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A Machine Learning Approach to Pomegranate Leaf Disease Identification

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Abstract— Pomegranate is a fruit with the highest yield and the greatest geographic distribution in Asia. On the other hand, the plants are susceptible to a diverse range of illnesses as a consequence of a number of factors, which leads to the total destruction of the plants and a harvest that is significantly reduced. In order to avoid reductions in agricultural output, it is necessary to diagnose plant diseases as quickly as is practically possible. It is a difficult and time-consuming task to manually monitor the progress of diseases on pomegranate leaves. Therefore, Deep Learning is utilised in the diagnosis of diseases affecting pomegranate trees (DL). The goal of this study is to develop an algorithm for automatically diagnosing diseases affecting pomegranate plants based on images of the plant's leaf structures. The process of a disease detection system includes the gathering of data, the analysis of that data, the categorization of gathered images, and their subsequent deployment. The Mendeley database is utilised in order to generate images of pomegranate leaves in both healthy and diseased states. After that, the original, unaltered raw image is polished. Two different DL models, AlexNet and VGG-16, are put to use in this classification technique. To determine the optimal model, it is necessary to do accurate and loss-oriented measurements. According to the measurements, AlexNet does a good job of recognising diseases that affect leaf tissue. Later, an AlexNet-based smartphone app is developed to assist farmers in performing disease detection on pomegranates without the assistance of professionals. This software is intended to help farmers save time and money.

Keywords- Pomegranate Leaf; Images; Healthy; Disease; AlexNet; Mobile app

I. Introduction

The recent years have seen several new trends emerge in the horticulture industry, all of which have made major contributions to the sector's overall financial performance. As a result of developments in cold storage and shipping, there has been a rise in the amount of fruit that is sent around the world. Visual inspections performed by trained professionals are necessary for exports of high quality. Because of their isolated position, the farms take significantly more time and resources to access. Precision agriculture is now able to offer farmers data and management solutions that are both effective and economical because to its development and implementation in other industries. The goals are to achieve maximum profitability, standardise agricultural inputs, and reduce ecological footprints to the greatest extent possible [1]. Pomegranates are widely considered to be one of India's favourite fruits [2]. According to research published by the International Trade Center, India is the dominant nation in terms of pomegranate production around the world. Around five percent of the fruit that is grown here in the United States is sent abroad each year. We receive substantial payments from a variety of different nations for the pomegranates that we export [3]. The ability to assess whether or not a fruit is normal after it has been harvested is essential, given the significance of marketing and exporting.

People have been so focused on increasing their production that they have neglected to consider how this will impact the environment, which has resulted in a general decline in the state of the earth as a whole. Infectious plant diseases lower both the quantity and quality of crop output. Pests and illnesses are significant challenges for pomegranate plantations. It is almost guaranteed that considerable crop loss will occur in the absence of a correct diagnosis and quick treatment. The disease can infect any part of the pomegranate plant, including the fruit, stem, and leaves. Pomegranate fruit is susceptible to a number of different diseases, the most common of which are bacterial blight, alternaria, and phomopsis. The infected components of the plant will initially show themselves on the stem, followed by the leaves, and finally the fruit. The disease initially presents itself on the leaves of the plant as tiny spots that are asymmetrical in shape and have the appearance of being damp in the centre. When illuminated, a spot's opacity can be seen to change into a more transparent state. It is possible to make out the moist margins that surround the brown spots, which range in tone from light to dark [4]. Patches are made by stitching together a number of smaller patches to produce the larger patch. There is a possibility that sick leaves higher up will fall off. The disease is most likely to spread in environments that have high temperatures and a high humidity level. This disease is spread by contaminated cuttings and rain carried on the wind to healthy plants in order to spread it. The analysis of photosynthesis and the development of plants is highly dependent on the measurement of leaf area. When determining leaf area, there are both invasive and noninvasive approaches available. The initial stage in destructive methods is to remove a leaf from the plant and then measure and record its weight. If you employ a method that does not involve destroying the leaf, you can determine its circumference without having to take it off the plant. By analysing samples of leaf tissue with today's technology, farmers may do a screening for the earliest signs of disease. The creation of a technique that can determine whether or not a leaf is affected by the disease.

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The purpose of this research [5] is to devise a method for accurately detecting and categorising the illnesses that can be transmitted from pomegranate plants to other types of fruit trees. The framework is able to extract features from images and perform processing on them as an essential component of its structure. During the training and testing phases of the approach, pictures of diseases that can affect pomegranate leaves are employed. Enhancement and segmentation are two examples of techniques used in image processing that establish the framework for identification. Following this, a supervised learning model will be used to construct an image classification system. The outcomes of the study indicate that the model that was provided has a success rate of 98.39% when it comes to differentiating between leaves that have been damaged and leaves that are healthy. This demonstrates that it may be advantageous in some situations. The authors of this research [6] anticipate that by combining techniques such as Law's mask, Gray-Level Co-Occurrence Matrix (GLCM), and Local Binary Pattern, they would be able to more accurately classify leaf diseases (LBP). The methodology that was suggested demonstrates that ensembles of classifiers are superior to their individual members in their ability to accurately predict outcomes. When arranging ensembles into categories, it is essential to make use of relevant criteria. The PlantVillage database was utilised to do an analysis on sick leaf photos of bell peppers, potatoes, and tomatoes. This issue of the magazine [7] will focus on leaf diseases that can be found on corn, grapes, mangos, and peppers, as well as early warning signs and treatment options. They classified the four leaves based on the same criteria that are utilised when diseases are categorised. In order to complete the data analysis, CNN-based DL models were utilised, and the performance of four distinct CNN models was evaluated and compared. The computations that our updated model carried out were accurate to a 99.91 percent degree. In addition to this, it has been discovered that DL is an efficient diagnostic technique that can differentiate between healthy plant leaves and unhealthy plant leaves.

The early diagnosis of Rice leaf disease is the focus of this study [8], the goal of which is to increase production by more than 20%. In this article, plant diseases such as stem borer, sheath blight, brown spot, and false smut are organised according to a CNN-style classification system. Because the illness can infect leaves of any size, finding the source of the problem can be challenging. As a direct consequence of this, the dataset for the KNN model contains 1045 photographs. KNN is responsible for making the preliminary decision as to whether or not a leaf is healthy. In the second step, you will identify the specific nature of the illness by consulting CNN. In 95% of the cases, they found healthy leaves, and in 90% of the cases, they found sheath blight (the highest of any illness). Locating sick plants and making a manual diagnosis of their conditions would require a significant amount of time. The Centers for Disease Control and Prevention (CDC) has reached the conclusion that machine learning (ML) is the most effective technique for addressing this problem. Plant diseases are able to be discovered through the use of image processing. A graphical representation of the development of plant disease diagnostics has been created with the help of data taken from the journal [9]. The proliferation of mobile technology as well as digital learning (DL) platforms has made it possible to design DL apps that are optimised for usage on mobile devices. These apps can be downloaded for free. The research community is beginning to receive a greater amount of attention from the networking sector as well as service providers. However, this improvement in performance does come at a cost in the form of the higher resources that are required in order to operate these models. The use of mobile devices is fraught with significant difficulties. The use of more powerful computational resources, higher memory capacity, and maybe the participation of other network nodes are all necessities for on-the-go intelligence. In order to demonstrate the current state of affairs in this sector, we have divided it into two categories: local optimization on mobile devices, and distributed computing based on DL issues [10]. This will allow us to demonstrate the state of affairs as they currently stand.

Cultivating pomegranates in the Kingdom of Bahrain can be a viable and rewarding endeavor, given the country's warm and arid climate. Here are some specific considerations and tips for growing pomegranates in Bahrain dure to its Climate, Soil, watering and water quality, sunlight, Pruning, Fertilization, Pest and Disease Management. The Kingdom of Bahrain has a desert climate with hot summers and mild winters. Pomegranates thrive in such conditions, as they are well-suited to arid climates, ensure that the selected pomegranate varieties are suitable for high temperatures and can withstand the heat. The soil gives the chance to economically farm it. The Pomegranates prefer well-draining soil. Sandy loam or loamy soil is ideal for their cultivation where consider amending the soil with organic matter to improve its fertility and water-holding capacity. While pomegranates are drought-tolerant once established, regular and deep watering is crucial, especially during the growing season that Irrigate to keep the soil consistently moist but not waterlogged. Pomegranates thrive in full sunlight. Ensure that the planting site receives plenty of direct sunlight, as this is essential for fruit development. Choose pomegranate varieties that are well-suited to high temperatures and can tolerate the specific conditions in Bahrain. Prune the pomegranate plants to shape them and remove any dead or weak growth. Proper pruning helps maintain good air circulation and sunlight penetration into the canopy. Fertilize the pomegranate plants with a balanced, slow-release fertilizer in the spring before the onset of new growth. Excessive nitrogen, that easily supplied in the Bahrain can lead to vegetative growth at the expense of fruiting. Monitor for common pests such as aphids, scales, and whiteflies. Treat as necessary. Fungal diseases may be a concern in humid conditions, although Bahrain's climate is generally dry. Keep an eye on the plants for any signs of disease. Pomegranates typically ripen in the fall. Harvest the fruits when they have developed their characteristic color and make a metallic sound when tapped. Mulch around the base of the pomegranate plants to conserve soil moisture and regulate soil temperature.

II. METHODOLOGY

This chapter describes the procedures that were followed in order to carry out the research for the study. This research is carried out into six distinct steps. The first step in the process is to acquire information. This information was gleaned

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from the data stored in Mendeley. The following stage is the data pre-processing, which consists of two phases: resizing the data and normalising it respectively. Training the DL model and determining how accurate it is are the responsibilities of the third and fourth stages of the study, respectively. Training uses eighty percent of the leaf shots whereas validation uses only twenty percent of the images. AlexNet and VGG-16 are the two deep learning models that are utilised in this work. In Step 5, we choose and finalise the model that is the best overall candidate. Developing a mobile application is the last step in the process. Using this application, the farmer will be able to determine how well the pomegranate is doing. A timeline of the study's development may be found in Figure 1.

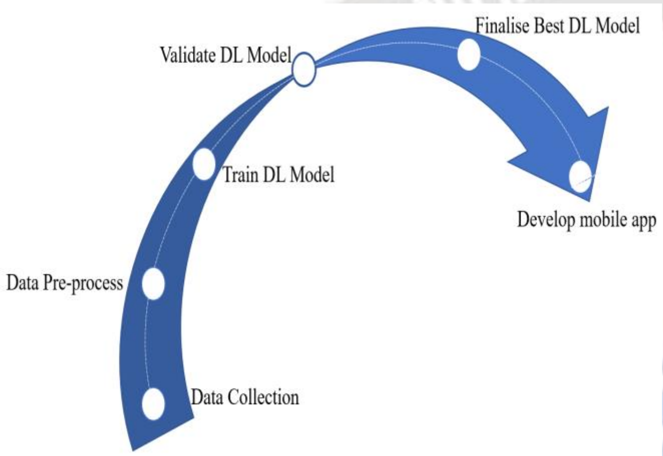

Fig. 1. Process flow of research

III. DATA COLLECTION AND PROCESSING

This research makes use of the information obtained from looking at pictures of pomegranate leaves. In order to comprehend what is being shown, a DL system requires numerical representations of the information that is being provided. As a result, it is unreasonable to anticipate that the DL model can be trained by merely supplying it with raw data. Data The next step, which is known as the DL pre-processing phase, will involve cleaning, normalising, and encoding the data in preparation for the computer's utilisation of the information later on. As a result, the model algorithm is able to quickly evaluate the characteristics of the data.

A. *Collection*

Plants engage in a variety of exchanges with the environment in which they live. They contribute a variety of nutrients to the natural environment. One of the ways in which plants contribute to mitigating the consequences of global warming is by reducing the amount of carbon dioxide emissions. As a direct result of this, this work has contributed to the identification of plant leaves, as well as the detection of plant diseases and other sectors that are connected. Mendeley [11] includes a total of twelve types of crops that are commercially viable and ecologically favourable. Photos of healthy leaves as well as damaged leaves were collected, and both sets of images were organised in their own distinct way. The images were analysed and categorised as either "healthy" or "diseased," thereby representing the whole range of potential outcomes. It is necessary to categorise and label the plants in order to prepare them for inclusion in photos. There were around 559 photographs taken, 287 of which were of healthy leaves, and 272 of which were of unhealthy leaves. The Shri Mata Vaishno Devi University in Katra is where the images of the leaves were obtained. These photographs were captured within a confined area. It is possible for the full process of acquisition to be carried out wirelessly. Each and every picture was taken with a Nikon D5300 that had been calibrated for JPEG capture using the settings that provided the maximum possible quality. A selection of the example photos can be shown in Figure 2.

Fig. 2. Pomegranate leaf image data

B. *Processing*

The pre-processing of data has a substantial impact on the ability of a DL algorithm to generalise its results. The quantity of data used for training grows at an exponential rate proportional to the size of the input space. It is estimated that pre-processing takes up between 50 and 80 percent of overall classification time, which highlights the significance of pre-processing in the process of model-building [12]. Enhancing the quality of the data is another crucial step in the process of achieving improved results.

[1] Resize: The image is scaled to fit the form. Because transfer learning was used in this study, the model's input form is fixed and cannot be changed. AlexNet's input shape is 227*227, while VGG-16's input shape is 224*224. The image is resized using the model, preserving all of the image data. The author of the study [13] uses segmentation and quantification techniques to evaluate if scaling images from exported datasets improve or lowers the prediction power or performance of the U-nets of interest.

[2] Normalization: Normalization is applied to a scaled image. Pixel values range from 0 to 255. In this stage, the pixel value is reduced to a value between 0 and 1. This stage is crucial in terms of minimizing training time and memory needs.

IV. DEEP LEARNING

Standard ML algorithms cannot be used to determine the health of a leaf without manual feature extraction and a classification process. When using DL strategies, the network classifies the data on its own, without the intervention of a human. During the course of the training phase, the model acquires its model weight and bias by learning from a sizable data set. After then, a number of different network models are evaluated using these weights. There is a possibility that the weights from the previous network will serve as the basis for the new one. Using the aforementioned domains, a model has been trained. The article will highlight the various advantages of utilising one of the several pre-trained designs that are currently available. In the beginning, there is a need for a greater processing capability in order to educate these enormous models using this massive dataset. Second, there is a possibility of a delay lasting many weeks while a network is being trained. When training a new network, it is sometimes beneficial to make use of weights that have been trained in the past. In this work, AlexNet and VGG-16 are being utilised.

A. AlexNet

The 650,000 neuron count and 60 million parameters that AlexNet possesses show the bigger network scale that it possesses in comparison to Lenet-5. In the 2012 ImageNet picture classification competition, ImageNet came out on top with a lead of 11% over the competitor who came in second place. Figure 3 shows that AlexNet has a total of 5 convolutional (conv) layers, 3 full connection (FC) layers, and a maximum pooling (MP) function that takes place after the third convolutional layer in the network. The activation function of AlexNet is ReLU, which is distinct from the standard functions that were utilised by earlier neural networks. Dealing with gradient vanishing and gradient expansion in an effective manner is one of the ways that ReLU boosts the performance of model training and makes it simpler to build a terrific network [14]. The ReLU function is shown in the box that is below the equation:

The Maximum ReLU Function, or x, Equals the ReLU (0,x)

Dropout is utilised by AlexNet in order to mitigate the effects of overfitting. The generalisation capabilities of the model are improved by turning off neurons in a random order as it is being trained. This makes it less dependent on nodes that are relevant to the immediate area. When the number of parameters in a convolution kernel is raised, however, the danger of losing local features during feature extraction also increases. This risk is enhanced when the kernel size is increased. It is vital to increase the number of parameters for the conv section at the same time that the number of parameters for the FC layer is increased. This is due to the fact that the outcomes are greatly influenced by the characteristics created by the conv section.

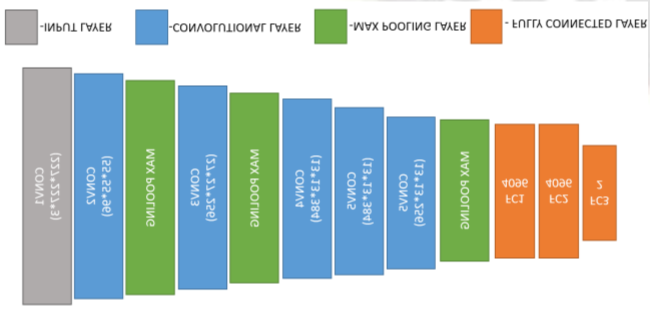

Fig. 3. AlexNet Architecture

B. VGG-16

There are 13 conv layers in the VGG-16 model, along with 2 FC levels and 1 SoftMax layer. It is anticipated that the VGG-16 architecture would be made available in the year 2014. It was built with a 16-layer network that incorporated FC and conv layers as part of the construction process. The intricate network architecture of the VGG-16 model is seen in detail in Figure 4.

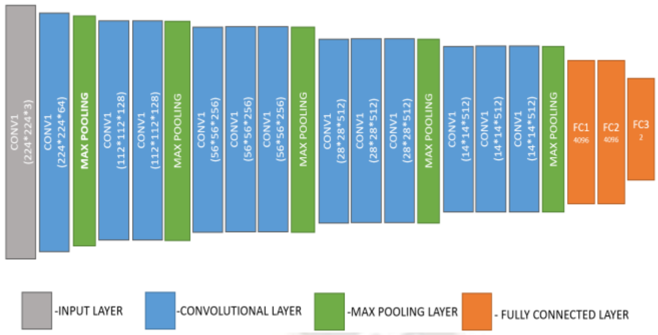

Fig. 4. VGG-16 Architecture

1)There are 64 3x3 kernel filters (KF) in each of the first and second convolution layers. Prior to being sent to the input layer, the input image has its dimensions adjusted to 224 on each of the two axes. The information is sent to the MP layer after being processed. 2) The 3rd and 4th convolutional layers, both 3*3, use the 124 KF. After these two levels, the MP is present and it provides the output of 56x56x128. 3) The conv layers at the 5th, 6th, and 7th levels have sizes of 3*3. In all three levels, 256 feature maps are employed. Following these layers, there will be an MP layer. 4) The 8th through 13th layer depicts two sets of conv layers with kernel sizes of 3*3. There are 512 KF in each of the conv layer sets here. The MP layer comes next, after these ones. 5) The FC layer, which consists of 4096 neurons, may be found between levels 14 and 15, and the 16th-level output layer, which consists of just two neurons, follows.

V. Model Deployment

Maintenance is required on a consistent basis for DL systems because they are complicated software architectures. This provides developers with their own unique set of challenges, some of which are comparable to challenges faced in the operation of more conventional software applications, while others are peculiar to distributed ledger technology (DL). DevOps is a subset of engineering that focuses solely on the procedures and software applications that are utilised to ensure that everything is functioning normally. As a consequence of this, businesses are investigating various methods by which the ideas of DevOps might be applied to their DL infrastructure. Some of the concepts introduced by DevOps are immediately applicable, but it would appear that DL production comes with its own unique set of difficulties. Some of these problems include a dearth of high-quality sensor data and the absence of a standardised method for obtaining such data; difficulties in collecting labels, which render supervised learning methods inapplicable; and a lack of any established best practises for managing DL models. Another problem is that there are no established best practises for managing DL models. In this section, we will discuss the procedures that must be followed in

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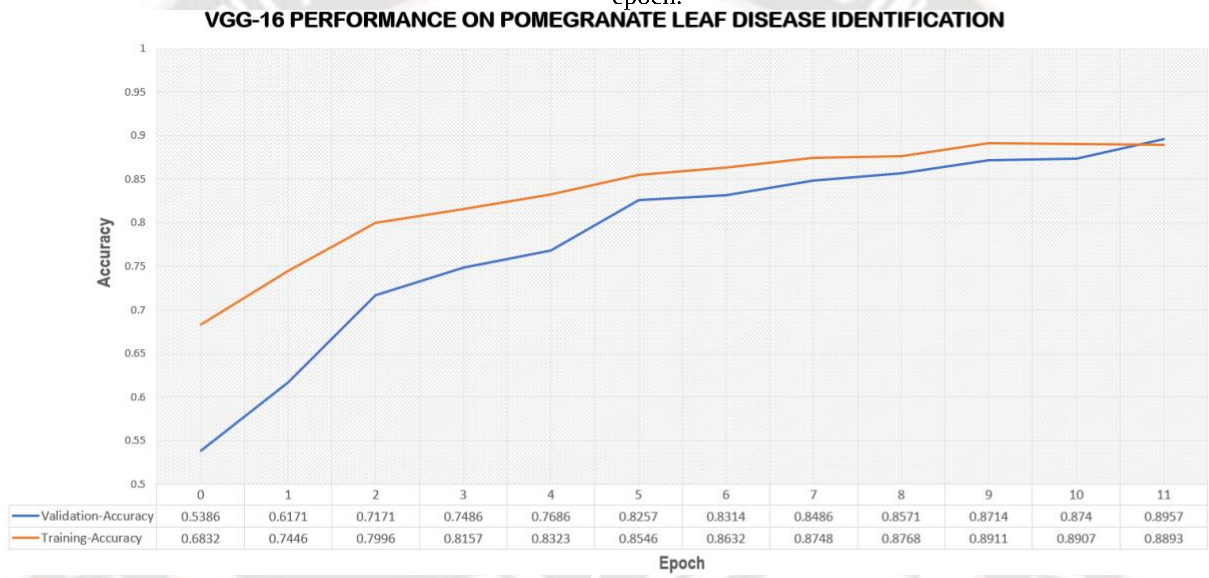
order to successfully deploy a model. These procedures include integrating the model, monitoring it, and keeping it up to date. The model integration phase has a number of important features, two of which are the building of models and the execution of models in a manner that is both usable and maintainable. Without consistent monitoring, the software service will not be able to operate properly. After a model has been put into production, one of the typical requirements is to ensure that it is kept current with the most recent data and conditions. On the basis of the aforementioned strategy for the creation of mobile apps, the production environment makes use of the best DL model.

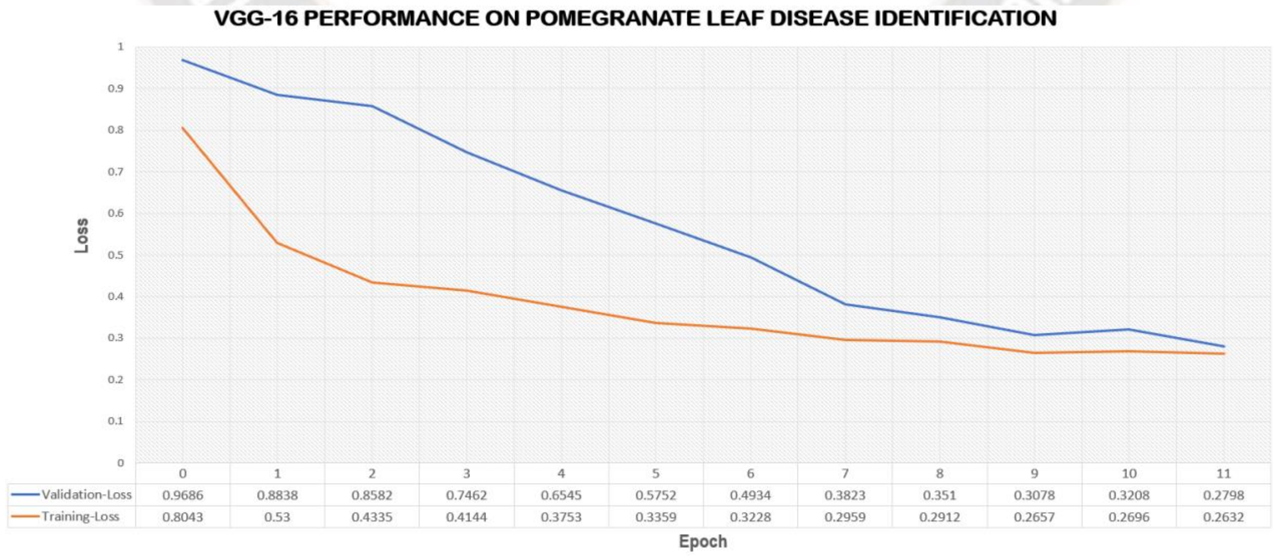
VI. Result and Discussion

The collected pomegranate leaf images go through some pre- processing. Image scaling and normalisation are the pre-processing steps taken in this work. The image is reduced in size to 224*244, and the VGG-16 network is granted access to it. A 20% and 80% split is made amongst the photos. There are 12 epochs used in total. Figure 5 shows the VGG-16 accuracy plot. Accuracy for training and validation are plotted in figure 5. The validation accuracy is represented by the blue colour in the blue and orange plot, while the training accuracy is represented by the orange colour. The accuracy value will be 0.68 and 0.53 for training and validation respectively at the beginning of training, or at the zeroth epoch. As the number of training sessions increases, the accuracy similarly rises. The accuracy values for training and validation will be 0.88 and 0.89 at the 12th and final epoch. Similar to figure 5, figure 6 displays the VGG-16 loss plot. The accuracy plot also enjoys the colour indicator. For training and validation, the loss value will be 0.80 and 0.96 at the starting epoch. As training progresses, the loss value gradually lowers until it reaches 0.26 and 0.27 at the 12th epoch.



	0	1	2	3	4	5	6	7	8	9	10	11
Validation-Accuracy	0.5386	0.6171	0.7171	0.7486	0.7686	0.8257	0.8314	0.8486	0.8571	0.8714	0.874	0.8957
Training-Accuracy	0.6832	0.7446	0.7996	0.8157	0.8323	0.8546	0.8632	0.8748	0.8768	0.8911	0.8907	0.8893

Fig. 5. VGG-16 Accuracy plot



	0	1	2	3	4	5	6	7	8	9	10	11
Validation-Loss	0.9686	0.8838	0.8582	0.7462	0.6545	0.5752	0.4934	0.3823	0.351	0.3078	0.3208	0.2798
Training-Loss	0.8043	0.53	0.4335	0.4144	0.3753	0.3359	0.3228	0.2959	0.2912	0.2657	0.2696	0.2632

Fig. 6. VGG-16 Loss plot

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After that, the image is scaled down to 227 by 227 pixels and sent to AlexNet. In the training phase, we use eighty percent of the photos, whereas in the testing phase, we use twenty percent. There are a total of twelve epochs in history. Figure 7 presents the AlexNet accuracy plot for your perusal. Figure 7 illustrates the degree of accuracy achieved through training and testing. The plot in red and green is used to illustrate the differences. The degree to which the validation was carried out correctly is shown by the red colour, whereas the degree to which the training was carried out correctly is represented by the green colour.The accuracy numbers for training and validation will both start off at 0.64 and 0.68, respectively, when the training process is first initiated, also known as the zeroth epoch. Your accuracy will improve in direct proportion to the number of times you practise. At the end of the 12th epoch, the accuracy of the training set will be 0.97, while the accuracy of the validation set will be 0.95. Figure 8 illustrates how connections might be lost in AlexNet. The same colour scheme was utilised for both the accuracy plot as well as the loss plot. The loss values will start off at 1.07 and 1.54 during the first epoch of training, and they will gradually decrease until they reach 0.10 and 0.08 after the 12th epoch of training, respectively.

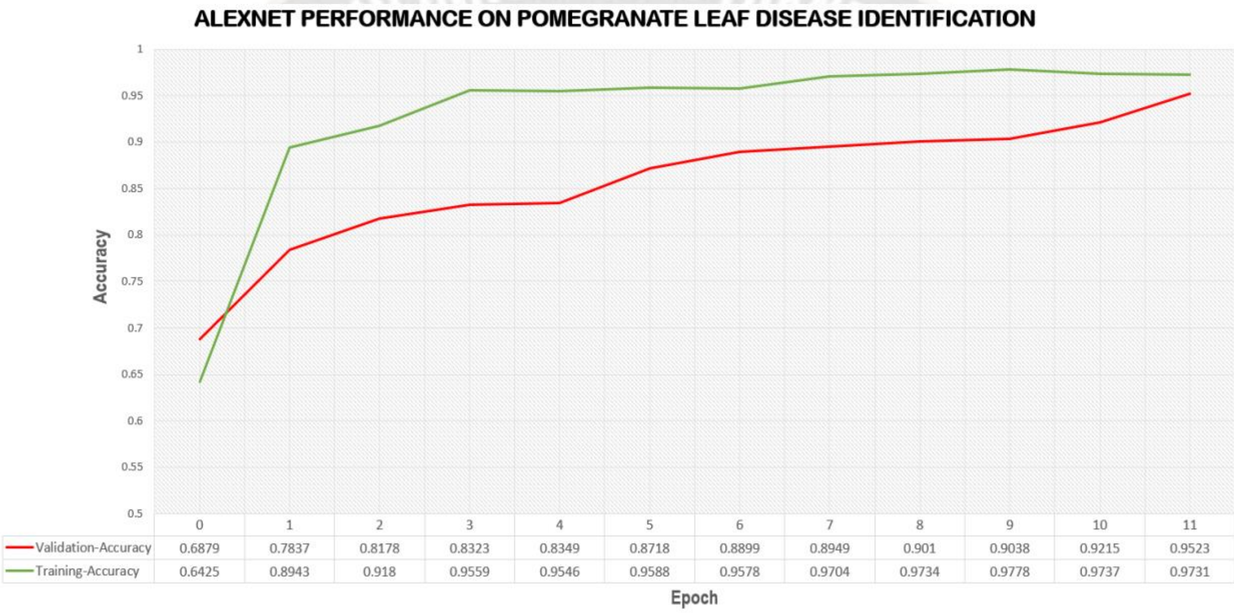

Fig. 7. AlexNet accuracy plot

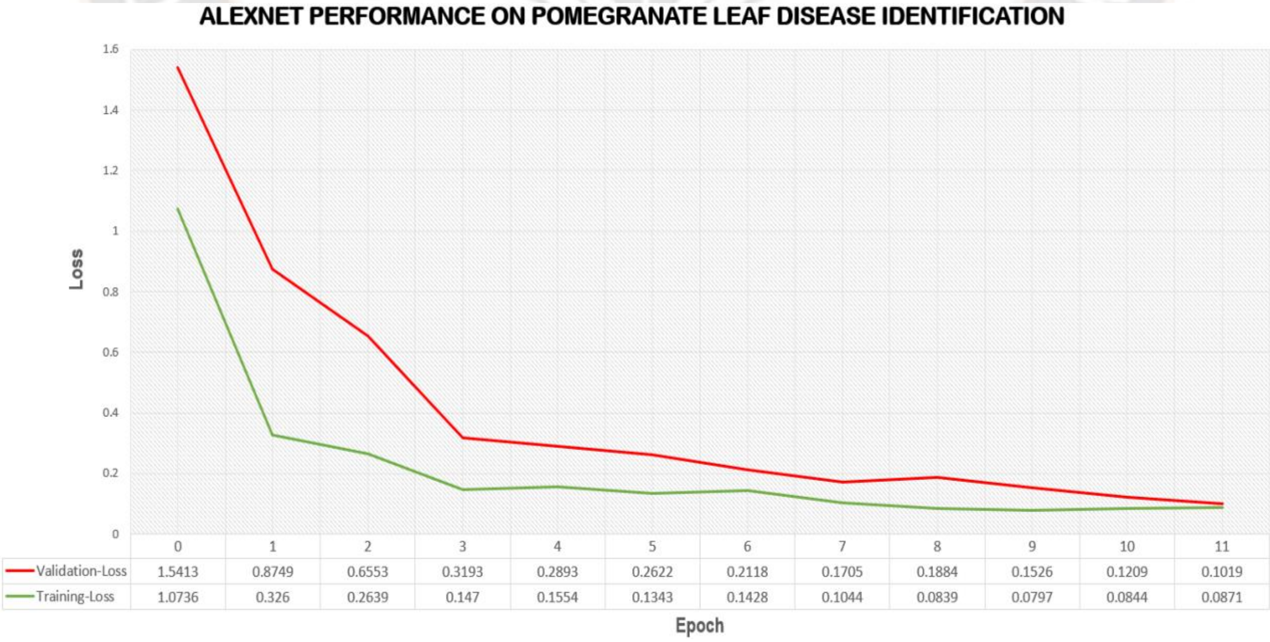

Fig. 8. AlexNet loss plot

The plot comparison, concludes that the AlexNet outperforms the VGG-16 in both the training and validation process. So, the AlexNet model is finalized and used at the backend to develop the mobile app. The mobile app was developed more easily, this will be helpful for the farmer to access the app without any programming knowledge or training. The working of the mobile app is shown in figure 9. Once open the app, the upload page is shown to the user which is seen on the left side of the image. The user just clicks and uploads their leaf image. Next, the result button will have appeared to the user, the user can click the button and be able to know the health status of the pomegranate plant. The final result page is shown on the right side of an image.

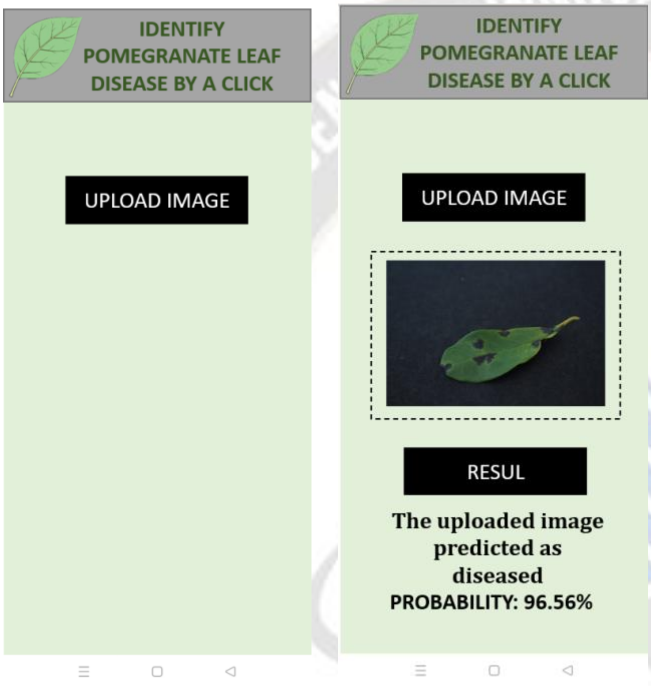

Fig. 9. Mobile app working

VII. ACKNOWLEDGMENT

Plant diseases have the potential to cause significant damage to a wide variety of crops and garden plants all over the world. As a consequence of this, the treatment of diseases places a significant amount of reliance on technologies that reliably identify diseases prevalent in various areas of the plant. Recently, a wide range of computer vision and computational intelligence methodologies and techniques have been used to a variety of plants in order to identify and cure a wide range of plant diseases. These applications have been made possible by advancements in computer technology. As a result, the objective of this study is to devise a strategy for the automatic detection of pomegranate leaf illnesses. The first step in using this method is to collect information on the leaves. The technique that is used for the processing is one that involves shrinking and normalising the data. Examples of the two different resizing forms that are involved include 224244 and 227227. After that, the values of the pixels are transformed so that they range from 0-255 to 0-1. AlexNet and VGG-16 are both deep learning models that are utilised here. When employing the validation method, AlexNet and VGG-16 are able to obtain an accuracy of 89.57% and 95.23%, respectively, although during training, they are only able to acquire an accuracy of 88.93% and 97.31%. The findings of the test indicate that AlexNet is the most efficient model for diagnosing diseases that can affect pomegranate leaves. In order to give farmers with more actionable information into the health of their pomegranate harvests, the AlexNet model was employed in the development of the mobile app that was made available to them.

According to the results of the output, it is suggested to use the model for the management of the farms in the Kingdom of Bahrain to increase the yield and the efficiency. As the preliminary output that is promising for the economical production of the pomegranate and improve the management of farms in the country that is required to implement it. According to the results of the output, it is suggested to use the model for the management of the farms in the Kingdom of Bahrain to increase the yield and the efficiency. As the preliminary output that is promising for the economical production of the pomegranate and improve the management of farms in the country that is required to implement it. According to the results of the output, it is suggested to use the model for the management of the farms in the Kingdom of Bahrain to increase the yield and the efficiency. As the preliminary output that is promising for the economical production of the pomegranate and improve the management of farms in the country that is required to implement it. As the preliminary output that is promising for the economical production of the pomegranate and improve the management of farms in the country that is required to implement it.

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