



Deep Learning Techniques For Chili Disease Detection And Classification

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Abstract: This research studies chilli disease image classification by using the deep neural network (DNN) algorithms. The disease-affected input images mainly focus on the disease category and five types of chilli disease have been used in this paper. Convolutional neural network (CNN) algorithms have been chosen as the best option for the training process because they produce a high percentage of accuracy. Results are discussed in terms of the accuracy of the image classification in percentage. Chilli disease is classified into four diseases, with 120 images collected for each: black circle spot, straw colour chilli, white colour chilli, and rotten chilli. 70% of the data set was trained, whereas 30% was tested. The hyperparameter epoch is used to tune the CNN model, which gradually increases and gives 96.65% accuracy.

Keywords: DNN, Deep Learning, CNN

I] INTRODUCTION:

India is an agriculture land and a major part of its economy depends on the agricultural sector. The share of agriculture in the Indian Gross Domestic Product (GDP) and total exports are 16% and 10%, respectively. About 75% population of India depends on the agricultural sector either directly or indirectly[1]. Chilli is rich in vitamins C, A, and B for its dried form and green fruits. It's a main crop for both home and export markets, grown mostly in tropical locations such as Africa, Japan, and India. India leads the world in production, followed by China, Pakistan, and Mexico. Despite this, they can suffer large yield losses from bacterial, fungal, and viral illnesses[2]. Therefore, disease-free good quality chilli crop production is essential for the growth of the country's economy. Manual disease detection in chilli plants is done either by farmers or by agricultural scientists. However, this is a very challenging and time-consuming task. To address this problem, many researchers across the globe presented different systems for plant disease detection and classification with the help of various Machine Learning and Deep Learning techniques[3]. Crop disease detection and classification are important in agriculture to increase yield and quality by reducing the economic and appealing damage caused by plant diseases. Therefore, researchers are applying new technologies to efficiently classify diseases has been conducted and recently, research on detecting plant diseases using deep neural networks. Convolutional Neural Network is a specialized method to recognize or assign images and consists of fully connected layers, numerous convolution layers, and pooling layers[4]. Three types of layers are arranged and connected differently depending on the model architectures and model performance is affected by this architecture. This work provides the research progress of deep learning technology in the field of chilli disease identification in recent years[5]. for the detection of plant chilli disease using deep learning and advanced imaging techniques. This work will be a valuable resource

for researchers who study the detection of chilli diseases along with discussing some of the current challenges and problems that need to be resolved[6].

In Section II, we review the existing literature work. Section III explores use of deep learning for classifying and diagnosing chilli diseases. The data collection process and methodology are detailed in Section IV. Section V discusses the experimental results and Section VI conclude the work and future directions for upcoming researchers.

II] RELATED WORK:

Plant disease detection and classification using Convolutional Neural Networks (CNNs) has been a popular research area in the field of computer vision and agriculture. Here are some related works that provide insights into different approaches and techniques in this domain. In most cases, agricultural experts are used to identifying on-site or farmers identify chilli diseases and pests based on experience. This method is not only subjective, but also time-consuming, laborious, and inefficient[7]. Convolutional Autoencoder (CAE) and Convolutional Neural Network (CNN) are combined in a hybrid model for early plant disease detection that reduces training parameters and improves classification accuracy. With just 9,914 parameters, the model achieves 99.35% training accuracy and 98.38% testing accuracy by compressing leaf image representations using CAE. This speeds up plant disease identification and training[8]. To address the problem of leaf degeneration across diseases, a CNN architecture is proposed to categorise nine types of tomato diseases. Modules for dissemination of data, model setting, dataset production, and optimisation are all included in the design. High performance is demonstrated by evaluation criteria like accuracy, precision, recall, and F1-score, which show 99.99% training accuracy and 99.64% validation accuracy[9]. With a CNN architecture, the work demonstrated the effectiveness of deep learning in plant disease detection with high accuracy. This work's success was increased by the integration of OpenCV, which improved image processing and feature extraction. Furthermore, the capacity to suggest suitable treatments enhances agriculture and facilitates farmer decision-making. Precision farming in conjunction with future developments holds the potential to enhance production, sustainability, and efficiency in both agricultural and disease detection[10][11]. The conclusion after analysing the existing work we can say that the advanced plant disease detection using image recognition is now possible, developments in deep learning have completely changed the management of plant pesticide cost. According to recent research spanning 2015–2023, cooperation between agriculture specialists, deep learning experts and equipment integration is essential for optimising technological benefits in plant disease analysis and prevention.

III] DEEP LEARNING CLASSIFICATION:

Deep learning has significantly advanced plant disease detection and classification by providing sophisticated techniques for analyzing plant disease complex data. Convolutional Neural Networks (CNNs) are particularly effective in examining images of plant leaves to identify and categorize diseases based on visible symptoms. Additionally, deep learning models can process spectral data from sensors, detecting disease signs that are not visible to the naked eye. Overall, deep learning fosters more effective and sustainable agricultural practices by improving early detection and precise disease management[12]. There are so many networks that are applied to classify the diseases but the Convolutional Neural Network is the most useful network applicable for finding the diseases on chilli. Convolutional Neural Network (CNN) techniques are used in many computer vision applications due to their effectiveness on image data[13].

1) Convolutional Neural Network

CNN's, also known as ConvNets, consist of multiple layers and are mainly used for image processing and object detection. CNN's are widely used to identify satellite images, process medical images, forecast time series, and detect anomalies. These techniques use convolution operations to extract various spatial and temporal features from image data. CNNs are used to classify input images to their respective classes and reduce the dimensionality of an image efficiently. A convolution neural network has multiple hidden layers that help in extracting information from an image[14]. The important layers in CNN are as below:

- i. Convolution
- ii. ReLU
- iii. Pooling

iv. Fully connected

- i) **Convolution Layer:** This is the first step in the process of extracting valuable features from an image. A convolution layer has several filters that perform the convolution operation. Every image is considered a matrix of pixel values. Consider the following 5x5 image whose pixel values are either 0 or 1. There's also a filter matrix with a dimension of 3x3. Slide the filter matrix over the image and compute the dot product to get the convolved feature matrix[15].

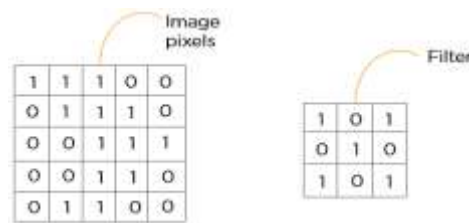


Figure-1 Convolutional Feature Matrix

This layer performs a series of mathematical procedures to obtain the feature map of the input feature vector. The filter shrinks the input function vector. From top to bottom, the filter is moved incrementally.

- ii) **ReLU layer:** ReLU stands for the rectified linear unit. Once the feature maps are extracted, the next step is to move them to a ReLU layer. ReLU performs an element-wise operation and sets all the negative pixels to 0. It introduces non-linearity to the network, and the generated output is a rectified feature map. This ReLU function is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $\max(., 0)$ over the set of and the input x . Below is the graph of a ReLU function:

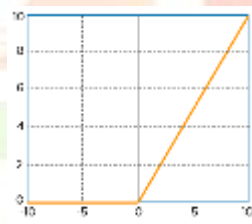


Figure-2 ReLU Function

The original image is scanned with multiple convolutions and ReLU layers for locating the features.

- iii) **Pooling Layer:** Pooling is a down-sampling operation that reduces the dimensionality of the feature map. The rectified feature map now goes through a pooling layer to generate a pooled feature map. The pooling layer uses various filters to identify different parts of the image like edges, corners etc.

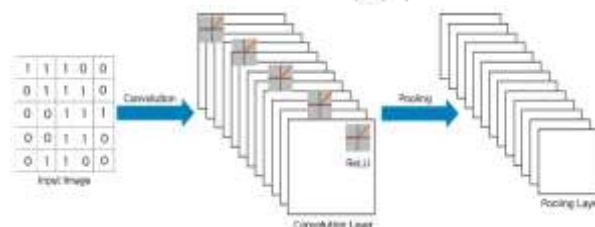


Figure-3 Structured of the pooling layer

After the Convolutional layer, the pooling layer is typically added. Although different-size filters can be used in the pooling layer, the size of the output matrix obtained from the Convolutional layers is reduced in this layer(Sachin B. Jadhav)

iv) Fully connected layer

The final fully connected layers compile the data gathered by the previous layers to generate the final output. Although the CNN method could not automatically derive the best classification features from chilli disease images, it did learn from a feature vector of chilli disease images that was given as input (Rinu R)

IV] MATERIAL AND METHODS:

1) Chilli Fruit Disease Dataset:

The dataset is a collection of huge amounts of data that is unprocessed and needs to be trained in order to yield some useful information out of it. The dataset used in our system is collection of images of chilli plants that fall into one of the diseased categories. Figure 4 shows samples of images from the PlantVillage dataset showing various diseases in chilli and various images from other datasets showing diseased chilli, respectively. The disease name is a class on sample-based learning that the classifier model has acquired during training in the process of classification. This paper uses CNN to divide the chilli diseases into five kinds. The diseases that were discovered during sample training in the database include rotted chillies, black circular spots, straw colour chillies, and white colour chillies.



Figure 4 Black circular spot (a) Straw colour chilli (b) White colour chilli (c) Rotten chillis (d)

To design the model's architecture and then 70 % training and 30% testing ratio to evaluate its performance of model [16]. As expected, the small dataset size weakens the model's learning capacity, requiring additional samples to achieve exact weight changes throughout its layers. As such, the obtained accuracy is significantly less. We consider the use of data augmentation to improve learning with this smaller dataset[17].

2) Using Convolutional Neural Network Model:

To better fit the model to the problem, we design a CNN from scratch. The baseline of our network is formed by two blocks of a 2D convolutional layer and a 2D max pooling, followed by a dense output layer with a 'softmax' activation function. The model has represented the performance of this baseline model can be seen in terms of accuracy and loss. All the experiment results provided are based on k-fold validation[18]. To refine the model hyperparameter that optimizes the validation accuracy results using:

i) Optimizer:

CNNs require optimizers because they direct parameter adjustments that minimise the loss function. They use several different algorithms, including Adam, RMSProp, Adagrad, Adadelta, AdamW, Nadam, SGD, and Nadam. To determine the ideal parameter set, each optimizer modifies parameters according to gradients. The choice of optimizer affects final performance, convergence speed, and computational economy. Trial and error is the way to find the best optimizer for a given task or dataset[19].

ii) Learning Rate:

The learning rate regulates the weights of our neural network concerning the loss.

iii) Momentum:

Momentum in neural networks is a parameter optimization technique that accelerates gradient descent by adding a fraction of the previous update to the current update.

iv) Activation function:

An Activation Function decides whether a neuron should be activated or not. This means that it will decide whether the neuron's input to the network is important or not in the process of prediction using simpler mathematical operations[20].

v)Epoch:

An epoch means training the neural network with all the training data for one cycle.

These hyperparameters are applicable for increasing the accuracy of Chilli disease classification. The CNN model is trained with Adam optimizer with a batch size of 10. The learning rate is set to 0.001, and momentum to 0.9. The 2-fold approach improves test accuracy[21]. CNN uses hyperparameters, i.e., epoch, activation functions, number of filters etc. For optimal performance, apply the epoch size performance hyperparameters. The impact of the accuracy's growing epoch size and another performance metric varies. In Convolutional Neural Networks, an epoch is a single loop over the whole training dataset; that is, a situation in which the whole dataset is only passed through the neural network once, forward and backwards. One epoch is too big to feed the machine all at once, therefore it splits into smaller batches. The CNN's performance is displayed in Table 2.

V] RESULT AND DISCUSSION:

This section discusses the results of experiments performed in the current research work. First, the results of the CNN network are shown. The accuracy has been used to evaluate the performance of the CNN network.

Table 1 Number of images used for training and testing for different diseases.

Class	Train Set	Test Set
Black circular spot	400	120
Straw colour chilli	400	120
White colour chilli	400	120
Rotten chillis	400	120

Training a neural network typically takes many epochs. The number of batches or steps through partitioned packets of the training data required to complete one epoch is called iterations.

Table-2 CNN Result Table with Epoch:

Epoch	Accuracy	Precision	Recall	F1_Score
5	92.01	0.80	0.78	0.60
10	93.44	0.76	0.68	0.69
15	94.21	0.67	0.98	0.81
20	96.65	0.60	0.83	0.84
25	94.34	0.54	0.80	0.89

The table shows that the whole training processes of CNN are stable after 15 epochs and provide a maximum of 96.65 % accuracy at 20 epochs which is the limit. It decreased at epoch 25. The number of parameters is reduced because of parameter sharing in CNN; thus, the computations also decrease. Recently, a convolution neural network (CNN) has been successfully applied due to its feature learning power. This framework fuses texture-based features as input and learns during training. Moreover, this framework overcomes the problem of input size selection due to large features and image size.

VI] CONCLUSION:

We presented in this study a efficient computational architecture that opens up new perspectives for the classification of chilli plant diseases. Chilli diseases affect crop production so the major diseases we are focused on for this study. Namely Black circular spot, Straw colour chilli, White colour chilli and Rotten chilli. In this paper, the CNN model was proposed for chilli plant disease detection and classification. This CNN model was tuned by hyperparameter epoch. If the number of epoch values increases gradually then accuracy will increase. When the model was set to epoch value 20 it gave a maximum accuracy of 96.65%

and then it decreased. Diseases detection and classification success of CNN architects with convolution kernels of different sizes on chilli disease images is investigated. The obtained results classify the training and testing ratios as 70 % and 30% respectively. In the future work, Extended data set and Optimize the model. Through the experiment. This model has achieved good recognition accuracy and is worthy of further study and optimization. At the same time, we should design a network model which can classify others crop images with higher accuracy

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