How to Cite:
Dhanalakshmi, P., Sivakumar, N., Kumari, K. A., Kumar, S., & Alla, P. C. R. (2022). Image-based classification of healthy and diseased bell pepper using the transfer learning method. *International Journal of Health Sciences*, *6*(S4), 6773–6784.
https://doi.org/10.53730/ijhs.v6nS4.9631

Image-based classification of healthy and diseased bell pepper using the transfer learning method

Dr. P. Dhanalakshmi
Professor, Department of Computer Science and Systems Engineering, Sree Vidyanikethan Engineering College (SVEC), Tirupati, Andhra Pradesh 517102, India
Corresponding author email: mallidhana5@gmail.com

Dr. N. Sivakumar
Assistant Professor, Department of Computer Engineering – AI & BIG DATA, Marwadi University, Rajkot, Gujarat 360003, India
Email: sivakumar.nadarajan@marwadieducation.edu.in

Kukati Aruna Kumari
Sr. Assistant Professor, Department of Electronics and Communication Engineering, Prasad V Potluri Siddhartha Institute of Technology, Vijaywada, Andhra Pradesh 520007, India
Email: gudipudiak@gmail.com

Senthil Kumar
Assistant Professor, Department of Computer Science and Engineering, KIT-KalaignarKarunanidhi Institute of Technology, Coimbatore, Tamil Nadu 641402, India
Email: jsenthilkumarphd20@gmail.com

Prof. Poorna Chandra Reddy Alla
Assistant Professor, Department of Computer Engineering, Marwadi University, Rajkot, Gujarat 360003, India
Email: allapoorna.reddy@marwadieducation.edu.in

***Abstract*---**The bell pepper is a fruit that is often misunderstood as a vegetable due to its usage. The plant which grows bell pepper grows for about three to six feet. These plants do not require intensive care but some necessary steps have to be taken to increase the productivity of the plant. Plant diseases like bacterial spots can heavily affect growth. The consequences of such diseases can be reduced if they're detected in their early stages. This research aims the comparison of two Deep Learning (DL) models which were

Manuscript submitted: 27 March 2022, Manuscript revised: 9 May 2022, Accepted for publication: 18 June 2022

developed using VGG-16 architecture and the AlexNet. For training and testing the efficiency of the models, images of the bell pepper plant's leaf are obtained from Kaggle. This data acquired further undergoes some pre-processing techniques like resizing and rescaling to reach the desired format. The cleaned data is then split into three divisions. One of them is used to train both DL models and the second one is used to validate the models. The last part is used to test the accuracy and loss of the two models. In the end, the accuracy and loss of both the models are compared and the results are tabulated. With the obtained results, two graphs are generated for better understanding. From the results, the best algorithm which can be used to detect bacterial spot disease for bell pepper plants is identified.

***Keywords*---**disease, DL, VGG-16, alexnet, accuracy, loss.

Introduction

Plant diseases are a major threat to farmers. These diseases not only damage the growth of the plant but will increase its intensity drastically. If a plant is affected by a bacterial disease, it has to be found and eradicated as soon as possible. If the disease was not detected in its early stages, there are a lot of chances for the plant to die due to the disease or heavy reduction in the yield. Bell pepper is a type of plant which is well grown when it is treated well with biofertilizers and only less amount of water is used [1]. But somehow farmers and other agriculturists have some basic knowledge about plant diseases while people who are interested in gardening but don't have professional knowledge about gardening and agriculture can struggle with these diseases. The pandemic situation caused by the coronavirus has simulated the urge in various indoor activities like painting and gardening even in urban areas [2]. Bell pepper is a plant that is widely grown in many parts of the world as it does not require much maintenance. Thus, bell pepper plants will always be on the top plant list for home gardeners. The plants can also yield bell pepper fruits which are widely used in a variety of cuisines. This disease is caused by a bacteria named Xanthomonas. It can result in defoliation of the plant and the formation of black spots on the leaves and fruit. This disease can be treated by the removal of other vegetable debris from the pot. This process has to be repeated periodically to ensure the rest of the plant is not affected by bacterial spots. But the problem arises when the owners of the plants were not aware of the fact that the plants were affected. To address this issue, this study attempts to create the best DL model that can be employed to indicate the existence of bacterial spots in bell pepper plants using images of the leaf.

Literature Survey

Researchers of the Kyambogo University of Uganda reviewed the consequences of the bacteria Xanthomonas in various plants. Many Xanthomonas phages have been used as agents that are used for the bio controlling process. for Xanthomonas species, as per the review. The bulk of them have so far been recognized as belonging to the order Caudovirales, and they are lytic to a wide variety of host strains. They also suggested that, even though little investigations on this part of biology have been conducted, more investigation is warranted to fully understand their life cycle. In a variety of outdoor conditions, the Xanthomonas bacterium can lower illness severity or restrict bacteria development. More study is required when they convert to commercial goods to capitalize on the seemingly limitless potentials of Xanthomonas phages for several Xanthomonas-related plant ailments [3]. According to the research done by the researchers from the University of Florida, it’s become clear that there isn’t enough research on the caused chemical changes that both insects and diseases are attacking the host plant at the same time. According to their findings, both the bacterial infection, as well as beet armyworm damage, can create a broad variety of pepper plant volatile profiles when it is used on a single host. They observed that, regardless of compatibility, third instar survival to pupation was considerably more when eating on diseased crops than when feeding on healthy crops [4].

The analysis of the images of leaves to find the type of plant disease is not a new technology. Several types of research have been done in the identification of various plant diseases using the images of leaves. One of them states that Digital image analysis methods are helped in agriculture for a multi-purpose, including vigor diagnosis, vegetation measuring, phenotyping, and more. The diseased picture attributes in the localized image, such as spots and damage to the leaf region, give the keys to distinguishing healthy photos from sick images, which may be easily obtained via Fisher vector extraction. Using the Support Vector Machine (SVM) approach, they were able to attain average accuracy of 0.93 and 0.97. Overall, the categorization approach provided by them outperforms state-of-the-art techniques [5]. The detection of antimicrobial illnesses in bell pepper plants was studied by a group of researchers from the Universidade Federal de Viçosa in Brazil. They also suggested that peptide discovery be aided by statistical testing in large protein databases. Peptides are very small compounds [6]. The researcher used the YOLO-V5 algorithm to determine the type of plant disease affecting bell pepper plants. Their system effectively detects bacterial spots in pepper plants in the preliminary steps itself. When compared to other models, the findings produced with YOLOv5 are more accurate. Results are produced faster since the comparative training time using the YOLO algorithm is just 9.5 percent of the prior model using YOLOv4. As a consequence, the technology detailed in their study produces faster and more accurate findings than prior versions of YOLO and is suited for improving farm productivity by detecting and diagnosing plant illnesses [7].

Convolutional Neural Network (CNN) using the VGG-16 architecture was utilized by researchers from India's Visvesvaraya Technological University to classify rice illnesses. Using the VGG-16 architecture, they were able to obtain greater accuracy of 92.24%. Researchers in the field of computer-assisted farming and agriculture should take note of these findings, which look promising. Because the study examines more datasets than previous studies, the suggested approach experimental findings are satisfactory. Their method may be used in many agricultural fields like the growth of cereals, horticulture crops, commercial crops, vegetables, fruits, etc. [8]. Another group of researchers from India's Visvesvaraya

Technological University used automated algorithms to diagnose viral and bacterial sickness signals in plants based on how they looked. They were effective in recognizing and classifying the symptoms of the plant disease using their methods. For overall mean classification and computation time, they found that the SVM classification classifier aided by the co-occurrence-based color moments technique outperformed the ANN and CNN classifier. The findings are encouraging because they explain the differences in symptoms between viral and bacterial illnesses. Their method might be used to detect plant disease symptoms in a range of plant crops automatically [9]. Researchers from The University of Sheffield in London used a DL system called AlexNet to restore and identify merged images. Their research yielded integrated frameworks for image restoration and recognition that perform both tasks simultaneously. A combined framework is made up of common layers, categorization layers, and restoration layers. The AlexNet architecture was used in the first layer of their inquiry. They also put the photographs through their paces with occlusion, noise, and rotation, among other image degradation factors. Finally, the collaborative frameworks they propose aren't restricted to the application in question; they may be used for a range of image recognition/restoration jobs and could use several inner network architectures [10].

Materials And Methods

This chapter discusses the methods which were used in this research with the help of a workflow diagram. A dataset containing the images of both healthy and bacterial spot-affected leaves of the bell pepper plant is obtained from Kaggle. The total dataset of divided into three parts training, testing, and validation. The dataset is then preprocessed for further analysis. This preprocessing step includes resizing and rescaling the images into a certain format so that it will be easy to proceed with the further steps. The entire process of disease prediction in a bell pepper is explained in figure 1.As shown in figure 1, the processed images are then fed into two DL models and the models are trained using the images. The models are then validated and tested. After testing, the model with higher efficiency based on the two parameters – accuracy and loss are chosen as the best algorithm that can be used to detect bacterial spots of the bell pepper plant.

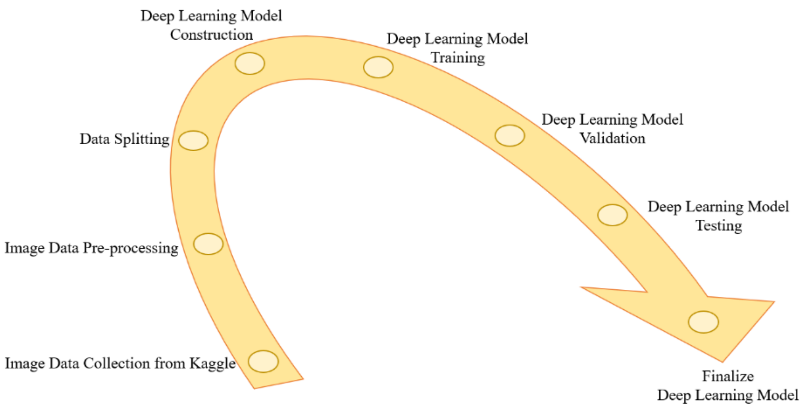

Fig. 1. Workflow of the disease detection

Data And Its Preprocessing

This chapter discusses how the data was collected and split for train, validation, and test purposes. The preprocessing techniques which were used in the images will also be elaborated on in this chapter.

Data Collection

A dataset consisting of 4000 images of the leaf of the bell pepper plant is collected from Kaggle. From the 4000 images, half of them are the images of the healthy leaf while half of them were the images of leaves affected by bacterial spots. The difference between the two leaves can be clearly understood by referring to figure 2. Out of the 4000 images, 2800 images were used to train the DL models, 800 images were an aid to validate and 400 images were employed to test the models which were developed using VGG-16 and AlexNet. The detailed split-up of the obtained images was shown in table 1

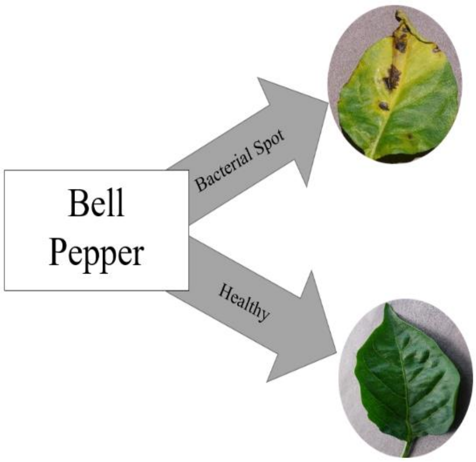

Fig. 2. Classification of Bell pepper leaves

Table 1. Split-up of images

Data Sample	Bacterial Spot	Healthy
Total	2000	2000
Train	1400	1400
Validate	400	400
Test	200	200

Image Resizing

Image resizing is the process of altering the dimensions of all the photographs in a dataset so that they are all the same size. It is necessary to reduce the weighted average distortion energy of all handles to resize the image [11]. The total number of pixels in an image can be increased or decreased when resizing it. When an image is zoomed or extended, picture resizing guarantees that image quality is preserved.

Image Rescaling

The rescaling or resampling procedure is used to create a new version of an image with a different size. These procedures aren't quite flawless, as it turns out. Certain researchers also use rescaling to consider the interdependencies among the channels [12]. This is a challenging procedure that requires a delicate balance of sharpness, efficiency, speed, and smoothness. Another key advantage of picture scaling is the ability to remove unwanted image portions.

DL Model Construction

This chapter clearly explains what is a DL model. Along with that, it also explains how a DL model is constructed by developing VGG-16 architecture and AlexNet architecture. A DL model is a computer-generated classification system for photos, texts, and even sounds. Various DL methods can be used to create this DL model. CNN, radial basis function networks, recurrent neural networks, transfer learning, and other techniques are among them. In this research, two DL models which were developed using the VGG-16 architecture and the AlexNet architecture are used.

VGG-16 Architecture

The VGG-16 architecture uses the transfer learning approach to train the DL model. VGG-16 has several advantages, including the fact that it is a pre-trained model that does not require a lot of training and testing. The VGG-16 model has 16 layers, thirteen of which are convolutional and three of which are completely linked. The topmost layer and the bottommost layer are the only two levels that may be adjusted to meet the user's needs. As a result, it does not need substantial training, testing, or validation, making it an easy algorithm to use [13]. In this case, the model is trained in such a way that it can identify the images containing leaves of the bell pepper plant which were affected by bacterial spots.

AlexNet Architecture

AlexNet Model is an eight-layer CNN with 5 convolutional and 3 fully connected (FC) layers. It's a pre-trained model that doesn't require much in the way of validation or training. Alexnet's major purpose is to prove that learning-based features may be defeated by created features, shattering the visual object's previous model. To extract the most characteristics from the photographs, utilize the max-pooling layer. The AlexNet architecture is used in various fields of technology including medicine [14]. Several convolution processes are utilized in photographs of bell pepper leaves. Edges, curves, and lines are among the characteristics that have been recovered. The collected important features are sent via FC layers, which summarize all collected characteristics into best features, and the CNN classifier produces a final image with a single dimension that can be used for classification [15].

Result And Discussion

This chapter debates the observation results and also compares the pros and the cons of both the DL models. Two DL models were developed using the VGG-16 architecture and the AlexNet architecture. Once the models were developed, they are trained, validated, and tested. The test results are then analyzed based on some performance metrics. The performance metrics include the accuracy and loss values provided by the models during training and validation.

Another parameter named the time taken to predict the presence of bacterial spots is also taken into account. Figure 3 shows the outcome of the VGG-16 architecture during training and validation.

```
Epoch 1/10
88/88 [==============================] - 1344s 15s/step - loss: 0.3345 - accuracy: 0.8671 - val_loss: 0.2876 - val_accuracy: 0.
8822
Epoch 2/10
88/88 [==============================] - 671s 8s/step - loss: 0.1336 - accuracy: 0.9518 - val_loss: 0.1444 - val_accuracy: 0.94
23
Epoch 3/10
88/88 [==============================] - 651s 7s/step - loss: 0.0831 - accuracy: 0.9700 - val_loss: 0.1601 - val_accuracy: 0.93
03
Epoch 4/10
88/88 [==============================] - 657s 7s/step - loss: 0.0679 - accuracy: 0.9761 - val_loss: 0.1377 - val_accuracy: 0.95
43
Epoch 5/10
88/88 [==============================] - 661s 8s/step - loss: 0.0535 - accuracy: 0.9857 - val_loss: 0.1537 - val_accuracy: 0.93
03
Epoch 6/10
88/88 [==============================] - 663s 8s/step - loss: 0.0496 - accuracy: 0.9829 - val_loss: 0.1337 - val_accuracy: 0.94
95
Epoch 7/10
88/88 [==============================] - 684s 8s/step - loss: 0.0374 - accuracy: 0.9900 - val_loss: 0.1335 - val_accuracy: 0.94
47
Epoch 8/10
88/88 [==============================] - 1066s 12s/step - loss: 0.0275 - accuracy: 0.9943 - val_loss: 0.1254 - val_accuracy: 0.
9495
Epoch 9/10
88/88 [==============================] - 1115s 13s/step - loss: 0.0266 - accuracy: 0.9946 - val_loss: 0.1502 - val_accuracy: 0.
9471
Epoch 10/10
88/88 [==============================] - 987s 11s/step - loss: 0.0237 - accuracy: 0.9954 - val_loss: 0.0926 - val_accuracy: 0.9
639
```

Fig. 3. Training results of the VGG-16 architecture

As shown in figure 3, the VGG-16 accuracy is approximately 86% during the first epoch. As the number of epochs increases, the accuracy of the model increases and it reaches an approximate accuracy of 99% during the tenth epoch. The loss value produced by the model is inversely proportional to the number of epochs. For instance, the loss value of the model during the first epoch is 28% and as the number of epochs is increased, the loss rate is decreased and it reaches the loss value of 9% during the final epoch.

Time taken to complete the detection process is also taken into as mentioned before and it is found that the VGG-16 architecture takes a maximum of 1344 seconds during the first epoch. The time taken is also reduced to 987 seconds during the final epoch. Yet, this amount of time is large for a DL model. Figure 4 contains the graphical representation of the above-mentioned data. In other words, it contains the accuracy value of the VGG-16 architecture during every single epoch.

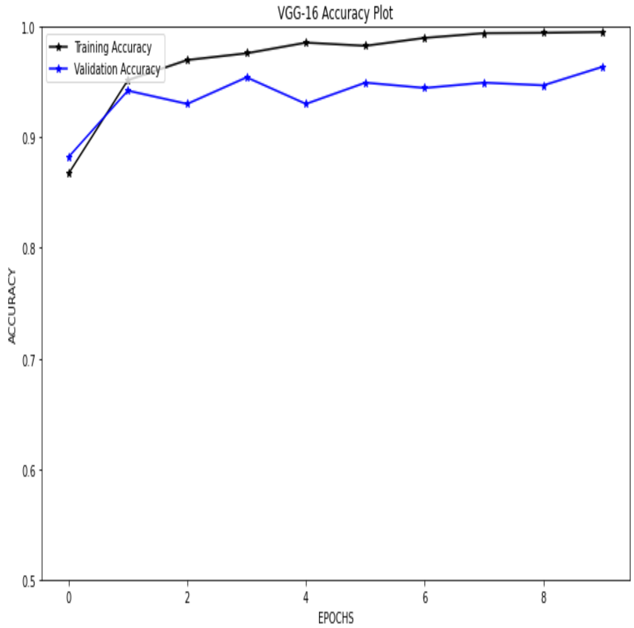

Fig. 4. Accuracy plot of the VGG-16 architecture

This can be observed that as the range of epochs increases, the positive performance of the model keeps on rising. Figure 5 depicts the pictorial depiction of the VGG-16 architecture's loss value at each epoch.

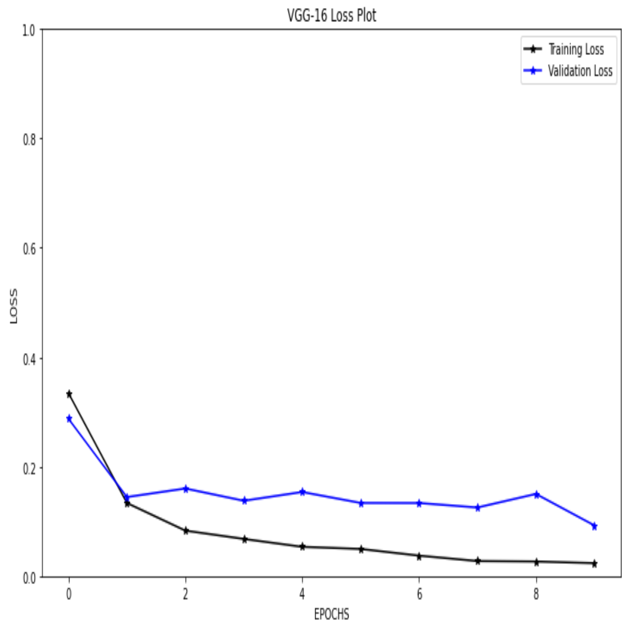

Fig. 5. Loss plot of the VGG-16 architecture

It can be observed that as the number of epochs increases, the model's loss decreases. Figure 6 shows the results of the Alexnet architecture during training and validation.

```
Epoch 1/10
88/88 [==============================] - 304s 3s/step - loss: 0.6140 - accuracy: 0.8014 - val_loss: 2.6320 - val_accuracy: 0.57
50
Epoch 2/10
88/88 [==============================] - 328s 4s/step - loss: 0.3229 - accuracy: 0.8707 - val_loss: 0.5593 - val_accuracy: 0.77
75
Epoch 3/10
88/88 [==============================] - 293s 3s/step - loss: 0.2803 - accuracy: 0.8861 - val_loss: 0.4307 - val_accuracy: 0.81
00
Epoch 4/10
88/88 [==============================] - 294s 3s/step - loss: 0.2578 - accuracy: 0.8861 - val_loss: 2.1139 - val_accuracy: 0.64
13
Epoch 5/10
88/88 [==============================] - 280s 3s/step - loss: 0.2589 - accuracy: 0.8918 - val_loss: 4.1463 - val_accuracy: 0.51
88
Epoch 6/10
88/88 [==============================] - 305s 3s/step - loss: 0.2011 - accuracy: 0.9154 - val_loss: 1.0417 - val_accuracy: 0.69
25
Epoch 7/10
88/88 [==============================] - 309s 4s/step - loss: 0.1390 - accuracy: 0.9461 - val_loss: 0.6156 - val_accuracy: 0.77
13
Epoch 8/10
88/88 [==============================] - 294s 3s/step - loss: 0.1601 - accuracy: 0.9364 - val_loss: 5.1851 - val_accuracy: 0.55
50
Epoch 9/10
88/88 [==============================] - 287s 3s/step - loss: 0.1245 - accuracy: 0.9521 - val_loss: 0.5218 - val_accuracy: 0.85
25
Epoch 10/10
88/88 [==============================] - 301s 3s/step - loss: 0.1150 - accuracy: 0.9554 - val_loss: 0.4246 - val_accuracy: 0.87
50
```

Fig. 6. Accuracy and loss values of AlexNet architecture

The model’s accuracy during the first epoch is roughly 80%, as shown in figure 6. The model’s accuracy improves as the number of epochs grows, reaching an approximate accuracy of 95% during the tenth epoch. The model’s loss value is inversely proportional to the number of epochs used. For example, the model’s loss value is 263 percent during the first epoch, but as the number of epochs increases, the loss value decreases until it reaches 42 percent at the last epoch. The time taken for the completion of every step remains similar to 280 to 305 in all epochs. Though the accuracy value of the AlexNet architecture is similar to that of the VGG-16 and the time is taken for the completion of every process is low, the loss value is very high even in the final epoch. Figure 7 and 8 depicts the graphical representation of the results of the AlexNet architecture i.e., the accuracy and loss values of the DL model.

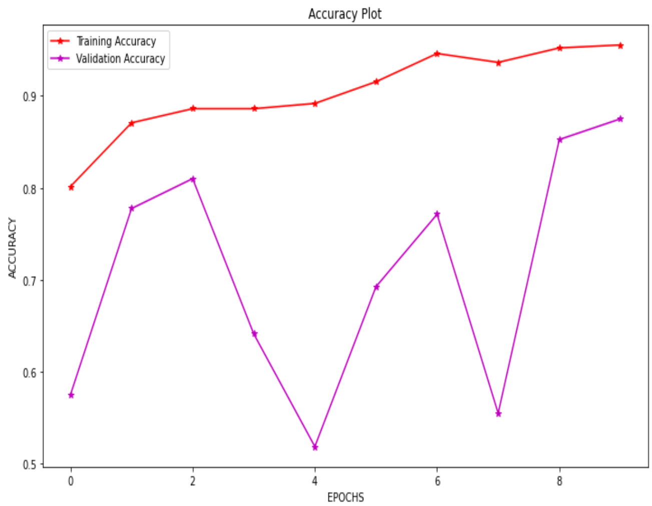

Fig. 7. Accuracy plot of the AlexNet architecture

From figure 7, it can be found that the accuracy value of the AlexNet architecture is not stable. It gradually increases in the first two epochs of validation, only to reduce in the next two epochs. The consistency of the accuracy values is missing in the AlexNet architecture. Figure 8 represents the loss plot of the AlexNet architecture.

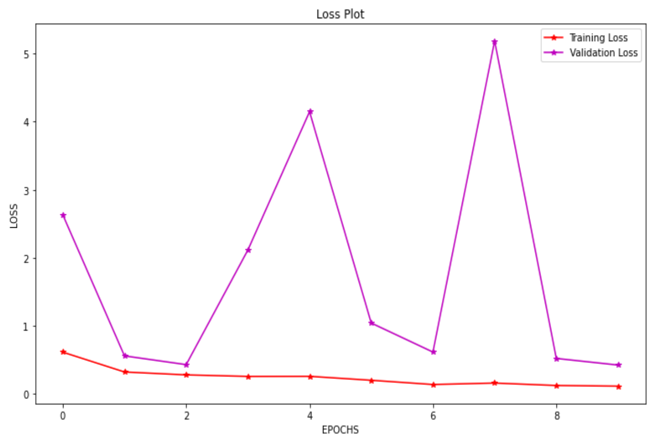

Fig. 8. Loss plot of the AlexNet architecture

Just like the accuracy plot, the loss plot also fails in maintaining the consistency of the values. The loss value reaches its maximum in the seventh epoch of validation which is the second last epoch. This makes the model the one with unpredictable outputs. Figure 9 cumulates the results of both the DL models on test data with all three parameters such as time, accuracy, loss.

```
VGG-16 OUTPUT ON TEST DATA
13/13 [==============================]
121s 9s/step
loss: 0.0891
accuracy: 0.9575
ALEXNET OUTPUT ON TEST DATA
13/13 [==============================]
8s 622ms/step
loss: 0.3868
accuracy: 0.8900
```

Fig. 9. Final outputs of both the models

From figure 9, it can be inferred that the VGG-16 architecture is best in a performance like an accuracy and loss and the Alexnet architecture is the best in terms of running time.

Conclusion

The Kaggle database provided the dataset consisting of 4000 images of leaves of the bell pepper plant out of which half contained healthy leaf images and the other half had the leaves of plants that were affected by bacterial spots. The collected sample is then preprocessed by resizing and rescaling images. The processed images are then split into three parts for training, testing, and validating the DL model. Two DL models were developed using two different DL architectures named the VGG-16 and the AlexNet architecture. The trained models were then validated and tested. The results of training and validation were tabulated and represented in the form of graphs for better understanding. After testing the models, it is observed that in terms of accuracy and loss, the VGG-16 architecture is the best, whereas the Alexnet design is the fastest. When it comes to disease prediction, accuracy is more important than the time taken. The model may take a lot of time but it should not predict an affected leaf as a healthy one. It may lead to some worse consequences. In the end, it can be concluded that the VGG-16 architecture is the best when it comes to identifying the plant diseases like bacterial spots of the bell pepper plants.

References

1. Joao de Lima Neto, Antonio & Cavalcante, Lourival & Dantas, Tony & Diniz, Adriana & Dantas, Stenio & Souto, Antonio, "Productivity and photosynthetic pigments in bell pepper plants grown in soil with biofertilizer and protected against water loss", Revista Ceres, vol. 68, pp. 39-46, 2021
2. Lal, R, "Home gardening and urban agriculture for advancing food and nutritional security in response to the COVID-19 pandemic", Food Sec, vol. 12, issue. 4, pp. 871–876, 2020.
3. Nakayinga, Ritah & Makumi, Angela & Tumuhaise, Venansio & Tinzaara, William, "Xanthomonas bacteriophages: a review of their biology and biocontrol applications in agriculture", BMC Microbiology, vol. 21, 2021.

4. Cardoza, Y.J., Tumlinson, J.H, “Compatible and Incompatible Xanthomonas Infections Differentially Affect Herbivore-Induced Volatile Emission by Pepper Plants”, J Chem Ecol, vol. 32, issue. 8, pp. 1755-68, 2006.
5. Kurmi, Y., Gangwar, S., Agrawal, D.K., Kumar, S., & Srivastava, H.S, “Leaf image analysis-based crop diseases classification”, Signal, Image and Video Processing, vol. 15, pp. 589-597, 2021.
6. Games, P.D., daSilva, E.Q.G., Barbosa, M.d.O., et al, “Computer-aided identification of a Hevein-like antimicrobial peptide of bell pepper leaves for biotechnological us”, BMC Genomics, vol. 17, 2016.
7. Mathew, M.P., Mahesh, T., “Leaf-based disease detection in bell pepper plant using YOLO v5”, SIViP, 2021.
8. Yakkundimath, R., Saunshi, G., Anami, B. et al, “Classification of Rice Diseases using Convolutional Neural Network Models”, Journal of the Institution of Engineers, India Ser. B, 2022.
9. Yakkundimath, R., Saunshi, G. & Palaiah, S, “Automatic methods for classification of visual-based viral and bacterial disease symptoms in plants”, International Journal of Information Technology, 2021.
10. Chen, R., Mihaylova, L., Zhu, H. et al, “A DL Framework for Joint Image Restoration and Recognition”, Circuits System, and Signal Processing, vol. 39, pp. 1561–1580, 2020.
11. Guo-Xin Zhang, Ming-Ming Cheng, Shi-Min Hu, Ralph R. Martin "A Shape-Preserving Approach to Image Resizing" Computer Graphics Forum, vol. 28, pp. 1897-1906, 2009.
12. W. Zhang et al., "A Wavelet-Based Asymmetric Convolution Network for Single Image Super-Resolution," in IEEE Access, vol. 9, pp. 28976-28986, 2021.
13. Krishnaswamy Rangarajan Arvind, Purushothaman Raja “Disease classification in eggplant using pre-trained VGG16 and MSVM” Scientific Reports, vol. 10, pp. 2322, 2020.
14. Çınar, A., Tuncer, S.A, “Classification of lymphocytes, monocytes, eosinophils, and neutrophils on white blood cells using hybrid Alexnet-GoogleNet-SVM”, SN Applied Science, vol. 3, 2021.
15. Singh, R.K., Tiwari, A. & Gupta, R.K, “Deep transfer modeling for classification of Maize Plant Leaf Disease”, Multimed Tools Appl, vol. 81, pp. 6051–6067, 2022.
16. Widana, I.K., Dewi, G.A.O.C., Suryasa, W. (2020). Ergonomics approach to improve student concentration on learning process of professional ethics. *Journal of Advanced Research in Dynamical and Control Systems*, *12*(7), 429-445.
17. Herliah, A., Baso, Y. S., Hidayanty, H., Syarif, S., Aminuddin, A., & Bahar, B. (2022). Effect of web-based she smart education models on adolescent girl’s knowledge, attitudes, and practice about obesity. *International Journal of Health & Medical Sciences*, *5*(1), 50-55. https://doi.org/10.21744/ijhms.v5n1.1832