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Image processing based system for the detection, identification and treatment of tomato leaf diseases.

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Abstract

Disease detection and treatment in tomato plant at its early stage contributes towards better production. It is a natural phenomenon that normally tomato plant got disease and if a proper care and remedial action have not taken on time, it badly affects the respective product quality, quantity or productivity. Health monitoring and disease detection of leaves in tomato crop is very critical and if left untreated, can cause serious problems with the plant and fruit, resulting in large losses, especially in fresh markets. Traditional manual methods of disease detection and treatment is based on naked eye observation which cannot provide accurate and on time information at a very early stage of its attack. This paper presents an image processing based techniques for the automatic detection and treatment of leaf diseases in tomato crop. In the proposed method, 13 different statistical features are calculated from tomato leaves using Gray Level Co Occurrence Matrix (GLCM) algorithm. The obtained features are classified into different diseases using Support Vector Machine (SVM). The processed leaf is compared with the stored features on the basis of which disease is recognized. Data are collected from local tomato crop fields and the dataset is divided into a training set and a test set used in the experiments. Experimental results show that the proposed method provides excellent annotation with accuracy of 100% for healthy leaf, 95% for early blight, 90% for septoria leaf spot and 85% late blight. The proposed method is implemented in the form of a cell phone application.

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Keywords Image processing · Tomato crop · Leaf diseases · Early blight, late blight · Septoria leaf spot

1 Introduction

Tomato is an important vegetable enriched with minerals, vitamins, fibers and amino acid [6]. Researchers have proven that tomato is useful in minimizing cancer risk [14]. It is an important cash crop and gives handsome yield. On a global scale, the annual production of fresh tomatoes accounts for approximately 159 million tons, more than a quarter of those 159 million tons are grown for the processing industry, which makes tomatoes the world's leading vegetable for processing [19].

Tomato fruit diseases have always been a complex issue in agricultural production and one of the main factors confining the sustainable development of agriculture. Among others, tomato leaf diseases severely distress plant development and yield Tomato leaf diseases consist of numerous symptoms. Traditional methods for the detection and identification of leaf diseases are difficult, costly and required a large team of experts as well as continuous monitoring of plant. Nevertheless, in several developing countries, farmers do not have proper facilities or even idea that they can contact to experts. Due to which consulting experts even cost high as well as time consuming too [12]. Farmers mostly adopt the traditional approach by cutting leaves or branch from their field and take it for diseases identification and treatment to the expert. Expert mostly rely on naked eye observation for disease identification which is more laborious task and at the same time, less accurate and can be done only in limited areas. This practice of farmer leads to more complications in term of diseases because farmers are mostly in rural areas and it takes time due to which the cut leaf or stem shows others symptoms than other they have.

Efforts have been made by various researchers to adopt image processing techniques for the detection of diseases in the plant leaf. Software solution for the detection and classification of plant leaf and stem diseases was proposed by [2]. In the proposed approach, classification of statistical features were carried out on the basis of classifiers. The proposed technique is robust and can detect and classify the disease with precision between 83% and 94%. [1] proposed an approach for the classification and recognition of plant species. In this approach, different classifiers were used for the classification purpose. A software based solution for chili crops diseases was proposed by [13]. In this approach, healthy, risky and high risky leaves were recognized. The recognition results of the proposed system were about 93.3% for 120 different chili images. [16] proposed an algorithm for disease detection in soybean and tomato. The proposed algorithm identifies disease by calculating the percentage of the affected area.

Another method for the detection of late blight disease in tomato crops was proposed by [4]. In this method, K-means clustering algorithm was used and the accuracy of the proposed system was 84%. [18] presents the concept of Gabor Wavelet Transform technique for features extraction along with Support Vector Machines in tomato crop. For disease identification, Kernel functions were used and the accuracy of the system was 99.5%. Pattern recognition approach was proposed by [9] for the vegetable crops diseases. The proposed algorithm is based on three steps i.e. segmentation, feature extraction and classification. About 300 images of three different crop diseases were tested for which the recognition rate was 95.3%. [24] proposed an algorithm for the automatic detection and classification of leaf diseases. The proposed system used genetic algorithm for segmentation. The algorithm was tested on different plants leaves, obtained results were good and useful for diseases detection at initial stages. (M. Z. [8]) proposed an image processing framework for plant disease identification and classification. The proposed framework consists of three stages such as images segmentation, feature extraction and classification. For segmentation multithresholding were used. GLCM was used for feature extraction and Support Vector Machines for classification. Experiments were conducted on Tomato leaf dataset that comprising of 4 different classes. The overall average accuracy of the proposed framework was 98.3% with 10- fold cross validation. [5] in the proposed system random forest and decision tree classification algorithms were used for leaf disease classification Color histograms, Hu Moments, Haralick and Local Binary Pattern features are used for training and testing purpose. Based on the experiments conducted, it showed that the random forest classifier is more accurate than decision tree classifier. The classification accuracy is 90% for decision tree classifier and 94% for random forest classifier respectively.

For plant disease diagnosis (X. [17]) investigate the visual plant disease recognition system. In the proposed system, a new large-scale plant disease dataset with 271 plant disease categories and 220,592 images was developed. Based on this dataset, the authors tackle plant disease recognition via reweighting both visual regions and loss to emphasize diseased parts. Extensive evaluations on the dataset and another public dataset demonstrate several advantages of the proposed method. The proposed system provide new research dimensions for plant disease recognition in the community of image processing.

In this paper, an automatic image processing based system is proposed in which the farmer capture image of tomato leaf through an android application named Leaf Disease Identification system (LDI) and send the captured image to a server where image processing based techniques are applied to the image. The input image is first segmented and then 13 different statistical features are extracted from the segmented image using Gray Level Co-occurrence Matrix (GLCM). The extracted features are classified into different diseases by using Support Vector Machine (SVM) algorithm as a classifier. A database consists of extracted features is created and the input image features are compared with the stored extracted features. The disease is recognized by comparing the features of the input image features with the stored extracted features. In this way disease is detected, identified and remedy is prescribed. Farmer is informed instantly through back notification about the status of crop through android application (LDI). To demonstrate the computational efficiency and accuracy of the proposed approach, extensive experiments were performed. The obtained results show that accuracy of the proposed system is 100% for healthy leaf identification and classification, 95% for early blight, 90% for septoria leaf spot and 85% late blight. The proposed approach is also robust, reliable and will help plant pathologists to properly diagnose tomato diseases.

The potential contributions of this paper include: Automatic detection and recognition of leaf related diseases in tomato crop. This will facilitate advancements in tomato crop by providing rapid, cost-effective and reliable monitoring system. Moreover, the proposed system will provide on the spot solution to the farmer and will lessen a huge labor of monitoring the large farms of crops, at a very early stage of its attack.

This paper is organized as follow: section 2 provide the proposed method, experimental results are discussed in section 3. Section 4 provide summary of the paper and future directions.

2 Material and methods

The proposed method consists of different steps. These steps include image acquisition, preprocessing, segmentation, feature extraction, classification and notification. The proposed approach begins with acquiring and collecting digital images from different tomato fields. Pre-processing is used to improve the quality of the images and to make the feature extraction phase more reliable. Pre-processing is performed by image-processing techniques such as leaf image cropping, image resizing and image enhancement. After preprocessing the image is segmented for further processing. Segmentation is performed using Otsu segmentation techniques. In feature extraction phase, 1560 texture-based features have been extracted, and are stored in a database. After features extraction, image is classified is either healthy or disease one. In the final stage, the farmer is informed back about the status of the crop along with remedy (in case of diseases). These phases are described in detail in the following subsections and depicted in Fig. 1.

A. *Image Acquisition*

This is the first step in the proposed Leaf Disease Identification system (LDI). In image acquisition, images are selected carefully in order to achieve the intended task. The dataset used in experiments is constructed from sample of healthy and infected tomato leaves having three diseases early blight, late blight and septoria leaf spot. The dataset were collected from different tomato fields in Nagri Payeen, Lower Dir, Khyber Pakhtunkhwa, Pakistan. Image acquisition was performed through capturing images by using an android based digital camera. The proposed android based Leaf Disease Identification system (LDI) is shown in the Fig. 2. Figure 3 shows sample of diseased and healthy tomato leaves while the detail of captured images is depicted in Table 1.

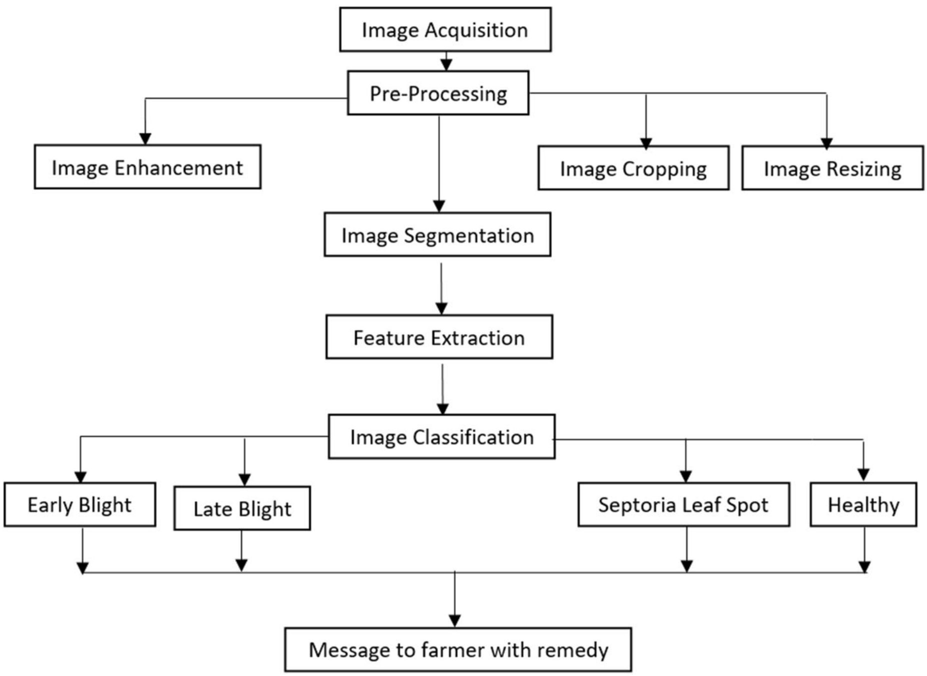
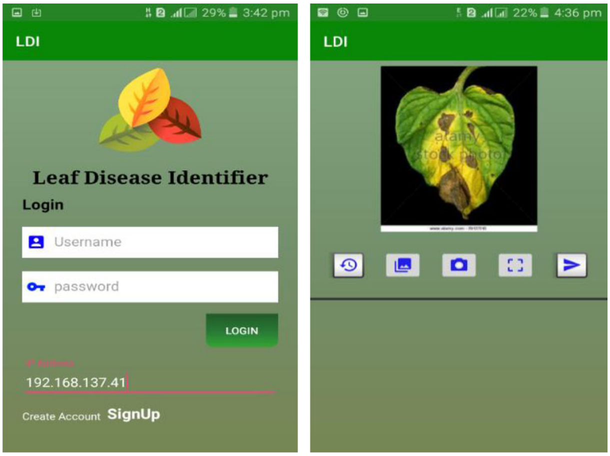


Fig. 1 Layout of the proposed Leaf Disease Identification system



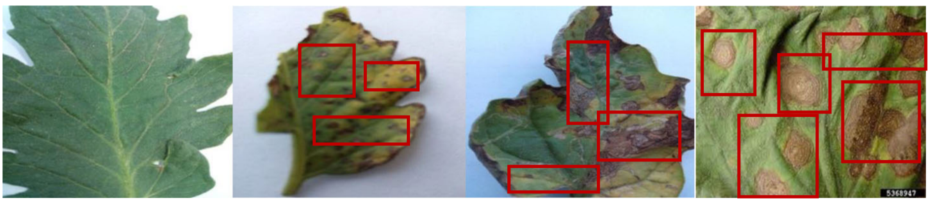
(a) (b)

Fig. 2 **a** Represent Android Application Interface **b** shows image captured through android application

B. *Image Pre-Processing Phase*

Image pre-processing is carried out to bring the image at the lowest level of abstraction. The task of preprocessing is to improve the image data and to enhance some of the image features which is important for further processing. In the proposed system, image pre-processing is carried out to refine the image for further analysis. The process include image cropping, image resizing and image enhancement.

Image cropping refers to the removal of image unwanted parts and to select region of interest. In other words, it refers to removing unwanted areas from a captured image. This is needed in the system in the part of the disease detection. Image cropping is performed through android application camera which cropped the image and select the region of interest. After cropping, the image is resized with a standard size. Since the input images may be of different size, initially, captured images were resized to 512 × 512 resolution. The purpose is to utilize the storage capacity and to reduce the computational time in the later processing. In the third step, image enhancement is carried out for processing the given input image so that the output image is more suitable and informative than the input image. The Image enhancement is carried out to elaborate the hidden information and to refine the region of interest in image.



(a) (b) (c) (d)

Fig. 3 Some tomato leaf samples with different characteristics: **a** Healthy leaf. **b** Septoria leaf spot. **b** Late blight. **d** Early blight. The diseased parts are annotated by red boxes

Table 1 Sample of images for the proposed system

S. No	Sample Images	Quantity
1	Healthy	100
2	Early Blight	100
3	Late Blight	100
4	Septoria Leaf Spot	100

C. *Image Segmentation*

Segmentation is partitioning a digital image into multiple segments and the basic purpose is to simplify the representation of an image into something that is more meaningful and easier to analyze [22]. Image segmentation is typically used to locate objects and boundaries such as points, lines, edges and regions in images. Segmentation plays an important role in image processing since separation of a large image into several parts makes further processing simpler. It makes the image simple, informative and easy to understand [25]. In segmentation step the region of interest is extracted from the image. In the proposed system, Otsu segmentation techniques were used because of its simplicity and effective global thresholding [25]. Developed by [20] Otsu segmentation is a global thresholding selection method and it depends on the gray value of the image. It is widely used because of its simplicity and effectiveness.

D. *Features Extraction*

After segmentation, feature extraction is performed. The purpose is to represent image on a vector of fixed features. In the features extraction step, the image data is converted into meaningful form. The image consists of different features such as shape, texture and color [16]. Statistical texture feature technique is used in the proposed system because of its capability for separating leaves into different classes of diseases. Statistical texture features can be classified into first order and second-order. In the prior order, features of every pixel are calculated and the neighbor relationship of the pixels are ignored. In the second one, the neighbor relationships among pixels are considered. The example of second order is Gray Level Co-Occurrence Matrix (GLCM) [3].

In the proposed system, the concept of GLCM is used for feature extraction. In GLCM, number of rows and columns are equal to the number of gray levels in the given image. The concept of GLCM was proposed by Haralick (Haralick, R.M. and K. Shanmugam). The features of GLCM are helpful in texture features recognition [26], image segmentation [23], image retrieval [15], color image analysis [], image classification [7], object recognition [10], and texture analysis methods [21]. 13 attributes of texture based on GLCM were used in the proposed work including, mean, median, mode, standard deviation, entropy, contrast, correlation,energy, homogeneity, skewness, variance, smoothness, inverse difference moment (IDM). The extracted statistical features for sample training image is shown in Table 2. In the Table, details of images for feature extraction are shown.

E. *Image Classification*

In the proposed system, Support Vector Machine (SVM) is used to test the performance of the proposed system for identification of the category of diseases that infect the tomato leaves. The

Table 2 Sample of images used for feature extraction

S. No	Quantity of sample of leaf for feature extraction	Total features extracted for each category	Nature of leaf
1	30	30*13 = 390	Healthy
2	30	30*13 = 390	Early Blight
3	30	30*13 = 390	Late Blight
4	30	30*13 = 390	Septoria Leaf Spot

inputs of this phase are training dataset features and their corresponding classes, whereas the outputs are the decision that determines type of disease that infected the tomato leaf along with remedy. Database was created from the extracted features of 30 healthy and 30 each disease tomato leaf images.

The images are categorized as disease and healthy. The images are labeled with the name of the disease they have and are stored with the name Train_Label. The images are pre-processed and extracted statistical features are stored with name Train_Feat. There are 120 rows and each row has 13 columns which consists of 120 samples such as 30 from each class and the 13 columns representing different statistical features extracted from particular image. Train_Label file consists of one row and 120 columns, the row has a numbered from 1 to 120, which represents the disease type allocated to it. In this allocation, '1–30' columns is assigned '0' which represents Early Blight, '31–60 is assigned '1' represents Late Blight,'61–90′ is assigned '2' represents Septoria Spot and '91–120′ is assigned '3' represents Healthy Leaf. Table 3 shows the images label and the disease assign to each label. A supervised learning method (SVM) is used for the identification of the class of the image and for the identification of the image K-nearest neighbor algorithm is used. The image is masked through Otsu thresholding techniques and the affected area is separated from the leaf.

SVM is used for classification of diseases. For this purpose the feature values are passed to the classifier for comparing values already stored in the database. For the classification of diseases texture analysis has been adopted. The segmented RGB image is converted to gray scale image. The texture values of the segmented image are calculated using GLCM.

3 Experiment and results

The datasets used for experiments were constructed based on real sample images of tomato leaves. These dataset were collected from different tomato fields in Dir, Pakistan. These images were captured using android based mobile camera with high resolution in the JPEG format. The used dataset consisted of one healthy and three infected categories. The diseased

Table 3 Images label with name of the disease they have

S. No	Label Assign to each class of disease	Class represent disease	Name of disease assign to each class
1	1–30	0	Early Blight
2	31–60	1	Late Blight
3	61–90	2	Septoria Leaf Spot
4	91–120	3	Healthy

leaves include early blight, late blight and septoria leaf spot. The algorithm was implemented in Matlab and tested on a laptop with Intel(R) Core (TM) i3 CPU 2.40 GHZ with 4 GB of RAM. Total 400 tomato leaf images were captured. Out of these 400 image, 120 images were used for training and 280 for testing. The proposed approach has been implemented considering the following steps: The approach started with image preprocessing phase. In preprocessing phase the input image is prepare for further processing. In preprocessing phase the image was cropped, image cropping is performed through android application as shown in Fig. 4.

After cropping the images were resized to 512× 512 resolutions followed by image enhancement an order to elaborate the region of interest in image, the Image enhancement is shown in Fig. 5.

After pre-processing the images were segmented by using Otsu segmentation techniques. This step consists of converting RGB images into binary formats, separation of color spots and eature extraction from gray scale images. Figure 6 shows the segmented images.

After segmentation statistical features were extracted from the images using Gray Level Co-Occurrence method (GLCM). For training purpose 13 different statistical features were extracted from 120 images, each 30 images for healthy and for diseased, the details of extracted features is depicted in Table 4.

After feature extraction, the images were classified into four different categories such as healthy, early blight, late blight and Septoria leaf spot through a Support Vector Machine (SVM) classifier. Details of the classification is shown in Fig. 7.

Farmer is informed through notification about the status of the crop along with remedy prescribed for diseased leaf automatically through our android application named Lead Disease Identifier (LDI). Figure 8 shows LDI along with notification.

Fig. 4 Leaf crop through android application camera

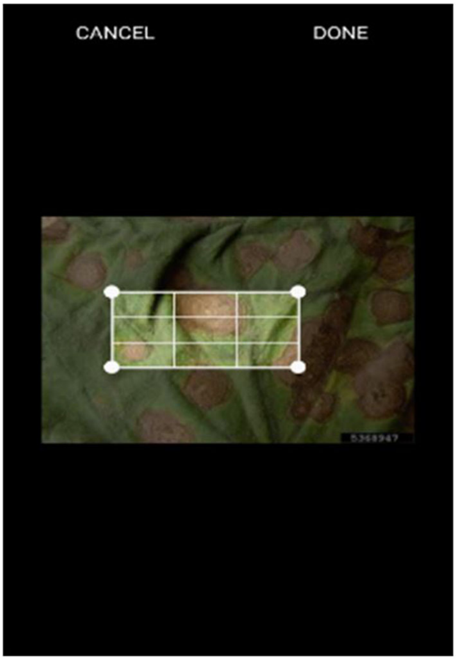


Fig. 5 Image (**a**) represent input image and (**b**) represent output enhanced image

In the proposed approach, 30% of images are used for training and 70% for testing. The proposed system classify 100% healthy images 95% early blight, 90% late blight and 80% septoria leaf spot. Figure 9 shows experimental results of the proposed system.

The available literature is silent for the provision on the spot solution to the farmer regarding the diseases of tomato crop due to which farmer can take on time actions against the diseases. Table 5 shows the comparison of the proposed approach with the existing approaches. Some of the existing algorithms are faster in recognition, but these algorithms are not specific to tomato, some of them are for plant diseases and other for vegetable diseases. Secondly, these systems does not provide on the spot solution to the farmers due to which the desired goals of treatments are not achieved timely. We can observe that our technique is accurate and efficient compared with other systems. Our system specific to tomato diseases detection identification and provide remedy to the affected crops. One of the contribution of our system is that we have used our own dataset.

In this study, the proposed method is implemented in Matlab R2014b on a laptop with Intel(R) Core (TM) i3 CPU 2.40 GHZ with 4 GB of RAM. Dataset consist of 400 tomato leaf images, out of 400 image, 120 which is 30% and 280 which is 70% of the dataset were used for training and testing respectively. The proposed approach started with Image preprocessing. In preprocessing phase the image is cropped through android application. Images are resized to 512× 512 resolutions followed by image enhancement. Otsu segmentation techniques were used in which the RGB images were converted into binary formats, separation of color spots and feature extraction from gray scale images. Statistical features were extracted from the images using Gray Level Co-Occurrence method (GLCM). For training purpose 13 different statistical features were extracted from 120 images, each 30 images for healthy and for diseased. After feature extraction, the images were classified into four different categories such as healthy, early blight, late blight and Septoria leaf spot through a Support Vector Machine (SVM) classifier. Farmer is informed through notification about the status of the crop along with remedy prescribed for diseased leaf automatically through android application named Lead Disease Identifier (LDI).

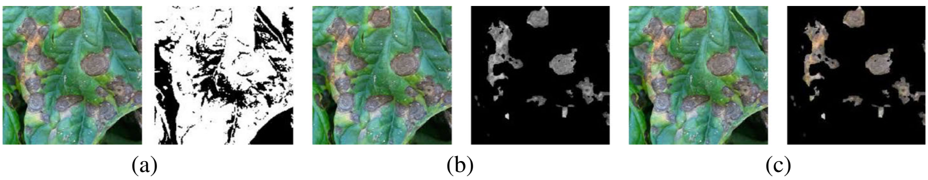


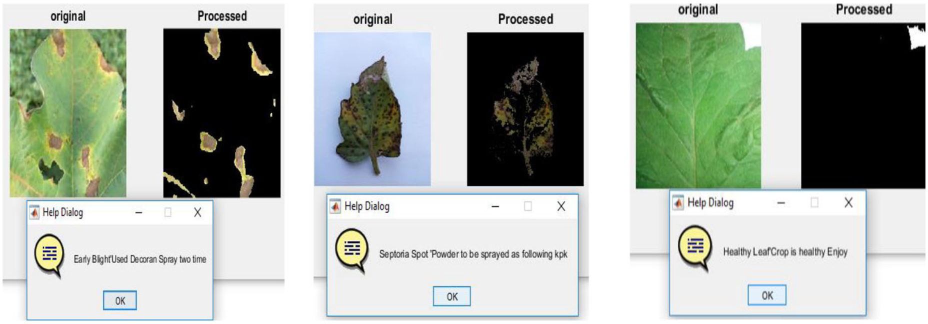
Fig. 6 **a** RGB to Binary conversion **b** RGB to Gray conversion **c** color spots segmented from RGB image

Table 4 Statistical features extracted from a sample image

Contrast	Comlation	Energy	Homogeneity	Mean	Standard Deviation	Entropy
0.2312806	0.9508854	0.7732615	0.973455	18.139882	54.403047	2.8211223
0.4653339	0.9370395	0.7719307	0.9769582	23.833379	69.624405	1.078274
0.5010876	0.9378515	0.6587808	0.960255	29.228648	67.448743	2.4231625
0.3317708	0.8788634	0.8311776	0.9717032	10.299179	40.007072	1.069103
0.5525888	0.8757947	0.6618724	0.9486512	22.265274	53.790863	2.5240113
0.3317708	0.8788634	0.8311776	0.9717032	10.299179	40.007072	1.069103
0.9107996	0.9067806	0.4342823	0.9341851	48.561422	75.777544	3.7117383
0.5109988	0.96115	0.4622898	0.932137	54.271027	87.282752	3.4603561
0.9413756	0.8744634	0.5725711	0.9186305	32.869492	66.748185	2.5176661
0.7104626	0.8051323	0.7973392	0.9551481	14.38121	47.586257	1.3889778
0.4980086	0.7423694	0.7038997	0.9533673	13.273758	37.730075	2.1050081
1.0097426	08242293	0.7031821	0.9389305	21.245107	56.986734	1.7854406
0.8072151	0.9594174	0.2790962	0.9323643	106.92725	106.09952	4.6617827
0.8674939	0.9243383	0.6826923	0.9625757	33.87852	77.689259	2.490166
0.4295037	0.8547784	0.7373471	0.9574515	14.731374	44.338805	15,673,787
0.777451	0.9048824	0.4471333	0.9040912	43.67278	71.918147	3.4349897
1.4172947	0.7536495	0.5962054	0.9130653	26.838765	60.228349	2.348455
0.6026808	0.8316513	0.7434588	0.9537099	15.878133	47.79801	14,441,275
1.106296	0.8410984	0.5336149	0.9115976	31.96081	64.201394	2.840821
05547181	09075332	0.3722538	0.9123707	42.642069	62.529536	3.9040636
0.79231	0.7450315	0.7913669	0.9542137	12.276622	43.928928	1.1179799
0.6617953	0.8152939	0.7615013	0.9524435	14.587514	47.101123	1.2846202
0.8890319	0.8171155	0.5877673	0.9244858	24.270452	54.393411	2.3131318
0.79231	0.7450315	0.7913669	0.9542137	12.276622	43.928928	11,179,799

Table 4 (continued)

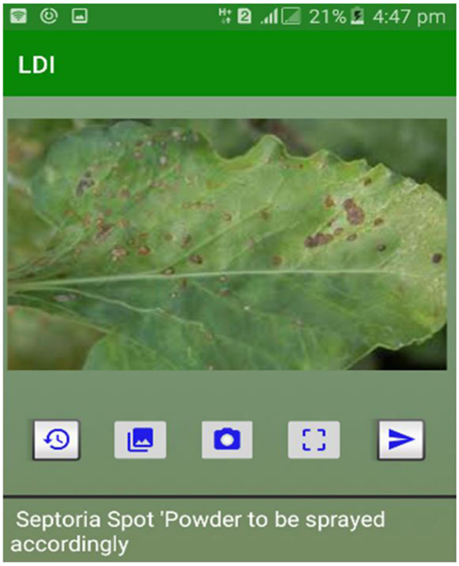
Contrast	RMS	Variance	Smoothness	Kurtosis	Skewness	IDM
0.2312806	5.8804101	29,383,584	0.9999997	13.816132	3.4170267	255
0.4653339	4.3402016	3756.4629	0.9999998	8.9264878	2.7580332	255
0.5010876	6.1078704	3937.5635	0.9999998	6.3297867	2.18862	255
0.3317708	3.4486481	1443.8012	0.9999995	22.452865	4.3832522	255
0.5525888	5.349946	1899.8818	0.9999998	9.0617465	2.621059	255
0.3317708	3.4486481	1443.8012	0.9999995	22.452865	4.3832522	255
0.9107996	9.2438066	5456.8611	0.9999999	2.9659626	1.2121624	255
0.5109988	8.9783722	6994.2821	0.9999999	2.6229836	1.1808358	255
0.9413756	7.4733759	4276.9544	0.9999998	4.9581682	1.8349529	255
0.7104626	4.8415829	2184.0206	0.9999996	14.097814	3.4431337	255
0.4980086	6.4758179	1146.4571	0.9999996	22.259895	4.070185	255
1.0097426	5.2232368	2793 5046	0.9999998	9.0702729	2.6923793	255
0.8072151	11.44756	9682.1236	1	1.1509525	0.0906983	255
0.8674939	5.1149688	3739.3501	0.9999998	5.3797869	2.0277829	255
0.4295037	5.4355666	18,262,775	0.9999997	14.938326	3.4269335	255
0.777451	8.4754337	46,235,634	0.9999999	3.4992301	1.3856849	255
1.4172947	7.0021598	3509.3312	0.9999998	6.6290725	2.1858771	255
0.6026808	5.1824576	2164.3997	0.9999997	12.721141	3.2014779	255
1.106296	7.5409511	3602.3655	0.9999998	5.5711436	1.9457963	255
05547181	9.6128908	3537.4516	0.9999999	3.720459	1.3206248	255
0.79231	4.4050184	1859.349	0.9999996	18.203173	3.914576	255
0.6617953	4.6110141	1977.7503	0.9999997	14.398086	3.442991	255
0.8890319	6.9751495	2763.8314	0.9999998	7.728035	233,439	255
0.79231	4.4050184	1859.349	0.9999996	18.203173	391,457	255



(a) (b) (c)

Fig. 7 **a**, **b**, **c** Shows Input and output processed images

Fig. 8 Farmer is informed through LDI along with remedy



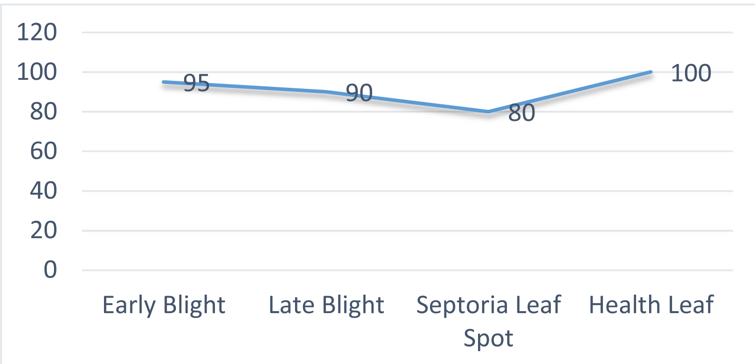


Fig. 9 Experimental results of the proposed system

Table 5 Comparison with state of the art techniques

Method	year	Segmentation techniques	Feature type	Classifier	Dataset	Disease	Accuracy
Al-Hiary et al. [2]	2011	K-means clustering method	Color and texture features	Neural Network	192 leaf plant images	Early scorch, Cottony mold, ashen mold, late scorch, tiny whiteness	between 83% and 94%
Mokhtar et al. [18]	2015	–	Texture features	(SVMs) with alternate kernel functions	Own dataset 200 images	tomato leaves infected with powder or early blight diseases	99.5%
El Massi et al. [9]	2017	K-means clustering method	Color, texture, shape	Neural Network	300 vegetable images	Vegetable and crops diseases Early blight, Late blight and Powdery mildew	95.3%
M. Z. Din et al. [8]	2018	Multi Thresholding	texture feature	SVM	Plant village, 200 images	Bacterial Spot, Early Blight Spider Mites and Healthy	98.3%
Audre Arlene Anthony et al. [5]	2020	–	Color, texture, shape	Random forest and decision tree classification algorithms	500 images 300 for training, 200 for testing,	Bacterial, Mosaic, Septoria leaf spot Yellow curved and Healthy,	90% for decision tree classifier and 94% for random forest classifier
Proposed system	2021	Otsu method	Statistical	SVM	Own 400 images 120 images for training and 280 for testing	Healthy, Early blight, Late Blight, Septoria leaf spot	100% 95%,90% and 85%

4 Conclusion

In this study, an automatic image processing based system for tomato leaf disease detection, identification and diagnosis is proposed. The proposed system provide several benefits to the formers and increase the productivity of tomato crop. It also provide solution to the farmer at doorstep on a single click. In the proposed system, three important tomato diseases such as Early Blight, Late Blight and Septoria leaf Spot were efficiently and accurately detected, identified and proper remedy is recommended.

There are several future research directions. One direction is to find a way to solve the problem of detection failures caused by lighting environment and acquisition at different angles. Another future work is to find a way to solve the problem of detection failures caused by low image resolutions. One more direction is to extend this method from tomatoes to other crops.

The current research focus on automatic detection and recognition of leaf related tomato diseases. Current work is carried out for identifying most devastating tomato leaf related diseases in local area of Nagrai Payeen, Talash, Dir Lower, KPK, Pakistan. Dataset of the proposed system is collected from the mentioned area tomato fields. The proposed technique facilitate advancements in tomato crop by providing rapid, cost-effective and reliable monitoring system along with preventive measures. Comparison against state-of-the art techniques is represented in Table 5.

4.1 Novelty statement

The current research focus on automatic detection and recognition of leaf related diseases in tomato crop. The proposed technique facilitate advancements in tomato crop by providing rapid, cost-effective and reliable monitoring system.

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Author's contribution Sami Ur Rahman: Designed experiments, technical and language check.
Fakhre Alam: Help in writing and editing. Analyzed data.
Niaz Ahmad: Carried out the field work and analyzed data.
Shakil Arshad: Review the manuscript for technical and language.

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