# Corn Leaves Disease Detection Using Convolutional Neural Networks [CNN]

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**Abstract** - A proposed approach for accurately determining prevalent corn diseases involves utilizing a convolutional neural network-based method for corn disease identification. Four different types of maize leaf pictures are produced by adding corrected linear unit activation to the enhanced CNN model, which is used for training and testing functions and the Adam Optimizer, changing the settings, combining processes and cutting down on classifiers. When three different kinds of maize leaf diseases were identified, this model attains an average detection accuracy of 93.75%, which is the maximum precision only attained in the identification of maize illness from leaves with faster rates of training convergence to the highest quality our deliberation. All things considered, this method is quick, easy to use, and offers a dynamic means of identifying leaf maize disease. This will help low-income farmers avoid crop loss and encourage support for the agricultural system across the country.

***Key Words***: Convolutional Neural Network [CNN], Deep Learning, Activation Function, RectifiedLinear Unit [ReLu], SoftMax,

## 1. INTRODUCTION

India is an emerging country that relies heavily on agriculture for its development. The foundation of India's economy is farming, which involves the cultivation of various crops throughout the year. These crops are categorized into four main groups: food grains, plantation crops, cash crops, and horticulture crops. They are cultivated in three major crop seasons known as rabi, Kharif, and Zaid. Corn, which falls under the food grains category, holds great importance for both humans and livestock in India and many other parts of the world. It is highly nutritious and widely consumed. Rural communities depend on agriculture as their primary source of income. However, corn is susceptible to diseases [1], posing a significant challenge for farmers. Illnesses can occasionally cause disturbances in the growth of maize plants and even impede the attainment of a desired crop yield. The degree of assault on the maize plant determines how much of an impact there will be. Numerous maize diseases are impacting maize yield, leading to significant reductions in growth, deteriorating quality, and driving up the cost of maize. Plants afflicted with diseases typically have disruptions in their d++333333333333333333333333333333evelopment, resulting in abnormal cell activities and tissue activities. When a plant dies, its ability to develop is hindered, and its leaves may turn yellow or dry. Zea maize, often referred to as maize in many regions, is an annual grass belonging to the Poaceae family. Around the world, maize is cultivated as a main food crop. With the exception of wheat and rice, it produces the most grains globally [2-4]. However, the variety of maize diseases and the extent of their harm have also grown in recent years. This is due to a variety of factors, including modifications to farming practices, insufficient plant protection measures, and environmental changes.[5] Few of these diseases have leaf consequences, which can be challenging for novice farmers to identify from visual signs even though a qualified plant pathologist may be able to.

The most common maize leaf diseases are typically grey leaf spot, curvularia leaf spot, northern leaf blight, southern leaf blight, round spot, rust, brown spot, and dwarf mosaic [6-10]. Our major goal is to use a productive disease detection strategy for maize leaves based on Convolutional Neural Networks (CNNs) [11].With the assistance of the Plant Village dataset, a CNN-based model version is put into practice and evaluated for the categorization of illnesses.

## 2. LITERATURE

Even though scientists are testing a number of techniques for the rapid identification of diverse plant diseases with varying symptoms, novice farmers find it more difficult to diagnose these conditions than do qualified plant pathologists. An automated system for diagnosing plant illnesses is designed to identify various diseases based on the way plants look, which might be very beneficial for novice farmers.

Numerous techniques have been used in an attempt to diagnose leaves illness accurately and quickly. The identification and categorization of leaf diseases are accomplished with the use of digital image processing techniques, support vector machines (SVM), artificial neural networks, and a few other approaches. With an accuracy of 89.6%,[12] Song et al. have used an SVM technique to detect several maize leaf diseases. Large and small datasets can benefit from this SVM-based classification approach, however its accuracy may not be the greatest. Chen and Wang have presented a probabilistic neural network (PNN) and image processing methodology for the detection of maize leaf disease.[13] These techniques have a 90.4% accuracy rate. Here, the PNN classifier's disadvantage is that as training sample numbers rise, accuracy and procedure speed both decline.[14] Adaptive weighted multi-classifier fusion is the basis of Xu et al.'s technique for detecting maize leaf disease, and it has been tested on seven different varieties of maize leaves. 94.71% is the average recognition rate attained. To diagnose illnesses of maize leaves, Wang et al., Qi et al., and Zhang [15-17] have suggested a variety of image processing techniques and combination characteristics. The greatest recognition accuracy for these investigations is 95.3%. The best recognition accuracy that is currently required cannot be met by this suggested model. Excellent advancements in deep learning have been made recently. It is able to extract representative aspects of the bigger input image that are helpful. Additionally, it aids in the precise diagnosis of crop diseases by detectors, which enhances precision and broadens the application of computer vision in the agricultural industry. Convolutional Neural Network (CNN) model has been suggested by Md. Al-Amin et al.[18] to forecast potato illness from the potato leaves. Their methodical model has the best accuracy, at 98.33%. In order to identify ten distinct types of rice illnesses, Lu et al.[19] have suggested several algorithms, pooling operations, and filter sizes. Their CNN-based model has an accuracy of 95.48%. Using the CNN model, Dechant et al. [20] were able to detect the disease known as northern leaf blight in maize with an accuracy rate of 96.7%. Even though these techniques have longer convergence times and higher accuracy, the recognition rate is negatively impacted by the amount of factors.

## 3. RELATED WORK

### A. Dataset

The pictures are taken from Plant Village, which has over 50,000 distinct kinds of pictures. Analysis is done on 4190 photos of maize leaves in total. Three categories—one representing a healthy leaf and the other three depicting diseased maize leaves—are used in this work, as shown in Table 1. Fig 1, Fig 2, Fig 3, and Fig 4 depict many maize plan diseases.

Table 1: Visualization of Image Dataset Statistics

| DISEASES | NO. OF IMAGES |
|---|---|
| Blight | 1146 |
| Common Rust | 1306 |
| Grey Leaf Spot | 576 |
| Healthy | 1163 |
| TOTAL | 4190 |

**Fig 1**: Blight Leaf

**Fig 2**: Common Rust

**Fig 3**: Grey Leaf Spot

**Fig 4**: Healthy

### B. Methodology

Using maize leaf datasets, the CNN model predicts the occurrence of maize leaf disease. A block diagram that divides the process into two main phases—image processing and CNN model—is shown in Figure 5. Prior to being put into any machine learning or deep learning algorithms to increase performance, the raw data is transformed into a predetermined format during the picture pre-processing step. The training process has to be accelerated by the pre-processing techniques. Prior to the model being trained, it is completed for the CNN classifier. The most effective method for adjusting the size of the photos is normalization. Python scripts are used in our study to resize all varied sized colored pictures to 150*150 pixels for use with the OpenCV framework. Subsequently, the photos are labelled using the binarized method in accordance with the class labels.

**Table 2**: Splitting of the dataset

| Class | Train | Test | Validation |
|---|---|---|---|
| Blight | 916 | 115 | 115 |
| Common Rust | 1044 | 131 | 131 |
| Grey Leaf Spot | 460 | 58 | 58 |
| Healthy | 929 | 117 | 117 |
| Total | 3348 | 421 | 421 |

## C. Architecture

As seen in Figure 6, this suggested CNN model only takes into account two completely linked dense layers and three convolution layers when designing it for illness prediction. In the first, second, and third convolution layers, it employs 32, 64, and 128 filters, respectively. All layers employ the ReLu activation function; the sigmoid activation function is used for the final layer. For the first three layers, a 3 x 3 filter was employed. Our architecture uses three max-pooling layers, each of which has a pool size of two by two. Two thick layers that are totally coupled have been employed in this model. The first dense layer uses 128 filters, while the last dense layer uses four filters for four outputs. The weights are updated by implementing the Adam optimizer. This design makes use of a number of distinct operations, which are described below.

**Convolution layer:** The convolutional layer is one of the primary components of a CNN. Activation is the outcome of the straightforward application of multiple-sized filters on the input picture. A map known as a feature map is produced in the activation by repeatedly using the same input picture and filter. This shows how well the characteristics in the supplied image were identified. Each feature map in CNNS has become more complex with the assistance of several input feature graphs. If an input X of the convolution layer i , it calculates which is shown in Eq. (1).

$$CO = F(Y*X) \quad \ldots (1)$$

'F', here is defined as the activation function, and Y indicates the convolutional kernels of a layer. This (*) symbol represents the convolution operation between the convolutional kernels (Y) and the input of the convolutional layer (X). The kernel can be defined by the equation (2);

$$Y_i = [Y_i^1, Y_i^2, \ldots, Y_i^k] \qquad (2)$$

k is the convolutional kernel number and each kernel $Y_i^k$ is of the size M×M×N, representing the weight matrix. (M is the window size and N is the input channel number).

Fig. 5 shows the convolution operation in the convolution layer for a 5x5 input image and a 3x3 filter.

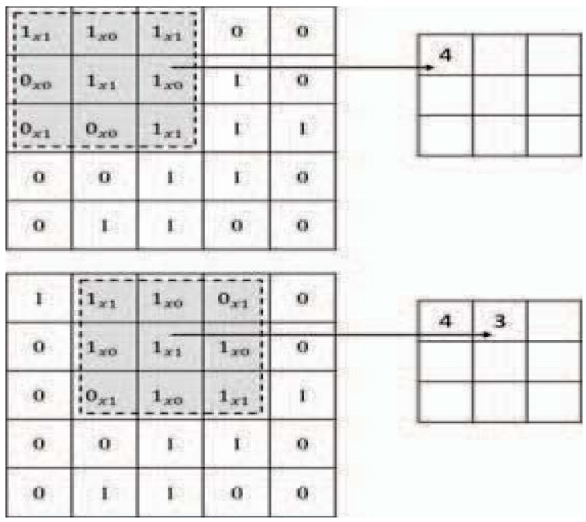

**Fig. 5**:. Convolution operation for 5x5 input image and 3x3 filter.

**Activation Function:** The activation function of artificial neural networks creates a curvilinear connection between the input and output layers. Performance of the network is impacted by this.. The network may learn non-linearly thanks to the activation function**.** One of the most popular activation functions that may be applied to the hidden layers is the rectified linear unit (ReLu). The ReLu activation function was applied to this study in order to improve accuracy and solve the gradient dispersion issue. Values larger than zero in ReLU remain unaffected, but values less than zero are transformed to zero.

$$f(x) = \begin{cases} 0 & , \quad \text{if } x < 0. \\ x, & \end{cases}$$

**Pooling Layer:** As the number of convolution layers rises, the network's parameters also rise exponentially. These pooling actions minimize the network parameters in an effective and efficient manner. In order to reduce the parameters, pooling procedures are performed for entire areas by calculating their statistical significance, which yields the features of the entire region.

**Adam Optimizer:** The parameters are optimized by the application of the Adam optimizer method. Rather of employing the traditional stochastic gradient descent process, the optimization method is employed to optimize the parameters. Based on the training data, it modifies the network's weights for a set number of iterations. Because it produces accurate and timely results, deep learning has seen a rise in its popularity.

**Dropout:** Dropout is a regularization technique that keeps neural networks from overfitting. Neurons that are selected at random are disregarded during training. Dropout is compatible with both visible and buried layer implementations. The output layer might not be utilized.

### D. Training Model Parameters

The training model of a CNN depends on a number of factors, including learning rate, batch size, epochs, etc. Learning rate and hyperparameters, which regulate the degree to which the model should be adjusted to an estimated mistake, are two important factors. Our suggested model has a learning rate of $10^{-3}$, and the model weights are adjusted every time. The factors that regulate the quantity of training samples in every batch are the batch size and hyperparameters. The batch size of 32 is utilized in our model. The gradient descent's epochs and hyperparameters, which regulate how many full passes over the training dataset are made. Our training model makes advantage of the thirty epochs. After an epoch is over, the entire dataset is shuffled using the shuffle function. This study's fitness function indicates which value in our training model is true.

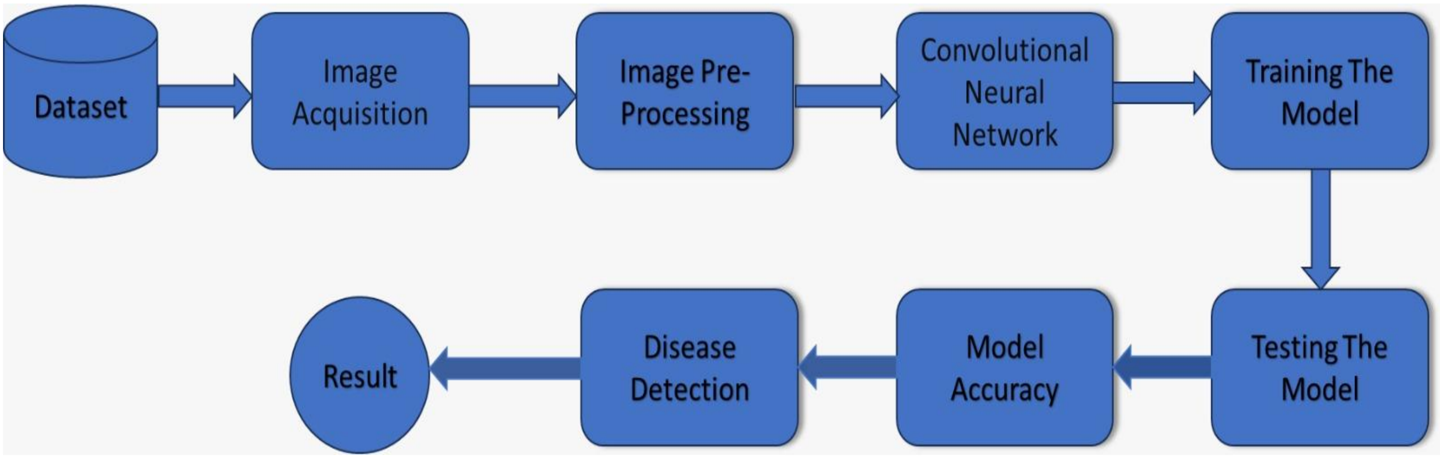


**Fig 6**: Block Diagram for the proposed methodology

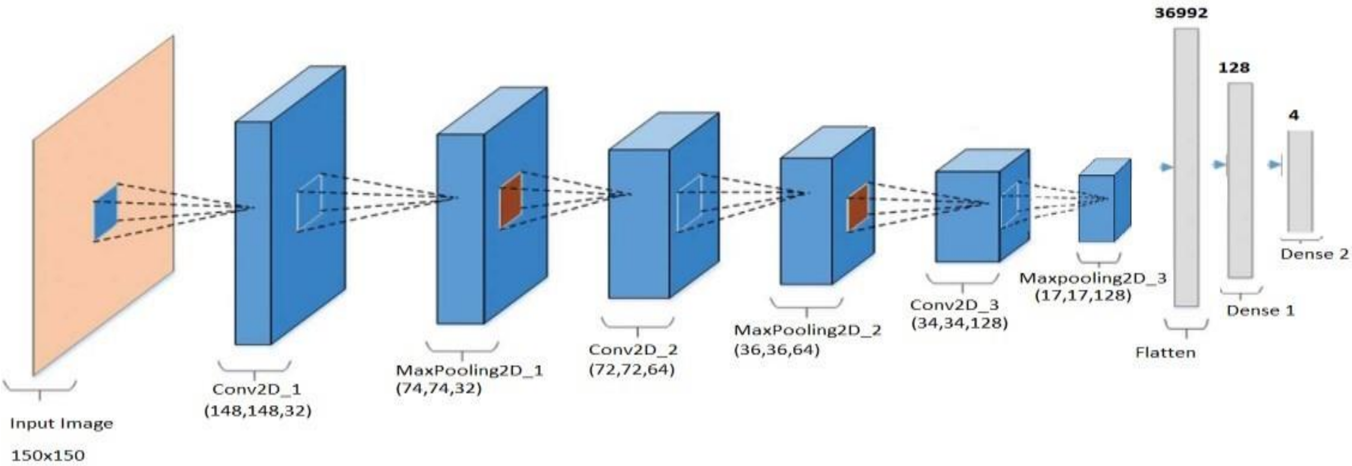


**Fig 7**: Working of the CNN model

### E. Analysis and Evaluation Tools

Python is used for the algorithm's preprocessing, implementation, and classifier assessment. The Python 3X version, which has a thorough standard library for deep learning and machine learning, has been utilized. The model is trained and tested on an Intel Core i3 CPU with 8 GB of RAM and Windows 10, a 64-bit operating system. The suggested solution has been implemented using the Jupyter Notebook environment.

## 4. EXPERIMENT RESULT AND DISUSSION

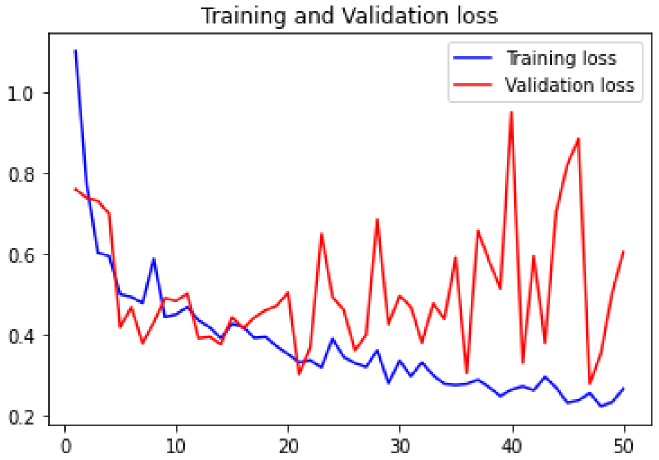


**Fig 8**: Training and Validation Loss

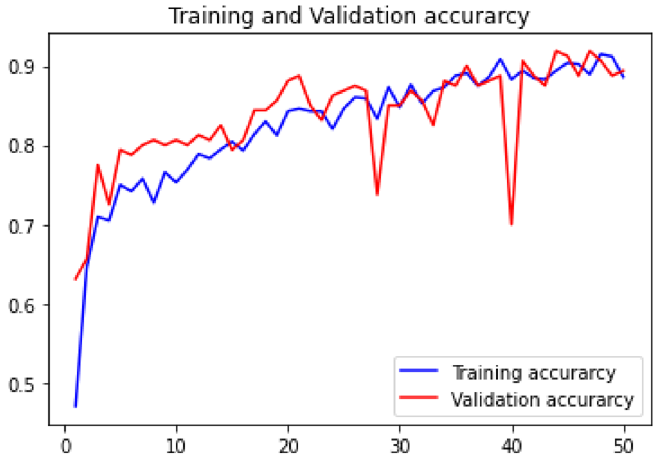


**Fig 9**: Training and Validation Accuracy

Fig8 and Fig9 displays a line graph for the proposed model's loss and accuracy function for both the train and test data, with blue and red colored lines representing the train and test data, respectively. It can be seen from the figure that the model's over-fitting has decreased as the iterations have progressed. To obtain the model's output, the experiment's iterations are repeated about 50 times.

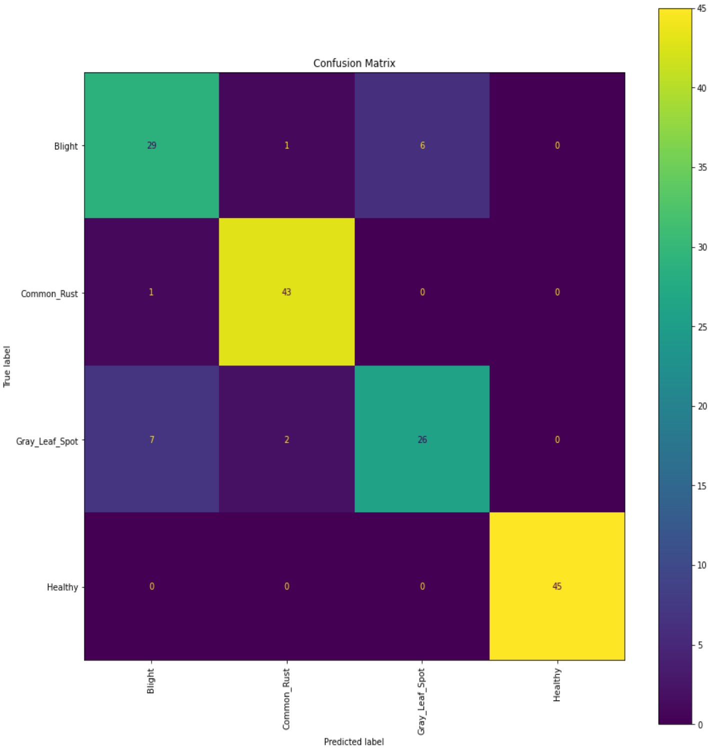


**Fig 10**: Confusion Matrix

The confusion matrix for a particular collection of test data that is used to assess how well the classification models perform. Although the matrix itself is simple to understand, there may be confusion with the associated jargon.

**Table 3**: Training & Testing Accuracy for the given Model

| | |
|---|---|
| **Training Accuracy** | 95.16% |
| **Testing Accuracy** | 93.75% |

We can observe from the results that the model performs admirably, with 93.75% accuracy.

## 5. CONCLUSION

In addition to the healthy leaf, a CNN-based model has been put into place to identify the three most prevalent diseases of maize: Gray leaf spot, common rust, and leaf blight. With shorter convergence training time and an accuracy of 93.75%, the best result as compared to previous studies on maize leaves was obtained. Experiments have shown that adding the ReLu function, pooling operations, Adam optimizer, and various model parameter adjustments may all improve detection accuracy. This is a practical method for raising maize productivity. Farmers may apply this technique, which offers a time- and money-saving strategy for detecting maize diseases and supports digital agricultural systems. In further research, this model may be tested and trained to identify other varieties of maize leaf diseases by combining it with additional deep learning approaches and algorithms.

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