Grape and Bell Pepper leaf disease classification using CNN

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Abstract. Plants being infected by diseases is one of the most concerning issues in the agriculture sector. Because of this problem, the production of plants, as well as the crops, are decreasing drastically, which affects the food supply of the people. In a circumstance, where due to the vast urbanization all over the world, agricultural lands are already decreasing. If disease contamination occurs, it will basically boost the reduction of food supply. Every possible way to enhance the production and supply of crops will assist to overcome the above-mentioned issue. This research demonstrates an approach for the classification of 3 grape leaf diseases and 1 Bell pepper leaf disease, apart from the healthy leaves of both of the plants. The mentioned diseases for Grape are Grape Leaf Blight, Grape Black Rot, Grape Black Measles and also Bell Pepper's Bacterial Spot disease. This article aims to identify and categorize grape leaf diseases by applying the Convolutional Neural Network, which is also known as CNN. Among all the deep learning models, CNN is one of the commonly used methods. The used images are collected from the website called PlantVillage. The proposed model successfully worked with an accuracy of 98.12%.

Keywords: Deep learning · CNN · Image Processing · Batch Normalization · Bell Pepper disease · Grape disease · Regularization.

1 Introduction

In today's world, the population is growing at an exponential rate; therefore, the main concern is to provide food for all of them. The production of any crop is becoming more challenging for numerous types of reasons, including the infection of diseases. Researchers are continually trying to find the best possible ways to prevent or mitigate this problem. Typically, people look at the hues of plant leaves or the patterns of spots to try to detect illnesses. However, this form of identification is not always reliable. Therefore, some high-end technology to identify diseases is needed. To increase agricultural productivity, plant diseases need to be recognized and appropriate precautions should be taken to prevent

them from spreading.
Numerous research studies employed various DL or deep learning and ML or machine learning models for the classification and prediction of different plant diseases. [8] By implementing different models, the plant diseases can be classified and predict which is the infected plant with which disease and take measures to control it from spreading throughout the field. It will improve the agricultural production of different plants, which will ultimately help the food production for the people.
To detect plant diseases, one of the most efficient methods is image processing. Though there are plenty of image processing methods available, the accuracy rate differs in all of them. [5] This research study worked with a Convolutional Neural Network to classify and predict plant diseases. Here, 6 different classes of the diseased and healthy leaves for two different plants. In particular, we attempted to categorize and identify three diseases affecting grape leaves: “Grape Leaf Blight”, “Grape Black Rot”, “Grape Black Measles” and also Bell Pepper’s Bacterial Spot disease.

The objective here is the classification of the diseases of the leaves of Grape and Bell Pepper. There exist many models which worked with multiple plant leaves and achieved different results from that. In every nation, Grapes and Bell Peppers are two of the most popular crops. These two crops’ productivity can be improved by the classification and identification of their diseases, which ultimately benefits global agriculture. To overcome the challenge, the Convolutional Neural Network (CNN) model was applied. After evaluating the model with the respective classes of diseased and healthy leaves, we demonstrated the distinct precision of the classes as well as the two crops, Grape and Bell Pepper.

2 Literature Review

In the research at [1], the author suggests a CNN framework for the development of a classification model for bacterial and healthy pepper leaves. ”Machine learning” algorithms are used to evaluate the model. Model evaluation metrics like Recall, F1 scaling, accuracy, and precision etc. were computed using a variety of ”Machine learning” algorithms such as ”Logistic Regression”, Decision Tree (DT),K-Nearest Neighbor(K-NN) and Naive Bayes(NB). The accuracy achieved by Logistic Regression, DT, K-NN and NB model are respectively 74.31%, 86.62%, 77.69%, 60.62%, while the accuracy achieved by CNN is 98%. Therefore, it’s clear that for the classification of bacterial and healthy pepper leaves, the CNN model was the most accurate one.
However, the authors added that the future work could include incorporating useful Deep Learning architectures into existing methods for visually assessing plant health and bacterial load. These methods allow for real-time detection, and the use of strategically placed cameras at varying heights above the field to track the leaves over time. To examine and anticipate the severity of plant classification, it’s needed to constantly monitor and adjust Deep Learning models.

In [2], the authors looked at using a spectroradiometer to measure reflections from pepper leaves to identify fusarium-infected peppers (Capsicum annuum) and healthy peppers. They were able to go from 2150 characteristics utilized in the classification to 75 features using wavelet decomposition, then from 75 features to 4 features using the statistical values of the wavelet coefficients.The growth of mycorrhizal fungus-infected, fusarium-diseased, and healthy pepper leaves took place in a small confined space at wavelengths between 350 nm and 2500 nm. K-nearest Neighbor (K-NN), Artificial Neural Networks (ANN) and Naive Bayes (NB) were used for classification. The average rate of accuracy of the various algorithms used for classification were determined to be 100% for KNN and 97.5% for ANN for the first two groups of peppers—those with illness and those in excellent health—while the rate was 90% for NB. Similar to this, these rates were determined as for KNN it's 100%, for ANN it is 88.125%, and for NB 82% for the categorization of all groups. Overall, the findings indicate that illness may be detected accurately using leaf reflections.

In paper, [3], The authors proposed a CNN model to classify the plant leaves. By feature extraction, training and classification, their model predicts a leaf. GoogleNet served as the CNN model for this research. To extract different feature points, GoogleNet employs inception modules that run numerous convolutions concurrently.
Their dataset was collected from the Flavia dataset and it had 8 different types of leaves, they sorted the training photos into 8 categories totaling 3,767 images, while they chose randomly 100 images for testing. They chose and tested two CNN models which are GoogleNet and a variation of GoogleNet. They achieved an accuracy of 94% even after 30% of the leaves were damaged, which is 4% greater than the previous models (90%). However, there is still some future work here; a visual system can be developed that can mimic the way used by people to distinguish plant varieties.

In [4], the author provides a high-level review of current plant-based disease detection technologies. In this study, a CNN outfitted with a bell pepper plant picture dataset was used, and a range of simulation methodologies for neurons and layers were applied. Here, CNN was implemented to detect bacterial spots on bell pepper leaves. The image was analyzed using Keras and the TensorFlow library. In this study, several hundred leaves were used for testing. The method uses neural networks to determine if a leaf is healthy or sick. The test accuracy was 96.78%. They gathered the photos of bell peppers from the garden manually. This research proposes a neural network-based image recognition technique for identifying and recognizing disease. However, building an embedded IOT application that can quickly distinguish between healthy and diseased plant leaves will be a good future work for them. [5] In agriculture, crop yield and product quality may suffer from the late diagnosis of plant diseases. Early identification is therefore critical and a significant challenge that the authors of this paper have attempted to implement. The authors here have tried to do so for Chili plants.

According to them, for the first time ever done in any study, a Segmented SVM has been utilized to convert an image into grayscale before it is input to SVM for feature extraction. An 8 MP Raspberry Pi Camera V2 was used to capture 8 images of Chili plants.

The captured images were further analyzed in MATLAB. Using MATLAB's rgb2gray function, the photos were preprocessed by converting them from RGB to grayscale by lowering the hue and saturation. K-means clustering was utilized to divide the photos into various clusters during the image segmentation process. Under fitting may occur when the number of clusters is high, while overfitting may occur when the number of clusters is low. In this instance, 5 clusters performed better than 6 clusters. The feature extraction process that follows involves extracting features like texture and color and computing them using MATLAB. The final step was future classification where SVM has been used as a classifier. 100 photos were utilized by the authors to train their classification models. For this job, the dataset was partitioned into 5 separate ones, each having 20 randomly selected photographs, and 5-fold validation was once more applied. Multiple SVM classification models which have been used are Coarse Gaussian SVM, Quadratic SVM, Medium Gaussian SVM, Linear SVM, Fine Gaussian SVM and Cubic SVM.

Among all the models, Quadratic and Medium Gaussian SVM were the ones with the greatest accuracy score, which is 90%. On the other hand, Fine Gaussian SVM was the fastest with a speed of 2300 obs/sec followed by Cubic SVM and Quadratic SVM. The winner of these SVM classification models, Quadratic SVM, was utilized to test 20 photos with 100 segmentation results since model accuracy is the most important factor and speed is an added benefit. With an accuracy of 90.9% for both background and healthy plants and 57.1% for Cucumber Mosaic, the model correctly categorized 22 out of 24 background segmented images, 4 out of 6 Cucumber Mosaic segmented images, and 11 out of 12 healthy plants. This yielded an average accuracy score of 79.6%.

One of the limitations of this paper is certainly the accuracy score compared to that of many NN algorithms. However, this can be improved by using a larger dataset, as only 8 images with segmentation were used. In [6], the authors create a computer vision framework for real-time picture classification using the deep learning classifier Deep Belief Network (DBN). This framework includes feature extraction, image classification and image acquisition. The classification accuracy of the DBN framework is verified by contrasting it with that of several alternative classifiers, such as the Recurrent Neural Network (RNN), Deep Neural Network (DNN), the Back Propagation Neural Network (BPNN), the Convolutional Neural Network (CNN) and the Feed Forward Neural Network (FFNN). The experimental findings on the detection of leaf diseases in pepper plants show that the suggested method by the author has a better classification rate than other approaches that are already in use. The categorization findings show whether the leaf is afflicted with the disease or not. Successful classification of healthy and diseased leaves will boost pepper yield. They obtained their data from the PlantVillage website, and on an advanced powerful computer system, MATLAB was used for the implementation. DBN classification performance is assessed using 1,500 pepper leaf pictures of healthy and sick leaves. 300 healthy and 35 sick pepper leaf photos are used to train and evaluate the system. The datasets of pepper leaves are used to assess the accuracy, sensitivity, and specificity of the test, as well as the f-measure. The automated framework is made up of a variety of functions, such as image pre-processing, acquisition, classification, and extraction. The classifier distinguishes normal and abnormal pepper leaves. Train and test images are separated after pre-processing. The network is trained with leaf disease features and normal features from train data. The DBN classification technique classifies the leaf as unhealthy or healthy based on the features collected from a test image. A 256 x 255 matrix known as the gray level co-occurrence matrix (GLCM) is used to extract characteristics from the data. Comparing the proposed method's findings to those of previous classifiers—namely, BPNN, RNN, DNN, CNN and FFNN—reveals a slight but significant gain in classification accuracy (91,956). If this model is implemented in a mobile application, that would make the farmers' hassle go away as well as ensure a good pepper production. In the study at [7], the precision of grape leaf disease detection through the use of ECA or "efficient channel attention", SE which is also known as the "squeeze-and-excitation networks", and a "convolutional block attention module" or CBAM attention mechanisms have been evaluated. The results revealed that "SSD+SE" demonstrated maximum real-time performance with comparatively high detection accuracy 3.46 whereas "Faster R-CNN+SE", the hybrid model, had a lower detection precision which was around 79.80%. "YOLOx+ECA" required the fewest parameters, which is around 34.87 while having the best detection precision of 87.77%. It quite helped with the issue of difficult grape leaf disease detection being resolved and few new models were given for automated agricultural production. [8] India is one of the highest grape exporters in the world and yet there's a 10 - 30% loss in crop production due to grape plant diseases. It might be reduced, though, if diseases could be identified early. In this study, the authors discuss their research on grapevine leaf diseases. The dataset includes 137 photos of leaves, out of which 62 are of Powdery mildew and 75 are of Downy mildew. Most of the images are taken from Pune, Nasik using digital cameras while some are taken from the internet. Firstly, the images were preprocessed and turned into a size of 300x300. Then the images were segmented using K-means clustering. Later, for Powdery Mildew and Downy, color and texture characteristics were retrieved at the feature extraction stage. Lastly, Linear Support Vector Machine or Linear SVM has been used by the authors for the classification of the diseased leaves. According to the SVM classification results, the model did a great job at recognizing Downy Mildew, scoring 93.33% by correctly identifying 14 out of 15 photos. On the other hand, it received a slightly lower score for Powdery Mildew as it correctly identified 10 out of 12 photos, giving it a score of 83.33%. However, when the photos of both diseases were combined, the model scored 89.89%, which is higher than Powdery Mildew's score.

A Neural Network model was also trained using the images, and it scored nearly

100% even though there were significantly fewer samples provided than for SVMs. The number of features for NN was 9 which were of texture type only, while the number of features for SVM was 18 in total among which 9 were texture and the rest were color features. The future scope of the paper could be to use ensemble techniques. Another option would be to completely automate farming using IoT, spraying fungicides as soon as a disease is discovered. In paper, [9], a method for incorporating image analysis methods into diagnostic expert systems is presented. Grape diseases are used as a case study to illustrate the outcome of using this strategy. The authors used RGB, the Mask and Hue Images to show the infected areas in a leaf. For this investigation, a total of 100 plant leaves from different natural grape plant types in the state of Maharashtra were gathered. They worked on 3 different diseases of grapes. The achieved results were 40% for Powdery Mildew, 95% for Black Rot and 40% for Downy Mildew disease. They must include a segmentation block in the main operation, which takes less time overall, to increase classification accuracy. Farmers can save production costs by using this method to detect grape leaf disease early.

In paper, [10], the author introduced multiple artificial intelligent methods for automatic plant disease detection. They mainly focused on the grape leaf disease here. Once their model is trained, it can detect the leaf disease without maintaining any expertise. The proposed model has 3 main parts to detect and classify the diseases which are the extraction of the leaf color of grape, color extraction of the disease and classification of it. Here, using the SVMs, they focused on 2 types of grape diseases which are Scab and Rust. The detection accuracy was 97.8%. However, extraction of uncertain, confusing color pixels from an image's backdrop is still subject to some restrictions. In the study at [11], provides an overview of various classification methods that can be applied to the classification of plant leaf diseases. An "n" number of observations are divided into k groups using the partition clustering technique known as the K-means segmentation approach. In this method, the segmented image contains "k" clusters, and the clustering is done using the image's colors. The fact that segmentation-based K-means clustering uses both local and global picture information is its key advantage.

The proposed study in [12] entails developing a monitoring system that uses a Hidden Markov Model to identify early indications of grape disease and SMS alerts to the farmer and an expert. A leaf wetness sensor, relative humidity, moisture, and Zig-Bee for wireless data transmission are all included. For data analysis in this case, they employed two methodologies. The statistical approach is the first, while the hidden Markov model is the second. By comparing the outcomes of the two approaches, they found that the HMM performs and is more accurate than the conventional approach. It had an accuracy of 90.9% whereas the statistical method had 63.63%. In addition to recommending pesticides to protect crops from such diseases and reduce the need for manual disease detection, this model uses machine learning to quickly and accurately detect infections. They can utilize more sensors in the future to cover a larger area of the vineyard.

In [13], A fungus called "black rot" can cause crop damage and affect yield and wine quality. Here, images of healthy leaves and leaves with Block Rot Disease damage from grape plants were taken from the PlantVillage Dataset. For segmentation, the HSV and "L*a*b*" color models are utilized. The good and diseased parts of the leaves are sorted using color-based approaches, and the features of each leaf are saved. The SVM Classifier is used for machine learning, and the results are analyzed using different SVM Kernels. With the Linear Kernel, the accuracy was calculated at 93.3%, with the RBF Kernel at 94.1%, and with the Polynomial Kernel at 93.9%. The found accuracy is 94.1%, which is the highest. In paper, [14] The researchers tried to present a review of approaches developed by several researchers in the field of image processing for detecting diseases in plants. It entails plant disease detection research on plants like the apple, grape, pepper, pomegranate, tomato, and others. They gave an overview of technological implementations in the study field of plant disease detection utilizing the image processing techniques in this publication. According to the research study, color, texture, and morphological traits are the best for identifying and classifying plant diseases. For classifying plant diseases, ANN and SVM are most frequently utilized. The problem of pricey domain experts will be solved by automatic identification of plant diseases.

The paper, [15] presents 4 updated deep learning algorithms for diagnosing and categorizing grape leaf disease, each of which was based on a created dataset of grape leaves. In this study, the authors used the transfer learning methodology which is based on the 3 pre-trained ML models AlexNet, MobileNet and VGG16. The authors mainly focused on the illnesses including Black Rot, Black Measles, Leaf blight and Phylloxera. Based on these four generated models, an ensemble model enhances final detection and classification accuracy. Among their proposed models, the ensemble model had the highest accuracy, which was 100%, whereas Vanilla CNN and VGG16 had 98%, MobileNet had 86% and AlexNet had 77%. They did, however, also suggest collaborating on a real-time smart farming system based on data from cameras, drones, and remote sensing to provide real-time multidimensional disease detection and classification using their models in the future. In [16], Dual attention approaches are used in the proposed "Grape leaf disease detection network" or (GLDDN) in this study for feature assessment, detection, and classification. At the evaluation stage, testing on a benchmark dataset shows that the disease detection network may be more efficient than current approaches, since it can identify and find diseased or infected regions. With the suggested disease detection method, the authors were able to identify Esca, Black-Rot, and Isariopsis with an overall accuracy of 99.93%. The proposed model network was built using a faster R-CNN, multitask learning, and multi-level feature extraction utilizing spatial and channel-wise attention procedures.

In the study at [17], transfer learning was carried out using two pre-trained deep learning models called "Single SSD_MobileNet v1" and "Faster R-CNN Inception v2.". 95.57% of the images evaluated were correctly classified by the Faster-R-CNN Inception v2 model, with classification accuracy ranging from 78% to 99%. This model's accuracy was higher with a slower processing time. However, the SSD_MobileNet v1 model took less time than Faster-R-CNN Inception v2 and it accurately categorized just 59.29% of the testing photos. It provided a higher classification accuracy, which was in between 90% to 99% for uniformed backgrounds and well-organized images only that had minimal noise. Otherwise, the accuracy rate dropped significantly to between 52% to 80% including an elevated proportion of misclassifications. The authors concluded that while the Faster-R-CNN Inception v2 may perform significantly better, SSD_MobileNet v1 may not be as successful for real-time classifications. Since this model accurately recognized between 78% and 99% of the test photos, it successfully classified roughly 95.57% of them. This model's average processing time per picture was between 25 and 30 seconds. Therefore, it might be quite beneficial for real-time image categorization for this purpose.

To categorize a multi-class dataset, the authors employed SVM in [18]. Images of leaves with Black-Rot, Leaf Blight, Esca infection, and healthy leaves are included in the dataset of grape disease obtained from PlantVillage. In the feature extraction step, HSI image attributes have been added to the dataset since, in the case of HSI, the hue remains consistent even after making the background of the image darker, making the diseased parts easier for the SVM model to detect. Additionally, before being converted into LAB and HSI color models, the images were resized and smoothed. K-means clustering has then been used to divide the photos into three clusters. The segmented images were later processed using MATLAB and GLCM to extract both the textural and color characteristics. These features, together with the images, were utilized to train the multi-class SVM. The model was trained using a total of 22 features. In comparison to using simply the LAB color model, the authors' results for the three diseases were approximately 90% accurate when they combined the two-color models. In [19], a model has been proposed for distinguishing 3 distinct diseases which are "Black Rot", "Black Measles" and "Isariopsis", from the healthy leaves of grape and analyzes the confidence value of the system in properly recognizing the classes. Using RCNN and transfer learning , the model was primarily focused on recognizing many diseases in a single montage image. To determine which of the pre-trained networks, AlexNet, GoogleNet, and ResNet-18, would be the greatest fit for combining with RCNN in order to perform multiple object detention in a given image, the authors conducted a comparative analysis. The ground truth table including the image files and associated bounding box coordinates for the annotated picture data used to train the models was made available. The most accurate pre-trained network on the RCNN among the models evaluated

was AlexNet, with an accuracy of 95.65%. On the other hand, The accuracy of the remaining two models, ResNet-18 and GoogleNet, was 89.49% and 92.29%, respectively.
Isariopsis is the simplest illness to diagnose in a single montage image, with all three algorithms detecting it with 100% accuracy. Black Rot comes in second with an average accuracy of 92.75% across all models, followed by Black Measles at 89.86% and Healthy at 87.30%. To improve performance, ResNet-18 can identify Black Rot with 100% accuracy, while AlexNet can detect Black Measles and Healthy leaves with 95.65% and 100% accuracy, respectively. However, Fast-RCNN or Faster-RCNN would improve the models' performance considerably.

3 Methodology

For this research, the dataset of grape and pepper has been collected from PlantVillage. This dataset of grape and pepper contains 4 classes of grape which are grape black measles with 1383 images, grape black rot with 1287 images, grape healthy with 470 images and 889 images of leaf blight infected grape leaves images. On the other hand, among two classes of pepper, the pepper bell bacterial spot class contains 1067 images whereas images of the healthy pepper class contain 1539 images.

All the images had the height and width of 256 pixels initially. However, the images were resized into 128 x 128 as it reduces both the computation time and power. All the pictures were afterward normalized to train the model.

The CNN architecture used in our research contains 5 convolutional layers where the first 3 layers have 64, 128 and 512 filters respectively and the last two layers have 128 and 64 filters. The filter size of the first two convolutional layers is 2 x 2, whereas the filter sizes of the following two layers are 3 x 3 and the final layer is 5 x 5. This increment in the size of filters is due to how CNNs identify lines and edges in the first layers and keep increasing their focus area to identify bigger features as the number of layers increases. Padding has been used throughout all the layers to keep important data.

The same number of max pooling layers have been used, where the filter size and strides have been kept 2 throughout all the layers.

Then, after flattening the matrix, it has been passed onto a dense layer of 128 neurons which is connected to a dense layer of 64 neurons. Lastly, there's a layer with 6 neurons, as there are 6 classes in this dataset. "He normal" has been used as the kernel initializer to set the weights of the filters of convolutional layers initially. Lastly, batch normalization has been used after each convolutional layer and L2 regularization in the hidden layers with a lambda value of 0.01 to solve the overfitting.

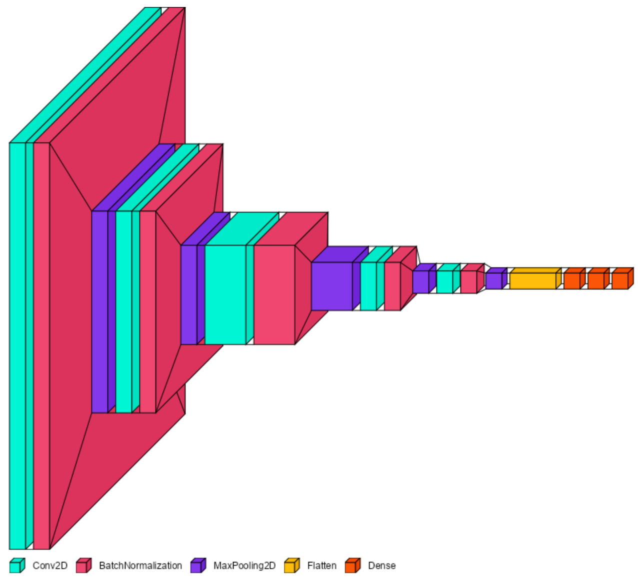

Fig. 1. Proposed CNN Architecture

While training the model, Adam optimizer has been used with its default learning rate and spare categorical entropy has been used as the loss function whereas the metrics used was accuracy. Last but not least, the model has been trained using a 32-batch size across 30 epochs. The program has been run on the GPU on Google Colab.

4 Results

The accuracy of training and validation of the proposed model are 100% and 98.87% respectively whereas the test accuracy is 98.12% which is quite high compared to other models used for classifying grape and pepper diseases.

On the other hand, the training loss is 1.5% whereas the validation loss is around 4.61%. Lastly, the training loss is around 7%.

From the confusion matrix it can be seen that the model guessed class 3 better compared to other classes as it guessed 193 images correctly and 0 images incorrectly out of 193 images of that class. On the other hand, it guessed 94 out of 103 images of class 2 correctly and the rest of the images incorrectly.

From the table it can be seen the model performed best in the case of healthy grape class as the f1-score of this class is 1. On the other hand, it performed

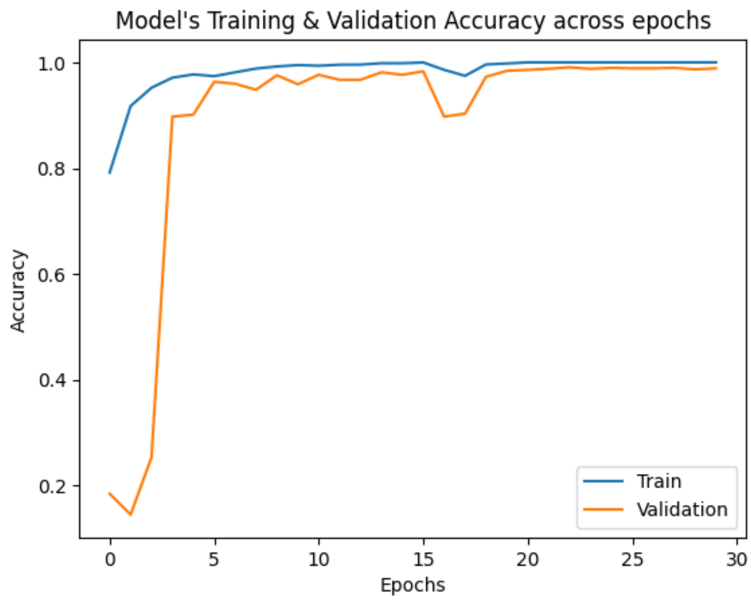

Fig. 2. Training vs validation accuracy

Fig. 3. Training vs validation loss

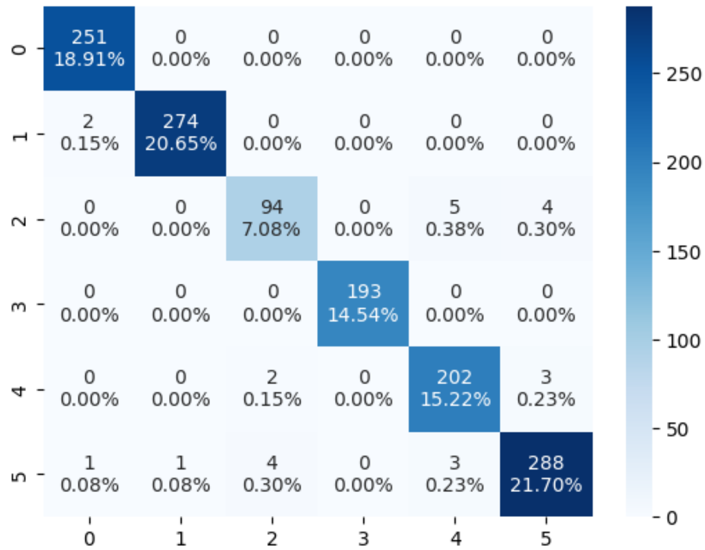

Fig. 4. Confusion matrix

worse in the case of black rot of grape class compared to other classes, which is due to the reason that class 2 had fewer images compared to other classes while training the model.

5 Conclusion

In this paper, CNN has been used to classify the leaf disease of grape and pepper. The model has performed better than machine learning models used for doing this task, with an overall accuracy of 98.12% with a relatively small dataset. The model has been able to classify both the grape and the pepper diseases with an accuracy of 97.5% which is quite well. The number of images for the pepper leaves class was less compared to that of the grape leaves. The accuracy of the model could be increased by augmentation or by using a bigger dataset.

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