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Image Analysis and Detection of Olive Leaf Diseases using Recurrent Neural Networks

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Abstract

The widespread adoption of DL has led to a rise in academic interest in image recognition approaches, enabling applications such as automated image classification and the detection of plant diseases. The world's largest producer of olives is Morocco. Plant health might be harmed by illnesses, which therefore affects its development. Numerous illnesses affecting olive leaves specifically target crop growth rate. The objective of this research is to create deep RNNs to identify olive plant illnesses using a collection of leaf images, collected from various sources (Disease note The peacock eye falls on olive trees, Field Guide to Olive Pests, Diseases and Disorders in Australia. Thus, this technique is the best RNN model and is employed in further applications to enhance diagnostic measurements regarding olive leaves and other plant leaves.

Keywords: Recurrent Neural Network (RNN), Texture Based Image Retrieval (TBIR), Disease diagnosis, Image analysis, Deep learning.

الخلاصة

أدى الاعتماد الواسع النطاق للتعلم العميق إلى زيادة الاهتمام الأكاديمي بأساليب التعرف على الصور، مما يتيح تطبيقات مثل التصنيف الآلي للصور والكشف عن أمراض النبات. أكبر منتج للزيتون في العالم هو المغرب. قد تتضرر صحة النبات بسبب الأمراض، مما يؤثر بالتالي على نموه. العديد من الأمراض التي تصيب أوراق الزيتون تستهدف على وجه التحديد معدل نمو المحصول. الهدف من هذا البحث هو إنشاء شبكات RNN عميقة لتحديد أمراض نبات الزيتون باستخدام مجموعة من صور الأوراق، التي تم جمعها من مصادر مختلفة (ملاحظة المرض: سقوط عين الطاووس على أشجار الزيتون، الدليل الميداني لآفات الزيتون والأمراض والاضطرابات في أستراليا. وهكذا هذه التقنية هي أفضل نموذج للشبكة العصبية المتكررة (RNN) ويتم استخدامها في تطبيقات أخرى لتعزيز القياسات التشخيصية المتعلقة بأوراق الزيتون وأوراق النباتات الأخرى ..

INTRODUCTION

Olive tops the remaining varieties of fruit trees planted in Morocco, as it represents 65% of the area designated for planting fruit trees at the national level. Although it is present in 10 regions of the Morocco, the regions of Fez-Meknes and Marrakesh-Safi alone contain 54% of the areas planted with olives.

Currently, identifying plant diseases is only done by hand examination, which takes a lot of labor and calls for expensive equipment in laboratories [7]. A lot of chemical consumption, inaccurate disease identification, and unskilled personnel all contribute to the pathogen's long term struggle and decline in olive plant resistance to attack [1].

By using only Human eye, you may swiftly expand the complexity of an olive plant's leaves. Skilled botanist and agronomic might struggle to correctly identify the particular type of disease due to visual similarities between different diseases, the vast number of farmed crops and diagnostic issues. Additionally, it may result in erroneous conclusions and assumptions [9].

Even non-technical people could be considerably helped by an autonomous system to be capable of solving the issue in agricultural system through color and visual cues of the

plant [12]. This will prove to be a useful technique for farmers and make them aware of them as soon as possible before the onset of a serious illness [10].
Recurrent neural networks (RNNs) were demonstrated to outperform more advanced ML methods at present time, with computer vision being one of the most significant examples [11].
The automatic integration of feature extraction into the training phase is the primary factor in the success of RNNs. Large data sets have been successfully collected by RNNs, which also systematically incorporate performance evaluation into the development process [9]. With an effective computer-aided NN model, the suggested work aims to automate the identification of diseases in olive leaves.
RNN are employed in image processing in this case to detect plant illnesses. In the case our program is ever put into practice, that will assist farmers in minimizing their losses. Disease-induced leaf layer classification was carried out with the use of the RNN method.

OLIVE LEAF DISEASES

Figure 1 data leaves include 80 images of specific illnesses of the olive leaves, including red scab, blister blight, spot, and leaf blight. This image was taken from a data-set of a plant village.

A. **Rapid deterioration of olive trees (RDOT):** This disease is a very dangerous disease that affect olive and other wild and cultivated plants. The bacteria that cause the disease (Xylem) invade the wooden vessels in the family plant and multiply inside it, preventing the transmission of water and nutrients, as it causes a number of diseases, Symptoms: the burning of the ends of the leaves, the stiffness of a part or the entire tree, the wilt, and the death.
B. **Peacock stains or olive leaves stains:** This disease is active during the winter, and the high temperatures in the summer prevent the growth of germs, so most of the affected leaves fall before the summer and a number of them remain, and a new crop may later be produced from the woods that spread through the leaves in the fall season, and the bottom and side part The southern is more sensitive than the upper parts, and this is due to the fact that fungi grow faster within certain climatic conditions. **Symptoms:** Small spots appear and then develop into green circular spots with a diameter of 6 millimeters and a yellow aura can appear around it, and thus its fall, and the decrease in the number of leaves leads to a decrease in photosynthesis, which leads to poor growth of the branch and weak fruit.
C. **Frenulum wilted:** One of the most dangerous diseases that affect olive trees, as it is difficult to control, and the presence of high verteslium levels in the soil makes the Earth not suitable for olive trees, and to avoid the disease, must ensure that there are no verticilium micro sclerotic in the soil. **Symptoms:** wilting in the leaves, falling and palloring their color, as it is a dead structure connected to the branches, and the entire tree is pale and stops growing as the leaves wither and the tree dies [8].

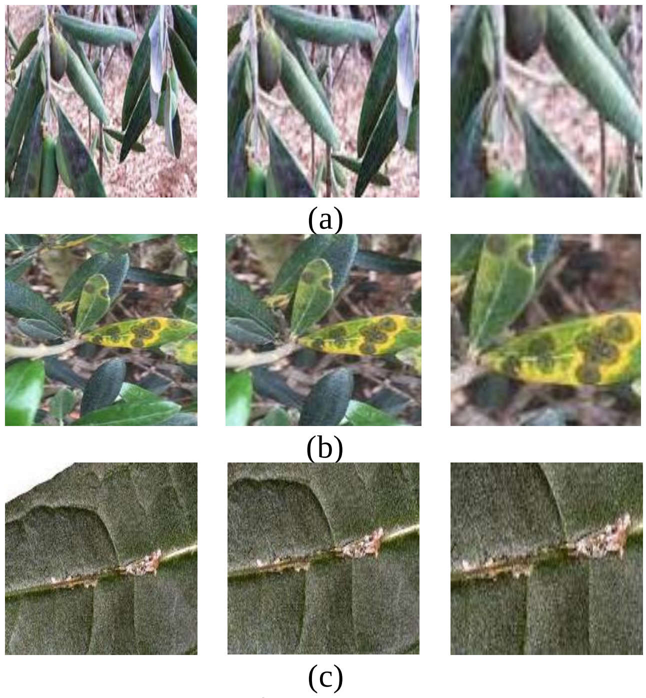

Figure 1. Olives Leaf Image Data Samples: (a) Rapid Deterioration of olive trees, (b) Peacock stains or olive leaves stains, and (c) Frenulum wilted.

RELATED WORKS

A few early publications in this topic are reviewed for reference in the cases that follow, the various methods of classification that are utilized to identify plant species.

The K-Nearest Neighbor (KNN) clustering algorithm makes use of class prediction for a specific test sample.

The image is converted to a grayscale to accomplish that. One of the SVM's disadvantages seems to be that it does not converge effectively if the available training data is not linearly segregated [3].

According to Sanjay B. *et al.* [7], they established a model that involves these three steps. Out of them, the main one is that a color transformation structure is created for provided input RGB image, using HSI as color descriptor. Unskilled pixels are hidden, deleted, and the ROI that is extracted in the second phase by choosing the brink price from the bar chart. The classification is finished in the last or 3rd main step.

The study of [11] provides a method for categorizing and diagnosing various plant diseases.

The color co-occurrence approach is the method provided in this study for color package extraction. In order to automatically identify illnesses in the leaves, ANNs were deployed. The suggested method looks to be a significant method in the case of vapor and root illness and could significantly support the proper identification of the leaf with less computational work.

In this study, four main steps formulate the procedure of disease identification: first, RGB color format of input image is converted into the HSI color format. After that, a threshold value is utilized for the identification and isolation of green pixels in the image. To extract ROI from the image, the method of segmentation has been utilized in the third step. Lastly, an illness has been diagnosed with the use of classifier based upon its characteristics. On 500 plant leaves from dataset, the proposed approach's robustness was proven [13].

The histogram matching method is allegedly used to detect disease, according to research [5]. This study emphasizes the importance of histogram matching, edge detection techniques, and extraction of color features. The green, red, and blue layers of the RGB image are separated from the plotted histogram, and the edge detection method is then applied to returned image.

In this study [6], K-means clustering, edge-based thresholding, and region-based extraction are presented as image analysis techniques.

The average difference value between the object was compared to extracted regions of the object. For calculating the index of similarity between two images, the correlation of objects in the image is evaluated.

To increase classification accuracy, PCA method has been employed in order to decrease the number of the features with various orientations. This method demonstrates that, in comparison to other methods, K-mean clustering method has been found good at producing high accuracy.

The research of [10] founds that fruit detection evolved utilizing texture and color for distinguishing the regions of objects in an image. The author offers a k-means clustering-based method for classifying and identifying diseases.

For classifying fruit and illness, many samples have been taken and used in the algorithm of segmentation. The image is first captured, the impacts of the fabrication hardware are eliminated during preprocessing, and the image is then segmented with the use of a segmentation algorithm. In order to classify images, feature extraction is completed and after that fitted with training data sets.

The cited papers have all been thoroughly examined [15].

Those publications provided a wealth of information about the selected subject and the several suggested algorithms. The basic foundation construct can thus usually be found near the top of the aforementioned works. And as a result, the most recent DL achievements were changed.

MATERIALS AND METHODS

Figure 2 shows the overall model for the suggested method.

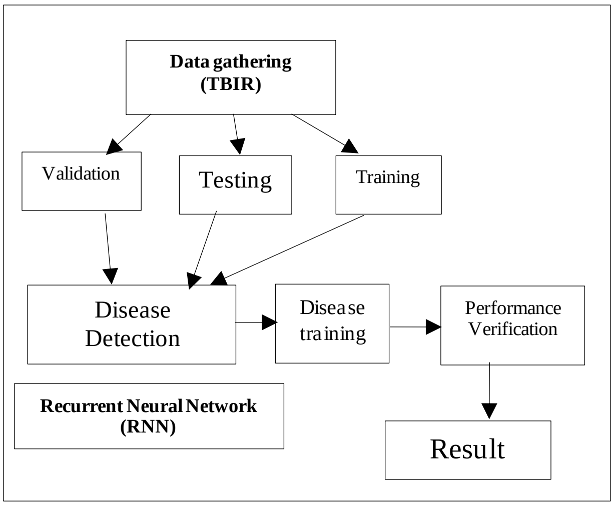

Figure 2. The Suggested model

A. Texture Based Image Retrieval (TBIR)

The process begins by extracting the basic features from a query image and comparing them to the ones from a data-base. The features in question are texture-based attributes for images. Texture characteristics of an image are therefore matched and compared to corresponding characteristics of a different image with the use of comparison and matching algorithms [5]. The entropy, energy, and contrast qualities of an image are used to accomplish this comparison. In order to access database images that match the query, these traits are ultimately extracted one by one. Algorithms are used for both feature matching and feature extraction, one for each characteristic of the features, to determine how similar they are [2].

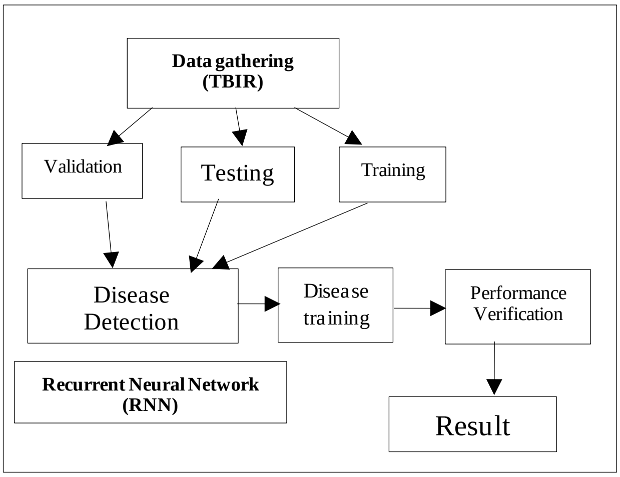

Figure 3. Flow chart of Texture Based Image Retrieval.

B. Recurrent Neural Network (RNN)

The RNN is mostly used for predicting the future data sequence using samples from the previous data. The RNN is frequently utilized when modeling sequences of data, like text or speech. Those networks haven't been widely deployed since it's thought to be challenging to train them in a way that effectively captures long-term dependencies [3].

Taking under consideration input sequence $x = (x_1, \ldots, x_T)$, a standard RNN calculates hidden vector sequence $h = (h_1, \ldots, h_T)$ and output vector sequence $y = (y_1, \ldots, y_T)$ through the iteration of the equations below for t = 1 to T:

$$h_t = H\,(W_{xh}x_t + W_{hh}h_t - 1 + b_h) \quad (1)$$

$$y_t = W_{hy}h_t + b_y \quad (2)$$

where W terms represent the matrices of weight (for example, W_{xh} represents input hidden weight matrix), b terms denote bias vectors (for example b_h represents hidden bias vector) and H represents hidden layer function. H is typically an elementwise application of sigmoid function. However, it has been found that LSTM architecture [11], using purpose-built memory cells for information storage, is better at the finding and exploitation of long range context. For LSTM version that has been utilized in the present study [6]

H has been implemented by the following composite function:

$$i_t = \sigma\,(W_{xi}x_t + W_{hi}h_t{-}1 + W_{ci}c_{t-1} + b_i) \quad (3)$$

$$f_t = \sigma\,(W_{xf}\,x_t + W_{hf}\,h_{t-1} + W_{cf}\,c_{t-1} + b_f\,) \quad (4)$$

$$c_t = f_t c_{t-1} + i_t \tanh\,(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (5)$$

$$o_t = \sigma\,(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \quad (6)$$

$$h_t = o_t \tanh(c_t) \quad (7)$$

where σ represents logistic sigmoid function, and i, o, f, and c respectively represent input gate, output gate, forget gate, and cell activation vectors, all of which are of a similar size as the hidden vector h. Weight matrices from cell to gate vectors (for example W_{si}) are diagonal, so element m in every one of the gate vectors only receives input from element m of cell vector.

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RESULTS AND DISCUSSION

When determining the disease condition of different Olive leaves from the image set, RNN classifiers were assessed using (column chart). The results of this assessment are displayed in Figure 4. System for disease detection and diagnostic accuracy is shown in Table 1 below. Due to the visible psychopathological symptoms and the ease of caution, Peacock stains or olive leaves stains sickness is producing the highest accuracy level with a yield of 97.55%. The next most correctly classified condition is frenulum wilted, with a yield of 86.84%; all other conditions are categorized as falling between 81 and 88 percent. According to the identified levels of accuracy, it is thought that this model is producing data with higher level of accuracy when compared to a standard back propagation network, which produces data with an accuracy of 83% for the Rapid Deterioration Disease.

Table 1. Accuracy of disease detection diagnosis system.

	Peacock stains	Frenulum wilted	Rapid deterioration	Acc.
Peacock stains	2	89	0	89.8
Frenulum wilted	124	2	0	
Rapid deterioration	0	0	94	
	97.55	86.48	85.31	

*Acc.: Accuracy

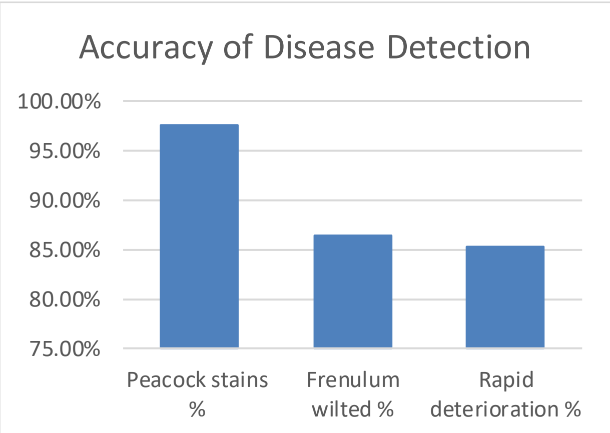

Figure 4. Accuracy of Disease Detection

CONCLUSIONS

This method dramatically reduces computational complexity that is needed to use a conventional NN. Because the RNNs have a high level of internal failure adaption, they can use incomplete or ambiguous foundation images, which significantly increases the accuracy of image recognition. The findings of the current study highlight the potential for using RNNs in the identification and evaluation of Olive's plant diseases, which can significantly increase disease recognition for Olive's ranch. Horticulture. Future tests may use the current approach in practice. The suggested model was used in our subsequent research to distinguish between additional yield diseases, such as those affecting mulberry and tomato leaves. Yet, in light of the unique circumstances surrounding the condition, this must be further examined.

Figure 5. disease detection output

Disclosure and Conflict of Interest: The authors declare that they have no conflicts of interest.

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