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ABSTRACT Citrus fruit diseases are the major cause of extreme citrus fruit yield declines. As a result, designing an automated detection system for citrus plant diseases is important. Deep learning methods have recently obtained promising results in a number of artificial intelligence issues, leading us to apply them to the challenge of recognizing citrus fruit and leaf diseases. In this paper, an integrated approach is used to suggest a convolutional neural networks (CNNs) model. The proposed CNN model is intended to differentiate healthy fruits and leaves from fruits/leaves with common citrus diseases such as Black spot, canker, scab, greening, and Melanose. The proposed CNN model extracts complementary discriminative features by integrating multiple layers. The CNN model was checked against many state-of-the-art deep learning models on the Citrus and PlantVillage datasets. The experimental results indicate that the CNN Model outperforms the competitors on a number of measurement metrics. The CNN Model has a test accuracy of 94.55 percent, making it a valuable decision support tool for farmers looking to classify citrus fruit/leaf diseases.

Keywords: Citrus leaf diseases; Citrus fruit diseases detection; Convolutional neural network; Deep learning,

1. Introduction

Agriculture research aims to increase food production and quality while lowering costs and boosting profits [1]. Fruit trees play an important role in any state's economic development. One of the most well-known fruit plant species is the citrus plant, which is high in vitamin C and widely used in the Indian sub-Continent, Middle East and Africa [2]. Citrus plants are associated with many health advantages, as well as being used as a raw material in the agricultural industry for the production of several types of other agri-products including jams, sweets, ice cream, and confectionery etc. [2, 3]. Citrus, Pakistan's most important fruit crop, accounts for a significant portion of the country's horticultural exports. In 2018, the annual citrus production in Pakistan was estimated to be around 2.5 million tonnes[1]. However, Citrus fruit plants, on the other hand, are susceptible to a variety of infections, including Black spot, canker, scab, greening, and Melanose. The canker is highly contagious and is found in citrus trees and is mostly on the leaves or fruit. There are reports of crop losses of approximately 22% in Kinnow, 25–40% in sweet orange, 15% in grease, 10% in sweet lime and 2% in lemon, respectively. A large proportion of quality export fruit is refused every year due to signs of citrus fruit diseases[1] . As a result, timely identification of citrus diseases has the potential to reduce losses and costs while also improving product quality.

For decades, identification of diseases has mostly been done by humans. The recognition and diagnosis process is judgmental, error-prone, time-consuming and expensive. Furthermore, new diseases will arise in previously unidentified areas where there is, by necessity, no local expert knowledge to address them [4]. As a result, there is a pressing need for an automated system for detecting citrus fruit/leaf diseases.

The development of sophisticated tools and rapid computer-assisted techniques have made it easier to scan and automatically detect anomalies in a crop in real time [4]. Conventional machine learning techniques have had considerable success in recognizing and diagnosing plant disease, but they are limited to the following sequential image processing tasks: image segmentation using clustering and other methods [5, 6], feature extraction [7], and pattern recognition using support vector machines (SVM) [8], k-nearest neighbor method [9], and Artificial Neural Network [10]. It is difficult to pick and extract the best observable pathological characteristics, necessitating the use of highly qualified engineers and experienced specialists, which is not only arbitrary but also inefficient of manpower and financial capital.

[1]https://www.freshplaza.com/article/9216529/citrus-greening-threatens-pakistan-s-citrus-production-export/.

Deep learning, on the other hand, can learn the hierarchical features of pathologies automatically, eliminating the need to manually design the morphological operations of feature extraction and classifier. The deep learning approach excels in several fields, including signal processing [10], pedestrian detection [11], face recognition [12], road crack detection [13], biomedical image analysis [14], and many others. Furthermore, deep learning techniques have produced promising results throughout the agricultural field, helping more farmers and food-producing workers, such as detection of plant disease [15], analysis of weeds [16], discovery of valuable seeds [17], insect detection [18], fruit processing [15], and so on, which has led to dealing with image analysis. Furthermore, a few implementations aimed to forecast future parameters such as crop production [19], climate conditions [20], and field soil water content [21]. We propose an integrated deep learning model, for automated citrus fruit disease detection, based on the tremendous results of CNN-based methods in image classification.

1.1 Research Motivation

Existing research [7, 22, 23, 24,] on the classification of citrus diseases from images uses supervised machine learning and deep learning methods. Liu et al. [24] used a deep learning model for citrus disease classification from photographic images. Furthermore, there is some performance degradation due to poor parameter and layer selection in the neural network model. However, in the suggested CNN model for classifying citrus diseases in both fruit and leaf images, we use a revised number of layers and parameter settings. Furthermore, we run experiments with various CNN model variants and compare the findings to the baseline studies. We suggest a CNN model for effectively classifying citrus diseases from fruit and leaf images. The proposed system can detect the following citrus plant diseases: Black spot, canker, scab, greening, and Melanose.

1.2 Problem Formulation

In this paper, we formulate the identification of citrus plant (fruit and leaves) diseases from images as a classification problem. The goal is to develop a model/classifier that detects and assigns the corresponding disease class to image CF_i=CF1, CF2, CF3,..., CF4 given a citrus disease image CF_i. In this paper, we test a number of machine learning (ML) classifiers, as well as a deep learning model, the CNN. While existing machine learning classifiers use classical feature representation techniques, the proposed deep learning classifier employs a sufficient number of layers and an optimal set of parameters.

1.3 Research Questions

In this paper, an automated Citrus fruit and leaf disease identification approach based on deep Learning Neural

Networks is applied to produce quick and precise recognition results by using the Softmax activation function. The aim of this research is to identify five distinct citrus diseases: Black spot, canker, scab, greening, and Melanose. CNN extracts features from raw inputs in an analytical manner. The features with the highest likelihood values are chosen for classification.

We'd like to find out the answers to the following research questions, which are listed in Table 1.

Table 1
Proposed Research Questions

Research Question	Motivation
RQ1. How to apply the CNN model to effectively classify citrus fruit and leaf diseases?	Investigate the proposed deep neural network model, CNN, to see how it can be used to predict diseases from citrus fruit and_leaf images.
RQ2. What is the proposed approach's efficiency in contrast to state-of-the-art ML techniques?	Examine the efficacy of the proposed deep learning model, CNN, which predicts citrus fruit and leaf diseases using various assessment metrics such as precision, recall, F1-score, and accuracy in relation to current baseline ML studies.
RQ3. What is the proposed approach's efficiency in contrast to state-of-the-art DL techniques?	Examine the efficacy of the proposed deep learning model, CNN, which predicts citrus fruit and leaf diseases using various assessment metrics such as precision, recall, F1-score, and accuracy in relation to current baseline DL studies.

1.4 Our Contributions

The proposed research is notable in terms of the following contributions: (i) The proposed method uses a state-of-the-art CNN model for classifying citrus diseases into different classes, namely Black spot, canker, scab, greening, and Melanose, (ii) The proposed deep learning model integrates a sufficient number of layers in the proposed deep learning model, and (iii) Contrasting the proposed model's efficiency to that of similar studies. The proposed approach helps in the development of more sophisticated practical applications in the field of plant disease recognition based on their visual symptoms.

1.5 Article Organization

This article is structured as follows. The second segment begins with a description of related works. Section 3 introduces the dataset and data preprocessing, as well as the proposed CNN Model in detail. In Section 4, we conduct all of the experiments, address the proposed deep learning Model's drawbacks, and look forward to future work. This paper comes to a conclusion in Section 5.

2. Related Work

The diagnosis of leaf and fruit disease has been a matter of study for many decades. Researchers have researched a variety of methods using machine learning and pattern detection to increase the recognition rate of disease diagnosis. These advanced technologies are used for a wide range of crops, including wheat [25], and rice [26.], maize [27], and corn [28], Different experiments on neural network approaches used for recognizing and classifying diseases from plant leave and fruit photos have been presented by Golhani et al. [29]. Wetterich et al. [30] used an SVM and a fluorescence imaging system to detect Citrus canker and Huanglongbing (HLB). The method's classification accuracy for identifying citrus canker and scab was 97.8%, while the method's accuracy for detecting HLB and zinc deficiency was 95%. K. Padmavathi et al. [31] adopted the Recursively Separated Weighted Histogram Equalization (RSHE) methodology to better distinguish Citrus diseases. In the second phase, the noise is eliminated from the citrus images. The suggested solutions enhance the quality of citrus images that can be used for further analysis.

As discussed by Patel et al. [32], K-Means segmentation has been used to find the diseased region in pre-processed orange images. Both the colour, texture, and the shape of the affected region were taken from the training set and classified using the SVM classifier. GLCA models yielded a 67.74% accuracy. To identify citrus leaf diseases in 2020, Singh et al. [33] used the Support Vector Machine, Linear Discriminant Analysis, K-Nearest Neighbors, and Multi-Layer Perceptron techniques. The kmeans clustering method was used to segment diseased areas in leaves, and color and texture characteristics were collected. To choose the most relevant characteristics, the ANOVA F-test is used. Finally, the pathogens were identified using the methods described above. A total of 236 diseased citrus leaves were included in the study. The use of a combination of color and texture characteristics improved precision. For color and texture characteristics, the precision of LDA, MLP, KNN, and SVM was 84.32 percent, 81.36 percent, 77.12 percent, and 80.93 percent, respectively. The approach suggested by [22] is based on the recognition of the citrus disease. The suggested procedures have been tested on infections in citrus fruits. Color and texture features are used to classify the proposed classifiers. The experimental findings show that the proposed strategy is much superior, and that it can support an accurate detection of citrus infection with minimal computational effort. Within the classification accuracy, there is a lot of room for improvement. Deep learning has become more popular in recent years, not only in image processing, image recognition, and categorization [17–19], but also in other areas like agriculture. Deep learning avoids the time-consuming feature extraction and threshold-based segmentation, making it a promising candidate for citrus disease

classification [24]. Using a weakly thick linked convolutional network, Xing et al. [34] presented a recognition model for citrus disease and pests. They used a self-dataset for citrus and applied it to various CNN models. The NIN-16 model gained a test precision of 91.66 percent, which was higher than the SENet-16 model's 88.36 percent and 80.93 percent, respectively. Liu et al. [24] trained MobileNetV2 to classify six common citrus diseases and to diagnose them. Comparing the model correctness, model size and model validation speed with other network models, we can see that MobileNetV2 is good at classifying and recognizing citrus diseases. MobileNetV2 is a portable network with comparable accuracy and rapid validity to other network architectures. To diagnose diseases of the citrus leaf, Barman et al. [35] compares two distinct CNN designs, such as MobileNet and Self-Structured (SSCNN) classifiers. At epoch 10, the MobileNet CNN's greatest training accuracy was 98 percent, with 92 percent validation accuracy. However, the SSCNN's greatest training accuracy was 98 percent, with 99 percent validation accuracy at epoch 12. An intelligent technique convolutional neural networks is proposed by Khanramaki et al. [36] to detect following three citrus pests: citrus Leafminer, Sooty Mold, and Pulvinaria. A collection of 1774 citrus leaf photos was used to test the suggested approach. The accuracy of CNNs is measured using 10-fold cross validation in experimental study. Based on the results of the experiments, the suggested ensemble beat other competing CNN algorithms with an accuracy of 99.04 percent. Kukreja et al. [37] suggested a robust CNN algorithm for identifying and providing an effective approach for identifying apparent citrus fruit problems. The suggested method is compared to a dense model that does not employ data augmentation or pre-processing methods. The suggested model has an accuracy rate of 89.1%. The findings reveal that data augmentation and preprocessing strategies have yielded good results in estimating citrus crop damages. Partel et al. [38] created an autonomous system that monitors ACP in groves using machine vision and artificial intelligence. A tapping mechanism was used to catch insects from the tree's branches, and a board with a grid of cameras was used to capture images. Two convolutional neural networks were used to create software that efficiently detects and distinguishes psyllids from other insects and tree detritus. Detecting ACPs on a collection of 90 immature citrus plants yielded accuracy and recall of 80 percent and 95 percent, respectively.

2.1 Research Gap Identified from Literature
Despite the fact that simple ML and DL techniques have been shown to be efficient and commonly used in crop disease prediction, most earlier works had difficulty increasing classification accuracy rates to some extent. Moreover, due to poor parameter and layer selection in the neural network model, there is some performance degradation. We use a different number of layers and parameter settings in the proposed CNN model for classifying citrus diseases in both fruit and leaf photographs. In addition, we test different CNN model variants and compare the results to the baseline studies. For accurately classifying citrus diseases from fruit and leaf photographs, we propose a CNN model with multiple layers.

3. Methodology
Fig. 1 depicts the flowchart of our proposed system. In this paper, a Multilayer Convolutional Neural Network is proposed for the classification of Citrus Fruit and leaves infected with different diseases.
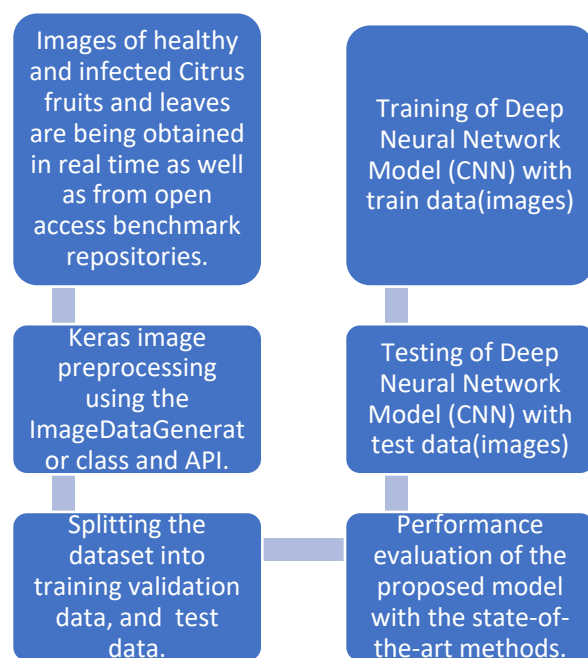
Fig. 1 Flowchart of the proposed System

3.1 Dataset Acquisition and Splitting
Datasets are needed at all stages of image analysis study, from training to evaluating algorithms. This study used a total of 2293 images, taken from the citrus dataset [39] and PlantVillage dataset [40]. The benchmark repository, called PlantVillage, aims to provide researchers with information on plant health [40]. The infected images were divided into four groups, each representing a different disease of citrus fruits and leaves. Black spot, Canker, Scab, Greening, and Melanose were the diseases we studied in the datasets. Table 2 shows the dataset description.

Table 2
Dataset Description

Category	Disease	Image count

	Black spot	291
	Greening	310
Citrus leaves	Canker	268
	Melanose	140
	Healthy	58
	Total	1067
Citrus Fruit	Black spot	341
	Greening	144
	Scab	321
	Canker	178
	Healthy	242
	Total	1226
Total images in our dataset		2293

There are three parts of the dataset: (i) training data, (ii) test data, and (iii) validation data. On an Intel Core m3 7th Gen, 64-bit operating system, the proposed CNN model was introduced using the Keras library [41], TensorFlow, Intel Core m3 7th Gen, 64-bit operating system, and 8GB RAM.

3.1.1 Training data

A CNN model is developed using 80% of training data and this percentage may change depending on the needs of the experiment. It's used to train the CNN model, which tries to learn from the training data set. Both the input and the predicted result are included in the training data.

3.1.2 Test data

The test set is 20% of the original data and is used to evaluate the CNN model on new data. It is used for the model's evaluation process once it has been fully trained.

3.1.3 Validation data

Data validation can also be used to reduce overfitting and under fitting [33], which occurs when the training phase's efficiency is significant and performance degrades when tested with new data. As a result, while performing parameter tweaking, a 10% validation set is intended to prevent efficiency errors. We used automated dataset validation [34] for this purpose, which provides an impartial model evaluation and reduces overfitting [39].

The sample dataset in Fig. 2 consists of Citrus Fruit and Leaf images captured in the field as well as images from the Citrus and PlantVillage dataset.

Disease: Black Spot

Disease: Canker

Disease: Scab

Disease: Greening

Disease: Melanose

Fig. 2 Sample dataset of Citrus Fruit and Leaf images

3.2 A Short Overview of the Proposed Approach

The proposed method consists of the following modules (see Fig. 3): (i) pre-processing input image, (ii) CNN layer-1, (iii) CNN layer-2, (iv) Flatten layer, and (v) classification.

- Preprocessing of image input: In this module, we perform Keras image preprocessing using the ImageDataGenerator class and API [41]. This class allows normalisation, pixel scaling, and data normalisation.

- **Layer 1 of CNN**: It is the CNN model's first convolutional sheet. To obtain a feature map, a convolutional operation is performed on the input image matrix.

- **Layer 1 of Maxpooling**: The features of the CNN layer-1 are reduced in size when they are transmitted to this layer. This layer decreases the sensitivity of filters to noise and variations [42].

- **Layer 2 of CNN:** The second convolutional layer works in the same way as the first, except that the first layer collects low-level features from the image, whereas the second convolutional layer extracts high-level features.

- **Layer 2 of Maxpooling**: In the second Maxpooling layer, the identical function of lowering the dimensionality of the feature map is undertaken as in the Maxpooling layer-1. This layer created a pooled array of features.

- **Flatten Layer:** The flattening procedure is executed on the matrix, which is obtained from the 2nd Maxpooling layer. This layer converts the pooled feature matrix into a feature vector, which is a column or vector.

- **Classification:** The feature vector acquired from the flatten layer is used for classification, as well as the softmax activation functions are used [42]. Finally, the citrus fruit and leaf images get inspected for disease classification.
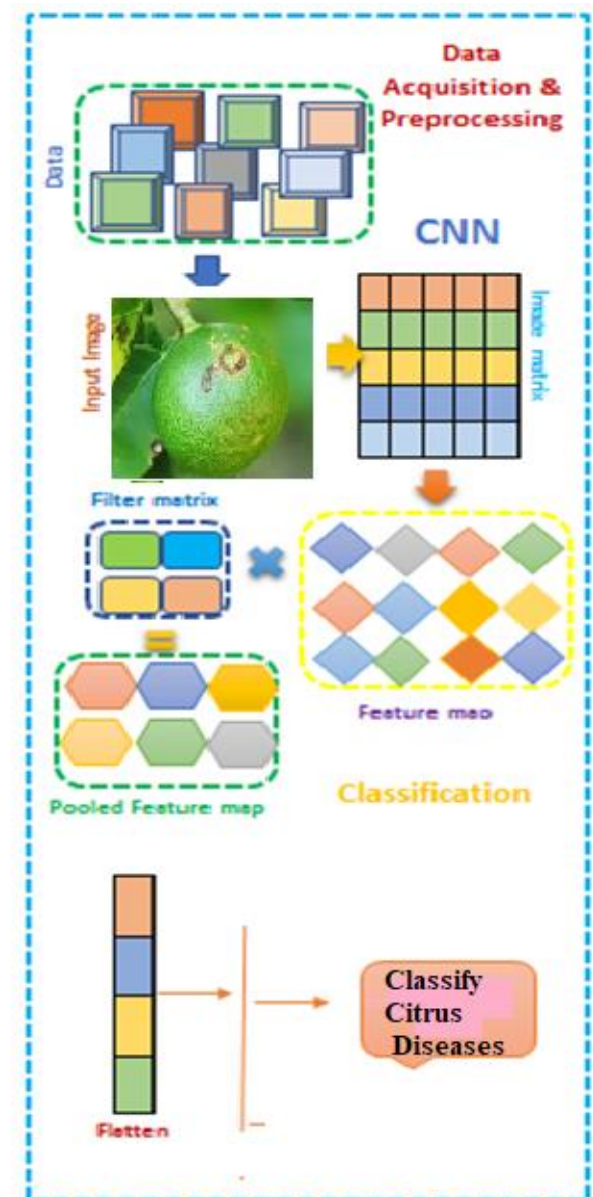
Fig. 3 A Brief Description of the Proposed System

The efficacy of the convolutional neural network in image identification/recognition tasks is the primary reason for using it as the proposed technique [25]. It currently reinforces major advancements in the field of computer vision, with applications in robotics, self-driving cars, medical imaging, defense, and drones [26]. We now use a convolutional neural network model to identify citrus fruit and leaf diseases based on a collection of images (see Fig. 4), as follows:

3.2.1 Input image

The input citrus fruit/leaf image is made up of an array of pixels that spans the width and height of the screen. A three-dimensional input image matrix is generated using an "input shape" parameter [26]. The input citrus fruit/leaf image is now ready for a convolutional layer,

which will perform additional processing on the images. Eq. 1 is used to compute the matrix F, which is as follows:

3.2.2 Convolution Layer -1

The convolutional layer is the first layer in a CNN, and its task is to perform feature extraction [5]. The feature matrix is created by convolving learnable filters (small matrix) with the input image matrix in the convolutional layer. A filter matrix K is applied to image matrix I for convolutionary use and a function map F is created. The following is how the feature map F is created:

$$F_{r,c} = R(K_{w,b} \circ I_{r+w-1, \ c+h-1} + b) \qquad (1)$$

where r denotes the matrix row and c denotes the matrix column; r is a number that ranges from $1 \leq w \leq l$; c is a variable that ranges from $1 \leq h \leq l$; the width of the filter matrix is w; h stands for the filter's height; I is the width and height limit of the filter; R is an activation function (ReLU,), and "∘" is a convolutional function involving K and I; and b stands for the bias value. The essential purpose of ReLU is to portray non-linearity in the CNN model, using the following formula: $f(x) = max(x, 0)$ [24].

Eq. 2 is used to calculate matrix F, as follows:

$$F = [f_{1,1}, f_{1,2}, \dots \dots f_n] \qquad (2)$$

3.2.3 Maxpooling Layer-1

After the convolution layer, the pooling layer, also known as the sub-sampling layer, produces a down-sampled version of the input function maps. For our suggested model, we've run a Maxpool operation on the feature map in order to decrease its size.

The following formula is used to measure the maxpool function:

$$M_{r,c} = max(F_{r+w-1, \ c+h-1}) \qquad (3)$$

The pooled feature map can be calculated using Eq. 3 as follows:

$$M = [m_{1,1}, m_{1,2}, \dots \dots m_{n,m}]. \qquad (4)$$

3.2.4 Convolution Layer-2

The second convolution layer is used to extract high level attributes from the input (pooled functional matrix) that was acquired in the Maxpooling layer. The second convolution layer's computation is identical to the first convolution layer's (Eq. 1, and Eq. 2).

3.2.5 Maxpooling Layer-2

The aim of the second max-pooling layer is to reduce the matrix's scale. The second layer of pooling is computed similarly to the first layer of Max-pooling (Eq. 3, and Eq. 4).

3.2.6 Flatten Layer

This layer works with the second max pooling layer's output (pooled function map). The flattening layer's goal is to convert a column or feature vector from a pooled feature matrix. The features or elements of the pooled feature map M are reshaped into feature vectors within this layer by restructuring the function [31], which is described as follows.

$$V = pooled. reshape[(f - w + 1)x(v - h + 1)] \qquad (5)$$

3.2.7 Classification

For classification, the probabilities for the various categories of citrus fruit/leaf diseases are calculated by manipulating a dense layer with multiple neurons using softmax functions. Thus, the net input is obtained as follows (Eq. 6):

$$uj = \sum_i^l wixi + b \qquad (6)$$

where "w" is a weight vector, "x" is an input vector, and "b" represents a bias term.

3.2.8 Applying Activation Function: At the classification layer, the softmax activation functions are used.
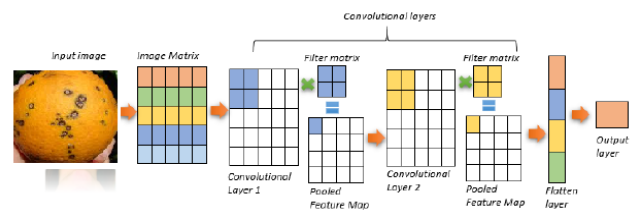

Fig. 4 A detailed view of the proposed architecture

3.3 Applying a Citrus disease classification example using the CNN model

This segment explains how the proposed model recognizes diseases from citrus fruit/leaves images. Fig. 5 depicts disease identification from the source image using the proposed CNN model into various classes: Black spot, canker, scab, greening, and Melanose.

3.3.1 Interpretation of the image input

The first step is to divide the image into pixels. The image is represented as a three-dimensional matrix (7x8x3 in our case) with red, green, and blue layers in the case of a colored image.

3.3.2 Deep convolutional layer-1 feature extraction

The convolutional layer extracts features from the input image matrix after the input image has been interpreted. A convolutional operation is applied between the filter matrix and the input image matrix within this layer. A resulting feature matrix is obtained by convolving a filter matrix over an input image (Eq. 1, Eq.2).

3.3.3 Using Pooling Layer-1 to reduce dimensionality.

After applying the convolution layer acquired from the previous layer of the CNN model, the convolved feature

map is subjected to a maxpooling process. The pooling layer reduces the size of the image matrix.

3.3.4 Convolutional Layer-2 for Feature Extraction

The main objective of the second convolutional layer is to extract high-level features from the feature map using all of the filtering activities mentioned in section 3.4.2. Since the CNN model extracts features layer by layer, the layer at a deeper level can obtain high-level features [39].

3.3.5 Max Pooling Layer-2 for minimizing dimensionality

The aim of the second pooling layer is to reduce the dimension size so that the features can be easily detected using the method described in section 3.4.3.

3.3.6 Using Flatten Layer to flatten

Eq. 5 is used to convert the output from the second pooling layer (pooled feature map) into a long feature vector.

3.3.7 Using Activation Functions for Classification

The classification of the image takes place in this module. The flatten layer's input (feature map) is used to perform classification of citrus fruit/leaf diseases. For this purpose, a softmax activation function is used to calculate the probability of each of the five distinct citrus fruit/leaf diseases. The net input can be estimated for the classification of the final image representation (Eq. 6) .Using the softmax function, we get the following probabilities for each citrus disease: 0.301 (Black spot), 0.713 (Canker), 0.230 (Scab), 0.319 (Greening), 0.142 (Melanose), and 0.244 (healthy). Using the above computation, the "Canker" disease class has the highest probability, P=0.713, and hence the input citrus picture is projected as "Canker" (see Fig. 5).
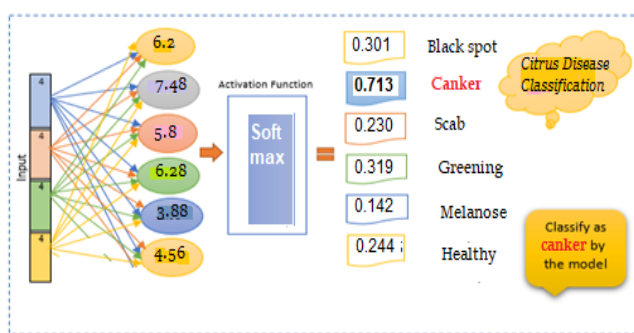

Fig. 5 Citrus Disease classification using the CNN model.

The pseudocode steps of the proposed Convolutional Neural Network model for disease recognition of citrus fruit/leaves are presented in **Algorithm 1.**

Algorithm 1. Pseudo code for the Convolutional Neural Network for disease recognition of citrus fruit/leaves

```
    I.        Dataset Input (training_set and test_set)
   II:   Procedure  CONVOLUTIONAL   NEURAL
NETWORK MODEL (training_set , test_set)
   III.        Parameter Initialization:
#Keras-based preprocessing
```
$from\ keras.preprocessing.image\ import\ image$

```
#Create a deep learning model with multiple layers
```
$Model = Sequential()$

```
#Layer 1 of the convolutional network
```
$Model.add(Conv2D(32,(3,3),input\ shape = (64,64,3),activation =' relu'))$

```
#1st Max pooling layer
```
$Model.add(MaxPooling2D\big(pool\_size = (2,2)\big))$

```
Layer 2 of the convolutional network
```
$Model1.add(conv2D(32,(3,3),activation =' relu$

```
#2nd Maxpooling layer
```
$Model.add(MaxPooling2D\big(pool\ size = (2,2)))$

```
#Flatten layer
```
$Model.add(Flattn())$

```
#Softmax Function
```
$Model.add(Dense(units = 128,activation =' softmax))$

```
#Compilation Function
```
$Model.compile(optimizer =' adam', loss = binary\ \ crossentropy', metrices['acccurcay']$

```
#Fit the model  to the training data
```
$training\_set = train\_datagen.flow\_from\_directory('F:\backslash\backslash dataset\backslash\backslash citrus\_fruit\_leaf\_diseases\backslash\backslash training\_set', target\ size, batchsize, class\ mode)$

```
#Fit the model  to the test data
```
$test\_set = test\_datagen.flow\_from\_directory('F:\backslash\backslash dataset\backslash\backslash citrus\_fruit\_leaf\_diseases\backslash\backslash test\_set', target\ size, batchsize, class\ mode)$

```
#Model Fitting
```
$Model.fit\_generator(taining\_set, steps\_per\_epo\ test\_set, validation\_steps))$
```
#Model's Output:
 return accuracy
    End Procedure
```

4. Results and Discussion

This section presents and evaluates the findings obtained by framing experimental settings and performing various experiments to address the research questions.

4.1 Addressing Research Question#1

To find an answer to "RQ1. How to apply the CNN model to effectively classify citrus fruit and leaf diseases?" Using various parameters, we tested different CNN classifiers for recognizing citrus fruit and leaf images into different diseases such as Black spot, canker, scab, greening, and Melanose.

The proposed CNN model parameters for citrus disease recognition are shown in Table 3. We examined different settings and used different numbers of convolutionary layers: from 1 to 6. The number of filters ranges from 8 to 64, the number of epochs from 2 to 10, and various filter sizes, such as 3 x 3 and 2 x 2, are employed, as well as some fixed size parameters, such as max pool layers, image size, activation function, and batch size. Table 4 illustrates the layout of all system parameters for the varying CNN models (number of convolutional layers, Filter size, and number of filters).

Table. 3

Establishing CNN model parameters for citrus disease Recognition

Parameter	Value
Image Dimensions	64
Number of layers in a convolutional neural	1..6
The maximum number of pool layers	2
The total number of filters	8,12,16, 32,64
Filter Dimensions	2 and 3
Functions of activation	Softmax , Sigmoid, Relu
The cumulative number of epochs	2..10
Batch Dimensions	32

The number of convolutional layers in each CNN model varied depending on the number of epochs and filter size. All CNN models' structure settings are described in Table 4.

Table. 4

Citrus fruit/leaf Disease Recognition parameter settings for all 10 CNN models

Model for citrus disease	Convolutional layer count	Filter count	Filter Dimensions	The number of epochs
CNN-citrus-disease (1)	6	64	3	5
CNN- citrus-disease (2)	5	16	2	3
CNN- citrus-disease (3)	1	8	2	2
CNN- citrus-disease (4)	4	12	2	3
CNN- citrus-disease (5)	4	8	2	4
CNN- citrus-disease (6)	5	16	3	2
CNN- citrus-disease (7)	3	12	2	3
CNN- citrus-disease (8)	1	64	2	4
CNN- citrus-disease (9)	3	32	3	10
CNN- citrus-disease (10)	2	16	2	8

We noted the test accuracy, training time, and training loss after conducting experiments with all CNN models with different parameter settings, as shown in Table 5. The proposed CNN model (CNN-Citrus (10)) with two convolutional layers (), filter size=2, number of filters =16, and number of epochs=8 performed better and achieved the best accuracy of 94.55%. The proposed model CNN's training loss score is decreased by increasing the epochs and decreasing the number of convolutional layers.

Table. 5

CNN models for citrus fruit/leaf disease recognition accuracy, training time and loss of training

Model	Test accuracy	Training loss	Training time(s)
CNN- citrus-disease (1)	72.81%	0.06	49s
CNN- citrus-disease (2)	77.16%	0.26	485s
CNN- citrus-disease (3)	78.06%	0.26	21s
CNN- citrus-disease (4)	81.50%	0.1	151s
CNN- citrus-disease (5)	82.23%	0.14	63s
CNN- citrus-disease (6)	85.85%	0.26	164s
CNN- citrus-disease (7)	86.4%	0.26	38s
CNN- citrus-disease (8)	90.20%	0.01	49s
CNN- citrus-disease (9)	90.56%	0.04	214s
CNN- citrus-disease (10)	94.55%	0.01	60s

Tables 6 and 7 display output metrics such as precision and recall for each disease detected by the proposed CNN model.

$$Precision = True\ class/True\ positive$$

Table 6

CNN models' precision (%) for each class of citrus-fruit-leaves (Diseased and healthy)

Model	Black spot	Canker	Scab	Greening	Melanose	healthy
CNN-citrus-disease (1)	26	99	98	50	98	33

CNN-citrus-disease (2)	59	33	79	82	91	63
CNN-citrus-disease (3)	68	57	81	69	67	71
CNN-citrus-disease (4)	78	95	81	79	39	0.6667
CNN-citrus-disease (5)	56	91	71	73	91	71
CNN-citrus-disease (6)	89	83	72	83	84	41
CNN-citrus-disease (7)	82	91	72	93	90	71
CNN-citrus-disease (8)	65	93	92	95	98	98
CNN-citrus-disease (9)	69	95	97	97	98	98
CNN-citrus-disease (10)	78	99	99	100	100	100

$$Recall = True\ class/True\ negative$$

Table. 7
CNN models' Recall (%) for each class of citrus-fruit-leaves (Diseased and healthy)

Model for citrus disease	Black spot	Canker	Scab	Greening	Melanose	healthy
CNN-citrus-disease (1)	98	39	95	91	91	68
CNN-citrus-disease (2)	65	41	79	92	91	99
CNN-citrus-disease (3)	92	92	92	52	82	98
CNN-citrus-disease (4)	94	94	94	94	94	41
CNN-citrus-disease (5)	97	71	97	97	97	78
CNN-citrus-disease (6)	95	95	95	95	69	96

CNN-citrus-disease (7)	94	69	94	95	75	97
CNN-citrus-disease (8)	96	75	96	96	96	75
CNN-citrus-disease (9)	92	60	92	92	92	92
CNN-citrus-disease (10)	100	76	99	99	99	100

Fig. 6 depicts training and test accuracies of the proposed system while classifying different citrus diseases.

Greening Training Accuracy: 96.07%   Greening Testing Accuracy: 93.89%   Black Spot Training Accuracy: 98.43%   Black Spot Testing Accuracy: 92.68%
Canker Training Accuracy: 92.81%   Canker Testing Accuracy: 94.44%   Melanose Training Accuracy: 95.91%   Melanose Testing Accuracy: 94.01%
Healthy Training Accuracy: 96.51%   Healthy Testing Accuracy: 92.46%   Scab Training Accuracy: 94.74%   Scab Testing Accuracy: 93.52%
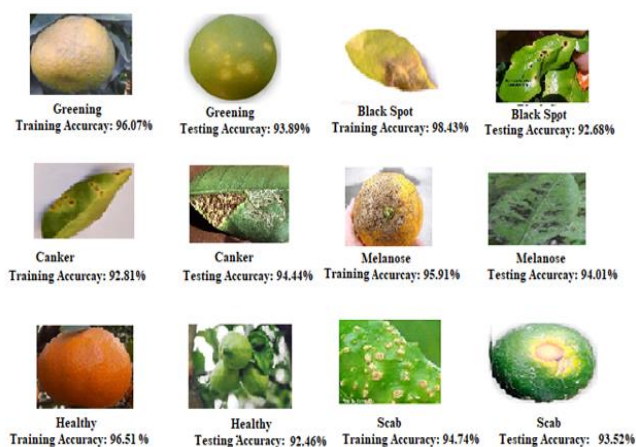
Fig. 6 Proposed system's training and test accuracies

The purpose of micro- and macro-averages is to compute somewhat different stuff, hence their connotation changes. A macro-average computes the measure separately for each class and then averages it (therefore considering all classes identically), whereas a micro-average aggregates all class contributions to compute the mean measurement.

$$Micro - precision = \frac{Tp1 + \cdots.. + Tpk}{Tp1 + \cdots Tpk + Fp1 + \cdots + Fpk}$$

$$Macro - precision = \frac{P1 + \ldots\ldots + Pk}{k}$$

$$Micro - Recall = \frac{Tp1 + \cdots.. + Tpk}{Tp1 + \cdots Tpk + Fn1 + \cdots + Fnk}$$

$$Macro - Recall = \frac{R1 + \cdots.. + Rk}{k}$$

$$Micro\ F - measure = 2 * \frac{micro - precision * micro - recall}{micro - precision + micro - recall}$$

$$macro\ F - score = \sum_{i=0}^{n} F - score(i)$$

where i is the index of the class/label and N represents the number of classes/labels. and Tp1, …Tpk are the true positives; Fp1, ….Fpk are the false positives; and Fn1, ….Fnk are the false negatives. Tables 8 displays output metrics such as micro and macro precision, recall, and f-measure for each disease detected by the proposed CNN model.

Table. 8
CNN models' Micro and Macro metrics (%) for each class of citrus-fruit-leaves (Diseased and healthy)

Model for citrus disease	Macro Precision (%)	Micro Precision (%)	Macro Recall (%)	Micro Recall (%)	Macro F-score (%)	Micro F-measure (%)
CNN-citrus-disease (1)	0.74	0.75	0.84	0.75	0.79	0.75
CNN-citrus-disease (2)	0.74	0.76	0.86	0.76	0.79	0.76
CNN-citrus-disease (3)	0.62	0.82	0.85	0.82	0.72	0.82
CNN-citrus-disease (4)	0.76	0.87	0.88	0.87	0.82	0.87
CNN-citrus-disease (5)	0.90	0.90	0.90	0.90	0.90	0.90
CNN-citrus-disease (6)	0.88	0.91	0.94	0.91	0.91	0.90
CNN-citrus-disease (7)	0.93	0.94	0.93	0.93	0.92	0.93
CNN-citrus-disease (8)	0.97	0.96	0.97	0.96	0.96	0.96
CNN-citrus-disease (9)	0.96	0.97	0.96	0.97	0.96	0.97
CNN-citrus-disease (10)	0.98	0.99	0.98	0.99	0.98	0.99

4.2 Addressing Research Question#2
In order to address RQ2. What is the proposed approach's efficiency in contrast to state-of-the-art ML techniques? We compared the efficiency of various machine classifiers on the acquired datasets to test the proposed CNN model citrus disease recognition. Table

9 shows the experimental findings obtained using the acquired dataset.

Table. 9
Implemented CNN model assessment in terms of Machine Learning techniques

Baselines	Study and Technique	Recorded Results on the dataset	Actual Results on dataset
Baseline#1	Machine Learning-based _ Patel et al. [32] citrus(orange) disease recognition	Accuracy SVM: 89.46%	Accuracy 55.58%
Baseline#2	Machine Learning Qadri et al. [23] Disease recognition in Citrus leaves	Accuracy KNN= 82.91%	Accuracy KNN= 65.84%
Proposed	Deep Learning-based (CNN with 2-layers)+ recognition of 5 citrus diseases	Accuracy 94.55%	

Baseline# 1 vs. CNN (proposed): The aim of this experiment is to compare our proposed deep learning-based CNN model to the machine learning-based work done by Patil et al. [7].The main disadvantage of the machine learning-based SVM model is that it performs poorly and achieves lower accuracy than the deep learning model, despite the fact that CNN produces impressive results for image classification. On the benchamark dataset, Patil et al. [7] achieved an accuracy of 89.46 percent. When tested on the same dataset, however, we got an accuracy of 55.58 percent.

CNN (proposed) vs (Baseline # 2): The proposed CNN model is compared to Qadri et al. [23]'s machine learning-based work. In comparison to the proposed deep learning methodology, the performance of machine learning classifiers is very limited in terms of different measures like precision recall and f1-measure. On the citrus dataset, Qadri et al. [23] reported an accuracy of 82.91 percent for KNN, but when we experimented, we received accuracy results for KNN=65.84 percent (see Table 10).

4.3. Addressing Research Question#3
In order to answer RQ # 3: *"What is the proposed approach's efficiency in contrast to state-of-the-art DL techniques?"*, We compared the efficiency of various deep classifiers on the acquired datasets to test the proposed CNN model citrus disease recognition. Table

10 shows the experimental findings obtained using the acquired dataset.

Table. 10
Implemented CNN model assessment in terms of Deep and Machine Learning

Baselines	Study and Technique	Recorded Results on the dataset	Actual Results on dataset
Baseline#1	Deep Learning-based recognition of citrus diseases Liu et al. [24]	Accuracy 87.28%	Accuracy 84.31%
Baseline#2	Deep Learning-based recognition of citrus diseases Luaibi et al. [7]	Accuracy 91.75%	Accuracy 88.20%
Proposed	Deep Learning-based (CNN with 2-layers)+ recognition of 5 citrus diseases	Accuracy 94.55%	

- **CNN (Proposed) VS Baseline#1:**

In this evaluation, the suggested CNN model's performance is compared to Liu et al. [24] 's study, which used a CNN model with four convolutional layers to recognize different citrus diseases. When compared to the suggested CNN model, the four convolution layer CNN model achieved lower efficiency (Acc: 88.20 percent,) as shown in Table 10, but when we tested it, we got an accuracy of 94.55 percent. Table 10 summarises the findings. The justification for the inefficiency of the baseline model is the lack of an adequate number of layers and various parameter configurations in the deep convolutional algorithm, so the performance of the neural network becomes less prominent when the number of hidden layers increases by more than two.

- **CNN (proposed) vs Baseline#2:**

The efficacy of the Deep Learning-based CNN model is compared to the work introduced by Luaibi et al. [7]. Due to various parameter configurations of layers in a convolutional neural network like filters, filter size, batch size, number of epochs, and various measures like accuracy, recall, and F1 measure, the proposed approach outperformed the baseline work. Luaibi et al.

[7] claim an accuracy of 93.75 percent on the given dataset, but we found an accuracy of 92.20 percent on the same dataset when we experimented.

4.4 Discussion of the Results Obtained

We ran an experiment to evaluate the suggested CNN model's performance to that of state-of-the-art research, and the findings are presented in Tables 10 and 11. However, a precise comparison of published methodologies is problematic for a variety of reasons. To begin, such models were tested on a wide range of datasets, making comparison difficult. Furthermore, the contributing authors' articles present the methodologies in an abstracted manner with inadequate information, making them unfeasible for future researchers.

Table 10 shows how well the proposed work performed with the Citrus dataset. In comparison to the baseline studies, the acquired findings show that the suggested CNN performed well. The results also show that the maximum accuracy was achieved through the use of CNN with various convolution layers. The aforesaid results demonstrate that, in terms of Citrus disease recognition, the suggested CNN model reached the best performance level (94.55% accuracy) than the other deep and machine-learning work [7, 23, 24, 32]. The proposed model's best accuracy over the benchmark works is due to the use of CNN, which is intended for image processing. In addition, for effective classification, various numbers of convolutional layers and a variety of parameters are used. Our model detects Citrus plant diseases from both the leaves and the fruits. Citrus diseases are classified into six categories: black spot, canker, scab, greening, and melanosis. Different measures, such as accuracy, recall, macro, and f-measure, are used to analyze experimental findings. In terms of classifying input images for various citrus diseases recognition, our model performed the best.

Why the proposed CNN model is better?

The suggested technique classifies citrus diseases into distinct groups using a cutting-edge CNN model, including Black spot, canker, scab, greening, and Melanose. It incorporates a suitable number of layers in the suggested deep learning model and compares the efficiency of the suggested model to that of similar research, exhibiting better performance. The proposed CNN model is an image feature separator that automatically extracts features. A pixel vector technique loses a lot of connectivity between pixels, whereas a CNN effectively downsamples the image via convolution and then employs a predictive layer at the end.

5. Conclusions and Future Work

The proposed CNN-based leaf disease identification model is capable of distinguishing between healthy and diseased Citrus fruits and leaves. We used the CNN model to tackle the problem of classifying diseases from citrus fruit and leaf images in this study. The modules in our proposed model are as follows: i) Data acquisition, ii) Data preprocessing, and iii) CNN model application.

Two convolutional layers were used in the suggested CNN model. The first convolutional layer separates low-level features from the picture, while the second convolutional layer collects high-level attributes, yielding disease classification of citrus fruit/leaves into Black spot, canker, scab, greening, and Melanose classes. On plant disease datasets, we tested a variety of machine and deep learning models and reported our findings. The suggested CNN outperformed other classifiers in terms of accuracy, scoring 95.65% for citrus fruit/leaf disease classification experiments.

5.1 Limitations

The suggested method for recognizing citrus diseases has the following drawbacks.

1. We conducted citrus fruit/leaf disease detection with one dataset in a single domain, but more domains for citrus fruit disease recognition need to be studied.
2. The citrus fruit diseases dataset used in this study is only 213 images in size, which is a limitation.
3. We only used one deep learning-based CNN model in this study; other deep learning models were not used.

5.2 Future Directions

1. The suggested system is based on a dataset of five citrus diseases. However, other citrus datasets may be explored for further experiments.
2. Multiple plant disease datasets of varying sizes may be used to improve the model's performance.
3. In the future, we will employ various deep learning models such as RNN, LSTM, Bi-LSTM, and hybrid models such as CNN+LSTM, CNN+RNN, and so on.
4. In the disease module, we split diseases into five categories. However, additional disease classes can be investigated for fine-grained analysis.
5. Creating and implementing a precision farming framework based on the internet of things (IOT).

Lastly, Table11 depicts the manuscript recap.

Table 11
Synopsis of the manuscript

Research Problem	Automatic diagnosis of diseases for plant growth and development
Motivation	monitoring and avoiding plant damage in order to benefit the environment and increase their financial benefit
Contribution	For classification of diseased and healthier citrus fruit and leaves, an automated, effective, and low-cost disease monitoring system is proposed.
Highlights	The application of deep learning ideas to real-time images of citrus fruit and leaves with greater economic benefits in all citrus-growing countries such as India and Pakistan
Future Directions	designing and introducing a precision agricultural framework based on the internet of things (IOT).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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