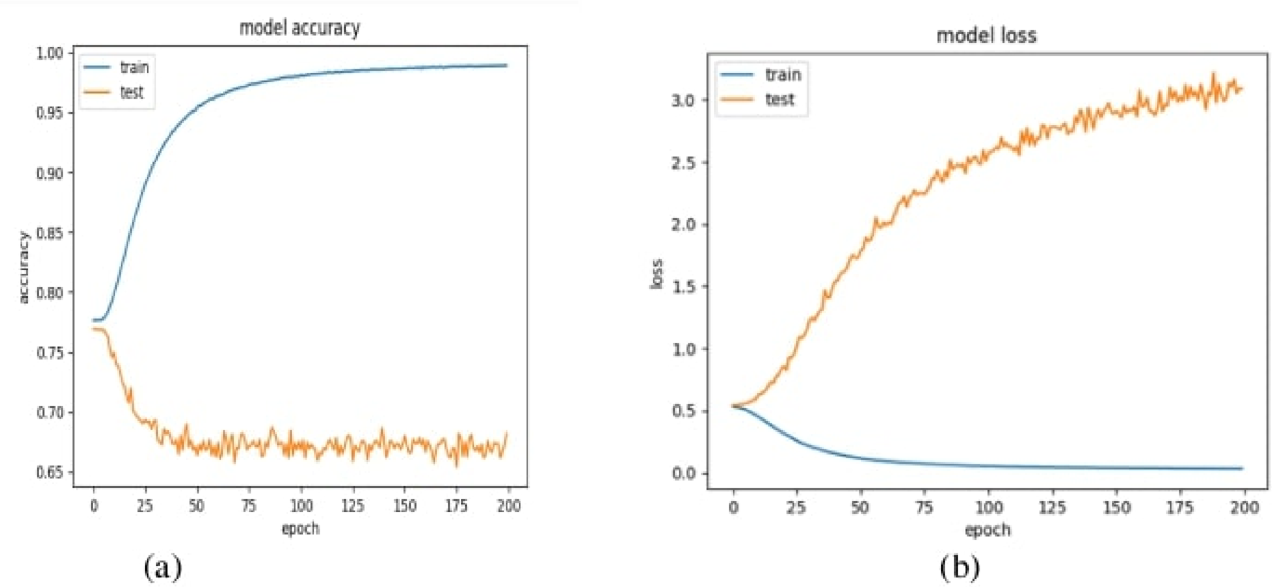

Figure 8. (a) Accuracy and (b) Value Loss

7. Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Data Availability Statement The secondary dataset generated from Plant Village dataset.

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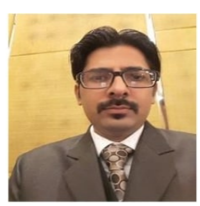
Prabhnoor Bachhal was born in India. She received B.Tech. and M.Tech. degrees in computer science & engineering from Kurukshetra University, Kurukshetra in 2014 and 2017, respectively. She is currently pursuing the Ph.D. degree from Chitkara University, Rajpura. Her current research interest includes deep learning and image classification.



Vinay Kukreja completed his Ph.D. in Computer Science & Engineering. He is presently working as a Professor at Chitkara University, Punjab, India and having more than 17 years of experience. More than thirty-four has been filed and five patents granted to him. He has authored three international books. More than 120 papers are Scopus indexed. He has won the first prize in the SIH Hackathon (2018) under the flagship of the Ministry of Housing & Urban Affairs, India. His areas of research interest mainly include machine learning, deep learning, agile software development and decision-making approaches.

Sachin Ahuja is presently serving as Professor & Executive Director at Chandigarh University. He has extensive research and academic experience. He has served at key academic positions at various reputed higher education institutes. He has guided several M.E. and Ph.D. scholars in areas like Artificial Intelligence, Machine learning, Deep learning and Data mining.