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Detection and Classification of Tomato Leaf Diseases Using DWT Algorithm with other Algorithms

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الكشف عن أمراض أوراق الطماطم وتصنيفها باستخدام خوارزمية DWT مع خوارزميات أخرى

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Abstract:
One of the most efficient strategies to stop the tomato plant disease's progress is to detect tomato plant infections. In this research, it was research to use the Principal Component Analysis (PCA) and Discrete Wave Transformation (DWT) algorithms to extract the characteristics of tomato leaf images from a database compiled from the (Kaggel) consisting of 1000 images. These images were divided into ten categories depending on the type of the disease: bacterial spot, target spot, mosaic virus, late blight, leaf rot, yellow leaf curl virus, spider spot mites, early blight, spot Septoria virus, and healthy. Where Support Vector Machine technology is used to categorize these attributes. where 70% of them were used for training, and 30% for testing. The final results of the accuracy obtained from the experiments of using the research mode is (92.33%).

Keywords: SVM, DWT, PCA, Detection, Classification, Tomato Leaves, Diseases.

الملخص:
يُعدّ الكشف عن أمراض نبات الطماطم إحدى الطرق الفعّالة للحدّ من انتشار المرض. في هذا البحث، تمّ استخدام خوارزميتي تحليل المكونات الرئيسية *(PCA)* وتحويل الموجة المنفصلة *(DWT)* لاستخراج خصائص صور أوراق الطماطم من قاعدة بيانات مُجمّعة من *(Kaggel)* مُكوّنة من 1000 صورة. قُسّمت هذه الصور إلى عشر فئات تبعًا لنوع المرض: البقعة البكتيرية، البقعة المُستهدفة، فيروس الفسيفساء، اللفحة المتأخرة، تعفّن الأوراق، فيروس تجعد الأوراق الأصفر، سوسة العنكبوت، اللفحة المبكرة، فيروس البقعة السبتورية، والصحية. حيث تمّ تصنيف هذه الخصائص باستخدام تقنية آلة المتجهات الداعمة. حيث استُخدم 70% منها للتدريب، و30% للاختبار. بلغت النتائج النهائية للدقة التي تم الحصول عليها من تجارب استخدام أسلوب البحث (92.33%).

الكلمات المفتاحية: *SVM*، *DWT*، *PCA*، اكتشاف، تصنيف، أوراق الطماطم، امراض.

Introduction

Tomato is one of the most caring foods in Libya, and it is popularly used for both Business and fast food and home use purposes. There is a vast potential for the internal market for domestic fresh tomato fruit, primarily in densely populated urban areas and the processing industries in the foreign market. It is one of the world's most important vegetables, with a total area and production of 4.4 million ha and 115 metric tons, respectively [1]. As it is a relatively short-duration plant with a high yield, it is economically attractive, and the area under cultivation is increasing daily. Its position in the world is after potatoes both in area and in production.

Diseases of plants are a major cause of plant damage and, consequently, agriculture and economic losses. Timely identification of plant disease is critical to make harvest healthy and fruitful. The experts' visual observation is the most common approach for identifying plant diseases. However, this approach can be time-consuming or challenging due to a need for more experts at the cultivation sites. Image processing methods can be effective for the continuous monitoring and detection of plant diseases [2-9].

In addition, "Plant disease is an impairment of the normal state of the plant that interrupts or modifies its vital functions" [3,10]. Several types of plant diseases could cause several losses to the production of crops. The presence of the pathogen depends on the favorable environmental conditions and varieties of crops grown, which is the reason for the occurrence and prevalence of plant diseases. Various plant disease management programs will help reduce yields and grain quality losses. An automatic plant disease recognition and diagnosis system can design by using image processing and pattern recognition techniques [2, 4,11-15].

Various abnormality states are present on the plant leaf, which can be identified by manual inspection. Image processing and pattern recognition techniques are valuable in converting manual processes to automate the process. The automatic diagnosis system based on plant disease features reduces the dependency on experts in the area concerned [5]. With its great commercial value and widespread production, the tomato crop is a vital staple in the Libyan market. Plant diseases have a negative impact on the health of the plant and hinder its growth. Monitoring the cultivated crop's growth is essential to ensuring that it suffers as few losses as possible. The crop's leaves are the target of several tomato disease types.

While skilled eye observation is the main method used to detect and identify plant diseases, it necessitates ongoing expert monitoring, which can be costly and difficult, particularly in big farms. As a result, it is essential to assist farmers in automatically identifying disease symptoms by analyzing digital photos as soon as they emerge. Computer-based applications have been developed with the goal of reducing primary production and economic losses, guaranteeing the amount and quality of agricultural products, and decreasing the use of agrochemicals. These applications have demonstrated excellent efficacy. Numerous of these applications concentrate on identifying diseases in different cultivars, like cotton, by looking for symptoms in the foliage [6,7], rice [8] ,cotton [11],pea [12].Thus, this paper discusses the use of the detection model to recognize tomato leaves diseases. Due to the evolution in human life, it has become necessary to made up an accurate, easy and inexpensive diagnostic system for plant diseases [13,16,17].

Research Methodology and Design

This Chapter introduces the methodologies used to conduct this thesis, briefly discussing materials and tools used, the selection of the appropriate model for classification, the architectural design of the research model, and evaluation techniques. It deals with the methodological analysis of diagnosing tomato leaf diseases from healthy and infected tomato leaf images from the tomato plant and preparing the necessary data set using different mechanisms. Then this chapter shows the design of an SVM model to detect and classify the disease, train and test the model, and finally, evaluate the effect of learning parameters.

Research Algorithm Methodology

To deploy SVM for classification and to compute the color features for a given image, the following steps are used:

1. Reading RGB tomato leaf image of the dataset obtained from (Kaggle) web consists of 1000 Tomato leaf images.
2. RGB image converted into HSV color spaces and grayscale for feature extraction.
3. The SVM algorithm uses these features for training and testing.
4. The tomato leaf images are classified in the testing phase into ten classes.

Research Algorithm Design

The research algorithm design consists of three stages: conversion, feature extraction, and classification. More Features were used to increase the system's quality for the research system design with PCA and DWT, as shown in Figure (1).

DATASET AND EXPERIMENTATION

Our model was constructed using a dataset of plant health photos; 1000 tomato leaf photos were utilized for training and testing, and a system capable of diagnosing tomato diseases was then created. The tomato leaves with the most prevalent disease types are depicted in Figure (2) below, and Table (1) lists the image numbers for each class. We tested our system using a few test image examples, where the outcomes of our disease recognition vary from one ailment to the next. For instance, the

tomato sample in Figure (3) and the mosaic virus sickness the results in the below Table (3) both had precision measures of 96.42 when compared to other diseases.
The wide variation in appearance amongst diseases is the cause of the wider disparity. The precision, recall, F-measure, and accuracy curves of that SVM model are shown in Figure (4) as histogram shapes. in Table (3), we show that our model, which combines DWT, PCA, and SVM, produces encouraging results on tomato illnesses. The classification Accuracy for all classes was 92.33.

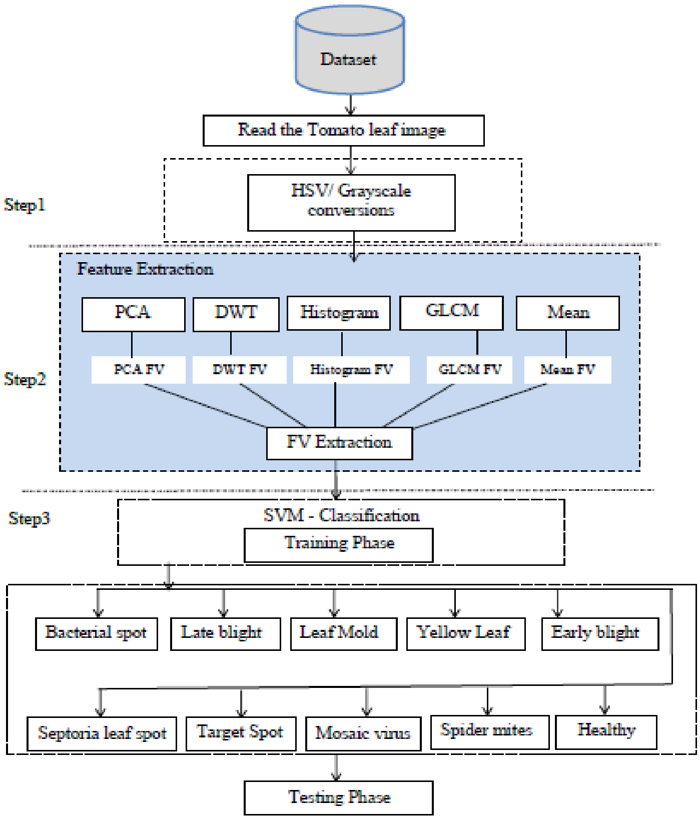

Figure 1: Diagram of the Research system by using PCA and DWT.

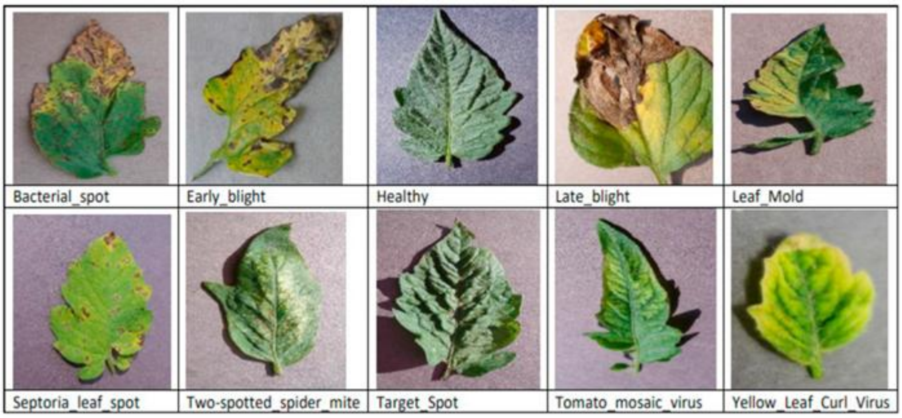

Figure 2: Tomato leaves with diseases.

Table 1: Dataset of tomato leaves images.

	Percentage	Bacterial spot	Late blight	Leaf Mold	Yellow Leaf Curl Virus	Early blight	Septoria leaf spot	Target Spot	Mosaic virus	Spider mites	Healthy
Training	70%	70	70	70	70	70	70	70	70	70	70
Testing	30%	30	30	30	30	30	30	30	30	30	30
Total	100%	100	100	100	100	100	100	100	100	100	100

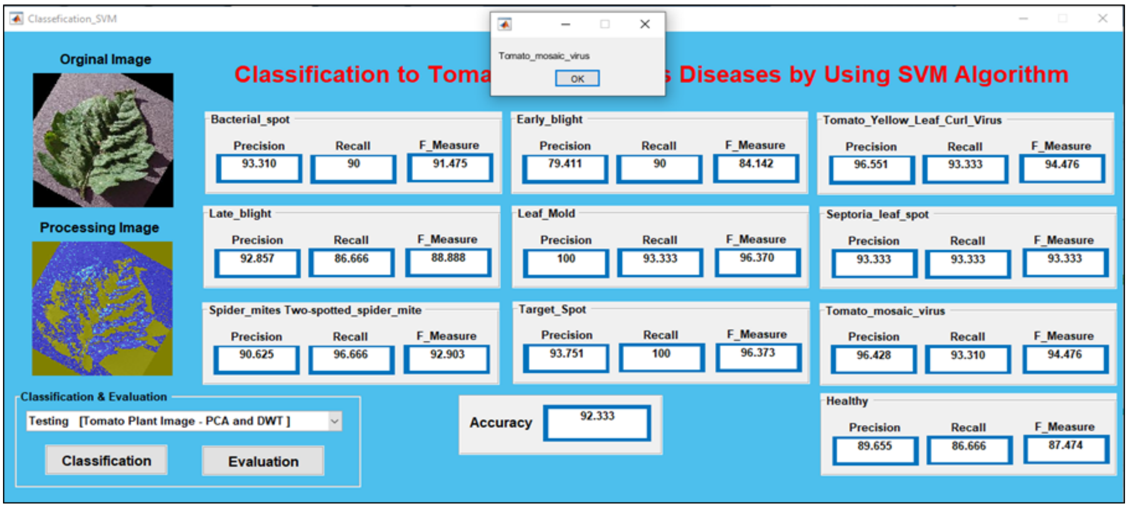

Figure 3: Tomato sample test image with predicted and expected results.

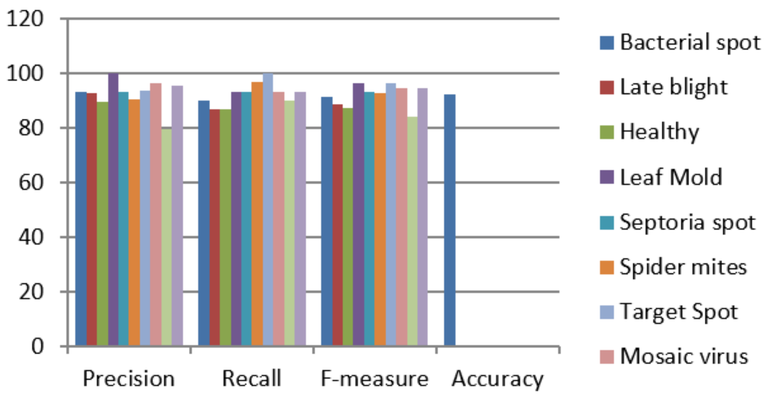

Figure 4: SVM Performance evaluation with PCA and DWT by using histogram shape.

The Results Classification

The classifier SVM was used to classify Tomato leaf images (Bacterial spot, Late blight, Healthy, Leaf Mold, Septoria leaf spot, Spider mites, Target Spot, Mosaic virus, Early blight and Yellow Leaf Curl Virus.) in classifying the data collecting in a dataset of Tomato leaf. The proposed algorithm was used to extract the features of Tomato leaf images. The proposed system also used the algorithms GLCM, Mean and Histogram with the proposed algorithm to improve system efficiency and results. U The classification results were extracted as values and distributed on the confusion matrix for ten classes as presented in Table (2):

Table 2: Confusion matrix to classification with PCA and DWT.

Predicated Label

Actual Label	Bacterial spot	Late blight	Healthy	Leaf Mold	Septoria spot	Spider mites	Target Spot	Mosaic virus	Early blight	Yellow Leaf Curl Virus
Bacterial spot	27	0	03	0	0	0	0	0	0	0
Late blight	0	26	0	0	0	0	0	1	3	0
Healthy	02	0	26	0	0	0	0	0	02	0
Leaf Mold	0	0	0	28	0	01	01	0	0	0
Septoria spot	0	0	0	0	28	0	0	0	02	0
Spider mites	0	0	0	0	0	29	0	0	0	01
Target Spot	0	0	0	0	0	0	30	0	0	0
Mosaic virus	0	02	0	0	0	0	0	28	0	0
Early blight	0	0	0	0	01	01	01	0	27	0
Yellow Leaf Curl Virus	0	0	0	0	01	01	0	0	0	28

SVM Performance Evaluation

The system's performance is measured using quantitative metrics such as Precision, Recall, F-measure, and Accuracy [14]. The following are examples of calculating Measures by using matrix terms for Bacterial spot tomato leaf images with PCA and DWT as shown in Table 3.

$$\text{Precision} = \frac{TP_i}{TP_i + FP_i} \times 100 \qquad = 27/(27+02) \times 100 = 93.103\%$$

$$\text{Recall} = \frac{TP_i}{TP_i + FN_i} \times 100 \qquad = 27/(27+03) \times 100 = 90\%$$

$$\text{F-measure} = \frac{2 \times precison \times recall}{precision + recall} \qquad = 02\times 93.1 \times 90/(93.103+90) = 91.47\%$$

The Accuracy for all classes is:

$$\text{Accuracy} = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} TP_i + \sum_{i=1}^{n} FP_i} \times 100$$

$$= 27+26+26+28+28+29+30+28+27+28/300$$

$$= 0.9233 \times 100$$

$$\text{Accuracy} = 92.33\%.$$

Table 3: SVM Performance evaluation with PCA and DWT.

Type of diseases to tomato leaf	Measures			Accuracy
	Precision	Recall	F-measure	
Bacterial spot	93.31	90	91.47	92.33
Late blight	92.85	86.66	88.88	
Healthy	89.65	86.66	87.47	
Leaf Mold	100	93.33	96.37	
Septoria spot	93.33	93.33	93.33	
Spider mites	90.62	96.66	92.90	
Target Spot	93.75	100	96.77	
Mosaic virus	96.42	93.31	94.47	
Early blight	79.41	90	84.14.	
Yellow Leaf Curl Virus	95.55	93.33	94.47	

The performance evaluation of the Support Vector Machine (SVM) classifier using PCA and DWT, as shown in Table 3, indicates that the model achieved a strong overall accuracy of 92.33% with balanced results across precision, recall, and F-measure. The classifier performed exceptionally well in detecting diseases such as Leaf Mold, Target Spot, Mosaic Virus, and Yellow Leaf Curl Virus, where both precision and recall were consistently high, reflecting the effectiveness of PCA and DWT in extracting discriminative features. Clearly, Leaf Mold achieved perfect precision (100%) and a high F-measure (96.37), while Target Spot reached perfect recall (100%) with a strong F-measure (96.77), highlighting the model's reliability in identifying these disease categories. Similarly, viral infections like Mosaic Virus and Yellow Leaf Curl Virus showed robust classification performance with F-measures above 94%. However, the model exhibited relatively lower performance in classifying Healthy leaves (F-measure = 87.47) and Early Blight (F-measure = 84.14), where reduced precision suggests possible overlaps with other categories or misclassification due to similar leaf symptoms. These variations imply that while the model is highly effective for most diseases, further refinement is needed to reduce false positives in certain cases. Overall, the results demonstrate that the integration of PCA and DWT with SVM is a powerful approach for tomato disease detection and offers significant potential for practical application in agricultural disease monitoring, though improvements in differentiating visually similar classes remain important.

Discussion

In the Implementation phase, the efficiency of detection and classification for Tomato leaf using PCA and DWT algorithms to create features vectors for classification by SVM. The proposed approach's performance was evaluated using several measures: Accuracy, Precision, Recall, Specificity, and F-measure. Based on the analysis of the results of the algorithms with PCA, DWT, the most important results were:

- Accuracy: when using (PCA) and (DWT) it was (92.33%). Regarding the detection of BMD, the percentages of all measures were as follows: when using (PCA) and (DWT), the Precision was

(93.31%). For the Recall, it was (90%) when using (PCA) and (DWT). The percentage of the (F-measure when using (PCA) and (DWT) was (91.47%).

- For the detection of late blight, the percentages of all measures were as follows: Precision, when using (PCA) and (DWT) was (92.85%). Sensitivity (Recall) when using (PCA) and (DWT) was (86.66%). The percentage of the (F-measure) was (88.88%) when using (PCA) and (DWT).
- To detect the Healthy leaves, the percentages of all scales were as follows: when using (PCA) and (DWT) the Precision was (89.65%). The Recall was (86.66%) when using (PCA) and (DWT). For the percentage of F-measure, it was (87.47%) when using (PCA) and (DWT).
- For the detection of leaf Mold in tomato leaves, the percentages of all measures were as follows: The Precision was (100%) when using (PCA) and (DWT). Also, the recall was (93.33%). Similarly, the percentage (F-measure) was (96.37) when using (PCA) and (DWT).
- As for the detection of Septoria virus spot disease in tomato leaves, the percentages of all measures were as follows: when using (PCA) and (DWT) the Precision was (93.33). The percentage of Recall when using (PCA) and (DWT) was (93.3%). The percentage of the scale (F-measure) when using (PCA) and (DWT) was (93.33%).
- For the detection of spot spider mite disease, the percentages of all measures were as follows: when using (PCA) and (DWT) the Precision was (90.62). The Recall was (96.66 %) when using (PCA) and (DWT). The percentage of the scale (F-measure) when using (PCA) and (DWT) was (92.90%).
- When detecting target macular disease, the percentages of all measures were as follows: Precision when using (PCA) and (DWT) was (93.75%). As for the Recall, it was (92.85%) when using (PCA) and (DWT). The percentage scale (F-measure) was (96.37%).
- For the detection of leaves with mosaic virus disease in tomato leaves, the percentages of all measures were as follows: when using (PCA) and (DWT) the Precision was (96.42%). The rate of Recall when using (PCA) and (DWT) was (93.31%). The percentage of the F-measure when using (PCA) and (DWT) was (94.47%).
- Regarding the detection of disease and early blight, the percentages of all measures were as follows: when using (PCA) and (DWT), Precision was (79.41%). The Recall was (90%) when using (PCA) and (DWT). The percentage of the F-measure was (84.14%) when using (PCA) and (DWT).
- When detecting yellow leaf curl virus disease in tomato leaves, the percentages of all measures were as follows: when using (PCA) and (DWT) the Precision was (95.55). The percentage of Recall was (93.3%) when using (PCA) and (DWT).The percentage of the F-measure when using (PCA) and (DWT) was (94.47 %).
- Mindful of the above, the results evidenced that the proposed system is more effective in classifying tomato leaf images when using PCA and DWT algorithms to extract features.

Conclusion

In this research, the efficiency of detection and classification for Tomato leaf as Bacterial spot, Late blight, Healthy, Leaf Mold, Septoria leaf spot, Spider mites, Target Spot, Mosaic virus, Early blight and Yellow Leaf Curl Virus is analyzed using PCA, DWT algorithms to created features vectors to be used classification by SVM. The performance of the research approach was evaluated using several measures: Accuracy, Precision, Recall, Specificity, and F-measure.

During the analysis and comparison of the results of the algorithms with PCA and DWT, the most important results were:

The efficiency and accuracy of the research system were measured by comparing the results with and without the two research techniques. Several measures were used, namely: Accuracy, Precision, Recall, and F-measure, and by analyzing and comparing the system results. Using the research techniques and without them, where the most important results were: Accuracy when using (PCA) and (DWT) is (92.33%), while the accuracy without using (PCA) and (DWT) is (88.66%).

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