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Citrus Disease Detection & Classification using Deep Learning and Machine Learning Models

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ABSTARCT - Citrus crops are vital contributors to the global agricultural economy, but they are susceptible to various diseases that can significantly impact yield and quality. Early detection and accurate classification of these diseases are essential for effective disease management and crop protection. In recent years, deep learning techniques have emerged as powerful tools for image-based disease detection in plants. In this study, we propose a deep learning-based approach for citrus disease detection and classification using state-of-the-art convolutional neural network (CNN) models. Specifically, we explore the efficacy of popular CNN architectures such as VGG16, ResNet, and Inception for automating the detection and classification of citrus diseases from leaf images. We train and evaluate these models on a large dataset of labelled citrus leaf images representing various disease classes. Experimental results demonstrate the effectiveness of the proposed approach in accurately identifying different citrus diseases, achieving high classification accuracies compared to traditional methods. The developed deep learning models offer promising potential for real-time monitoring and early intervention in citrus orchards, thereby contributing to improved disease management practices and sustainable citrus

Keywords —Deep Learning, Machine Learning, base learning and transfer learning, citrus diseases, VGG16, Inception Net, ResNet, NasNet, MobileNet

I INTRODUCTION

Pests and diseases are the two main features that affect the yield of citrus. There are many types of citrus pests in the wild. Some of them have similar appearances, making it complicated for farmers to identify them exactly in time. In current years, the development of machine learning algorithms has greatly improved the latest technological level of computer vision. These new network structures enable researchers to achieve high exactness in image classification, object detection and semantic segmentation [1]. Then, some studies use machine learning models to identify image-based disease categories. As an important part of the overall agricultural economy, the citrus industry requires citrus plantations to take appropriate disease control measures to minimize losses. Melanosis, oil slicks and crusts are the most devastating diseases threatening citrus crops. Technologies that can effectively identify these diseases will ensure the quality and safety of fruits and

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increase the competitiveness and profitability of the citrus industry. This study aimed to investigate the potential of using pattern classification techniques to detect citrus leaf lesions. The leaves are divided into four categories according to disease, namely scab, melanosis, oil stain and normal leaves. Four classifiers were designed for the comparative study to determine the best way to obtain disease classification. Use the function-weighted Mahalanobis distance to classify the extracted functions, which is a monitored classification algorithm. Plant disease detection based on images of leaves. They presented two versions of depth wise separable convolution comprising two varieties of building blocks. These depth wise separable convolutions achieved less accuracy and high gain in convergence speed. Models Reduced MobileNet achieved a classification accuracy of 98.34% with 29 times fewer parameters compared to VGG and 6 times lesser than that of MobileNet. However, MobileNet outperformed existing models with 36.03% accuracy when testing the model on a set of images taken under conditions different from those of the images used for training [2-6].

Hafiz Tayyab Rauf et.al [7] in this article the entire processes include four major steps to complete which are: (a) enhancing the dataset (b) lesion segmentation which highlights the infected region (c) extracting features from the infected region and finally (d) selecting feature visually and perform classification. Authors applied the Top-hat process and then Gaussian function to improve the contrast of the infected region. Jayme Garcia Barbedo [8] in this paper author explores the use of individual lesions and spots for the task, rather than considering the entire leaf. Since each region has its own characteristics, the variability of the data is increased without the need for additional images. This also allows the identification of multiple diseases affecting the same leaf.Muhammad Sharif et.al [9] have developed a hybrid method for detection and classification of citrus diseases namely anthracnose, black spot, canker, scab, greening, and melanose in citrus plants. The method consists of two primary phases; (a) detection of lesion spot on the citrus fruits and leaves; (b) classification of citrus diseases. The citrus lesion spots are extracted by an optimized weighted segmentation method, which is performed on an enhanced input image. Then, color, texture, and geometric features are fused in a codebook. The best features are selected by implementing a hybrid feature selection method, which consists of PCA score, entropy, and skewness-based covariance vector. Their results show that the proposed technique outperforms the existing methods and achieves 97% classification accuracy on citrus disease image gallery dataset. Yande Liu et.al [10] in this paper the feasibility was investigated for discriminating citrus greening by use of near infrared (NIR) spectroscopy and least square support vector machine (LS-SVM). The spectra of sound and citrus greening samples were recorded in the wave number range of 4000-9000 cm. The spectral variables were optimized by principal component analysis (PCA) and uninformative variable elimination (UVE) algorithms.

Fig.1.citrus disease leaf and fruit image

II RELATED WORKS

Deep learning It is a subcategory of machine learning; this greatly improves the acceptance rate for many traditional approval practices. In recent years, in -depth learning has not only been widely used in image dispensation, image appreciation or organization [11], but it is also widely used in agriculture and other fields. Contrast to previous artificial neural complex process, in-depth studies are more accurate in recognition and can solve the problem of image and visual representation. It is mainly hopeful expertise in modern agriculture [17]. Deep learning is similar to low-level neural network, but there are many neural networks with hidden systems. Typical deep learning networks include communication network (CNN), limited Boltzmann machine (RBM), deep trust network, Boltzmann deep machine (DBM) [12], DBN, RNN, GAN, Caps Net, etc. . Compared to superficial neural complex, deep learning has a stronger learning time, higher degree of accuracy, or requirements of external conditions. It can be used in real life or agricultural production, such as disease detection. Current disease analysis methods can no longer respond to current agricultural needs. In-depth study can replace physical activity with use of electronic devices to diagnose disease as well as prevent disease as a result of the product. To date, professional have used in-depth study technology to examine the acceptance of images. For diagnosis of some of above diseases, diagnosis of the disease in the breeding process depends on young technician. They use field observations and compare the record with recorded disease samples or disease samples to determine the type of disease. [13-16] However, the long-term use of this manual analysis method consumes significant energy or resources and cannot guarantee its validity and effectiveness; it cannot meet the needs of disease or disease prevention. Therefore, more and more researchers are identifying the diseases caused by the product through in -depth research. As the concert continues to improve, they also need more computing power. In -depth learning is limited to mobile applications with limited power consumption, computer equipment and storage space. Success depends on two aspects: storage speed and predictability. It is only by using CNN to solve the problem of efficiency that CNN can get out of the confines of the lab and have a lot of users on mobile phones. To improve its performance, the general approach is to force the trained model to solve memory and speed issues with a few network parameters. In addition, the lightweight model uses other methods to develop more efficient network computation methods (especially the convolution method), which can reduce the particle size without performance losses. MobileNet is a lightweight model provided by mobile devices and other installed devices, which effectively solves the problems mentioned above. Make full use of deep separations and folds to enhance your network structure [17]

Deep Learning Challenges - Deep learning has realize inspiring achievements in some tasks, include visual recognition, language or speech recognition arrangement, in addition to attracting attention and significant progress in its research site [18]. On the contrary, due to lack of universal public data accessibility or its difficult nature, DNN has hardly considered many areas. Therefore, it is a fertile country or creates imperative opportunities to compensate for future explore opportunities. This section converse some of biggest in-depth learning brave or probable solutions, counting hardware settings. Detection or organization of plant diseases based on deep learning also faces same problem. The lack of adequately labelled teaching examples is most difficult problem in deep learning tasks. It contains petabyte data every day excluding current zeta bytes. This enormous progress is accumulating data that cannot be felt without human help. The current success of supervised learning technology is usually due to the current large data sets or current existence of brands. Unsupervised learning technology is becoming the main solution to be considered or data complexity and scale are rising rapidly [19]. In addition, capturing approximate information rather than training throughout the observation process is a new problem (such as data confusion, lack of data, and frugality) that forces the path to change current deep learning model. In addition, low-sample, unlabeled, high-dimensional heterogeneous, or imperfect data sets are unlocked sites for deep learning technology. Due to the built-in black box suspicion of DNN, it provides the unique ability to process unattended data. Many improved deep learning models have been developed to process cluttered and noisy data. 80 million undersized images are a challenging database. Contains low-resolution RGB photos using 79,000 queries, such as [20]. To reduce noise mark in data, they adopted a new robust cost feature. In addition, a great amount of streaming real-time data is used in many function today, such as social networks, XML files, DNA / RNA sequencing, or time series. These enormous amounts of data are currently facing data imbalance, heterogeneity and incompleteness. This is a related issue. How deep learning models can learn in these areas is still under discussion[21].

CNN architecture- CNN is one of DL architectures. It is the most common for solving image classification problems and is the most efficient and powerful DL technology. CNN is a development of the traditional artificial neural network (ANN), which primarily focuses on the application of repetitive patterns in different areas of the modelling area for a specific image. Their main feature is that, compared to traditional feed forward neural networks, they use a hierarchical method to greatly reduce number of necessary structural elements (the number of artificial neurons). CNN is feed-forward and an extremely influential detection method. The network structure is simple; the training parameters are few. CNN represents a very efficient detection process. On the other hand, the complications of network model or number of weights are condensed. Shows CNN's main structure, which mainly contains five layers; input layer, folding layer with activation function, pooling layer, and fully connected layer and finally softmax layer [30].

VGG16- VGG16 is an independent network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Deep communication networks for large image recognition ". The model achieved an exam score of 5 for 92.7% on ImageNet, which has a database of more than 14 million images in 1,000 categories.

ResNet - ResNet is different from traditional network architectures such as AlexNet, Over Feat, and VGG. ResNet is a type of "exotic architecture" that relies on a micro-architecture model, also known as an "in-network architecture".

Inception - Szegedy et al. First presented the "creative" horizontal. In his 2014 paper Going Deeper with Convolutions: The goal of the start-up model is to function as a "multi-feature explorer" by calculating 1 × 1, 3 × 3, and 5 × conflicts. 5 in the same model of the network-these The filter results are applied according to the dimensions of the channel. To improve the capacity of deep neural networks before use, the most direct way is to increase the depth of the network. However, as the depth of the network width increases, there are too many internal dimensions, which results in more resource consumption. Therefore, in order to overcome these problems, Szegedy et al first introduced the Inception model into the GoogLeNet architecture. 35 And completed an impressive performance and read record as the winner of the ImageNet ILSVRC Challenge. The first model consists of an upper water-supply layer and a corresponding plate. The sizes of the mixed layers were 1 × 1, 3 × 3, and 5 × 5, which were combined. Between two matching 1 × 1 layers, the maximum reduction is used to reduce the dimensionality and a tandem filter is required to combine the different layers. In addition, by removing the 5 × 5 convolutions and introducing two 3 × 3 convolutions to modify the initial model change, it was widely used in later network configurations.

MobileNet - The MobileNet model is based on a detectable deep convolution, which is a form of broken convolution, which converts the normal convolution into a deep convolution and a 1 × 1 convolution called a smart convolution point. For MobileNets, convolution applies a single filter to each communication channel. The wise convolution then applies a 1 × 1 convolution to mix the deep convolution developments. Conventional convolution both filters the input and combines the use in a new production series in one step. The distinctive column divides it into two layers, a single layer for filtering and a single layer for blending. This deletion has an effect on the reduction of the calculation and the size of the model

NASNet,- In NASNet, although the general structure is defined as shown above, the barriers or elements are not defined by the author in advance. Instead, they are searched through a series of affirmative research methods. The number of phantom repeats N and the number of initial convolution filters are used as free parameters for scaling. Specifically, these cells are called normal cells and degenerative cells. Repeat the convolution element on a feature map of the same size. Returns to the convolution unit of the feature map, which reduces the height and width of the event map by twice. The regulatory RNN (repetitive neural network) searches only for the structure (or interior) of normal and degenerative cells.

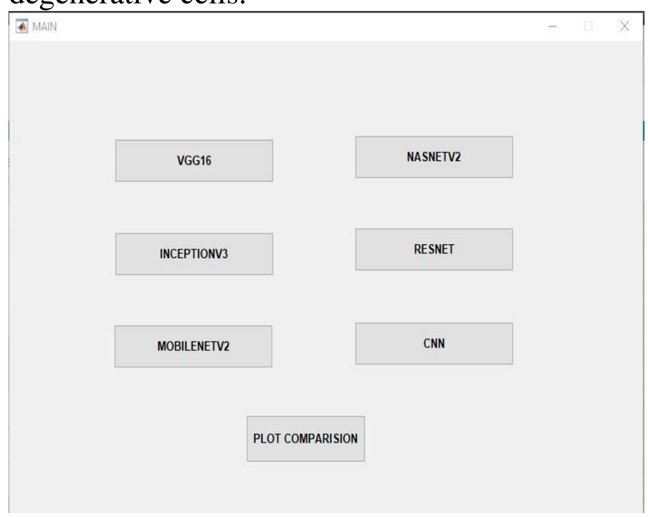

Fig.2 GUI different deep learning models

III EXPERIMENTAL DESIGN

Training and Evaluation Phases

If time or computing property tolerate, using the same hyperparameters for multiple training sessions can improve accuracy, as random initialization can affect results. When comparing hyperparameters, it is recommended to consider fixed random number generators to avoid skewing the comparison, which is also desirable. Testing more than one nature of architecture can also play a optimistic role. To obtain the same precision, it is more advantageous to choose the least complicated architecture from a prepared

Deep learning Architecture	Training Method	Validation Accuracy
VGG 16	ADAM	80%
	SGDM	90%
	RMS Propagation	77%
InceptionV3	ADAM	91%
	SGDM	85%
	RMS Propagation	96%
MobileNetV2	ADAM	93%
	SGDM	92%
	RMS	90%
ResNet	[illegible]	[illegible]
	SGDM	92%
	RMS Propagation	90%
NasNetV2	ADAM	93%
	SGDM	95%
	RMS Propagation	92%
CNN	ADAM	93%
	SGDM	91%
	RMS Propagation	86%

point of view. If related, relocate learning is suggested to recover computational time or generalize ability. After correcting all hyperparameters, the model must be retrained by combine images formerly used for preparation or legalization into overall training set. In fact, previously all hyperparameters are defined; it is no longer necessary to maintain validation set. So it's worth using this global training set to try to recover exactness one last time (i.e., no post-adjustment to any hyperparameters). The retrained model can be appraised on test apparatus. The visualization step is also imperative because it helps to better recognize what is happening in model or to ensure toughness of results. This advance can also supply prospect to recover routine.

Table 1 performance of deep learning architecture

Table 2 comparison of proposed model with existing techniques

Reference	Year	Deep Learning Architecture	Accuracy
Utpal [21]Barman	**2020**	MobileNet.	92%
OUR MODELS		CNN	90%
		VGG 16	95%
		Inception Net	93%
		Mobile Net	96%
		ResNet	92%
		NasNet	94%

IV RESULT AND DISCUSSION

Process performance is precise based on concert indicators such as precision, sensitivity, specificity, or time consumption. Performance Measure: In our data set, the sample size is fairly isolated among 11 categories. When the sample size is not biased towards any particular category, precision is a good performance indicator.

TP- is total number of properly categorized prospects (true positives).

TN- is total number of poorly classified prospects (true negative numbers).

FN- is total number of false rejections, which represents the number of false pixels of foreground pixels classified as background (false negatives).

FP- is total number of false positives, which means that pixels are mistakenly classified as foreground (false positives). Calculate presentation value for each frame of input video based on overhead indicators. Accuracy = correct number of predictions, total number of predictions

Accuracy = TP + TNTP + TN + FP + FN

Specificity: Specificity is distinct as proportion of definite refusals that can be predicted as negatives (or true negatives).

Specificity = (True negative) / (True negative + False positive)

Accuracy: In field of material retrieval, accuracy is quantity of recovered documents related to the query

$$\text{Precision} = \frac{(\text{True Positive})}{(\text{True Positives} + \text{false positives})}$$

Precision is used with the retrieval rate, which is the percentage of all relevant documents returned by the search

V CONCLSUION

A framework based on deep metric learning that can effectively identify citrus ailment from leaf images. The planned architecture includes an embedded module, a cluster prototype module, or a simple neural network classifier for performing disease recognition. The frame also includes a method of generating patches from blade images to further enhance performance. The proposed method involves several steps, including image capture, image segmentation, feature drag, feature selection, and classification. Almost all disease diagnostic techniques have achieved success with disease classification. The evaluation of our process with other deep complex baselines in terms of time competence shows equivalent or superior performance with other baselines. In addition, our framework shows better classification exactness than all other baselines. The most difficult and challenging part is image segmentation of citrus disease, which is further divided into two parts: background part location and extraction and then separation of disease part. In this article, we used pre-trained deep learning models like VGG16, Inception Net, ResNet, NasNet, MobileNet and CNN used for recognition of the citrus disease model.

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