Classifying Pepper Disease based on Transfer Learning: A Deep Learning Approach

Conference Paper · May 2022

DOI: 10.1109/ICAAIC53929.2022.9793178

Imdadul Haque
Daffodil International University

Md. Ashiqul Islam
Daffodil International University

Koushik Roy
Bangabandhu Sheikh Mujibur Rahman Science & Technology University

Abdul Alim Shohan
Daffodil International University

Classifying Pepper Disease Based on Transfer Learning: A Deep Learning Approach.

Imdadul Haque [1]
Dept. of Computer Science and Engineering.
Daffodil International University.
Dhaka, Bangaldesh.
imdadul15-1440@diu.edu.bd

Md. Ashiqul Islam [2]
Dept. of Computer Science and Engineering.
Daffodil International University.
Dhaka, Bangaldesh.
ashiqul15-951@diu.edu.bd

Koushik Roy [3]
Dept. of Electrical and Electronics Engineering.
Bangabandhu Sheikh Mujibur Rahman Science and Technology University.
Gopalgonj, Bangladesh.
koushikr683@gmail.com

Md. Mizanur Rahaman [4]
Dept. of Computer Science and Engineering.
Daffodil International University.
Dhaka, Bangaldesh.
mizanur15-1452@diu.edu.bd

Abdul Alim Shohan [5]
Dept. of Computer Science and Engineering.
Daffodil International University.
Dhaka, Bangaldesh.
abdul15-2141@diu.edu.bd

Md. Saiful Islam [6]
Dept. of Computer Science and Engineering.
Daffodil International University.
Dhaka, Bangaldesh.
saiful15-2584@diu.edu.bd

***Abstract*— Pepper is cultivated all over the world and many farmer's subsistence depend on this crops. But unfortunately, farmers who are involved in cultivation of pepper, have to fall on a huge loses because of low production of pepper caused by several diseases of pepper. If the diseases can be detected accurately and in a short time, then the losses can be prevented. The incorrect identification and time needed process can't release from the diseases and also can't be helpful for reducing the losses. For acquiring great accuracy within a short time to recognize the pepper diseases, multi-recognition methods can give promising result to the users. In this study, several pre-trained deep learning models such as VGG19, Xception, NasNet Mobile, MobileNet-V2, ResNet-152-V2 and Inception-ResNet-V2 have been used to extract the deep characteristic from the images and these models provide great accuracy. Most of the diseases of pepper are caused by fungal and bacterial attack. In this study, 386 images are used for training, 63 images are used for validation and 107 images are used for testing of 4 classes of pepper diseases and one healthy image of pepper for identifying the diseases types of pepper. The customized CNN models have achieved the highest accuracy and fulfilled the target of this study. The pick accuracy has been achieved from the VGG19 and ResNet-152-V2 is 96.26%. Also, Xception has provided better accuracy from Inception-ResNet-V2, MobileNet-V2 and NasNet-Mobile and that is 93.46%.**

Keywords*— *Convolutional Neural Network, VGG-19, NasNet Mobile, MobileNet V-2, ResNet-152-V2, Inception ResNet-V2.

I. INTRODUCTION

Pepper is the most broadly used spice and condiment in the world and is significantly priced for its pungency and adding superior flavor to many cuisines throughout the world. Historically it was used mostly for flavor and as medicinal plant, but today its use stretched to fresh and handled vegetable, spice, dried forms, used as food dye, bred as attractive plant and manufacture of abstracts for several pharmaceutical and cosmetics industry[1].

Motivated by growing request for pepper worldwide, the market is probable to remain a rising feasting trend over the next seven-year period. Market presentation is evaluation to decelerate, increasing with an awaited CAGR of +1.2% for the seven-year period from 2018 to 2025, which is projected to bring the market size to 840K tone's by the end of 2025.For various kinds of attacking viruses and diseases, we have to lose a large number of peppers.

Disease detection in crops involves several biochemical trials, careful remarks and laboratory kit. With these method agriculturalist can just take image of a crop and the model will guess if the crop has disease or not [2]. General work has been done in this field. We have measured some of the approaches to perceive shrub diseases. The aim of this research is to evaluate potential sources of resistance for use of early detection of disease so that we can prevent our lose peppers by good take care of the crops.

II. LITERATURE REVIEW

This paper [1] is mainly about the massive evolution of hot pepper revealed by the retroduplication and it played a vital role. They reported many genomes for the pepper and copy numbers of NLRs are vastly increased. Authors [3] mainly works with pepper disease & how to recognize these diseases by using Transfer Learning. To recognize these diseases, they used many techniques and found many limitations. But the Transfer Learning model performs best among them. The auhors [4] mainly used different types of Capsaicinoids and Vitamins according to disease types to recognize hot pepper disease. But capsaicin increases the risk of human health because it is associated with cancer. This paper [5] is regarding intercropping effects in hot pepper. Their used mechanisms are trying to reduce sunscald, microclimate, spore dispersal and increase the intercropping system of hot pepper-maize.

Authors [6] presents the new diseases in Korea of Hot Pepper. This paper expresses when a new disease is found, its economic impact & how they deal with this disease in hot pepper. They [7] survey almost 120 fields from two districts. Among them 116 fields were found to contain diseases like fungal and bacterial pathogens. Their prevalence was 96.7% and incidence disease was 86.4%. As conventional techniques achieved limited success, they [8] used linked

DNA makers for better results. Highly polymorphic, cross species transferable are highly preferred in SSR markers. They [9] works with better understanding CMV infection of hot pepper by using RNA sequence. They identified around 2143 DEGs at five stages. Around 1411 novel IncRNA was found in hot pepper. This paper identifies many issues that will improve in future cultivation. They [10] used to differentiate M for species-specific phenotype as they had N1a and VS1-S1 patterns. It may be the first report of this nematode. In 2017 & 2018 their [11] result was from the application 18.84 and 18.00 t ha-1, that was the lowest N rate, but in post-harvest it was high.

This paper [12] is mainly hot pepper's pathogen infection & fruit organs. To identify these issues they used agronomic traits, molecular mechanisms & massive parallel transcriptomes. This paper will help in fruit development. They [13] used binary logistic regression, gross margin analysis and descriptive statistics. This paper identifies all issues and maybe it could reduce hot pepper loss. The [14] hot pepper's antioxidant activities and seaweed liquid extract's impact. Their result shows that the increased rate of hot pepper by using TAM is 0.5% extra instead of NPK. Their paper suggests making the agricultural field more sustainable and reducing bad fertilizers for better pepper. They [15] developing fertilizer in cultivation of hot pepper. In this paper DLF is used as inorganic fertilizer and for liquid fertilizer and hot pepper plants, alkaline hydrolysis was used. They [16] used 415 localities & 40 wilted pepper plant samples for their research. Their research results may help to cultivate good cultivation in their location. They [17] used random leaf samples that were collected from many farmers' fields. Then they used antigen coated plate enzyme-linked immunosorbent assay (ACP-ELISA) to analyze the viruses. This [18] pepper is about the effect of hot pepper's aphid infestation & EPMV infection in netting duration. They used to collect data from the number of aphid populations. Their result suggests applying control measures when pepper is in at the early stage. The growth performance of hot pepper oil & trout of rainbow in blood parameters. For this research, they [19] used HPO 6‰, HPO 4‰, HPO 2‰, HPO 1‰, HPO 0‰ and a fish for 60 days. The HPO 4‰ performs the highest growth rate & lowest feed conversion rate.

This paper [20] mainly comares two hot peppers in different perspectives like key components of the fruit, biochemical composition, capsaicinoids, effects of processing on quality, and biochemical composition. The hot pepper's bioactive compound content and genetic, environmental factors variation in yield performance. They [21] used two different locations to investigate 14 hot pepper diseases. Their paper shares many valuable information about bioactive compounds & environmental variability. They used [22] GoogleNet, Faster R-CNN and Faster R-CNN-GC using image stitching. Though this process needs a vest of time, it provides good results. The pepper fusarium disease detection using machine learning algorithms. To detect these diseases they used spectral reflectance. Their used [23] process can successfully verify diseases by leaf reflection & its accuracy rate is too good. They used [24] deep learning approach for their research. It was a trained based transfer learning detection model and it provides a very good result.

III. Proposed Model

There have been applied different types of deep learning method for making the comparison among VGG19, ResNet-152-V2, InceptionResNet-V2, NASNet Mobile, MobileNet-V2, Xception pre-trained models. And as the pre-trained model it maintains a single rule like neural network where mainly focused input layer, hidden layer and output layers [25]. For the dataset preparation, it has been splitted into three divisions like training, validation and testing dataset shown in fig.1. Training data is for training the model and validation is for improving training qualities so that the model can learn more accurately and testing is for making the result which happens in output layers. Input data is hiddenly extracted and converted all the pixel values as RGB value after converting all the images into a single size of data where except Xception method all of the used methods are converted into 224x224 size and in Xception method images are converted into 299x299.

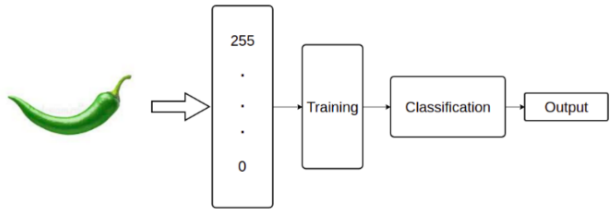

Fig.1. Proposed Model

IV. Dataset Description

From Table.1 (I) there are 556 pepper data have been used in the research article and from the dataset, 386 data is used for training, 107 data is used for validation and 63 data is used for testing in the whole model where are implemented NASNet Mobile, InceptionRestNet-V2, RestNet-152-V2, Xception, MobileNet-V2, and VGG-19. The dataset was collected from a GitHub repository (https://github.com/imdadulhaque1/Pepper_Dataset).

TABLE 1 (I): Dataset description.

Training Data	Validation Data	Testing Data
386	63	107

From the applied model, VGG -19 performance is better and acceptable which is less loss and more accurate. In the whole dataset, there are mainly for attributes as,
Disease Pepper Leaves, Disease Free Pepper Leaves, Disease Pepper Fruits, Disease Free Pepper Fruits.

Under these main attributes there are Bacterial, Fungal, Viral, Abiotic disease is used for classifying and recognize pepper disease or disease free leaves of fruits.

TABLE 1 (II): Pepper Leaves Disease

Bacterial Disease	Bacterial Spot
	Leaf Spot
	Crown Gall
Fungal Disease	Anthracnose
	Cercospora (frogeye) leaf spot

	Gray leaf spot
Viral Disease	Pepper leaf curl
	Pepper huasteco
	Pepper golden mosaic complex

TABLE 1 (III): Pepper Fruit Disease

Bacterial Disease	Bacterial canker
Fungal Disease	Charcoal rot
	Fusarium stem rot
Abiotic Disease	Blossom-end rot
Viral Disease	Tobacco etch

From Table.1 (II) and Table.1 (III), there are different disease have been used in the implemented model so that the model performs in different pepper disease and provides too accurate result [26]. So, the transfer based model is too helpful to detects and classify pepper disease with better performance.

V. PEPPER DISEASE DESCRIPTION

A. Pepper Leaves Disease Description

A1. Bacterial Disease

A1.1. Bacterial Spot

Bacterial spot is the most dangerous and common diseases for peppers almost all over the world. This destructive disease is caused by *Xanthomonas campestris pv. Vesicatoria, which is a gram-negative, rod-shaped bacterium. The surface of affected leafs looks like gray pimples and a little water-soaked spots [7]. If it can't possible to take* action on early *stage then it will be extremely difficult to cure and the pepper plants may die or the production of pepper may decrease significantly.*

A1.2. Leaf Spot

Leaf spot is a one kind of pepper plant infection that is caused by bacteria. It is an occasional disease that generally attacks in rainy, humid and warm climates. This disease appears as yellow and green spot on leaves and brown spot in the later stages on the leaves [22]. Leaf spot disease of pepper is spread by touch, so that early recognition of this disease is must needed to prevent large losses.

A1.3. Crown Gall

This disease is caused by the soil-inhabiting bacterium named *Agrobacterium tumefaciens. The abnormal growth and gall of pepper leaves near the branch is responsible for crown gall. This bacterium exacerbates the growth of pepper plant cells rapidly that is responsible for galls. It appears the outer layer of plant near the leaves brown and corky and the affected areas seems like woody and hard. It may damage the growth of the plant and also production of peppers. Normally crown galls attack the pepper plant during the warm months of the year.*

A2. Fungal Disease

A2.1. Anthracnose

This disease is caused by *Colletotrichum acutatum* fungi during stage of pepper plant growth. The symptoms of anthracnose is began as water-soaked lesions on the pepper leaves and fruits. Multiple lesions occur on the leaves and fruits of pepper and the surfaces of the lesions are covered by the wet salmon colored gelatinous spores. This disease can be very hazardous and pepper production can be totally damaged if early recognition and proper treatment cann't be possible [8].

A2.2. Cercospora (frogeye) Leaf Spot

This disease is caused by fungus named *Passalora capsicicola.* The symptoms of this disease is the round or extensive spots occur on the leaves that looks like dark marginal ring. This sores seem like frog's eye, hence frogeye leaf spot is another name of the disease. When the spot is raised then the leaves of the pepper may turn yellow. This disease can ruin the pepper cultivation.

A2.3. Gray Leaf Spot

Warm and humid session the gray spot disease of pepper attacks. The fungal spores spread with wind and infect the pepper leaves. Small beads develop on the infected leaves of the pepper. Mainly young plants are affected by this disease. The infection starts with brown spot and later it moves into white center and yellow margins. The infected leaves turn yellow in the final stage of infection and drop.

A3. Viral Disease

A3.1. Pepper Leaf Curl

Over watering and poor draining, excess light are the main cause of pepper leaf curl disease. The pests like aphids, thrips, mites and whiteflies are responsible for this disease. Yellow spots, crumped leaves, ring or bullseyes on the pepper leaves are the common symptoms of pepper leaf curl.

A3.2. Huasteco

Pepper huasteco disease is known as pepper huasteco yellow vein virus (PHYVV). This virus is first detected during the early 1990s in Mexico. The infected leaves of the pepper look as yellow near the vein of the leaves. Affected plants can't grow properly and slowly the plants die. Identification of this disease in early stage can be prevented.

A3.3. Pepper golden mosaic complex

This disease was first detected in Texas in 1987 and it is plant pathogenic virus and the family of the virus is *Geminiviridae*. After affecting by this virus, the leaves will be small, curved and look like rolled leaflets with chlorosis. Deformation of pepper leaves and fruits may be caused by this disease. In fig.2 shown some pepper leaf disease.

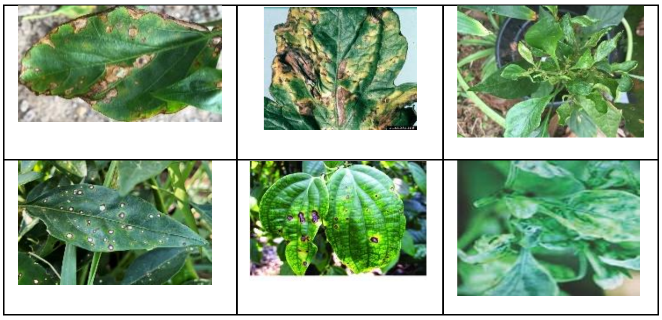

Fig.2. Pepper Leaf Disease

B. *Pepper Fruits Disease Description*

B1. Bacterial Disease

B1.1. Bacterial Canker

This is one of the most blasting disease of the pepper. The main symptoms of this disease is wilting and the wilting starts with the surface of the pepper fruits. Another symptoms of this disease is the white spots on the fruits with dark center. *Clavibacter* bacteria is responsible for this destructive disease.

B2. Fungal Disease

B2.1. Charcoal rot

This disease is caused by the *Macrophomina phaseolina and it is a fungus affected disease. The infected fruits occurs light gray of silver discoloration spots on the fruit. Also black specs can be noticed on the pepper fruits. The discoloration of internal tissue can be visible after cutting the infected plants but the leaves will remain unaffected and stay green.*

B2.2. Fusarium stem rot

This disease was first discovered in a commercial greenhouse in Canada from pepper. Generation of pepper fruits can be diminished for this disease. Dark brown or black can visible in the affected plant. Black lesions occurs around the fence of the infected pepper fruit and the leaves are wilted.

B3. Abiotic Disease

B3.1. Blossom-end rot

The lack of calcium (Ca) may be caused for this disease. Light green or yellow-colored sunken spots occurs at the first stage of the blossom-end rot disease and the spot expands its area with black colors. The affected area of the pepper fruits looks like rotten.

B3.2. Tobacco etch

This is an aphid-transmitted potyvirus that is occurred in pepper plant. The affected pepper fruits is decomposed with mud-colored shown in fig.3. Also wilting and mottling can be visualized in the affected leaves and fruits of pepper plants. This virus generally affects the young pepper plants and spreads rapidly if early identify and treatment can't be possible.

Fig.3. Pepper Fruit Disease.

C. *Data Preprocessing*

The dataset contain RGB images and the images are shaping as 200x200 input shape function. The dataset is rescaling in 1./255, zooming range 0.2, rotational range 10, brightness range [0.5,1.5], vertical and horizontal flip are false in the preprocessing stages. In the training set image batch size is 32, validation and testing set image batch size is 4. Applying 80% image data for the training and 20% image data for the testing purposes and the model gives high performance.

V. Model Description

Six CNN model are applying to utilize the best accuracy to classify the pepper disease. Fig.4 describe the full process of the image dataset.

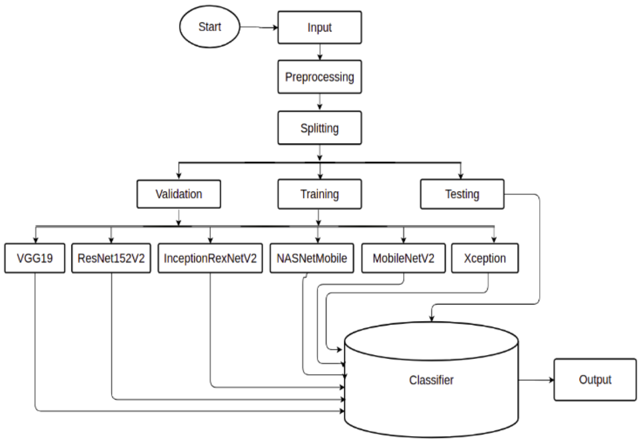

Fig.4. System Operation.

A. VGG-19

The Convolutional Neural Network Based model as keras API's updated version of VGG16 is VGG19 and there are mainly three layers which is the same as deep neural network based model as input layer, hidden layers and output layer. Classifier activation functions used are softmax function and the input shape 224x224 defines the RGB value and also has three channels [27]. The optional pooling's attribute is used for extract and include_top defines false for getting the better performance of the VGG19 model.

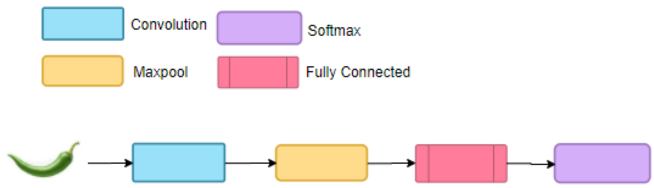

Fig.5. Basic architecture of VGG-19.

B. Xception

Xception is known as the deep learning based most accepted model with better accuracy as it mainly defines the most efficient model. There have been used softmax functions so that it will be able to provide better accuracy with better performance. The input shape has to be 299x299 with three channels which defines the RGB value of input data. Feature extraction terms of pooling layer's include_top is false. At the time of preprocess the input defines the scale input pixel between -1 and 1 [28]. It works with depthwise separable convolution layers to ensure the better performance of the implemented model as Xecption.

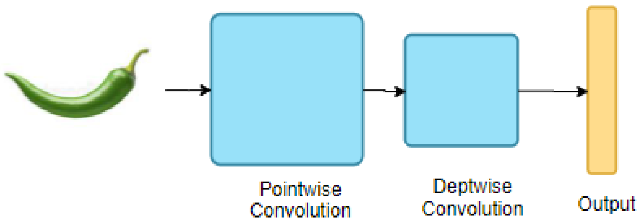

Fig.6. Xception models process diagram.

C. NasNet Large

The deep learning based model's NASNet Mobile have input shape is required as 224x224 with three channels, include_top define the fully connected layer, weights randomly initialize with respect to input shape, input tensor, pooling defines three categories (none, avg, max) and pooling as feature extraction function of include_top's works for none required for 4D tensor output, avg required for last convolutional layers output and max is for 2D tensor [28].

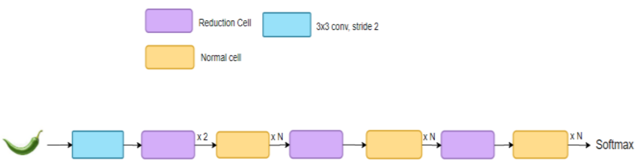

Fig.7. NasNet Large models process diagram.

D. MobileNet-V2

MobileNetV2 model able to provide better performance Instead of the MobileNet model with the help of bottlenecking features and the input size must be greater than 32x32 size of images because it ensures the more acceptable model with the better performance. The input image resolution is 224x224 with three channels. The pooling defines a boolean value false of include_top and there are three types of pooling as none, avg, max. None define the 4D tensor output, avg define global average pooling and max define the 2D tensor of output. The classifier activation function is used by the softmax function.

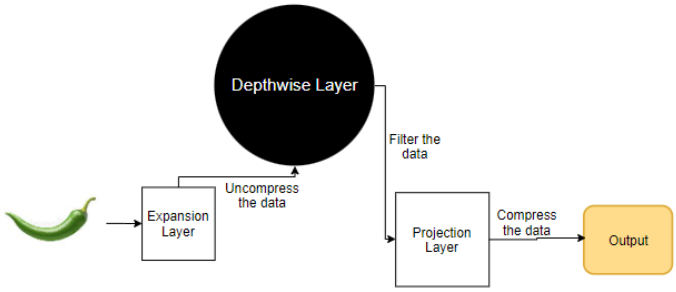

Fig. 8. Basic MobileNet-V2 built-in block.

E. RestNet152-V2

The RestNet152V2 is the most in acceptable model for transfer learning based algorithm and it allow the boolean value false of include_top and it defines the fully connected layer where the input shape's data format would be last channel as (224,224,3), first channel(3,224,224). For pooling as feature extraction have used none, avg, max and none defines 4D tensor output, avg defines 2D tensor, max defines the globally max pooling. There have been used the softmax function as activation function at hidden layers in the RestNet152-V2 model.

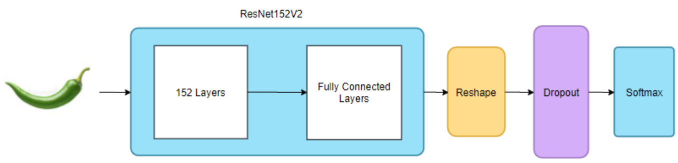

Fig.9. Basic ResNet152Net-V2 built-in block.

F.InceptionRestNet-V2

For image classification, InceptionRestNetV2 has been used with better performance with better accuracy and it is also known as a pre-trained model of keras as deep learning based. The top of the layer in the network as fully connected defines the boolean value as false and the input shape accepted with two different ways as last channel (299, 299, 3) and first channel (3,299,299) of the data format. The feature extraction technologies as pooling used none, avg, max and it defines as 4D tensor, 2D tensor, globally max pooling [25]. In hidden layers as a classifier activation has been used for better performance in multi class.

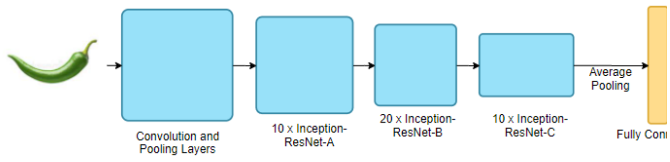

Fig.10. Basic InceptionResNet-V2 built-in block.

VI. FEATURE EXTRACTION

The developed research approaches have been implemented using different pre-trained models of keras application with different image input size. And for VGG-19, ResNet-152-V2, InceptionresNet-V2, NASNet Mobile, MobileNet-V2 used 224x224 size as the input size and for Xception have used 299x299 size of image and all are implemented to use 3 channels. Because of converting all the images into a single size of image, that feature extraction will be a perfect way which will provide the more acceptable accuracy [27]. There has been a MaxPooling function which completed the feature extraction in the hidden layer. After feature extraction all the images are converted into RGB value as (0-255).

VII. RESULT ANALYSIS

This study has executed six different convolution neural network pre-trained algorithms as mentioned in Table V with a training dataset of 386 to detect the pepper diseases. VGG-19 has showed the highest accuracy among six different CNN algorithms and the highest result is 98.13%. Similarly, VGG-19 has leaded in precision, recall, F1 score and AUC from all of them. After VGG-19, ResNet-152-V2 has obtained the better accuracy of 97.19% and then Xception has performed well with accuracy of 96.26%. InceptionResNet-V2 and MobileNetV2 have performed nearly same and the accuracy of 94.39% and 93.46% respectfully. NASNet Moble has achieved the lowest accuracy of 90.65% and not only the accuracy but also in precision, recall, F1 score and AUC it has performed the lowest score shown in Table.2. The number of epochs accounted 100 for all training processes and all these information is given and statistically analyzed in Table V.

Accuracy: After performing of the different models with same dataset, this research obtained different accuracy that is presented in Table V. The accuracy is computed from confusion matrix and accuracy is the most inherent performance calculation [29]. The formula is used to calculate the accuracy is given in Eq. (1). To obtain better accuracy, the values of false positive and false negative should be almost the equal in dataset.

$$\text{Accuracy} = \frac{TP+TN}{\text{TP+TN+FP+FN}} \quad (1)$$

Precision: The Precision calculation of the algorithms means to the ratio of correctly predicted positive values to total predicted positive values. The formula is used to calculate the precision is given in Eq. (2).

$$\text{Precision} = \frac{TP}{\text{TP+FP}} \quad (2)$$

Recall: The recall means the proportion of correctly predicted positive values to total positive actual class in the confusion matrix. The recall is calculated from the formula which is given in Eq. (3).

$$\text{Recall} = \frac{TP}{\text{TP+FN}} \quad (3)$$

F1 Score: F1 Score mentions that the harmonic mean of model's precision and recall. A pretty good F1 Score means that the model predicts less false positives and false negatives and F1 Score is better than accuracy. The formula that is used to calculate the F1 Score is given in Eq. (4).

$$\text{F1 Score} = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (4)$$

AUC: The Area Under Curve (AUC) is calculated from the Receiver Operating Characteristic (ROC) curve and the formula that is used for calculating AUC is given in Eq. (5).

$$\text{AUC} = \frac{SE+SP}{2} \quad (5)$$

Here, TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative, SE= Sensitivity and SP = Specificity

TABLE. 2. Performances of selected models.

Algorithm Name	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**AUC**
NASNet Mobile	90.65 %	81.48%	81.48 %	81.48 %	87.62 %
InceptionRestNet-V2	94.39 %	88.89%	88.89 %	88.89 %	92.57 %
RestNet-152-V2	97.19 %	96.15%	92.59 %	94.34 %	95.67 %
Xception	96.26 %	92.59%	92.59 %	92.59 %	95.05 %
MobileNet-V2	93.46 %	85.19%	88.46 %	86.79 %	91.76 %
VGG-19	98.13 %	96.29%	96.29 %	96.29 %	97.52 %

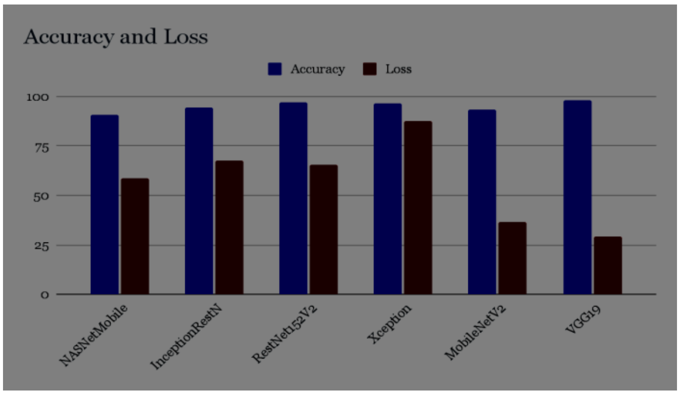

Fig.11. Performance of pre-trained model based on Accuracy and Loss.

After training the pre-trained model with respect to train and validation dataset is totally prepared for making testing result which means the model performance. From fig.11, with different accuracy and loss provides a different shape of column graph. It also primarily selected that VGG-19 is more acceptable based on high accuracy and precision, recall, f1 score and AUC and now it also cleared based on less loss of VGG-19 is more acceptable model.

VIII. DISCUSSION

This study can play a significant role in development of agriculture sectors in many countries. As many countries cultivate pepper and it takes part to develop economically. But low production caused by pepper diseases can be the reason of losses [17]. The inaccurate and slower process of detection can increase these losses. So, the accurate detection of pepper diseases with short time can reduces the losses. Since this study focuses on four classes of pepper diseases and uses six different types of pre-trained deep learning model for analyzing and achieving better accuracy. This study is more helpful and gives more satisfactory result for famers to easily and speedy detect of pepper diseases. For the purposes of achieving better accuracy, six convolution neural network pre-trained algorithms named NASNet Mobile, InceptionResNetV2, RestNet-152-V2, Xception, MobileNet-V2 and VGG-19 are used to analysis their performance. Among these algorithms VGG-19 satisfies with highest accuracy and the accuracy is 98.13%. VGG-19 also gives highest precision, highest recall, highest F1 score and highest AUC. On the other hand, NASNetMobile shows the lowest result and the accuracy is only 90.65%. NASNetMobile also gives the lowest performance in precision, recall, F1 score and AUC. The other pre-trained models give better accuracy and the accuracy of ResNet-152-V2 is 97.19%, it is more close to VGG-19. Xception also provides satisfactory result and its accuracy is 96.26%. The accuracy gets from the InceptionRestNet-V2 and MobileNet-V2 is respectively 94.39% and 93.46%. This experiment evaluates the result with accuracy, precision, recall, F1 score and AUC as these calculating tools help to understand the overall performance of the all six pre-trained algorithms [30]. In experiment, there are 386 training data, 63 validations data and 107 testing data has been used. This study can be applied to other plants diseases and as soon as possible this study will apply to others plants diseases. Also, this research will move forward with more datasets and developed algorithms. Here is a graphical representation of the performance analysis of the six pre-trained models in figure.11.

IX. LIMITATION AND FUTURE WORK

This study can be moved forward with more classes of pepper diseases and more developed pre-trained CNN model for acquiring better accuracy and assuring faster detection of pepper diseases [24]. More study about the diseases types and sign of diseases of pepper can carry this research to upper level. Although, this datasets have fairly enough images and classes, the increased datasets with more classes can enhance the study to achieve better result. The more smart way of visualizing the spot of diseases in pepper and pepper leaf may reduce the time of detection. This study can be enhanced by detecting the other types of peeper diseases with more datasets and accuracy can be amplified with other developed CNN models. Applying this study as a base to detect other plants diseases with better accuracy can be possible. Without delay, the research will be done to overcome all these limitation and will be applied this method to other plants diseases. Besides, the outcome of this study is inspiring us to enrich this model and apply this method for detecting other plant diseases for ensuring more accurate detection.

X. CONCLUSION

We have built this model for the identification of disease-affected pepper and healthy plants are done and this anticipated work is motivations on the accuracy standards during the real ground conditions, and this work is implemented by having several peppers disease images. By examining the algorithm's accuracy of 96.26% from the ResNet152V2 and VGG19 network architecture. The Xception network achieved the third-highest testing accuracy of 93.46%. Overall this work is executed from scratch and produces a decent accuracy. To reach a further accurate prediction of the pepper diseases, it was used to transfer learning methods. This version of transfer learning amplified the accuracy and summary the model training time complexity [3]. The upcoming work is to intensify the number of images present in the predefined database and adjust the construction according to the dataset for improved accuracy.

REFERENCES

[1] B. K. Saleh, A. Omer, and B. Teweldemedhin, "Medicinal uses and health benefits of chili pepper (Capsicum spp.): a review," *MOJ Food Process Technol*, vol. 6, no. 4, pp. 325–328, 2018.

[2] Z. Huang, X. Zhu, M. Ding, and X. Zhang, "Medical image classification using a light-weighted hybrid neural network based on PCANet and DenseNet," *IEEE Access*, vol. 8, pp. 24697–24712, 2020.

[3] H. Yin, Y. H. Gu, C.-J. Park, J.-H. Park, and S. J. Yoo, "Transfer learning-based search model for hot pepper diseases and pests," *Agriculture*, vol. 10, no. 10, p. 439, 2020.

[4] G. F. Antonious, "Capsaicinoids and vitamins in hot pepper and their role in disease therapy," in *Capsaicin and its human therapeutic development*, IntechOpen, 2018.

[5] Y. Gao *et al.*, "Pepper-maize intercropping affects the occurrence of anthracnose in hot pepper," *Crop Prot.*, vol. 148, p. 105750, 2021.

[6] I.-S. Myung *et al.*, "Bacterial spot of hot pepper, caused by Xanthomonas euvesicatoria, a new disease in Korea," *Plant Dis.*, vol. 99, no. 11, p. 1640, 2015.

[7] M. Assefa, W. Dawit, A. Lencho, and T. Hunduma, "Assessment of wilt intensity and identification of causal fungal and bacterial pathogens on hot pepper (Capsicum annuum L.) in Bako Tibbe and Nonno districts of West Shewa zone, Ethiopia," *Int. J. Phytopathol.*, vol. 4, no. 1, pp. 21–28, 2015.

[8] N. Jayaram, A. M. Rao, S. Ramesh, B. Manjunath, N. Mangalagowri, and M. Ashwini, "Tagging ssr markers to genomic regions associated with anthracnose disease resistance and productivity per se traits in hot pepper (Capsicum annuum L.)," *Env. Ecol*, vol. 34, no. 4A, pp. 1440–1446, 2016.

[9] C. Zhu, X. Li, and J. Zheng, "Transcriptome profiling using Illumina-and SMRT-based RNA-seq of hot pepper for in-depth understanding of genes involved in CMV infection," *Gene*, vol. 666, pp. 123–133, 2018.

[10] Y. Wang, X. Q. Wang, Y. Xie, Y. Dong, X. Q. Hu, and Z. X. Yang, "First report of Meloidogyne enterolobii on hot pepper in China," *Plant Dis.*, vol. 99, no. 4, p. 557, 2015.

[11] S. M. Hassan, A. F. El-Bebany, M. Z. M. Salem, and D. A. Komeil, "Productivity and post-harvest fungal resistance of hot pepper as affected by potassium silicate, clove extract foliar spray and nitrogen application," *Plants*, vol. 10, no. 4, p. 662, 2021.

[12] M.-S. Kim *et al.*, "Global gene expression profiling for fruit organs and pathogen infections in the pepper, Capsicum annuum L.," *Sci. data*, vol. 5, no. 1, pp. 1–6, 2018.

[13] O. A. Obayelu, O. M. Adegboyega, F. A. Sowunmi, and C. O. Idiaye, "Factors explaining postharvest loss of hot pepper under tropical conditions," *Int. J. Veg. Sci.*, vol. 27, no. 6, pp. 526–535, 2021.

[14] M. Ashour *et al.*, "Impact of commercial seaweed liquid extract (TAM®) biostimulant and its bioactive molecules on Growth and Antioxidant Activities of Hot Pepper (Capsicum annuum)," *Plants*, vol. 10, no. 6, p. 1045, 2021.

[15] S.-W. Kang, C. Jeong, D.-C. Seo, S. Y. Kim, and J.-S. Cho, "Liquid fertilizer production by alkaline hydrolysis of carcasses and the evaluation of developed fertilizer in hot pepper cultivation," *Process Saf. Environ. Prot.*, vol. 122, pp. 307–312, 2019.

[16] M. A. Ismail, A. Moubasher, A. M. El-Eraky, A. H. El-Shaer, and H. A. Gouda, "Virulence of wilt pathogens against pepper cultivars in Egypt," *Int. J. Tech. Res. Sci.*, vol. 1, no. 10, pp. 304–314, 2017.

[17] A. Olawale, B. O. Samuel, A. S. O. Solomon, and P. L. Kumar, "Surveys of virus diseases on pepper (Capsicum spp.) in South-west Nigeria," *African J. Biotechnol.*, vol. 14, no. 48, pp. 3198–3205, 2015.

[18] K. Dida, A. Chala, and F. Azerefegne, "Effect of netting duration on Ethiopian Pepper Mottle Virus (EPMV) infection and aphid infestation of hot pepper (Capsicum annuum L.) in Central Rift Valley Region of Ethiopia," *J Plant Pathol Res*, vol. 2, no. 1, pp. 6–12, 2020.

[19] V. Parrino, O. S. Kesbiç, Ü. Acar, and F. Fazio, "Hot pepper (Capsicum sp.) oil and its effects on growth performance and blood parameters in rainbow trout (Oncorhynchus mykiss)," *Nat. Prod. Res.*, vol. 34, no. 22, pp. 3226–3230, 2020.

[20] T. Hernández-Pérez, M. del R. Gómez-García, M. E. Valverde, and O. Paredes-López, "Capsicum annuum (hot pepper): An ancient Latin-American crop with outstanding bioactive compounds and nutraceutical potential. A review," *Compr. Rev. Food Sci. Food Saf.*, vol. 19, no. 6, pp. 2972–2993, 2020.

[21] P. Tripodi *et al.*, "Genetic and environmental factors underlying variation in yield performance and bioactive compound content of hot pepper varieties (Capsicum annuum) cultivated in two contrasting Italian locations," *Eur. Food Res. Technol.*, vol. 244, no. 9, pp. 1555–1567, 2018.

[22] S. Eser, "A deep learning based approach for the detection of diseases in pepper and potato leaves," *Anadolu Tarım Bilim. Derg.*, vol. 36, no. 2, pp. 167–178, 2021.

[23] K. Karadağ, M. E. Tenekeci, R. Taşaltın, and A. Bilgili, "Detection of pepper fusarium disease using machine learning algorithms based on spectral reflectance," *Sustain. Comput. Informatics Syst.*, vol. 28, p. 100299, 2020.

[24] Y. Zeng, Y. Zhao, Y. Yu, Y. Tang, and Y. Tang, "Pepper Disease Detection Model Based on Convolutional Neural Network and Transfer Learning," in *IOP Conference Series: Earth and Environmental Science*, 2021, vol. 792, no. 1, p. 12001.

[25] A. Islam, N. Rahman Shuvo, M. Shamsojjaman, S. Hasan, S. Hossain, and T. Khatun, "An Automated Convolutional Neural Network Based Approach for Paddy Leaf Disease Detection," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 1, pp. 280–288, 2021, doi: 10.14569/IJACSA.2021.0120134.

[26] T. Khatun *et al.*, "Performance Analysis of Breast Cancer: A Machine Learning Approach," in *2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA)*, 2021, pp. 1426–1434.