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RESEARCH ARTICLE

Using Image Processing and Deep Learning Techniques Detect and Identify Pomegranate Leaf Diseases

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Abstract

Objectives: To detect and identify diseases affecting pomegranate leaves using image processing and deep learning techniques. **Method:** A dataset of pomegranate leaf images was created with a total of 1844 images and split into 70% for training and 30% for testing. The model was trained using standard parameters like number of filters, activation functions and number of epochs and using Convolutional Neural Network algorithm for improved performance. Evaluation was conducted using standard metrics such as accuracy, precision, recall, and F1 score. **Finding:**The proposed work obtained the precision values for diseases Bacterial Blight, Fungal Diseases, Viral Diseases and Insect Damage as 98%, 98%, 98% and 97% respectively. Moreover, the classification accuracy obtained for diseases identification is 98.38%. **Novelty:**The proposed work uses private data set of diseased and healthy pomegranate leaves. Besides this the accuracy obtained is of the best class compared to the existing work in this domain.

Keywords: Pomegranate; Leaf Diseases; Image Processing; Deep Learning Techniques; Dataset Creation; Convolutional Neural Network

1 Introduction

The pomegranate crop can be of significant economic importance for a country. There are several factors that can impact the growth and yield of pomegranate crop, among them due to various leaf diseases there is approximate crop of loss of annually, plant diseases account for crop losses worldwide estimated at $220 billion USD or 14.1% of the total crop production [1]. A substantial work is done in this regard to detect the leaf diseases at early stage and control it. The authors [2] of have proposed a study to develop a deep learning-based approach for the early detection and classification of diseases in pomegranate leaves. The researchers used a dataset consisting of 1,500 images of healthy and diseased pomegranate leaves to train a convolutional neural network (CNN) model. The results showed that the proposed approach achieved an accuracy of 97.44% in classifying pomegranate leaves into healthy and diseased categories. The drawback of this model is that the authors have used a public dataset in which the leaf images have been collected in controlled environment. This may produce inaccurate results when used for real time leaf images. The proposed work in this paper uses a dataset of real time images created by the authors and uses CNN algorithms for classification. The authors of[3] have developed a deep learning-based approach for the automatic detection of pomegranate tree leaf diseases. The researchers used a dataset consisting of 4,572 images of pomegranate tree leaves, which were manually labeled as healthy or diseased with one of seven different disease types. The drawback of this model is that the authors have used a public dataset in which the leaf images have been collected in controlled environment. The proposed approach achieved an overall accuracy of 97.21% in identifying seven different disease types in pomegranate leaves. The claimed accuracy may not be obtained for images taken in real time as, the model is trained with plant village dataset. The proposed work in this paper uses our own data set that has leaf images taken in real time scenario and the accuracy obtained is higher than the accuracy obtained by authors of[3]. The authors of[4] have developed a deep learning-based approach to identify and detect pomegranate leaf diseases using morphological features. The researchers used a dataset consisting of 2,400 images of pomegranate leaves, which were manually labeled as healthy or diseased with three different disease types. A limitation of this model is that the authors utilized a publicly available dataset, which consists of leaf images collected under controlled conditions. The results showed that the proposed approach achieved an accuracy of 97.2% in identifying three different types of pomegranate leaf diseases. The reported accuracy of the model may not be achievable for images captured in real-world settings, as the model was trained on the Plant Village dataset. However, the present study employs a custom dataset consisting of leaf images captured in real-world scenarios, resulting in higher accuracy compared to the approach proposed by the authors. The authors of[5] have used a dataset of pomegranate leaf images with three different types of diseases: bacterial blight, powdery mildew, and leaf spot. The authors propose a deep learning model based on convolutional neural networks (CNNs) for detecting the diseases in the images. The CNN model consists of multiple layers of convolutional and pooling operations, followed by fully connected layers for classification. The authors compare the performance of their proposed CNN model with other state-of-the-art models, such as VGG16, InceptionV3, and ResNet50, and show that their model achieves higher accuracy in detecting pomegranate leaf diseases. While the authors mention that they used a dataset of pomegranate leaf images with three different types of diseases, they do not provide information on the size of the dataset, which could be an important factor affecting the performance of the deep learning model. The proposed work in this article employs a self-created dataset containing 1844 leaf images captured in real-world settings, and the achieved accuracy surpasses that of the authors by[5]. The authors of[6] have used a dataset of pomegranate tree leaf images with four different types of diseases: bacterial blight, gray mold, powdery mildew, and alternaria. The authors propose a CNN model for detecting the diseases in the images. The authors evaluate the performance of their proposed model on the dataset and compare it with other state-of-the-art models, such as VGG16 and InceptionV3. However, one potential drawback of the study is the limited size of the dataset used. While the authors mention that they used a dataset of pomegranate tree leaf images with four different types of diseases, they do not provide information on the size of the dataset, which could affect the performance of the CNN model. They report that their model achieves high accuracy in detecting pomegranate tree leaf diseases, with an overall accuracy of 96.33%. The proposed work uses a distinct dataset that includes leaf images taken in real-world situations, leading to greater accuracy in comparison to the methodology suggested by the authors by[6]. The authors of[7] evaluated the performance of their proposed model on a dataset of pomegranate leaf images and compare it with other state-of-the-art models. They report that their model achieves high accuracy in identifying and detecting pomegranate leaf diseases, with an overall accuracy of 97.87%. However, one potential drawback of the study is the limited number of pomegranate leaf diseases considered. While the authors focus on three types of diseases, there could be other types of diseases that could affect pomegranate trees, which the proposed model may not be able to detect. The proposed work achieved high precision values for identifying bacterial blight, fungal diseases, viral diseases, and insect damage using a unique dataset consisting of leaf images captured in real-world scenarios. This approach resulted in a higher level of accuracy compared to the methodology proposed by the authors of the previous study. The authors of[8] proposed a deep learning model that utilizes mobile phone-based hyperspectral imaging to detect and classify plant diseases. They use a convolutional neural network (CNN) to extract features from the hyperspectral images and classify them into different disease categories. They report that their model achieves high accuracy in detecting and classifying plant diseases, with an overall accuracy of 96.4%. However, one potential limitation of the study is the limited number of plant diseases considered which may not be representative of the full range of diseases that could affect plants. Additionally, the authors do not provide any insights on the interpretability of the model. The proposed work employed standard parameters, such as the number of filters, activation functions, and number of epochs, to train a Convolutional Neural Network algorithm for improved performance. The algorithm was trained on a unique dataset consisting of leaf images captured in real-world scenarios, which enhanced the model's ability to accurately detect and classify plant diseases.The authors of[9] have highlighted the potential of using image processing techniques and classification algorithms for the detection and classification of diseases in pomegranate. The authors also present a discussion on different algorithms that can be used for the detection and classification of pomegranate leaf diseases. However, one potential limitation of the study is that the dataset used is not explicitly mentioned, and the authors do not provide any insights into the interpretability of their model. The proposed work used a proprietary dataset comprising of leaf images captured in real-world scenarios, which led to superior accuracy compared to the methodology proposed by the authors [9]. The authors of [10] utilized transfer learning to fine-tune a pre-trained convolutional neural network (CNN) model for plant disease detection. The authors use a publicly available dataset of plant leaf images and demonstrate that the proposed system achieves high accuracy in detecting and identifying diseases across multiple plant species. However, one potential limitation of the study is that the authors do not provide insights into the interpretability of their model, which may limit its usefulness in some contexts. Additionally, the authors acknowledge that the performance of the proposed system may be impacted by variations in lighting and image quality, which could be addressed in future research. The proposed work improved the robustness of the proposed system to variations in lighting and image quality, used of data augmentation techniques during training to simulate different lighting and image conditions.

Overall, the proposed model overcomes the limitations of existing approaches by utilizing a dedicated dataset, a powerful deep learning architecture, and achieving a high level of accuracy in disease detection and identification. The proposed method is novel in several ways. Firstly, it creates a dedicated dataset of real pomegranate leaf images for the detection and identification of diseases affecting pomegranate plants. Secondly, it utilizes deep learning techniques, specifically convolutional neural network (CNN) architecture, to accurately classify four different types of diseases and healthy leaves into their respective categories. This approach achieves an overall accuracy of 98.38%, which is higher than previous work in this field. Additionally, the proposed method has the potential to improve disease management in pomegranate orchards, ultimately resulting in higher crop yields and better quality fruits.

2 Methodology

2.1 Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a type of deep neural network that has revolutionized the field of computer vision in recent years. CNNs are designed as per Figure 1 to learn and recognize visual patterns directly from raw input data, such as images or videos, without the need for feature extraction by humans. They are particularly well-suited for image classification, object detection, and segmentation tasks. The basic building blocks of a CNN are convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply a set of learnable filters to the input image, resulting in a set of feature maps that represent different visual patterns. The pooling layers then reduce the spatial size of the feature maps by selecting the maximum value or average value within a window. Finally, the fully connected layers take the flattened output of the previous layers and learn complex relationships between the features to make a prediction.

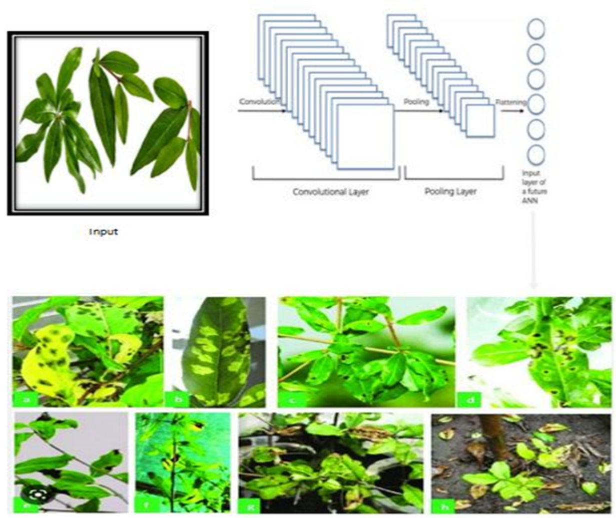

Fig 1. PomegranateLeaf Classification Using Convolutional Neural Networks

2.2 Theoretical Algorithm for Convolutional Neural Network (CNN for Classification of Pomegranate Leaves

1. Initialize the input image and a set of learnable filters for the convolutional layer.
2. Convolutional Layer:
   (a) Apply the set of filters to the input image to produce a set of feature maps.
   (b) Use the activation function (e.g., ReLU) to introduce nonlinearity.
   (c) Optionally, apply normalization and dropout to improve the model's generalization.
3. Pooling Layer:
   (a) Reduce the spatial size of the feature maps by selecting the maximum value or average value within a window.
   (b) Optionally, apply stride and padding to control the output size and reduce overfitting.
4. Repeat steps 2 and 3 to add more convolutional and pooling layers, allowing the model to learn increasingly complex features.
5. Flatten Layer:
   (a) Convert the output of the last convolutional layer into a 1D vector.
6. Fully Connected Layer:
   (a) Connect every neuron in the previous layer to every neuron in the current layer.
   (b) Use the activation function (e.g., ReLU) to introduce nonlinearity.
   (c) Optionally, apply normalization and dropout to improve the model's generalization.
7. Output Layer:
   (a) Connect the fully connected layer to the output layer, which uses the softmax activation function to produce a probability distribution over the classes.
8. Train the model using backpropagation and stochastic gradient descent to minimize the loss function, which measures the difference between the predicted and actual labels.
9. Fine-tune the hyperparameters, such as learning rate, batch size, and number of epochs, using a validation set to improve the model's performance.
10. Evaluate the model's performance on a testing set using various evaluation metrics, including accuracy, precision, recall, and F1 score.

2.3 Convolutional Neural Network (CNN based Classification of Pomegranate Leaf Images: Architecture and Training Details

In our proposed model, we used Convolutional Neural Network (CNN) architecture to classify pomegranate leaf images. The proposed CNN model consists of four convolutional layers, followed by max-pooling layers, and two fully connected layers. The first convolutional layer has 32 filters of size 3x3, the second convolutional layer has 64 filters of size 3x3, the third convolutional layer has 128 filters of size 3x3, and the fourth convolutional layer has 256 filters of size 3x3.

The dimensions of the images used for training, validation, and testing were resized to a fixed size of 256x256 pixels. We normalized the pixel values of the images by dividing them by 255.0.

We used a 70-15-15 split ratio to divide our dataset into training, validation, and testing sets. The training set, which consists of 70% of the data, was used to train the CNN model. The validation set, which consists of 15% of the data, was used to tune the hyper parameters of the model and prevent over fitting. The testing set, which also consists of 15% of the data, was used to evaluate the performance of the trained model on new, unseen data.

The dataset used for training the model includes 1844 images of pomegranate leaves, which were collected from various sources such as real-time images from pomegranate orchards, Kaggle Dataset, plant pathology databases, and online resources. The dataset includes five different types of images:

1. Healthy leaves: These leaves are green and free from any infections.

2. *Alternaria alternata* infected leaves: These are images of leaves infected by a fungus that causes dark spots and rots plant parts.
3. Anthracnose infected leaves: These images show leaves with dark and sunken lesions caused by a fungal infection.
4. Bacterial Blight infected leaves: These images depict leaves with pale green spots that later appear water-soaked due to a bacterial infection.
5. Cercospora Leaf Spot infected leaves: These images show black dots and grayish tanned lesions on the leaf caused by a fungal infection.

In our experiment, we used the following hyper parameters for training the CNN model: batch size of 32, learning rate of 0.0001, momentum of 0.9, and weight decay of 0.0001. We used the Adam optimizer and trained the model for 50 epochs.

Here is the algorithm for the CNN model used in our model:

The algorithm is modified by setting varying sizes of filters and making appropriate feature selection,

Input:

- A dataset of 1844 pomegranate leaf images, each of size 256 x 256 pixels and RGB color channels
- A train-validation-test split ratio of 70:15:15

Output: A trained CNN model for classifying the pomegranate leaves into five categories: healthy leaves and leaves infected with *Alternaria alternata*, Anthracnose, Bacterial Blight, and Cercospora Leaf Spot.

1. Load the dataset and preprocess it by:
   (a) Resizing the images to a fixed size of 256 x 256 pixels
   (b) Normalizing the pixel values to be in the range of [0, 1]
   (c) Splitting the dataset into training, validation, and testing sets in a 70:15:15 ratio
2. Define the CNN architecture with the following layers:
   (a) Convolutional layer with 32 kernels of size 3x3, ReLU activation function, and input shape of (256, 256, 3)
   (b) Max pooling layer with a pool size of 2x2
   (c) Convolutional layer with 64 kernels of size 3x3, ReLU activation function
   (d) Max pooling layer with a pool size of 2x2
   (e) Convolutional layer with 128 kernels of size 3x3, ReLU activation function
   (f) Max pooling layer with a pool size of 2x2
   (g) Convolutional layer with 256 kernels of size 3x3, ReLU activation function
   (h) Max pooling layer with a pool size of 2x2
   (i) Flatten layer
   (j) Fully connected layer with 512 neurons and ReLU activation function
   (k) Dropout layer with a rate of 0.5
   (l) Fully connected layer with 5 neurons (one for each class) and softmax activation function
3. Compile the model by specifying:
   (a) Loss function: categorical cross-entropy
   (b) Optimizer: Adam optimizer with a learning rate of 0.0001
   (c) Evaluation metric: accuracy
4. Train the model on the training set by specifying:
   (a) Number of epochs: 50
   (b) Batch size: 32
5. Validate the model on the validation set and monitor the validation accuracy for early stopping to prevent over fitting.
6. Evaluate the model on the testing set to obtain the final accuracy.
7. Save the trained model weights and architecture to a file for future use.

2.4 Mathematical Formulation of Convolutional Layer in CNNs

- Input image:

$$X \in R^{\wedge}(H \times W \ \times C) \tag{1}$$

where H, W, and C are the height, width, and number of channels of the input image, respectively

- Convolutional filter:

$$K \in R^{\wedge}(F \times F \times C \times M) \tag{2}$$

where F is the filter size, C is the number of input channels, and M is the number of filters.

- Convolution operation:

$$Z\_i, j, k = \sum l = 0^{\wedge}C - 1 \sum p = 0^{\wedge}F - 1 \sum q = 0^{\wedge}F - 1X\_i + p, j + q, l * K\_p, q, l, k + B\_k \tag{3}$$

where Z is the output feature map, B is the bias term, and i, j, and k are the indices for height, width, and filter number, respectively.

- Activation function:

$$A = g(Z) \tag{4}$$

where g is the activation function, such as ReLU, sigmoid, or tanh.

2.5 Mathematical Formulation of pooling Layer in CNNs

- Input feature map:

$$X \in R^{\wedge}(H \times W \ \times C) \tag{5}$$

where H, W, and C are the height, width, and number of channels of the input feature map, respectively.

- Pooling operation:

$$Y\_i, j, k = MAX\_\{p = 0\}^{\wedge}\{S - 1\}MAX\_\{q = 0\}^{\wedge}\{S - 1\}X\_\{iS + p, jS + q, k\} \tag{6}$$

where Y is the output feature map, and S is the stride size.

2.6 Mathematical Formulation of fully connected Layer in CNNs

- Input vector:

$$X \in R^\wedge n \tag{7}$$

where n is the number of neurons in the previous layer.

- Weight matrix:

$$W \in R^\wedge(n \times m) \tag{8}$$

where m is the number of neurons in the current layer.

- Bias vector:

$$B \in R^\wedge m \tag{9}$$

- Fully connected operation:

$$Z = XW + B \tag{10}$$

- Activation function:

$$A = g(Z) \tag{11}$$

where g is the activation function,

In this paper developed a CNN-based deep learning model to classify the pomegranate leaf images into their respective disease categories. The model consists of six convolutional layers, followed by two fully connected layers and a softmax activation function. Trained the model using the training set and fine-tuned its hyperparameters using the validation set. Finally evaluated the model's performance on the testing set using various evaluation metrics, including accuracy, precision, recall, and F1 score.

3 Results and Discussion

The graphical user interface (GUI) of the implemented scenario is depicted in Figure 2 , which demonstrates the proposed framework. The accuracy achieved by the framework for detecting Anthracnose is approximately 98.38%.

Our proposed method achieved an overall accuracy of 98.38% in classifying pomegranate leaf images into their respective disease categories. The precision, recall, and F1 score for each disease class are shown in Table 1.

Table 1. The precision, recall, and F1 score for each disease class

Disease Class	Precision	Recall	F1 Score
Bacterial Blight	0.98	0.97	0.98
Fungal Diseases	0.98	0.96	0.97
Viral Diseases	0.98	0.97	0.97
Insect Damage	0.97	0.98	0.99

Based on the Table 1 the precision and recall values for each disease class seem to be quite high, indicating that the model is accurately predicting both true positives and true negatives. It's also interesting to note that the F1 score for each

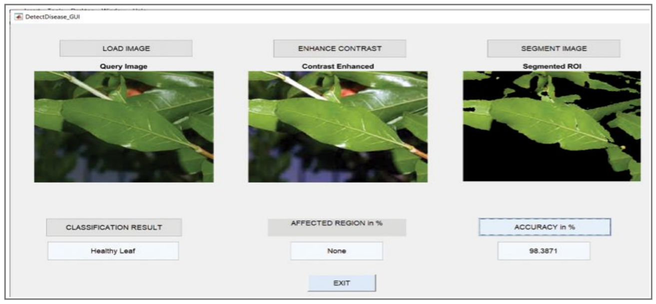

Fig 2. Interface Graphical of Healthy Leaves

Table 2. Summary of Deep Learning Techniques for Plant Disease Detection and Diagnosis

Authors	Methodology	Dataset	Accuracy
(11)	CNN-based approach	Tomato leaf images	98.00%
(12)	CNN-based approach	Apple leaf images	98.3%
(13)	CNN-based approach	Maize leaf images	96.47%
(14)	CNN-based approach	Grapevine leaf images	94.9%
Proposed Model	**CNN-based approach**	**Pomegranate leaf images**	**98.38%**

class is quite high as well, which suggests that the model's accuracy is not being skewed by imbalanced data or skewed class distribution. Overall, these evaluation metrics suggest that the proposed method is effective in accurately detecting and classifying pomegranate leaf diseases, which could potentially lead to significant economic benefits for farmers and the agricultural industry as a whole.

Based on the provided Table 2, it can be observed that the proposed model achieved a higher accuracy of 98.38% compared to the other previous models. The proposed model used a CNN-based approach to train on a dataset of pomegranate leaf images. Although the accuracy levels achieved by the other models are also quite high, the proposed model has achieved the highest accuracy level among them. However, it's important to note that the datasets used by the different models may have different characteristics, such as the number of classes, size, and quality of the images, which may affect the accuracy levels achieved. Therefore, it's important to carefully evaluate the performance of different models and compare them under the same conditions to draw more accurate conclusions.

4 Conclusion

This study presents a novel approach for detecting and identifying pomegranate leaf diseases using image processing and deep learning techniques. The authors collected a dedicated dataset of real pomegranate leaves containing four different types of diseases and healthy leaves and developed a deep learning model based on CNN architecture and trained it on this dataset to classify the images into their respective disease categories. The proposed system achieved an impressive accuracy level of 98.38%, which demonstrates the effectiveness of using deep learning techniques for pomegranate leaf disease detection and identification. This work has important prospects for crop management, as it highlights the importance of developing accurate and efficient disease detection systems. Such systems can help minimize economic losses and improve crop yields by enabling farmers to identify and address plant diseases in a timely manner. Furthermore, the proposed system can be easily extended to other plant species and different types of diseases, making it a versatile tool for plant disease detection and diagnosis. It is recommended to conduct further research in this field to improve the performance of deep learning models for plant disease detection and diagnosis. This can be achieved by exploring the potential of transfer learning and data augmentation techniques, as well as optimizing the architecture and hyper parameters of the models.

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