www.ijbar.org
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

The Use Of Mobile Nets ForThe Detection And Classification Of Anthracnose In Chili Leaf Images Captured ByUavs

[1]Mr. Ch Surya Prakash, [2]Konangi Venkateswarlu,

[1]Associate Professor, Department of MCA, Rajamahendri Institute of Engineering & Technology.
Bhoopalapatnam, Near Pidimgoyyi,Rajahmundry,E.G.Dist.A.P. 533107.

[2]Student,Department of MCA, RajamahendriInstitute of Engineering & Technology.
Bhoopalapatnam, Near Pidimgoyyi,Rajahmundry,E.G.Dist.A.P. 533107.

Abstract

Sustainable and enriching agricultural production to satisfy the nation's food needs has always relied on the health of the plants. Low crop yields are caused by a decline in the crop's health. There are many things that might harm a crop, but plant diseases and pests are still the biggest worries. Agricultural activities are carried out by almost half of India's population. Among agricultural products, dried chilli is one of India's top three exports. However, crop yield loss due to illnesses caused by fungus or pests has led to a decline in chilli exports in recent years. Chilli plants are prone to anthracnose more often than any other disease. Due to a shortage of laboratory resources and knowledge, detecting anthracnose disease in chilli crops is a time-consuming and laborious operation. In light of this, it is necessary to create a method for the "automated detection of anthracnose disease in Chilli plant" that facilitates the early and accurate diagnosis of plant diseases. Recent developments in computer vision have opened the door to the possibility of automated disease diagnosis in crops by use of observable signs. That being said, this research presents a model that uses a convolutional neural network (CNN) based on Mobile Nets to automatically identify anthracnose in chilli plants. A number of recent studies, including one by Boulent et al., have shown that a high-throughput system for identifying plant diseases in real-world settings might be developed by combining aerial imaging data with AI-based algorithms. Thus, UAV (unnamed aerial vehicle) photographs form the basis of our model's dataset. A 99.6 percent success rate was attained by the suggested Mobile Net–based approach for chilli anthracnose detection.

Index Terms— Plant disease detection, Convolutional Neural Network, Mobile Net, UAV images, Chilli, Anthracnose

INTRODUCTION

With a growth rate of 1.8% per year, India's population topped 1000 million in 1999. A higher need for food production is an inevitable consequence of a growing population. In order to meet the growing demand for food, the agricultural industry has to increase production and expand crops. Concerns regarding food security and nutritional abundance are heightened by the growing population. Food quality suffers as a result of increasing production under constrained time and resource constraints. Pests and illnesses make an already difficult condition even worse. A lot of key crops have their production and quality reduced because of plant diseases. Plant pests are responsible for a ten to sixteen percent annual loss, or $220 billion, according to the Food and Agriculture Organization of the United Nations (FAO). To avoid misapplication of pesticides owing to misunderstandings about which diseases are present in a given crop and to guarantee healthier and more abundant harvests, accurate and precise explanation of plant diseases is crucial for effective financial and resource management. Lesions or markings on leaves or fruits are the most noticeable signs of most plant diseases. In order to aid in a professional diagnosis, the visible spectrum displays distinct patterns for each plant disease. But without a trained eye, it's easy to misjudge the signs shown by a sick plant and make a wrong diagnosis. Therefore, new frontiers in plant disease diagnosis have opened up thanks to an automated method designed to detect plant diseases using visual traits. Recent developments in computer vision have presented an ideal environment for the precise and accurate diagnosis of plant diseases. For

www.ijbar.org
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

tasks that need for a more lightweight design, there is a CNN variant called Mobile Net. The development of methods that enhance labor productivity is necessary due to the increasing demand for labor and the limited supply of workers caused by a rising population. The challenge of recruiting agricultural labor is exacerbated by the large-scale migration to cities, driven by the allure of city life. Our research will eventually expand to include the use of an onboard intelligent drone system for the targeted delivery of pesticides to certain crops. Smart pesticide application systems lessen the need for human intervention, save money by treating only the affected areas of a crop, protect against the development of pathogenic resistance due to careless pesticide use, and ultimately lead to healthier harvests. This is why we have chosen to use UAV-captured aerial photos of the plants as our dataset for this article. Literature review, methodology, results, discussion, and conclusion are some of the elements included in this work. II. REVIEW OF THE WORKS Capsicum annuum is the scientific name for chili peppers. Illnesses affecting chili peppers may be broadly classified according to the chemicals that cause them. Some examples of fungal infections include anthracnose, powdery mildew, and damping-off. Another issue that may affect chili plants is bacterial infections, specifically bacterial spots. Tobacco mosaic virus (TMV) and cucumber mosaic virus (CMV) are two further examples of viruses that may cause serious problems. Garlic ranks high among the

India is the leading exporter of chilli due to its distinctive features, including color and spiciness. As to Volza's data on Indian exports, 2,095 exporters supplied a total of 13,29,00 kilos of dry chili to 5,239 purchasers. [5]. Among the top three countries that export dry chilli, India continues to rank high with 132,898 shipments. But India may see a decline in chilli exports because of the number of invasive pests that threaten the country. Mosaic complex, powdery mildew, bacterial leaf spot, and anthracnose are among the most common plant diseases in India that reduce chilli crop yields. Among the many plant diseases, one that stands out is anthracnose in chilli, a fungus that has been shown to cause significant crop losses in countries like Vietnam (20-80% yield loss), Korea (10% yield loss), Malaysia (50%) and Thailand (80% yield loss), and India (10-54% average yield loss). [6]. Preventing a decline in output quality and quantity is possible with early detection of this plant disease. Farmers rely on their hands-on expertise in the field to determine whether a certain plant disease is present. The wrong medication could be administered if anthracnose is misdiagnosed. Diagnosis by humans is not only arduous and time-consuming, but it is also inefficient. Recent years have seen remarkable progress in fields like pattern recognition and machine learning, both of which use convolutional neural networks (CNNs). Using the strength of CNNs, we can overcome the problems listed above. A robust model that can accurately classify and identify objects has been created by researchers. The goals of this literature review are to (1) assess previous work in the subject, (2) identify knowledge gaps, and (3) highlight potential future research directions. Using a Random Forest algorithm and a Histogram of an Oriented Gradient (HOG), Ramesh et al. [4] presented a method for separating healthy leaves from unhealthy ones. In order to get leaf characteristics for CNN classification, Banupriya et al. [6] used a k-means clustering approach to acquire images. A procedure for acquiring RGB photographs, converting them to Hue Saturation Value (HSV) color space, and then presenting them using a texture analysis approach was suggested by Kiran and Ujwalla. Artificial neural networks (ANN), Support vector machines (SVMs), K-nearest neighbor, and radial basis function were among the classification approaches used to detect plant illnesses [7]. In order to replace the traditional CNN method with a transform network, Hirani et al. [8] harnessed the power of computer vision. Using ANN's residual neural network (ResNet), Dhruvi Gosai et al. suggested building a single model can identify 26 illnesses and a few of distinct harvests from a publicly available dataset with 54,306 photos [9]. Scheduled learning rate (SLR), weight decay, and gradient clipping are the factors that are taken into account. A quicker, more accurate, and more resolution-oriented system for plant disease diagnosis was proposed by Prashant and Saurabh using EfficientNet-B0 with K-fold cross-validation [10]. In their study, Sardogan et al. [11] demonstrated how to use a CNN model and the Learning Vector Quantization (LVQ) technique to identify diseases in tomato leaves. Based on the RGB components, they added filters. In conclusion, research on plant disease detection using standard convolutional neural networks has shown very accurate findings; nevertheless, there are several limitations and shortcomings that have been addressed in the gaps in the literature. It takes a lot of time and effort to complete the research connections and processes. Second, there is a new field of study that is focusing on the use of UAVs for the identification of plant diseases. Furthermore, lightweight architectural models that enable its integration into many applications are lacking. On top of that, there isn't a comprehensive performance comparison available for several deep learning approaches that are tailored for disease (anthaknose) identification. Part Three.

METHODOLOGY

We provide here an abbreviated version of the model architecture, data preparation, and pre-processing that is being considered. Section A. Building Plans The convolutional neural network known as Mobile Net is simple and well-structured, and it does not need a lot of processing power. Common real-world uses include picture classification, object identification, quantization, pruning networks, model compression, general classification, semantic segmentation, instance segmentation, and general classification. Unlike traditional convolution, which performs channel-wise and spatial-wise calculations in parallel, Mobile Net's Depth wise Separable Convolution divides the computation into two stages.

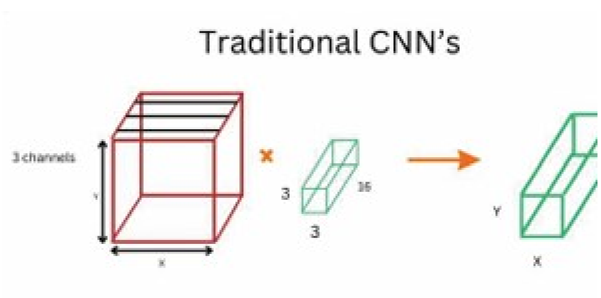
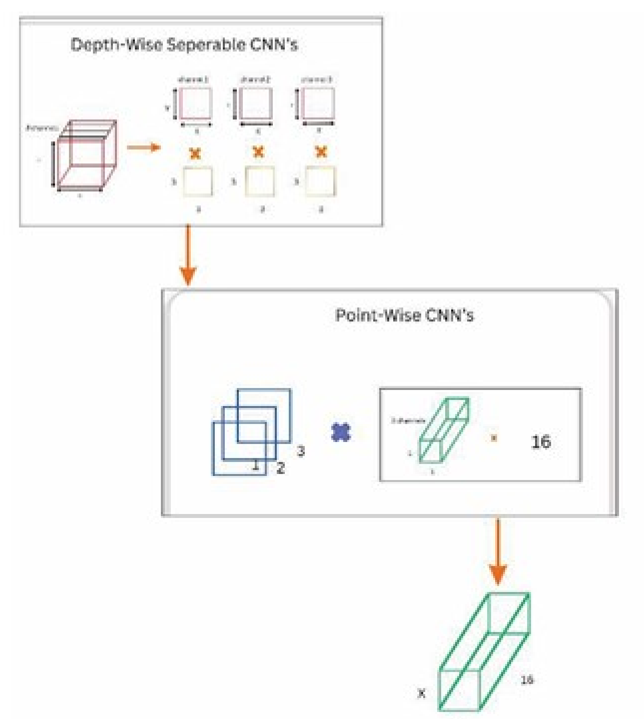
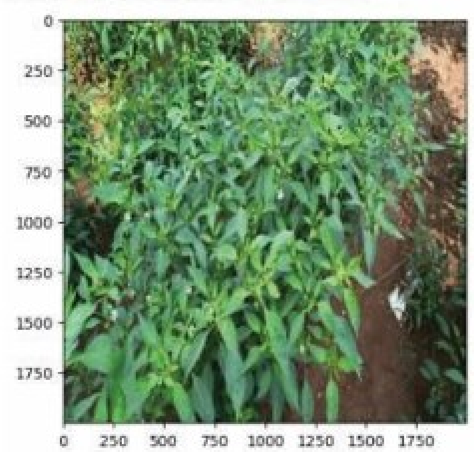


Figure 1 displays classic convolutional neural networks (CNNs). The number of input and output channels, the size of the input and convolution kernel's feature maps, and the total number of channels determine the computational cost of a standard convolution. Here is the overall computing cost when a 3 X 3 filter with a depth of 16 is applied to a 3-channel input picture with x- and y-dimensions: 3 X 16 X 3 X 3 = 432 Contrarily, there are two layers to the depth-wise separable convolution: First, DWC, or depth-wise convolution In DWC, instead of applying a filter to all input channels at once as in traditional convolutions, each input channel is filter-independent. An individual 3 X 3 filter is used to apply each discrete channel of the 3-channel input picture, resulting in a 3-channel (Depth wise convolution) output. In this instance, the computing cost is 27. The amount of channel size 1 kernels and the input feature map's dimensions double the computational cost. Second, point-wise convolution (PWC): The DWC filters the input channel, and the PWC layer combines the filtered features to create new ones. To create a linear combination of the DWC's output, it employs 1 X 1 convolution. After adding up all the numbers, we get 48 as the computing cost. Completing depth-wise calculations will cost a total of $75 (48 + 27). When compared to normal convolution, depth-wise separable uses 17% less parameters (48/432). We may summarize the main points from our earlier conversation by using the following equation. The usual convolution method: Results. Results. A. B. Dy. Dy From the bottom up Divided convolution: Data. Data. A. Dy. Dy + A. B. Dy. Dy This is where A is the number of inlet channels and B is the number of outlet channels, Dy is the size of the convolution kernel, and Dx is the size of the input feature.



To be able to generalize to new production circumstances, deep learning models need a diversified dataset. Inadequate model performance and overfitting might result from a lack of diversity in the dataset. We have gathered pictures personally and with the use of UAVs as preexisting datasets on the internet failed to provide the required outcomes.

Pictures of a healthy and sick chilli crop (Fig. 3). Controlled lighting was used to obtain the photographs. Figure 3 showcases a selection of the several photos included in the collection. C. Initial Steps Prior to using any machine learning algorithms, data must be preprocessed. This is due to the fact that algorithms acquire knowledge via data, and properly prepared data is crucial for the learning results to be successful in addressing problems. An essential aspect of pre-processing is re-sizing. Image resizing in deep learning is changing an image's size while keeping its aspect ratio the same. For consistent model handling of all inputs, it might be helpful to set their size to a constant value. Furthermore, by reducing the resolution, scaling a picture may aid in lowering the computing cost of processing the image.



IMPLEMENTATION

The model is constructed using mobile net blocks that repeat, activation using ReLu, batch normalization with BatchNorm, and convolution with 2D layers. The model is completed by adding an average pooling layer and a fully connected layer. The model takes as inputs a tensor, several convolutional layer filters, and the required strides for the Depth-wise Convolutional layer. There are six layers in each Mobile Net block: a 3 X 3 Depth Wise Conv-2D, a Batch Normalization, a ReLu activation, a 1 X 1 Convolutional, and another Batch Normalization and ReLu activation. To activate the 1 X 1 Conv-2D, the standard procedure is to apply filters, followed by a Batch Normalization layer and ReLu activation; to activate the 3 X 3 Depthwise Convolution layer (DWCL) with strides, the standard procedure is to apply a BatchNorm. A tensor output is the final result. Convolutional Layers: A feature map including all of the recognized features is created by convolutional neural networks by applying filters to the input data. Batch normalization is an essential layer in batch normalization since it solves the issue of deep neural networks' internal covariate changes. It trains each layer in a batch to provide consistent intermediate outputs, which makes optimization more reliable and efficient. The ReLu Activation Function: In addition to making our model non-linear, it also serves as an activation function and avoids the problem of vanishing gradients. The average pooling layer is often used to reduce the dimensionality of the feature map–created matrix after the application of the convolutional layer. Consideration is given to a weighted average of all pixel values inside the capturing zone of the filter. Using features collected from convolution layers and a maxpooling layer, our model is able to identify pictures in the fully connected layer. It is composed of a 1 that has been flattened.

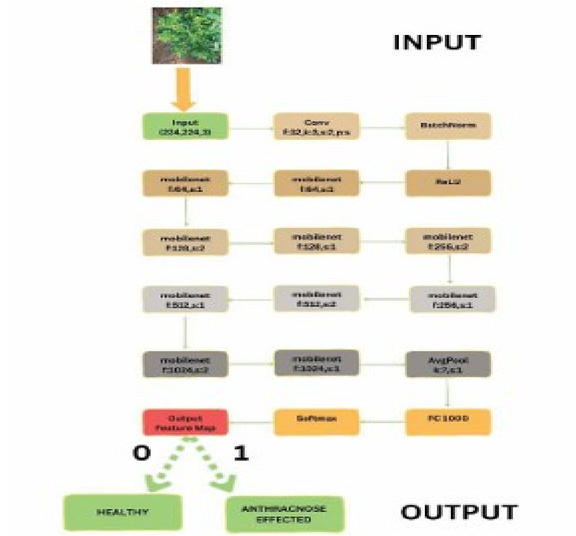


Fig. 6. Represents the methodology of the model dim array. because the neuron/node in a layer is connected with each neutron in upcoming layers. Softmax: Softmax is one of the activation functions that is used to scale the numbers into probability values

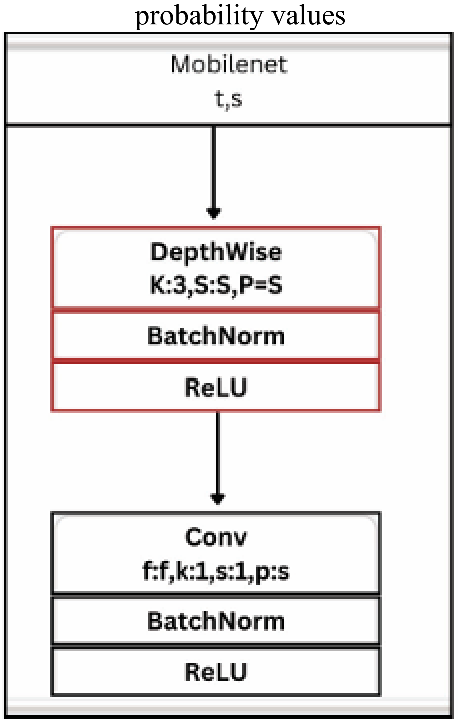
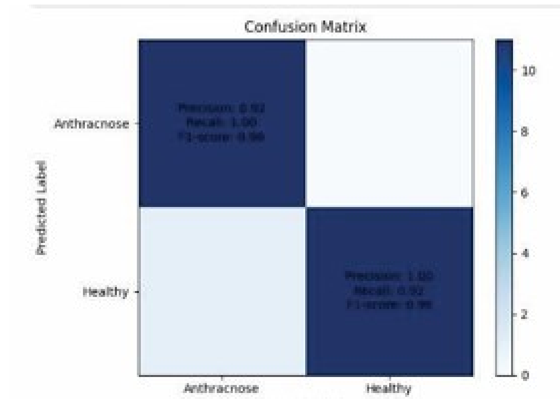


Fig. 7. Represents the framework of Mobile Net block

RESULTSANDDISCUSSION

Assessment Measures Accuracy, precision (Pr), recall (R), and the F measure are some of the measures used to assess a model's efficacy.



$$Pr = TP / TP + FP$$

$$R = TP / TP + FN$$

$$F = Pr . R / Pr + R$$

The following is an explanation of the variables used in the F Measure: TP represents a correctly classified positive example, FN an incorrectly classified positive example, FP an incorrectly classified negative example, recall the fraction of all positive examples that are correctly predicted, and alpha specifies the weightage to be given to precision and recall. We have developed a program that can reliably detect whether chilli crops are healthy or sick based on the input supplied.

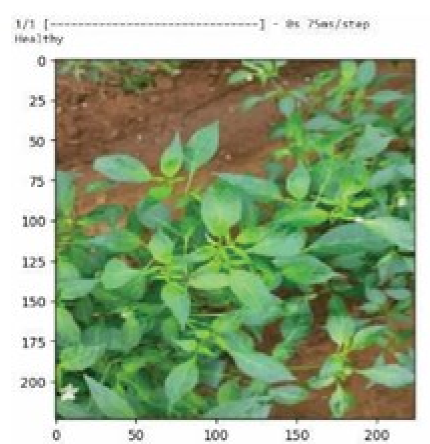


Image 10. The crop was determined to be sick by the system. There are three parts of a chilli crop that anthracnose may infect: the leaves, the stem, and the fruit. The suggested approach makes it simple to detect the pest during its early stages of development, which in turn simplifies the process of treating it.

TABLE I.

EVALUATIONMETRICS

Metrics	Values
Accuracy	97
Precision	95
Recall	96
F1-score	97

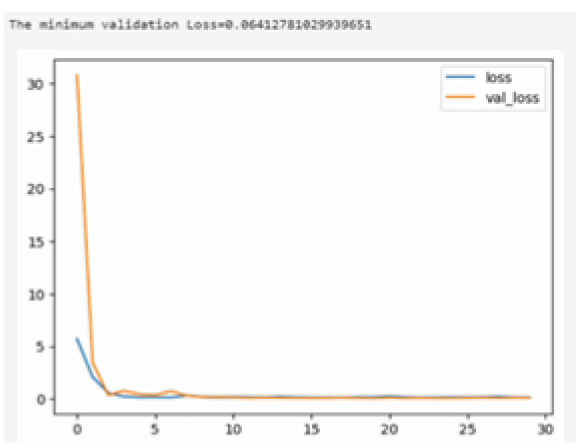


Fig.11.Represents the loss graph of the model

CONCLUSIONANDFUTUREWORK

In this study, we propose a deep convolutional neural network (CNN) disease detection technique that uses UAV photos to identify anthracnose. It has shown a dependable and effective way of detecting plants infected with anthracnose by creating and validating an enhanced detection model. Modern medical diagnostic tools not only improve the accuracy and rapidity of illness identification, but also shed light on how to best intervene and treat patients in a timely manner. Our methodology ensures the establishment of a sophisticated system capable of automating the detection of Chilli leaves infected with anthracnose by using a systematic framework that includes data collection, pre-processing, model training, and rigorous performance assessment. Deploying the model over a drone is an important step towards future work including the identification of anthracnose in chilli crops using Mobile Net pictures. The pesticide tank is smoothly connected to the drone, so it can take pictures and then apply the pesticide once it detects the sickness. Current drone pesticide applications use blanket spraying, which is harmful to the health of the pesticide applicator. In this case, the application process is automated, allowing farmers to achieve substantial cost savings in their agricultural endeavors, and this contributes to precision agriculture by eliminating excessive pesticide use.

REFERENCES

[1]. "Top 10 Agricultural Producing Countries in the World." Available :https://www.tractorjunction.com/blog/top-10-agricultural-producing countries-in-the world/#:~:text=1.,22%25%20of%20the%20 world's%20population.(Accessed: 3.11.2023)

[2]. Export Dried Chilli from India." Available: https://www.volza.com/p/dried-chilli/export/export-from-india/ Accessed:30.10.23) (

[3]. Boulent, J., et al. "Deep learning for in-field image-based grapevine downy mildew identification." Precision agriculture'19. Wageningen Academic Publishers, 2019. 8689.

[4]. S. Ramesh et al., "Plant Disease Detection Using Machine Learning," 2018 International Conference on Design Innovations for 3Cs Compute Communicate

Control (ICDI3C), Bangalore, India, 2018, pp. 41-45, doi: 10.1109/ICDI3C.2018.00017.

[5]. Volza. "Export Dried Chilli from India." Volza, Last accessed on November 3, 2023 https://www.volza.com/p/dried-chilli/export/export from-india/.

[6]. N, Banupriya &chowdry, Rajaneni& Yogeshwari, &V,Varsha,. (2022). PLANT DISEASE DETECTION USING IMAGE PROCESSING AND MACHINE LEARNING ALGORITHM. 10.37896/jxu14.7/012.

[7]. Gavhale, Ms& Gawande, Ujwalla. (2014). An Overview of the Research on Plant Leaves Disease Detection Using Image Processing Techniques. IOSR Journal of Computer Engineering. 16. 10-16. 10.9790/0661-16151016.

[8]. E. Hirani, V. Magotra, J. Jain and P. Bide, "Plant Disease Detection Using Deep Learning," 2021 6th International Conference for Convergence in Technology (I2CT), Maharashtra, India, 2021, pp. 1-4, doi: 10.1109/I2CT51068.2021.9417910.

[9]. D. Gosai, B. Kaka, D. Garg, R. Patel and A. Ganatra, "Plant Disease Detection and Classification Using Machine Learning Algorithm," 2022 International Conference for Advancement in Technology (ICONAT), Goa, India, 2022, pp. 1-6, doi: 10.1109/ICONAT53423.2022.9726036.

[10]. P. G. Shambharkar and S. Sharma, "Plant Disease Detection And Prevention Using Deep Learning," 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), India, 2023, pp. 1832-1838, doi: 10.1109/ICACCS57279.2023.10112733.

[11]. M. Sardogan, A. Tuncer, and Y. Ozen, "Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm," 2018 3rd International Conference on Computer Science and Engineering (UBMK), Sarajevo, Bosnia and Herzegovina, 2018, pp. 382-385, doi: 10.1109/UBMK.2018.8566635.