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Yemeni Plants Recognition System using Deep Learning Technique

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Abstract: Plants are commonly used for treating many disorders since the golden ages. One of these plants is Rumex Nervosus that belongs to the family of Polygonaceae, which is traditionally used to treat various diseases in many countries such as, Yemen, Saudi Arabia and Ethiopia. The various types of plants that are existed in the Yemen make the recognizing of them a difficult task that requires knowledge and greet experience. The recognition of plants has a significant and crucial role in the classification of plants and differentiation between leaves. In this paper, an intelligent system is proposed to design a model that classify four types of plants (Rumex Nervosus, Agave, Green Grass, and Junipers) by using three pre-trained transfer learning models (AlexNet, GoogLeNet and VGG19) based on deep learning techniques. The process of plant recognition goes as follows: images of the four types of Yemeni plants are collected through a smartphone camera, where the total number of images of plants was 600 images for each class of 150 images. Then the images are pre- processed by resizing and center cropping images to fit the inputs of the proposed models. To improve the image recognition process, data augmentation has been performed, where the number of images is increased by creating different versions of content similar to images in order to obtain more training examples, as the number images reached 1700 plant images, and after that the images are forwarded to the proposed pre- trained transfer learning models (AlexNet, GoogLeNet and VGG19) that trained on ImageNet dataset by fine- tuning the proposed plants images. The proposed models automatically extract and classify these features, which help the network to recognize the type of plant effectively. The result of proposed models (AlexNet, GoogLeNet and VGG19) give accuracies (99.83%, 98.38% and 98.75%,) respectively. We found that AlexNet model gives the best result with accuracy 99.83%. Vividly, the proposed system was tested and compared to other works. the experimental findings show the effectiveness of the proposed method. The recognition of this type of plant accurately will help many populations to reliable recognition and fast treatment. In future work, we propose to improve methods for extracting features of plants using image segmentation techniques with machine learning techniques to recognize plant images with high efficiency and accuracy. We also suggest adding other models of deep learning techniques and making improvements in their structure.

Keywords: Rumex Nervosus, Yemeni Plants, Recognition, Forest, Herbals.

نظام التعرف على النباتات اليمنية بواسطة تقنية التعلم العميق

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المستخلص: تستخدم النباتات بشكل شائع لعلاج العديد من الاضطرابات منذ العصور الذهبية. أحد هذه النباتات هو Rumex Nervosus ويسمى (العثرب) الذي ينتمي إلى عائلة Polygonaceae، والتي تستخدم تقليديا لعلاج الأمراض المختلفة في العديد من البلدان مثل اليمن والمملكة العربية السعودية وإثيوبيا. الأنواع المختلفة من النباتات الموجودة في اليمن تجعل التعرف عليها مهمة صعبة تتطلب المعرفة والتجربة. يلعب التعرف على النباتات دورًا مهمًا وحاسمًا في تصنيف النباتات والتمايز بين الأوراق. في هذا البحث تم اقتراح نظام ذكي لتصميم نموذج يصنف أربعة أنواع من النباتات (Rumex Nervosus وAgave وGreen Grass وJunipers) باستخدام ثلاثة نماذج تعلم نقل مدربة مسبقًا (AlexNet وGoogLeNet و VGG19)تعتمد على تقنية التعلم العمق .تتم عملية التعرف على النباتات على النحو التالي: يتم جمع صور الأنواع الأربعة من النباتات اليمنية من خلال كاميرا الهاتف الذكي، حيث بلغ العدد الإجمالي لصور النباتات 600 صورة لكل فئة 150 صورة. ثم تتم معالجة الصور مسبقًا عن طريق تغيير حجم الصور وتوسيطها لتلائم مدخلات النماذج المقترحة. لتحسين عملية التعرف على الصور، تم إجراء زيادة في البيانات، حيث تم زيادة عدد الصور عن طريق إنشاء إصدارات مختلفة من المحتوى مشابه للصور من أجل الحصول على المزيد من الأمثلة التدريبية، حيث وصل عدد الصور إلى 1700 صورة نباتية، وبعد ذلك يتم إرسال الصور إلى نماذج تعلم النقل المقترحة مسبقًا (AlexNet وGoogLeNet وVGG19) التي تم تدريبها على مجموعة بيانات ImageNet عن طريق ضبط صور النباتات المقترحة. تستخرج النماذج المقترحة وتصنف تلقائيًا هذه الميزات، مما يساعد الشبكة على التعرف على نوع المصنع بشكل فعال. أظهرت نتائج النماذج المقترحة (AlexNet وGoogLeNet وVGG19) دقة (99.83%، 98.38%، 98.75%) على التوالي. وجدنا أن نموذج AlexNet يعطي أفضل نتيجة بدقة 99.83%. بشكل واضح، تم اختبار النظام المقترح ومقارنته بالأعمال الأخرى. أظهرت النتائج التجريبية فعالية الطريقة المقترحة. إن التعرف على هذا النوع من النباتات بدقة سيساعد العديد من السكان على التعرف الموثوق به والمعالجة السريعة. في العمل المستقبلي، نقترح تحسين طرق استخلاص الخصائص للنباتات باستخدام تقنية تجزئة الصور مع تقنية تعلم الالة للتعرف على صور النباتات بكفاءة ودقة عالية. كما نقترح إضافة موديلات اخرى لتقنيات التعلم العميق وعمل تحسينات في بنيتها.

الكلمات المفتاحية: نبات العثرب، النباتات اليمنية، تقنية التعلم العميق، غابة، أعشاب.

1- Introduction

In recent years, the recognition of plants and their diseases have become a wide field for researchers in the field of plant science and the importance of linking them to the computer field, as the recognition of plants by traditional methods takes a long period and also the accuracy of recognition is weak. In addition, the recognition of medicinal plants has also become of importance in the field of plant science because of the common use of plants since ancient times to treat a variety of diseases. Yemen is distinguished by the diversity of its environment and its plants, especially medicinal plants. One of these medicinal plants is Rumex Nervosus, which belongs to the Polygonaceae family. It is used to treat diseases in Yemen and Saudi Arabia (Al- Asmari et al., 2015; Borokini & Omotayo, 2012; Croteau, Kutchan, & Lewis, 2000; Gebre- Mariam, Murthy, Ranganatham, & Hymete, 1993). One of the main problems in the research was the lack of a database of plants for Yemen, especially medicinal plants. To solve this problem, a dataset of medicinal plants was collected, which consists of four classes of medicinal plants (Rumex Nervosus, Agave, Green Grass, and Juniper), where the total number of images of plants was 600 images for each class of 150 images, and we increased the images to 1700 images using a data augmentation technique. Also, there is another problem regarding the recognition of medicinal plants with better performance and high accuracy, with this issue there remain three problems. First, the size of the leaves of plants, secondly the color of the leaves, and thirdly the texture of the leaves. Efforts have been made to overcome this problem by using modern techniques. There are different techniques for plants recognition with varying accuracy, so it was necessary to choose advanced techniques with high efficiency such as deep learning to recognize plants. Deep learning techniques have the ability to classify and predict the most complex problems, also these can deal with very large data that is difficult for other techniques to deal with these issues, one of the networks for deep learning is CNN, which has demonstrated an ability to recognize plants with high accuracy as shown by papers (Hang, Tatsuma, & Aono, 2016; Ghazi, Yanikoglu, & Aptoula, 2016; Choi, 2015). It also has the ability to improve the performance of layers, which led to the emergence of pre- trained models capable of recognizing different patterns and images as well as plants recognition with better performance and higher accuracy (Valeria et al, 2020).In this paper we used three pre- trained models (AlexNet (Krizhevsky, 2014), GoogLeNet (Szegedy et al, 2015) and VGG19 (Simonyan & Zisserman, 2014)) to recognize the proposed plants by fine- tuning on the proposed plant images that got better results compared to other techniques. The importance of the study lies in the creation of a dataset for the proposed medicinal plants, which can assist researchers in this field. Also, the proposed models can be used to identify other medicinal plants, as they have shown high results. The rest of this paper is arranged as follows: in the following section 2, We discuss the relevant literature on plant recognition. We define in section 3 our problem statement. We illustrate in section 4 our proposed method of Yemeni plant recognition. The results and performance of the proposed method are listed in section 4. Finally, section 5 addresses the conclusion of this paper.

2- Related Works

We present an overview of the literature that relates to work presented here. Many researchers have worked in the field of plants recognition through images of plant leaves and examining them on the Swedish or Falvia plants dataset by using traditional methods or modern techniques. While our study focus on recognizing the image of the plant as a whole, taking into account the size, shape, color, and angle of images of plants using three pre- trained models (AlexNet, GoogLeNet and VGG19). The literature was therefore reviewed to examine the available methods that can be used to recognize plant and their diseases. In the paper (Wang, Du, & Zhai, 2010) introduced a method of plant recognition based on Ring Projection Wavelet Fractal Feature. They extract from leaves around the border area by the white pixels and all pixel black background binary contour map. The one- dimensional is decomposed with Daubechies discrete wavelet transform. when using eight area geometric features of leaves 73.1575%, and with seven Hu moment invariants features the accuracy was 66.3741%. Furthermore, with ring projection wavelet fractal (RPWFF) the accuracy was 80.1241%. As shown by paper (Wang, Sun & Wang, 2017) that proposed an approach using deep learning to recognize plant diseases with fine grains as the system recognizes plants using threshold- based segmentation. A variety of deep networks are being trained to diagnose disease severity using black apple rot images in the Plant Village dataset, which were identified as ground truth by botanists with four gravitational points. The average accuracy of the VGG16 in the hold- out test set is 90.4%. In (Zhang, Wu, You & Zhang, 2017) introduced image- based cucumber disease recognition system with the current image- based algorithms. The characteristics chosen to differentiate between leaf photos are generally considered to be equally significant in the classification process consisting of three pipeline methods, segmenting diseased leaf images by K- means, extracting lesion information from the hue, and the use of sparse representation (SR) to recognize diseased leaf images with 85.7% average acceptance, better than the other approaches. Reference (Satti, Satya & Sharma, 2013) proposed the plant identifying system using digital imagery and computer vision technologies has a simple, computationally effective tool. The results have been evaluated and compared using Artificial Neural Network (ANN) and Euclidean (KNN) Classifiers. The results are also used inputs in the classifier for accurate classification. The 1907 sample leaves of 33 plant species taken from Flavia 's dataset were learned in the network. The suggested solution to ANN classification is 93.3% correct, and the analysis of classifications indicates that ANN takes less time to execute. The paper (Kan, Jin & Zhou, 2017) implemented a method focused on leaf images of medicinal herbs to perform automatic classification. That was the first pre- process of medicinal plant leaf images; then the ten shape characteristics (SF) and five texture characteristics (TF) will be computed; eventually, the leaves of medicinal plants will be categorized using a support vector machine (SVM) classifier. 12 distinct medicinal plant leaf photos were added to the classifier and an overall effective recognition rate of 93.3% was achieved. The accuracy of the device obtained reached 90.1%. The paper (B. Wang, Brown, Gao, & La Salle, 2015) introduced geometrical and morphological to extract features. Then, the obtained features are classified by SVM. Dataset consist of 80% samples for training and 20 samples for testing. The obtained accuracy is 94.50%. In (Mouine, Yahiaoui, & Verroust- Blondet, 2013) proposed both geometrical and morphological features are extracted and classified with k- NN. They also proposed a method for representing shapes by triangles, and calculated the lengths of the sides and also represented the angles of the triangle, and to achieve this, TOA was used, and this provided high accuracy. The dataset was divided into 60 samples for training and 20 samples for testing 95.20%. In order to find out the shape structure of tested plants, (Khmag, Al- Haddad, & Kamarudin, 2017) implemented an image processing system. This method takes advantage of the scaling approach, spin strategy, scaling change, and processes of filtering variants. Using the Support Victor Machine (SVM), the leaf contours of the same plants are determined where identical sequences of the same contours typically have the same characteristics, while different plant sequences have different contours. Reference (Javed, & Ashraful, 2010)suggested a probabilistic neural network (PNN) for classifying plants with two dimensions. In this study, the processes were applied to the image, converting it into a binary image, and then extracting the features. The network was trained on a leaf of 1, 200 sample consisting of 30 different species of plants. They reported an accuracy of 92.4%.

(Praveen & Domnic, 2020) proposed a scheme for segmentation of the plant area in the orthogonal transformation domain based on orthogonal transformation coefficients. They tested their scheme on the CVPPP benchmark dataset and on mobile phone images. The proposed scheme provided promising results. The paper (Jyotismita, Nilanjan, Luminiţa & Fuqian, 2019) proposed an approach to recognize images of segmented leaves using a fuzzy- color and edge- texture histogram by a multi- layer- perceptron classifier algorithm. The method attempts to solve the problem following a twostep process: First, by bag-of- feature the plant leaf images are recognized by features that are similar to a segmented image query and then the feature vector is created by combined features. (Bisen, 2021) proposed an automated system to identify plants through their leaves using convolutional neural network technique. The Swedish dataset for plants was used, where the recognition accuracy reached 97%. This paper presents the recognition of four Yemeni plants (Rumex Nervosus, Agave, Green Grass, and Juniper) using three pre- trained deep learning models (AlexNet, GoogLeNet, and VGG19).

3- Problem statement

Since ancient times, plants have been used commonly to treat a wide range of diseases throughout human history and this practice still continues today. This is mainly due to the fact that most of these herbs can be easily accessible and affordable and that the chemical extracted with little or no side effects compared with drugs manufactured in the laboratory. One of the problems that researchers faced is that there is no database for medicinal plants in Yemen. Here we selected four species of these plants (Agave, Green Grass, Junipers, and Rumex Nervosus) to identify them. Dataset was collected for these plants and the total number of images was 600 and 150 images were specified for each class, and the images were increased to 1770 images using the data augmentation technique. The traditional identification of these plants faced several problems, including: leaf size, leaf color, and leaf texture. Therefore, it was necessary to choose advanced techniques with high efficiency such as deep learning techniques, which is characterized by its ability to recognize with high accuracy. Three models of deep learning techniques have been proposed (AlexNet, GoogLeNet, and VGG19). These models maintain constant weights that have been trained on the ImageNet dataset by fine- tuning the proposed plant images. These models automatically extract, classify and identify the features of the trained plants, and demonstrate high performance and accuracy.

4- Methodology

In this section, we will present the method for recognizing the four proposed plants (Rumex Nervosus, Agave, Green Grass, and Junipers) by using three pre- trained transfer learning models (AlexNet, GoogLeNet and VGG19).

The proposed method is depicted in the following steps: Data Collection, Pre- processing and augmentation, Training phase, Testing phase and Plant recognition. The training and testing phases are conducted based on deep convolutional neural networks methodology.

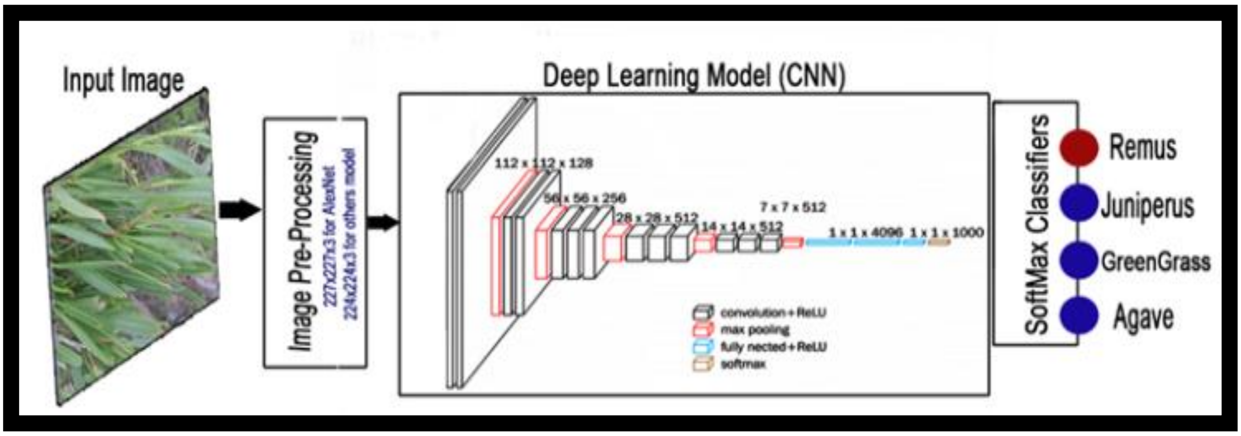

Figure (1) The proposed model to recognize plants

1. **Data Collection:** The dataset has been collected from scratch from Sawraq Mountain (Assardaf Mountain is its old name) that is located between three Yemeni provinces (Ibb, Taiz, and Aldhalea). It was collected from scratch using a smartphone camera on the 6th- 7th August 2020. About 600 images are collected. Each class includes 150 images.
2. **Pre- processing and augmentation:** In this step, the images of plant leaves will resize to 227x227x3 pixels for Alexnet model and 224x224x3 pixels for the other models and then the images will be cropped and then centered to fit the inputs of the proposed models. To make the images of plant leaves much more appropriate, data augmentation has been performed using the script that can be found at (https://github.com/AbdulfattahBaalawi/Data- Augmentation- Matlab). Then, the total used images are 1600 images. About 400 images are included for each class.
3. **Training Phase:**
   - **Training using Pre- trained model:** The processed data are divided into training and testing set. These datasets were divided into 70% for training phase and 30% for testing. Then, the training set is used to retrain the pre- trained model in our problem domain.
   - **Save the obtained expertise model:** The weight matrix is saved.
4. **Testing Phase:**
   - **Input the image:** The test sample is inputted using any terminal device.
   - **Image Pre- processing:** During image preprocessing, it is resized, cropped, centered and prepared to be processed with the obtained expertized model.
   - **Fine- Tuning:** we fine- tuned the proposed models on ImageNet dataset to optimize testing images.
   - **Test the sample:** The test sample is processed using the obtained expertise model.
   - **Show Test Result:** The obtained results with the recognized type are shown to the user.

4.1 Deep learning Models

Pre- trained models are deep learning models that are an evolution of neural network models and are distinguished by they have many hidden layers that are trained in large datasets such as the open source platform ImageNet. This open source platform was a huge asset for researchers in the field of deep learning. Pre- trained models mean that the models are trained on large and huge data sets to obtain final weights that can be used in training and testing other large data. Pre- trained models are used in classification and prediction. In this paper, we used three models (AlexNet, GoogLeNet and VGG19) to recognize plants, as follows:

1- AlexNet

AlexNet is an eight- layer deep convolutional neural network. More than a million images can be downloaded from the ImageNet database (Russakovsky et al., 2015). The AlexNet network collects images into large groups to train them and to obtain the correct final weights to be tested on other image sets. Images are represented in the input at a size of 227x227x3 as shown in Figure 2.

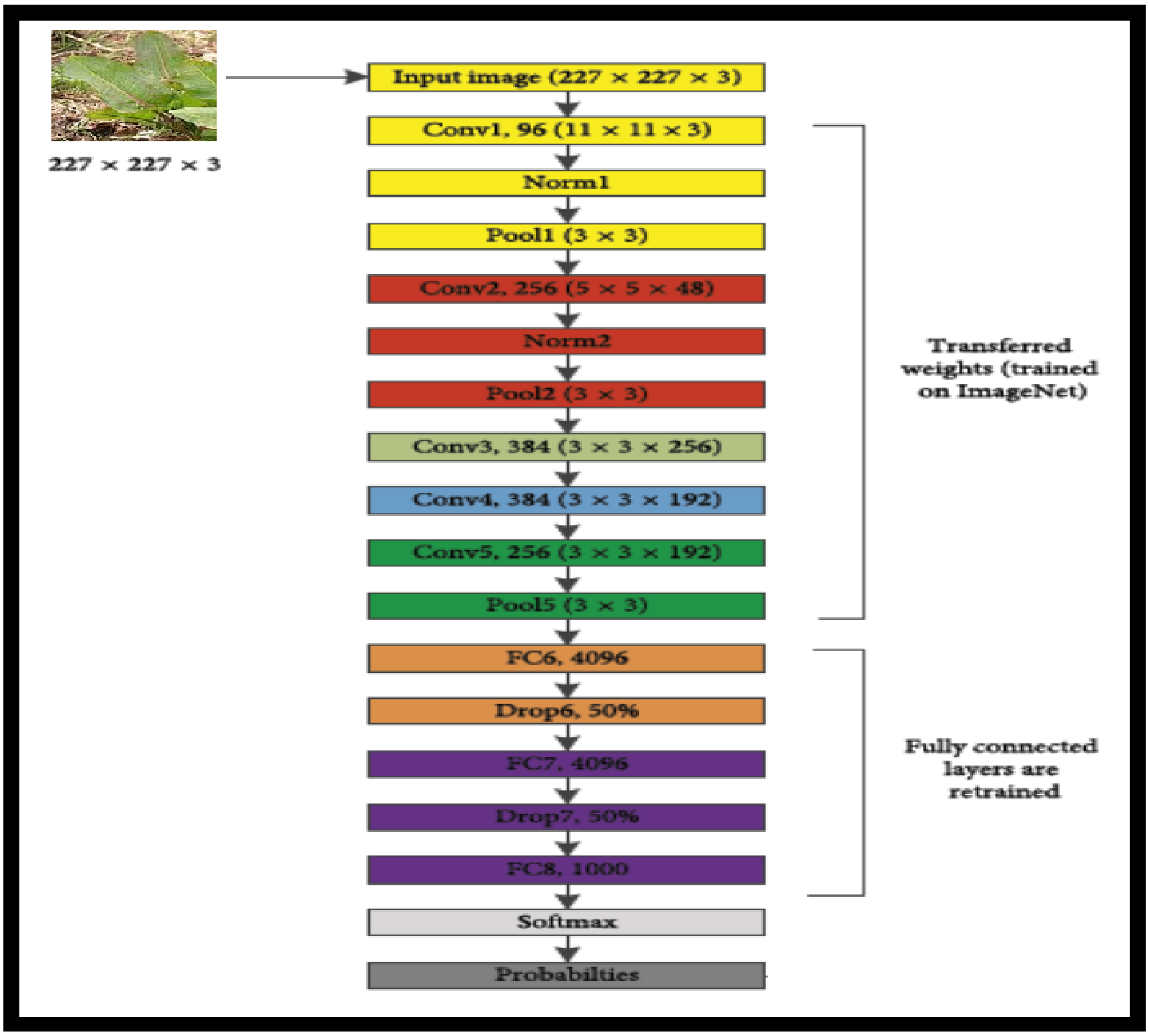

Figure (2) AlexNet Pre- Trained Model.

Most of AlexNet model has 8 layers including 5 for Convolutional layers and 3 for totally linked layers. For the non- linear component of the rectified linear unit (RLU) is used. ReLU is represented in equation 1.

$F(x)= \max(0, y)$ (1)

The advantage of ReLU over Sigmoid is that it can help to practice more rapidly, as Sigmoid in the saturated area is slow. This allows weight changes to vanish and is known as a concern of disappearing gradients. AlexNet is the first cortical neural network in which the ImageNet Broad Scale Visual Recovery Challenge (ILSVRC) reached the best- ranking accuracy in 2012. This deep structure consists of eight key tiers, with primary convolutions in the first five layers, while the last three layers have been entirely connected. The activating function layer (ReLU), which is to boost network efficiency, is followed by the activation layer of each convolution layer by rendering the exercise faster than "tanH" functions equivalents. A max- pooling is used in AlexNet after each convolution layer such that the network size is minimized. In addition, after the first two fully connected layers, a dropout layer is introduced to avoid duplication, helping to minimize the number of neurons. Finally, after the last layer, a layer is inserted to distinguish the data entered. The arrangement of the AlexNet.

2- GoogleNet

Alternatively named Inception VI is Google's CNN architecture, which was first introduced in 2014 and focuses on reliability and quicker delivery. In this way, the Deep network was created. AlexNet was available before GoogleNet and it uses 12 times fewer parameters than Oxford net when the matrix exists below zero. AlexNet solves the fitting problem by adding a dropout layer after each fully connected layer. The dropout layer has an associated probability that is distributed independently to each neuron of the reaction diagram. This is carried out depending on the assemblies by removal layers and by eliminating multiple neurons, separate layout will be shown and is trained along with each subset's weight and the amount of weight. The number of sub- set architectures developed will be 2n for n neurons connected to the dropout.

To allow the inference on each unit, even those with minimal computing resources and in particular, with low- memory space, the network was designed to be machine efficient and functional. This architecture is 22 deep layers without pooling and is used to measure pooling in 27 layers. For the construction of the network, the total number of layers (independent building blocks) is about 100. Given the relatively high network width, it was a problem to be able to efficiently spread gradients through each layer. By inserting classifiers for these intermediate levels, discrimination in the lower classification stage is expected to be promoted, the gradient signal is increased and regularization is given. During preparation, losses are applied to the network's overall weight loss, and at a point of inference, these auxiliary networks are disregarded. These losses have been weighted by 0.3. Since the implementation of CPUs was used alone, an unofficial calculation indicates that the network GoogLeNet can be trained for convergence in a few high- end GPUs within a week, with memory usage as a principal constraint. The architecture of GoogLeNet is shown in the following figure 3.

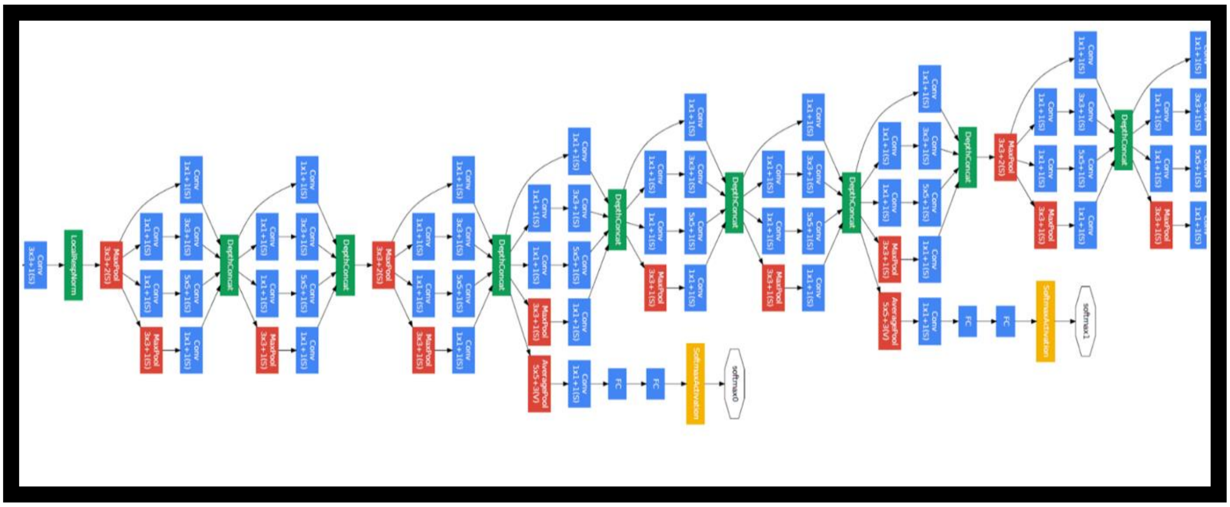

Figure (3) The architecture of GoogLeNet Network.

3- VGG19

VGG is a neural network model of convolution suggested by Simonyan, K., & Zisserman, A, from the University of Oxford, in his paper "Very Deep Recognition of the Picture" In ImageNet the model achieves the top- 5 evaluation accuracy of 92.7 percent and depicts a data collection of more than 14 million images in 1000 groups. The architecture of Vgg19 is shown in the following figure 4.

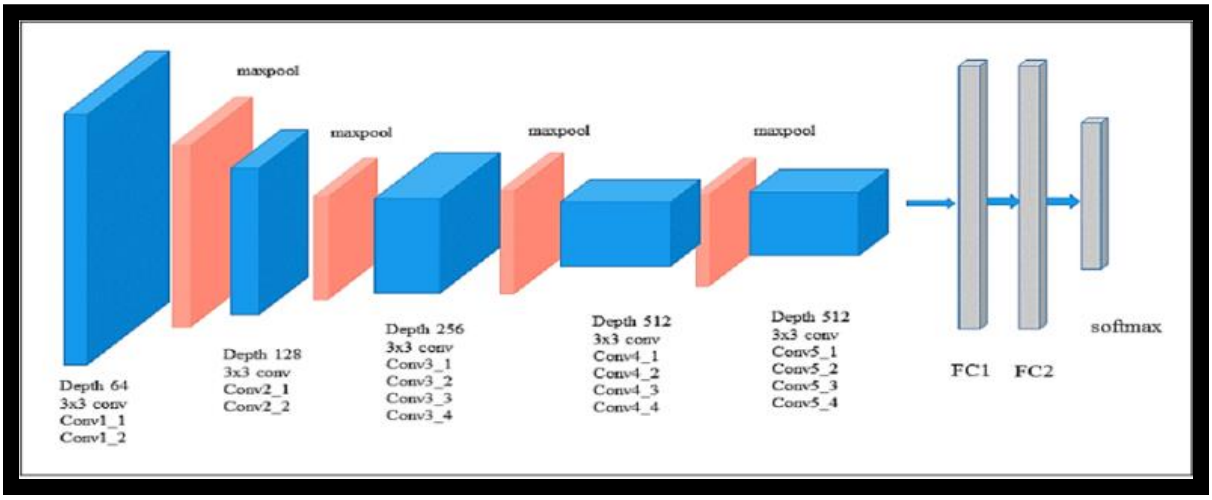

Figure (4) VGG- 19 Pre- trained model architecture.

5- Results

In this part, we will explain the results obtained during the implementation, where we divided the dataset into two parts, 70% for training and 30% data for testing. Figures (5 and 6) show the obtained training loss and training accuracy curve of the experiment using three pre- trained models. The proposed model is implemented using three pre- trained models; AlexNet, VGG19 and GoogleNet. Firstly, the AlexNet model is trained for 11 epochs and 128 batch size that take an hour on Core i3 CPU and a RAM of 8GB using matlab 2018a for AlexNet. In the other side, GoogLeNet tooks 2 hours and 5 minutes for completing the 11 epochs. VGG19 tooks 4 hours for training may be because of the architecture of the network especially when using Core i3 CPU.

Every model shows independent performance. As we can see from figures, that the AlexNet model and the GoogLeNet model achieved the lowest loss value ~ 0.07 and the highest accuracy of 99.30% and 98% respectively. While the VGG19 model achieved the largest loss value was 0.38 with 94% accuracy. Based on these results, the system achieved better results due to the Fine- tuning of the pre-trained deep learning models.

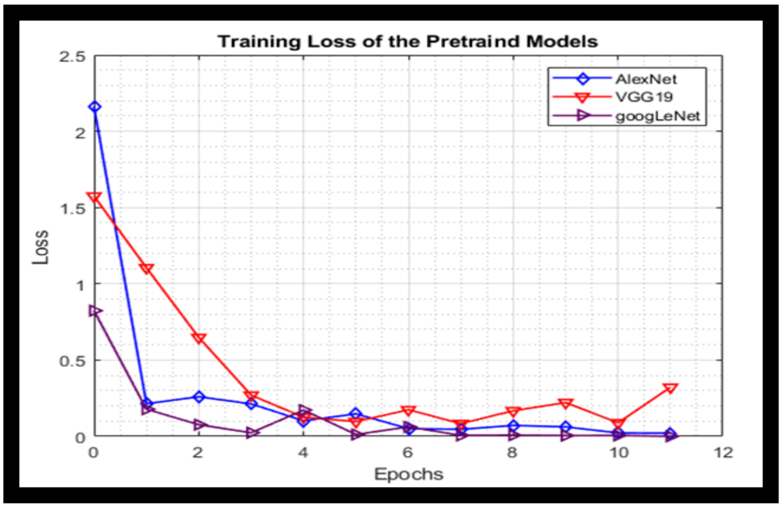

Figure (5) Training Loss of the pre- trained models.

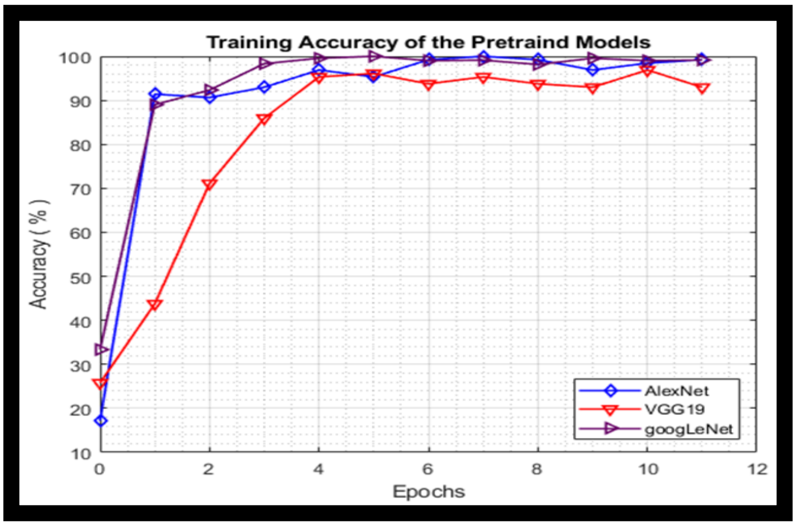

Figure (6) The training accuracy obtained using the pre- trained models.

Figures (7, 8) show the loss and validation accuracy curve during test phase with 11 number of epoch and 128 batch size. As we can see from figures, that all models achieved high results, but the best results with the lowest loss validation 0.0320 and the highest accuracy of 99.83%, were achieved by AlexNet. While the VGG19 model and GoogLeNet model achieved the loss validation value ~ 0.048 and the accuracy of 98.7% and 98.3% respectively.

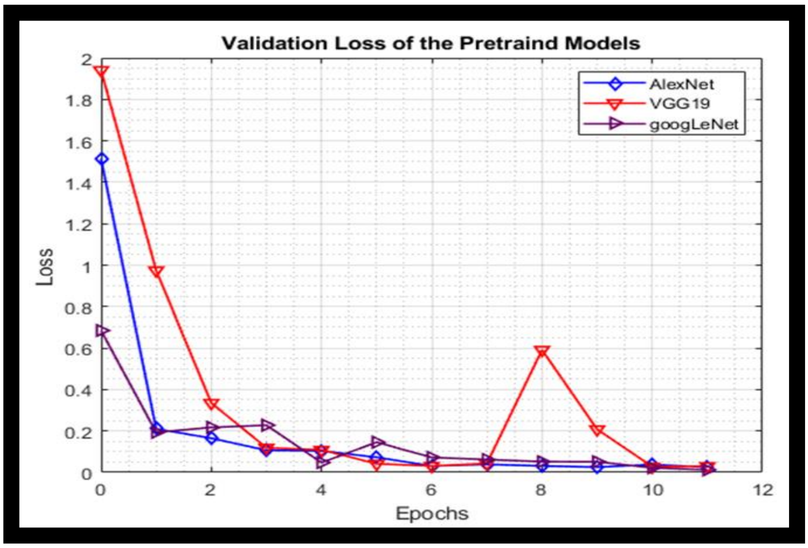

Figure (7) Validation Loss of the pre- trained models.

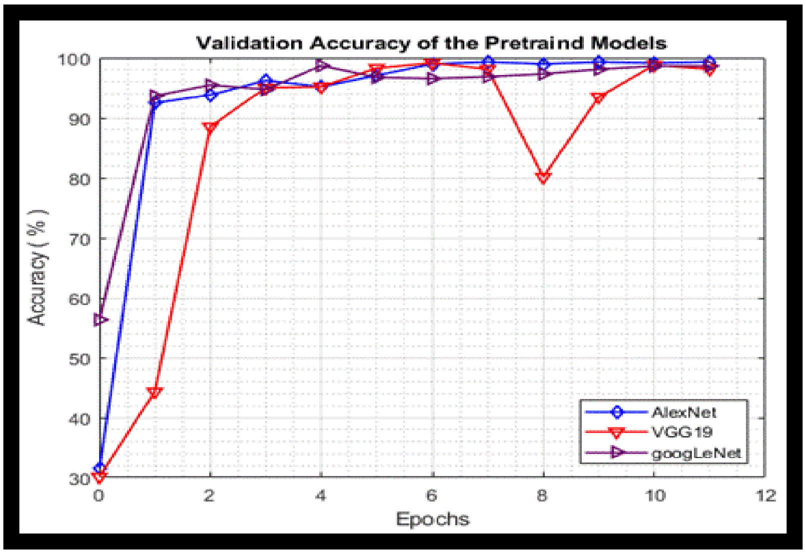

Figure (8) Validation accuracy obtained using the pre- trained models.

The obtained results of the pre- trained models are shown in the following table 1. To evaluate the performance of the recognition of Yemeni plants were used: Accuracy, Sensitivity, Specificity, Precision, False Positive Rate, F1_score and Matthews Correlation Coefficient. As demonstrated in the below table, the best results in all rating scales were obtained using AlexNet pre- trained model.

From the table shown below, we find that it clarifies the criteria which the effectiveness of the proposed models will be measured. We find that the accuracy of AlexNet reached 0.9983 and reached

0.9983 for the GoogLeNet model, while it was 0.9875 for the VGG19 model. As for the standard error rate, it reached 0.0017 for the AlexNet model, and for the GoogLeNet model it was 0162, and for the VGG19 it was 0.0125. As for sensitivity, AlexNet has got 0.9985 and GoogLeNet and VGG19 got 0.9785 and 0.9786 respectively. As for Sensitivity, AlexNet has got 0.9985, but for GoogLeNet and VGG19, they got 0.9785 and 0.9786 respectively. We note that the Specificity standard reached 0.9994 for the AlexNet model, and it reached 0.9900 for the GoogLeNet model, while for the VGG19 it reached 0.9865. As for the Precision standard, the percentage of 0.9982 was obtained for the AlexNet model and 0.9882 for GoogLeNet and 0.9877 for VGG19. If we look at the false positive rate, we find that the AlexNet model got 5.6180e- 04 and GoogLeNet got 0.0076, while VGG19 got 0.0054. Finally, the F1_score standard, we note that the AlexNet model got 0.9983, the GoogLeNet model got 0.9852, and the VGG19 got 0.9883.

Table (1) The performance of the proposed models.

Metric Measure\Classifier	AlexNet	GoogLeNet	VGG19
Accuracy	0.9983	0.9838	0.9875
Error	0.0017	0.0162	0.0125
Sensitivity	0.9985	0.9785	0.9786
Specificity	0.9994	0.9900	0.9865
Precision	0.9982	0.9882	0.9877
False Positive Rate	5.6180e- 04	0.0076	0.0054
F1_score	0.9983	0.9852	0.9883
Matthews Correlation Coefficient	0.9978	0.9771	0.9780

Here we compare the results of the proposed method with other approaches in plants classification. In table 2, we list the accuracy of different method related works. We can see that the proposed method is better than the other work in this area in terms of accuracy. The best result is obtained using AlexNet pre- trained model which reached 99.83%.

Table (2) Comparison of proposed models and another models

Studies	Classifier	Accuracy
(Qing et al, 2010)	RPWFF	80.12%
(Guan et al, 2017)	VGG16	90.4%
(Shanwen et al, 2017)	K- means	85.7%
(Satti et al, 2013)	ANN and KNN Best: ANN	93.3%
(Kan et el , 2017)	SVM	93.3%
(Wang et al, 2015)	SVM	94.50%
(Mouine et al, 2013)	K- NN	96.20%
(Khmag et al, 2017)	SVM	97.69%

Studies	Classifier	Accuracy
(Javed et al, 2010)	PNN	91.41%
Proposed models	AlexNet	99.83%
	GoogLeNet	98.38%
	VGG19	98.75%

6- Conclusion

The aim of this paper is to recognize Yemeni plants that are commonly used in treatments and herbal reasons with high accuracy. Consequently, an intelligent model is proposed to design a model that classify four types of Yemeni plants (Rumex Nervosus, Agave, Green Grass, and Junipers) using an image-based approach and recognize the plants effectively. This was done by using pre- trained transfer learning models (AlexNet, GoogLeNet and VGG19), and trained it on the 1700 images dataset. These models give accuracies (99.83%, 98.38% and 98.75%,) respectively. We found that AlexNet model gives the best result with and accuracy 99.83%. Vividly, the experimental findings show the effectiveness of the proposed method.

In future work, we propose to improve methods for extracting features of plants using image segmentation techniques with machine learning techniques to recognize plant images with high efficiency and accuracy. We also suggest adding other models of deep learning techniques and making improvements in their structure.

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