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Revisión / Review

Automatic detection and classification of disease in citrus fruit and leaves using a customized CNN based model

[Detección y clasificación automática de enfermedades en frutas y hojas de cítricos utilizando un modelo basado en CNN personalizado]

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Abstract: India's commercial advancement and development depend heavily on agriculture. A common fruit grown in tropical settings is citrus. A professional judgment is required while analyzing an illness because different diseases have slight variations in their symptoms. In order to recognize and classify diseases in citrus fruits and leaves, a customized CNN-based approach that links CNN with LSTM was developed in this research. By using a CNN-based method, it is possible to automatically differentiate from healthier fruits and leaves and those that have diseases such fruit blight, fruit greening, fruit scab, and melanoses. In terms of performance, the proposed approach achieves 96% accuracy, 98% sensitivity, 96% Recall, and an F1-score of 92% for citrus fruit and leave identification and classification and the proposed method was compared with KNN, SVM, and CNN and concluded that the proposed CNN-based model is more accurate and effective at identifying illnesses in citrus fruits and leaves.

Keywords: Automatic disease identification; Convolutional Neural Network; Long Short-Term Memory; Mummification; Canker

Resumen: El avance y desarrollo comercial de India dependen en gran medida de la agricultura. Un tipo de fruta comunmente cultivada en entornos tropicales es el cítrico. Se requiere un juicio profesional al analizar una enfermedad porque diferentes enfermedades tienen ligeras variaciones en sus síntomas. Para reconocer y clasificar enfermedades en frutas y hojas de cítricos, se desarrolló en esta investigación un enfoque personalizado basado en CNN que vincula CNN con LSTM. Al utilizar un método basado en CNN, es posible diferenciar automáticamente entre frutas y hojas más saludables y aquellas que tienen enfermedades como la plaga de frutas, el verdor de frutas, la sarna de frutas y las melanosis. En términos de desempeño, el enfoque propuesto alcanza una precisión del 96%, una sensibilidad del 98%, una recuperación del 96% y una puntuación F1 del 92% para la identificación y clasificación de frutas y hojas de cítricos, y el método propuesto se comparó con KNN, SVM y CNN y se concluyó que el modelo basado en CNN propuesto es más preciso y efectivo para identificar enfermedades en frutas y hojas de cítricos.

Palabras clave: Identificación automática de enfermedades; Red neuronal convolucional; Memoria a corto y largo plazo; Momificación; Ulceraciones

INTRODUCTION

Nowadays, the agricultural industry represents a crucial and novel context for computer vision researchers (Beck *et al.*, 2020). The basic purpose of agriculture is to generate a diverse range of significant crops and plants. With the world's population expanding, one of the most pressing concerns is food supply. Food consumption is expected to quadruple by 2050. As a result, agricultural manufacturing demands a higher and more stable atmosphere to improve plant yield (Mirvakhavoba *et al.*, 2008; Hunter *et al.*, 2017) and economic standards by improving food productivity.

Citrus fruit and family

The citrus crop is the principal kind of the "Rutaceae" family, the world's greatest common cultivated plant. Citrus is an essential plant planted as a basis of nutrition for generations due to its healthy, nutritious, financial, eco-friendly, and additional connected benefits. Its principal yields are fresh fruit and refined juice, traded as a product across the biosphere. On the other hand, citrus manufacturing outgrowths such as pectin and a basic lubricant are frequently used in various sectors such as cosmetics, sanitation, medicine, and so on, increasing the crop's economic importance. Fruit and vegetable diets have been linked to various health advantages, including reducing illness (Iqbal *et al.*, 2014). Citrus fruit contains limonoids, flavonoids, carotene, and various proteins, minerals, and vitamins, all of which show balanced biological activity. Flavonoids have anti-inflammatory, cytoprotective, and antioxidant properties. Citrus flavonoids have been demonstrated to improve lipid metabolism, and it is believed that this is due in part to their ability to act as antioxidants.

Health benefits of citrus fruit

There is a tremendous amount supporting citrus fruit's anti-inflammatory, anti-mutagenic, and beneficial effects on bone, cardiovascular, and immune system health. Because of the number of natural antioxidants present in crop yields and some sort of health risks could be decreased by a healthy diet that includes enough fresh fruits and vegetables (Sidana *et al.*, 2013). Citrus flavonoids have antimicrobial, antibiotic, anti-insulin, cardiac anticancer, painkiller, anti-inflammatory, anti-anxiety, and other biological properties. It contains vitamins C, carotenoids, potassium, dietary fibres, selenium, folic acid, and a wide range of phytochemicals (Negi & Kumar, 2020), as a consequence of which several epidemiological studies have demonstrated that the usage of citrus fruit in a variety of humanoid malignancies appears to be defensive. Citrus fruit intake is more commonly linked to risk reduction than vitamin C consumption. It demonstrates that citrus fruits deliver numerous chemo cancer avoidance agents.

Table No. 1
Typical diseases of citrus fruits

Citrus Species	Presence of citric acid (%)	Disease that affect citrus fruits
***Citrus sinensis* (Orange)**	**0.8 - 1**	**Bacterial citrus canker, leaf and fruits spot, melatose, Scab, Stem and end rots, Phytophthora, and Pencillium.**
***Citrus limon* (Lemon)**	**7 - 9**	**Anthracnose, Bacterial canker, citrus canker, citrus greening, Aphids.**
***Citrus reticulata* (Mandarin)**	**1.5**	**Alternaria rot, Blue mold, Green mold, Sour rot, Gray mold, Mucor rot.**
***Citrus paradise* (Grape fruit)**	**1.5 - 2.0**	**Melanose, Citrus scab, Anthracnose, Citrus black spot, Citrus blast, citrus greening**

Production of citrus fruit in india

Citrus is grown on around 923.2 thousand hectares in India, with an estimated annual production of 8607.7 thousand metric tonnes. Numerous species of citrus are significant economically. Only a few species, including grapefruit, lemons, limes, sweet oranges, and mandarins, are extensively cultivated in India. Citrus species, such Citrus Sinensis, Citrus Limon, Citrus Reticulata, Citrus Paradise, etc., are Rutaceae family members; moreover, table 1 demonstrates that these fruits and their leaves are afflicted by various diseases.

Disease in citrus fruit

Diseases in such plants can diminish output and affect the diversity and quality of the fruits. Fruit black spot, Canker, fruit greening, fruit scab, and Melanose are all serious diseases that can diminish plant productivity. Farmers are well-versed in these diseases, but most are unaware of early preventative strategies to safeguard them from additional loss. As a result, citrus fruit output suffers significantly. The difficult process is detecting and diagnosing the citrus leaf and fruit infections manually (Al-Hiary *et al*., 2011). Graphics computerized systems have proven to be more successful than prior systems since the introduction of smartphones and image sensors. Fruit and vegetable disease detection using computer vision has the potential to result in large autonomous monitoring of plant-based foods (Somov *et al*., 2018). This aids in enchanting early efforts to address particular challenges that disrupt real yields, such as the requirement to apply fertilizers to boost growth rate (Bharathi *et al*., 2021). It prompted us to build an automated method for plant disease identification (Pujari *et al*., 2013), as the manufacture of citrus fruits causes serious problems in both industrialized and developing nations (Gilligan, 2008; Adenugba *et al*., 2019). Currently, disease detection automation is the quickest, least costly, and most accurate solution (Zhou *et al*., 2014). It may be more expensive, but it can save time by automating the disease diagnosis procedure (Ali *et al*., 2017). The identification of plant diseases is becoming more automated. However, to give intelligent automated solutions, both machine learning and deep learning technologies are employed (Ashraf *et al*., 2019).

Artificial Intellgience based approach

Traditional Machine Learning methods have been successful in identifying and clarifying crop diseases. However, they are restricted to picture separation using grouping and additional ways (Singh *et al*., 2019), extraction of features (Luaibi *et al*., 2021), and design matching using SVM (Asghar *et al*., 2019a), the k-nearest neighbour method (Asghar *et al*., 2019b), and Artificial Neural Network (Ali *et al*., 2021). It is hard to choose and remove the greatest visible pathogenic traits, demanding the employment of extremely skilled engineers and practised professionals. It is haphazard, but it is also a waste of human and financial resources. Deep Learning has yielded encouraging results in agricultural fields such as plant disease diagnosis (Ji *et al*., 2020), weed analysis (Lottes *et al*., 2018), and seed identification (Luo *et al*., 2023). However, identifying and categorizing diseases with high accuracy and speed remains a difficult challenge. So, based on the incredible outcomes of deep learning-based approaches in image classification, an integrated deep learning model for automated Citrus fruit and leaf virus detection is presented.

Major contribution

- The Convolutional Neural Network-based technology that has been presented is aimed to automatically detect healthy fruits and leaves from those affected by major citrus infections such as fruit black spot, blight, fruit greening, and scab.

- This developed CNN-based model detects the diseases in citrus fruits and leaves more accurately and with other superior parameters.

We presented a reconfigurable CNN system to categorize and identify 'Citrus' infections in this research. Pictures of citrus fruits and collectively healthy and diseased leaves are included in our collection. As indicated in Figure 1, the targeted infections in the information groups are Blackspot, Blight, Scab, Greening, and Melanoses. To detect citrus illness among one of the targeted diseases, we create a Convolutional Neural Network-centered classifier to identify the fruit or theoretical leaf group and then create an LSTM model to detect the targeted infection in that grouping. The planned research is valuable in monitoring citrus infection because plant production harms can be decreased. Needless fungus treatment may be avoided, a major contributor to environmental emissions and a key source of spending. Controlling citrus disease in plantations destined for manufacturing or fresh berry production must be considered.

Figure No. 1
Sample Images from the Dataset

The following is how this article was organized. Section 2 starts with comparing related works, Section 3 delves into the proposed CNN-based technique in-depth, Section 4 discusses the work's implementation implications, and Section 5 wraps up the work.

Related works

Earlier, many studies focused on picture analysis, pattern recognition, and machine-learning methodologies, particularly farming. Initially, recording devices were employed to acquire pictures from their surroundings. The images are then subjected to certain processes to extract important characteristics. The primary goal is to detect unhealthy spots in images. Plant disease classification has become a research focus in recent years to establish practical plant diagnostics systems for farmers. A wide range of Artificial Intelligence technologies has been used to classify and recognize various crop infections. Several approaches for diagnosing plant diseases have been presented. Some of the potential strategies for diagnosing plant disease are mentioned here.

Yang *et al*. (2018), used the Parametric Exponential Nonlinear Unit (PENLU) by relocating the activated functionality of the neural net and enhancing the generalization capability of the neural network to increase the performance of a neural network framework. ResNet processing was improved, and the model was developed using pictures of regional urban navel orange lesions as a basis. The feature recognition rate was 100 percent overall, while the output sample forecasting accuracy was 98.86 percent. The significance of the research revealed that, under certain situations, the proposed Parametric Exponential Nonlinear Unit improved the DL model's performance and acquired superior accuracy at a very cheap cost. The experimental technique resulted in a novel notion of prospective ways of identifying plant diseases. Sunny & Gandhi, (2018), presented using the Contrast Limited Adaptive Histogram Equalization technique to identify blight in Citrus, which increased image quality.

Mostafa et al. (2021), employed a deep convolutional neural network (DCNN)-based data augmentation method based on color-histogram equalisation and the unsharp masking approach. The number of converted plant photos was increased by using nine angles from 360 degrees. Then, this enhanced data were used as input for cutting-edge classification networks. Prior to processing, the suggested approach underwent normalisation. For the experimental analysis, a locally gathered guava disease dataset from Pakistan was employed.

Perumal *et al*. (2021), proposed Support Vector Machine (SVM) and image preparation techniques to accurately and quickly diagnose guava leaf ailments. The suggested framework is divided into the following stages: pre-preparing the picture, segmenting the image, clustering the image using k-means, and extracting the information using the Grey Level Co-Occurrence Matrix (GLCM). The SVM classifier is then used to categorise the image.

Loey *et al*. (2020), examined the use of Deep Learning to detect plant diseases and evaluated the real efficacy. Throughout the survey, it has been noted that Deep Learning has resulted in a significant progression because it allows for a much higher level of accuracy and a wider range of plants and illnesses to be identified. Several differences between Deep Learning and traditional forms were made. The results showed that DL significantly outperforms traditional ML techniques and that using current state-of-the-art techniques in combination with transfer learning strategies improves presentation and arrangement exactness. According to the recent works done in the field, Deep Learning also enables the development of smart agriculture and smart farming robotics for the food and farming sectors.

Gaikwad *et al*. (2017), suggested and experimentally shown that there is a method for the identification and categorization of fruit illnesses. The proposed method for image processing consists of the following steps: segmenting the image using the K-Means clustering technique in the first step; extracting some features from the segmented image in the second step; and finally classifying the images into one of the classes using a Support Vector Machine.

Mari & Senthilkumar, (2020), devised a citrus disease mechanical recording and arranging system that featured a set of four core procedures: data pre-processing, segmentation, feature extraction, and classification. Pre-processing is used to increase image quality. As a result, an Otsu-based segmentation process was created, with initiation and a ResNetv2 feature extractor. As a result, the random forest classifier (RF) has been utilized to categorize several citrus illnesses. The proposed model is tested extensively utilizing Citrus Image Gallery dataset samples. The pretend results demonstrate that the planned method is beneficial in spotting and categorizing good illnesses with the highest exactness of 99.13 percent.

Sun *et al*. (2020), established a technique for creating a total plant lesion leaf image and making full and sparse plant disease leaf photos with a specific form to increase classification process recognition precision. The researchers present a system based on a bitwise generation system to consider how a generative adversarial network induced a scratch image with a specific pattern using edge-smoothing through the image pyramid methodology, which aids in overcoming the issue of replicating a total and utter lesion leaf image when synthetic edge pixels appear to differ. The actual output amount is fixed, but the actual dimensions of the disease are unknown. The methodology solved the issue of numerous crop injuries attributed to extremely related forms being difficult to handle. Thus the disease and leaf information must be combined to diagnose the related illness appropriately, allowing the DL platform to have minimal data training. In particular, compared to the presentation of identification by human experts and AlexNet, the suggested technique greatly enlarged the diseased crop datasets. It improved the identification exactness of an organization system.

Khattak *et al*. (2021), planned an integrated method for adopting the CNN method. The suggested CNN method distinguishes healthy fruits and leaves from fruits and leaves infected with common citrus diseases such as black spot, blight, shell, greening, and Melanoses. By combining several layers, the proposed CNN model captures complementing discriminative characteristics.

Syed-Ab-Rahman *et al*. (2022), employed leaf images to train a 2-step deep CNN method for crop infection identification and citrus disease categorization. The proposed method is separated into two stages: (a) utilizing a neural network approach to identify possible target sick regions and (b) using a learner to assign the most probable desired location to the appropriate disease class. The suggested method has a detection accuracy of 94.37 percent and an average precision of 95.8 percent. The results show that the planned method correctly recognizes and separates three distinct citrus illnesses: citrus black spot, citrus bacterial blight, and Huanglongbing. The suggested design is a valuable conclusion provision tool for citrus producers and agrarians in identifying and classifying citrus illnesses.

Çetiner *et al*. (2022), used photographs to identify and categorise the illnesses blackspot, canker, and greening, which are often observed in numerous locations. Preprocessing and segmentation procedures are initially carried out for this purpose on several pictures from the Citrus Leaves Prepared data set in the literature. After then, a distinctive architecture built around CNN is created.

Almadhor *et al*. (2021), used artificial intelligence to identify and categorize the most frequent guava plant diseases. Image-level and illness-level extracting feature techniques are applied to enable robust guava disease recognition. The presented research includes four guava diseases, including Blight, Mummification, Dot, and Rust, and classifies one additional class as healthy.

Pathmanaban et al. (2022), [36] categorized the quality of damaged and sick fruits, a convolution neural network (CNN) model based on digital images was created. Thermal imaging were used to measure the surface temperatures of the three maturity-indexed fruit levels and the damaged fruits. The temperature of the immature fruits was lower than half that of the mature fruits during the storage period.

Almutiry *et al*. (2021), created an automated technique to assist farmers in identifying major guava diseases. The local binary pattern (LBP) was utilized to extract features, and principal component analysis was applied to decrease measurements. Diseases grouping was performed using a variety of classifiers, including cubic support vector machine, Fine K-nearest neighbour (F-KNN), Bagged Tree, and RUS Boosted Tree methods, with the Bagged Tree approach achieving 100 % exactness for the diagnosis of fruit flies' infection. However, the results showed that cubic support vector machines (C-SVM) were the most accurate predictor for all guava illnesses. To detect illnesses, the authors focused solely on guava fruit.

Perumal, (2021), advocated employing image preparation methods and Support Vector Machines to detect guava leaf diseases earlier and accurately. The projected structure includes the following stages: picture pre-processing, image segmentation, image clustering using k-means, and removal using the Gray Level Co-Occurrence Matrix (GLCM). After that, the picture is classified using an SVM classifier. Compared to the present system, the presented structure detects plant leaves infection early and has a 98.17 percent accuracy rate. Table No. 2 reviews the existing research on fruit disease detection and classification.

Table No. 2
Review on existing fruit disease detection and classification

Citation	Technique used	Dataset	Training samples	Performance Metrics	Advantages
Yang *et al*., 2018	Parametric Exponential Nonlinear Unit (PENLU)	CIFAR 10 and 100	50,000	Accuracy – 89.72%	Higher accuracy
Sunny & Gandhi, 2018	Contrast Limited Adaptive Histogram Equalization (CLAHE) and Support Vector Machine classifier	Manually collected dataset	70 images	Accuracy – 94% and Execution time – 0.19	Less execution and high accuracy
Mostafa *et al*., 2021	DCNN	Manually collected dataset	70 images	Accuracy – 97.94%	Very low learning rate and increase in accuracy.
Perumal, 2021	SVM	Manually collected dataset	2889 images	Accuracy – 98.17%	It reduce the over fitting problems
Mari &	Inception-ResNet V2	Citrus	609 images	Accuracy –	Effective dataset

Senthilkumar, 2020	model	Image Gallery dataset.		95.80%	
Sun *et al*., 2020	GAN	Nikon D7500	7500 images	Accuracy – 97.5%	Accurately identify the corresponding disease
Kattak *et al*., 2021a	CNN	Citrus dataset, Plant village dataset	2293 images	Accuracy – 94.55%	CNN effectively down sample the images by convolution
Syed-Ab-Rahman *et al*., 2022	Two stage deep CNN	Kaggle dataset	-	Accuracy – 94.37%, Precision – 95.8%	To achieve improved accuracy, the proposed model does not necessitate extracting the object from the background.
Almadher *et al*., 2021	Fine KNN, cubic SVM	Manually collected dataset	393 images	Accuracy – 99%	More effective with LBP features
Pathmanaban *et al*., 2022	CNN	Mendeley dataset	-	Accuracy – 70%	Assist in human intervention
Almutiry *et al*., 2021	F-KNN	Fruits and Leaves dataset	-	Accuracy – 97.1%	Efficient results.
Perumal, 2021	SVM	Manually collected dataset	1070 images	Accuracy – 98.17%	Recognize the plant leaf disease with high accuracy.

However, most studies have concentrated on either fruits or leaves; no work has been done to discover the disease in both fruits and leaves. To address the shortcoming, this research proposes a novel model that can recognize and categorize diseases in fruits and leaves. The proposed illness identification approach will be briefly discussed in the following section of this study.

Customized CNN based model for detecting and classifying the disease in citrus fruits and leaves

With rising urbanization and an increasing population, it has become a serious responsibility to nurture and cultivate plants that are crucial in supporting nature and the requirements of living beings. Furthermore, there is a need to preserve plants of worldwide importance, both commercially and ecologically. Citrus is a popular fruit in Asia, where it ranks fourth in terms of production. Citrus plants are attacked by a variety of pathogenic and fungal diseases. Furthermore, postharvest infections have the potential to cause large productivity sufferers. Due to modest variations in several Citrus infection signs, a professional outlook is essential for disease investigation. Farmers who use pesticides incorrectly may incur financial losses due to the wrong diagnosis. Deep learning approaches have lately yielded favourable outcomes in various AI problems. We decided to use them to solve the challenge of identifying citrus fruit and leaf illnesses. A united strategy is employed in this research to provide a customized CNN-dependent model. Combined CNN and LSTM have been used to identify and order the Disease in Citrus fruits and leaves. Figure No. 1 depicts the architectural design of the newly proposed Disease diagnostic technique.

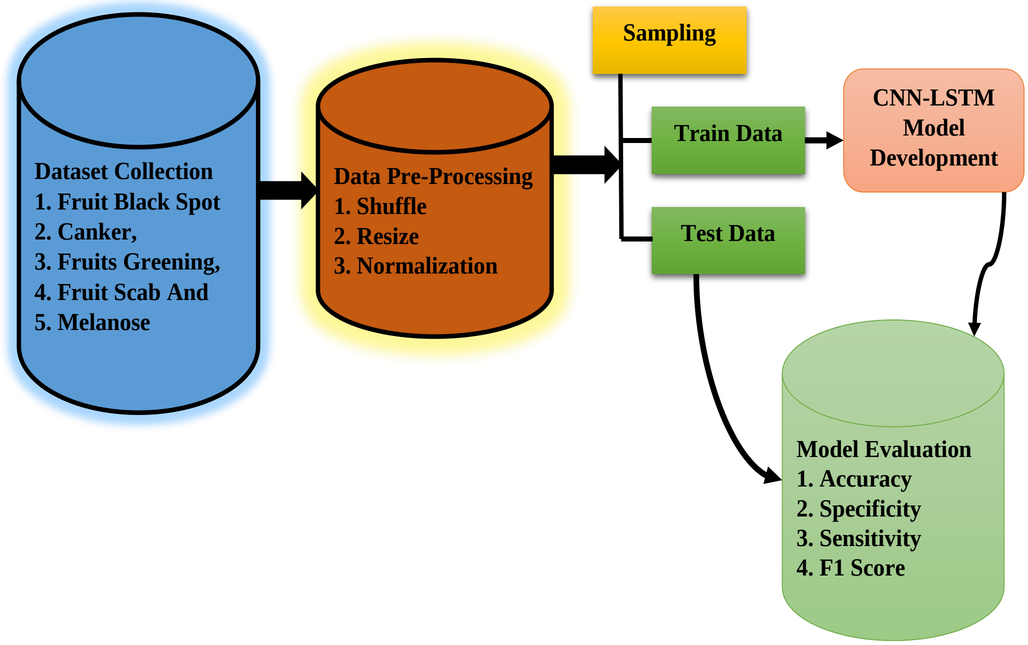


Figure No. 2
The architecture of the Proposed CNN based model

Data Collection

Citrus leaves and fruits, both healthy and diseased, were obtained from various sources for this study (Rauf *et al*., 2019). This data was collected in a naturally occurring environment with variable weather and light conditions. The majority of the images were taken in December in the orchards of Pakistan's Sargodha district, when the citrus plants had the most diseases and the fruit was just started to develop. Such sample pre-treatment was just not conducted out. Fruit black spot, Canker, fruit greening, fruit scab, and Melanose are among the illnesses addressed in this research. There were five main sorts of pictures collected. There are four different types of unhealthy photos and one for healthy fruit and leaf images (Rauf *et al*., 2019).

Data Pre-processing

Image pre-processing seems especially crucial for CNN models that use images from the dataset as input layers since it helps retrieve more features and improve discrimination abilities. Before training our model, we pre-process all of the photos in the dataset to ensure that they are all the same size and style. Each image is 256 * 256 pixels in size and has a 72-dpi quality. For each of the JPG images, the RGB colour space is used, with 256 shades for each RGB layer and 8 pixels for each shading layer. The pre-processing process included data resizing, shuffling, as well as normalizing. This pre-processed set of data was again split into training and test sets, and also the combined CNN-LSTM architectures were trained to utilize training data.

CNN-LSTM Model Development

The proposed design was created utilizing a deep CNN and long short-term memory system, briefly explained below.

Convolutional Neural Network

A CNN is indeed a sort of multilayered perceptron, also a dissimilar deep learning model; a basic neural net can't learn complicated features. Convolutional networks have demonstrated outstanding results in various domains, including categorization tasks, object identification, and medical image assessment. CNN's primary notion was that it could retrieve local characteristics from higher tier inputs and transfer those to lower tiers for even more sophisticated structures.

Convolutional, pooling, and fully connected (FC) layers make up a CNN. Each convolutional layer comprises a series of kernels used to compute a tensor of feature mappings. Such kernels use "stride(s)" to co-relate the entire input, resulting in numeric measurements toward an output sequence. Just after the convolutional layer gets utilized to conduct this striding operation, the dimensions of even an input volume shrink. Zero padding would be necessary to pad the input volume with zeros while maintaining the size of an input volume having low-level characteristics. The convolutional level's functioning is as follows:

$$F(a,b) = (I * K)(a,b) = \sum\sum I(a+m, b+n)\, K(m,n) \quad \textbf{(1)}$$

Where I would be the input matrix, K seems to be a 2Dimensional filter having size $m \times n$, while F became such a 2D feature map. I*K represents the functioning of its convolutional layer. A rectified linear unit (ReLU) layer has been utilized to enhance non-linearity within feature maps. While maintaining its threshold input equal to zero, ReLU evaluates activation. It may be stated as follows:

$$f(y) = \max(0, y) \quad \textbf{(2)}$$

Here, y is made up of the preceding layer's outputs after they have been passed through an activation function. The pooling layer downsamples an input data dimension to decrease the overall count of parameters. The much more systematic approach was max pooling, which creates the largest rate in such an input area. Each Fully Connected level serves as a classifier, making a judgment depending on characteristics gathered from the convolutional and pooling layers.

Long short-term memory (LSTM)

Long short-term memory augmentation is a recurrent neural network enhancement (RNNs). Rather than typical RNN units, computer memory is suggested by LSTM to tackle the disappearing and exploding gradient difficulties. It differs from RNNs because it has a memory cell for storing long-term states. A long short-term memory network may evoke and relate earlier knowledge to current data. LSTM is typically coupled with three gateways: an input gateway, a "forget" gateway, as well as an output gateway, where y_t denotes the present input, Z_t as well as $y_{t-1,}$ were both new & prior cell states correspondingly. Similarly, h_t and h_{t-1} were denotes the present and previous outputs. Figure No. 2 depicts the inner architecture of such LSTM.

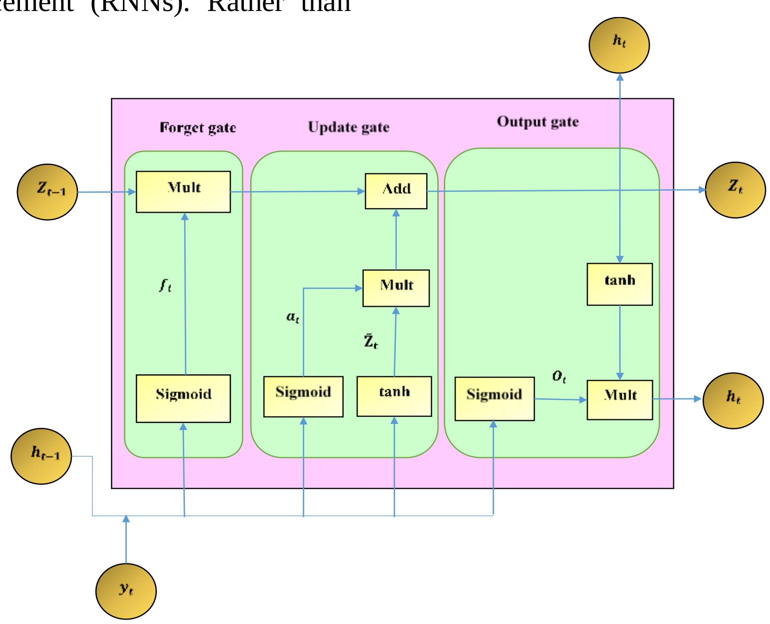


Figure No. 3
Long short-term memory's Internal Structure

The LSTM input gate principle can be seen in the proceeding forms.

$$a_t = \sigma(W_a.[h_{t-1}, y_t] + b_a) \quad \textbf{(3)}$$
$$\tilde{Z}_t = tanh(W_a.[h_{t-1}, y_t] + b_a) \quad \textbf{(4)}$$
$$Z_t = f_t Z_{t-1} + y_t \tilde{Z}_t \quad \textbf{(5)}$$

where Equation (3) has been utilized to select which chunk of data should be included bypassing h_{t-1} as well as y_t Via a sigmoid layer. In Equation (3) a_t denotes the input gate principle of LSTM. Define clearly. Following that, Equation (4) is being used to collect new information once, as well as yt that have gone through the same $tanh$ layer. In Equation(5), the present moment data $\tilde{Z}_t$, combined long-term memory data Z_{t-1} into Z_t, were integrated, where, W_a denotes a sigmoid output and $\tilde{Z}_t$ denotes a $tanh$ output in which W_a signifies weight matrices, while b_a specifies this same LSTM's input gate bias. The forget gateway of such LSTM subsequently enables the selective transfer of data via a sigmoid layer and a dot product. Equation (6) was utilized to decide whether to recall the necessary information from a primary cell with a certain probability or not. W_a refers to the weight matrix, b_f is indeed the offset, and σ represents the sigmoid function.

$$f_t = \sigma\left(W_f.[h_{t-1}, y_t] + b_f\right) \quad (6)$$

From equation (6), f_t denotes the decision probability. The output gate of the LSTM calculates the essential states for continuing by h_{t-1} as well as y_t inputs after (7) and (8). The final result is acquired as well as multiplied by the state decision vector, which transfers fresh data, Z_t via the $tanh$ layer.

$$O_t = \sigma(W_o.[h_{t-1}, y_t] + b_o) \quad (7)$$
$$h_t = O_t \tan(Z_t) \quad (8)$$

Where W_o and b_o were the weighted matrices as well as LSTM bias of the output gate, and O_t denotes the final output correspondingly.

Customized CNN Model

A combined technique was developed using photos of the fruit and leaves that identify four kinds of citrus infections: fruit black spot, blight, fruit greening, fruit scab, and melanoses. This architecture's framework was developed by integrating CNN with LSTM networks, including CNN, which was used to remove complicated information from pictures. Long short-term memory was employed as a classifier. The developed system for citrus disease detection is depicted in Figure No. 3. There are 14 layers in the network: 5 convolutional layers, five max-pooling layers, 1 FC layer, one flatten layer and a Long short-term memory layer, with one output layer that uses the softmax activation function. Every convolution unit is merged with 2 or 3 2D Convolutional Neural Networks and one pooling layer, complemented by a single hidden layer with a 25% dropout rate. This ReLU function activates the convolutional layer, which has a dimension of 3×3 kernels and is utilized to extract features.

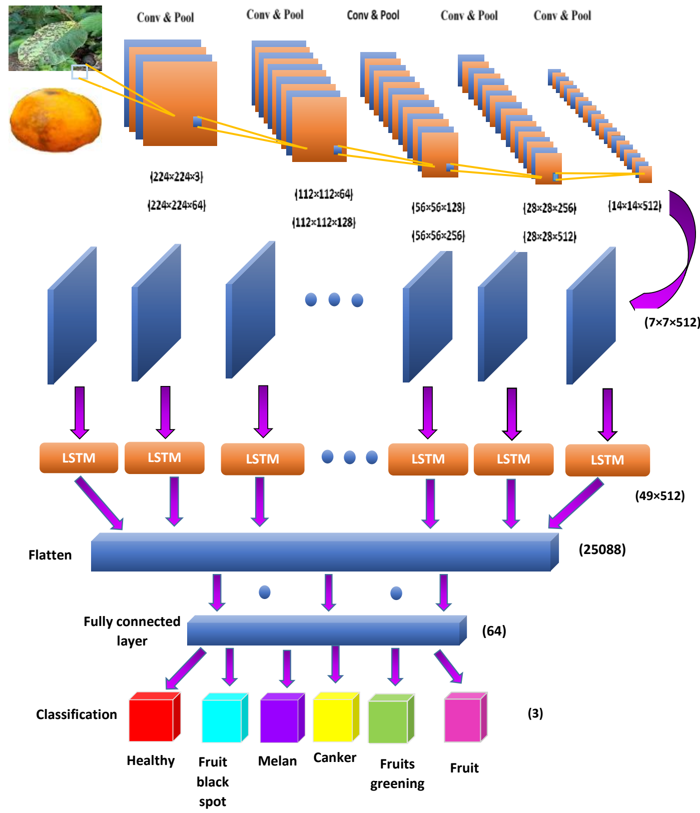


Figure No. 4
Schematic diagram of the proposed CNN-LSTM network for identifying and classifying Citrus diseases

To minimize the overall dimensions of an input picture, the max-pooling layer with either size of 2×2 kernels has been utilized. This CNN model extract the features from the input picture, which is fed into the long short term memory approach to classify the disease in citrus fruits and leaves. This function map will be sent to the LSTM layer at the end of the architecture to retrieve time data. Its output form is discovered after the convolutional block (none, 7, 7, 512). This LSTM layer's input size has been reduced by using a reshape approach (49, 512). This framework organizes the photos through a fully linked layer after assessing the temporal features to determine whether they correspond to the five categories (healthy, fruit black spot, Canker, fruits greening, fruit scab, and Melanoses). As a result, the proposed CNN-based method accurately detects and classifies the citrus fruit and leaf diseases. The next section of this paper provides the graphical illustrations of this proposed disease detection and classification approaches. This proposed approach is implemented on Phython 3 simulation tool which has a Windows 7 (64 bit) operating system, Intel premium processor and 8GB RAM.

RESULTS AND DISCUSSION

This section explores the implementation outcomes and the overall performance of our developed system. In addition, comparison findings of existing works were shown.

Dataset description:

Dataset of citrus fruits and leaves (Rauf *et al*., 2019): A gallery of good and harmful citrus fruits and leaves are included in the collection that researchers might use to avoid plant diseases using powerful computer vision algorithms. Black spot, Blight, Coating, Greening, and Melanoses are the infections targeted in the data sets. The collection contains 759 photographs of Citrus fruits and leaves, equally good and ill. Each image is 256 * 256 pixels in size and has a 72-dpi quality. The category of images is mentioned in Table No. 2.

Table No. 2
Image Categories in the dataset

Disease Name	Number of images
Fruit black spot	19
Leaves black spot	171
Fruit blight	78
Leaves blight	163
Fruit Greening	16
Leaves Greening	204
Fruit scab	15
Leaves Melanoses	13

Performance evaluation

This part displays the simulation results derived from the implementation and the calculated performance of the proposed system.

After each cycle, both training accuracy and loss were assessed. Simultaneously, validation accuracy in a loss was obtained using 5-fold cross-validation. The efficacy of this proposed system was assessed using the following metrics: correctness, specificity, understanding, and F1-score and graphical illustration given below,

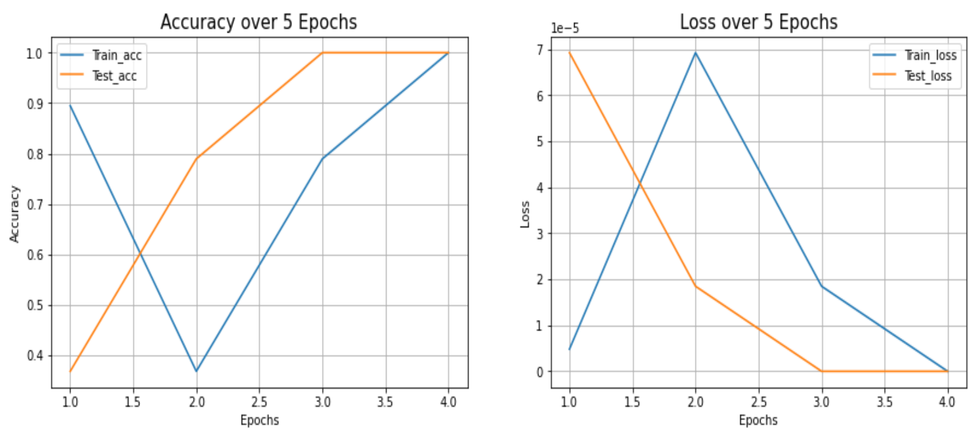


Figure No. 5
Training and Testing Accuracy and Loss over 5 Epochs

Figure No. 5 depicts the simulation results of the proposed customized CNN model's testing and training accuracy and its loss. Depending upon the given figure, we can deduce that the planned method will have a testing and training accuracy of 99.90% in the 5th epoch. Similarly, the proposed model will have a training and testing loss of 0.10 percent at the fifth epoch. The testing and training efficiency show that the presented method outperforms the typical CNN model.

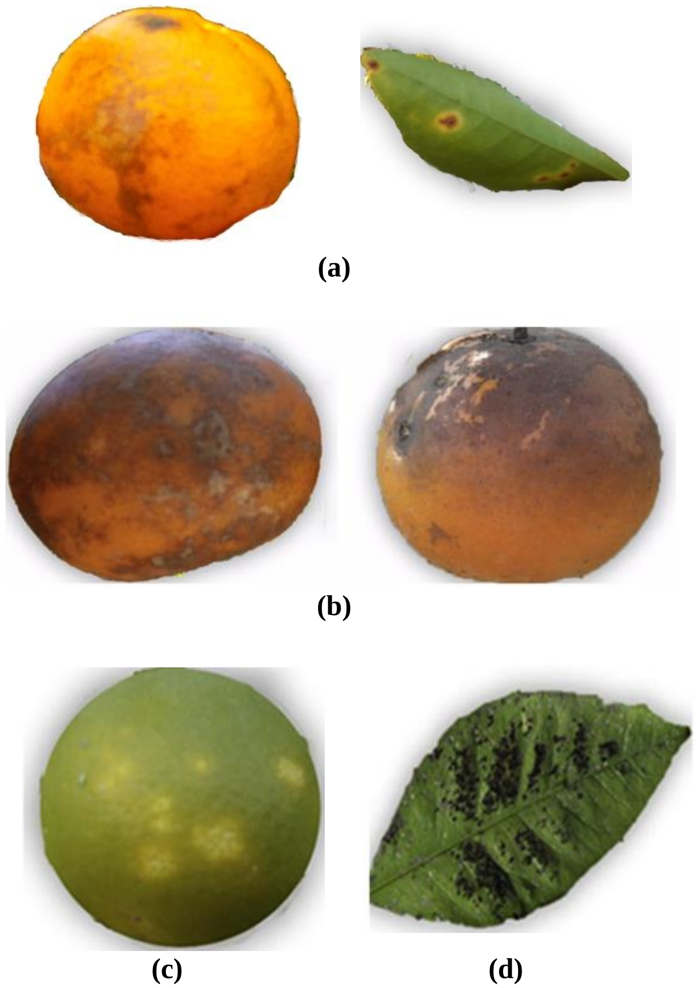
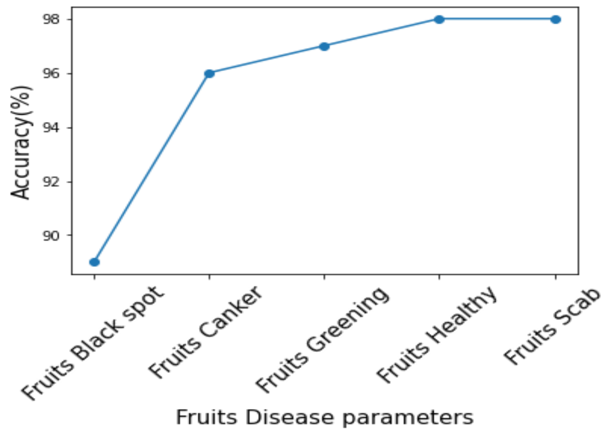


Figure No. 6
Feature Extraction Using CNN model

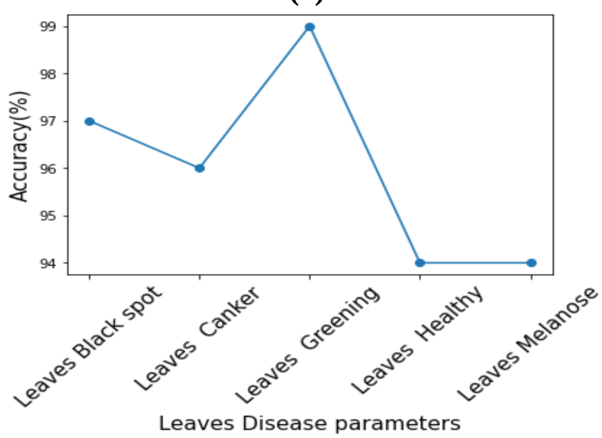
The feature extraction result of the input images is shown in Figure No. 6. Figure No. 6a depicts the fruit and leaf is affected by the blackspot, fruits canker diease in citrus fruits is shown in Figure No. 6b, following that, Figure No. 6c and Figure No. 6d shows the greening and Melanose disease in fruits as well as leaf. The diseased feature has to be retrieved accurately using the CNN model.

Figure No. 7 depicts the disease's categorization accuracy in citrus fruits and leaves. Figure No. 7a depicts the various classification accuracy of diseases in fruits, with the LSTM model providing 83% classification for black-spot, 96% classification accuracy for Canker, 97% classification accuracy for fruit greening, 98%classification accuracy for fruit scab, and 98% classification accuracy for healthy images.

Figure No. 7b depicts leaf disease classification accuracy using the LSTM model. It shows that the black spots have 97 percent classification accuracy, Canker has 96 percent and leaves greening has 99 percent. The accuracy of classifying the healthy fruit and melanose is 94 percent.



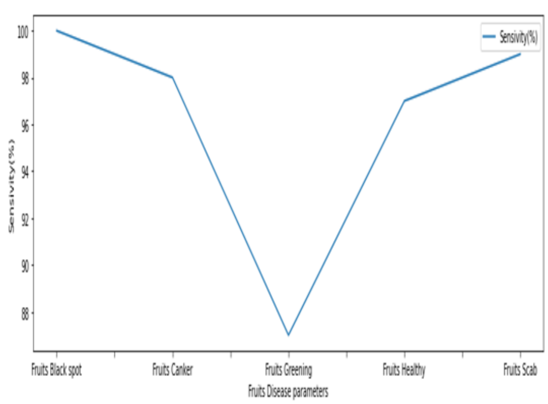
(a)



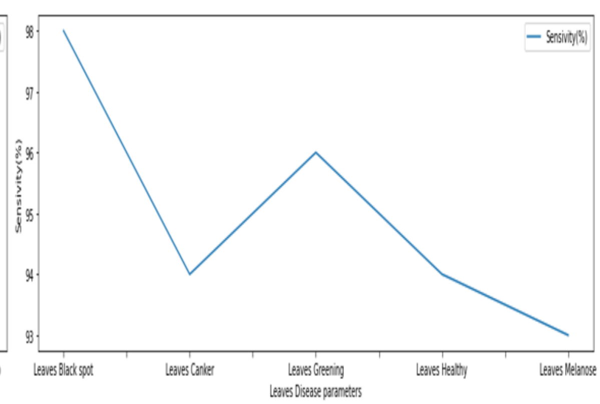
(b)

Figure No. 7

Accuracy in the classification of various diseases in fruits and leaves



(a) Fruits Disease



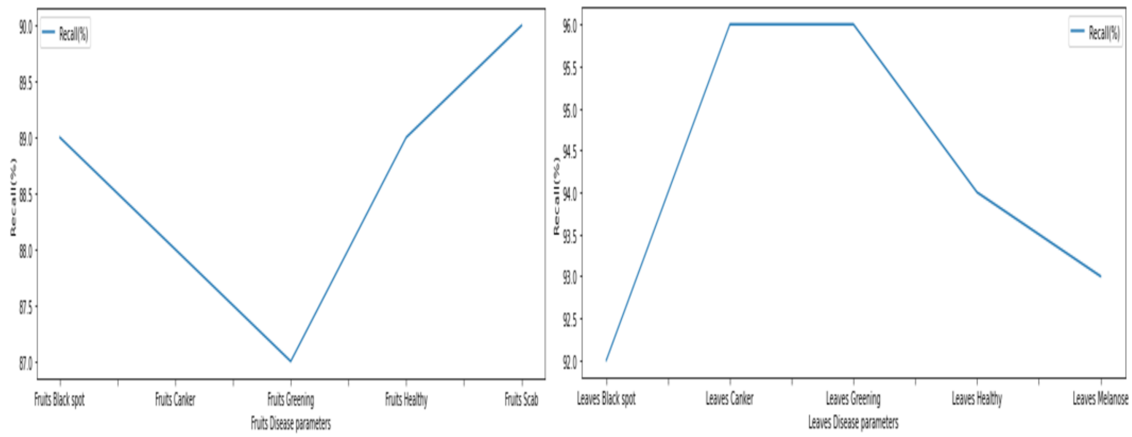
(b) Leaves Disease

Figure No. 8

Sensitivity in the classification of various diseases in Citrus fruit and leaves Figure 8 depicts the sensitivity in illness categorization, with Figure No. 8a depicting the sensitivity of the Fruit disease and Figure No. 8b depicting the sensitivity of the Leaves disease

Figure No. 8a demonstrates that fruit black spot has a sensitivity of 99%, fruit canker has a sensitivity of 97.6%, fruit greening has a sensitivity of 87%, healthy images have a sensitivity of 97%, and fruit scab has a sensitivity of 99%.

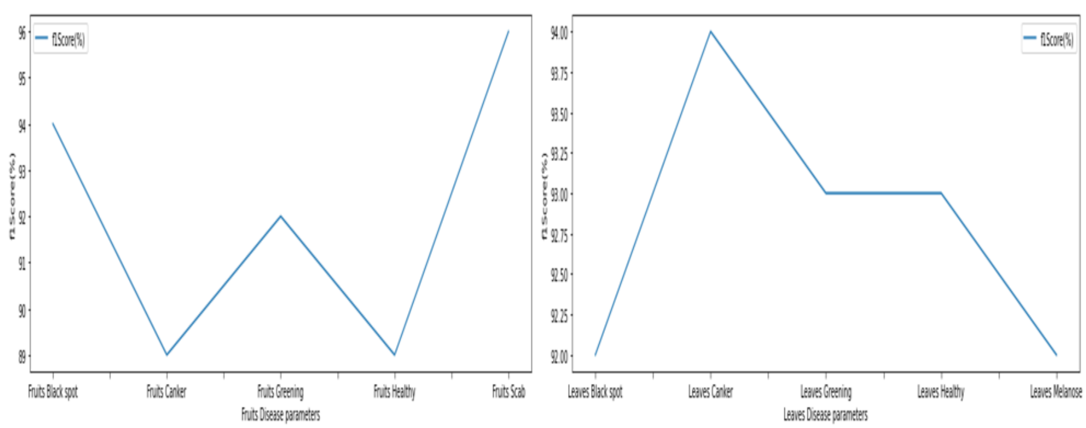
Figure No. 8b depicts the sensitivity of leaf diseases, with leaves black spot achieving 98%, leaves Canker scoring 94%, leaves greening scoring 96%, healthy leaves scoring 94%, and leaves melanoses scoring 93%.



(a) Fruits Disease **(b) Leaves Disease**

Figure No. 9
Recall the classification of disease in citrus fruit and leaves

Figure No. 9 depicts the recall in disease categorization simulation outcomes in citrus fruit and leaves. Figure No. 9a depicts the fruit disease recall findings, with 89% recall for fruit black spot, 88 percent recall for fruit canker, 87.25% recall for fruits greening, 89% recall for healthy fruits, and 90% recall for fruit scab. Figure No. 9b depicts the recall value of the leaves dataset, with leaves black spot accounting for 92%, leaves Canker accounting for 96%, leaves greening accounting for 96%, healthy leaves accounting for 93.75%, and leaves melanose accounting for 93%.



(a) Fruit Disease **(b) leaves Disease**

Figure No. 10
F1 Score in the classification of Disease in Citrus Fruit and Leaves

Figure No. 10 depicts the disease's categorization F1 Score in citrus fruits and leaves. Figure 10(a) depicts the various classification F1 Score of Disease in fruits, with the LSTM model providing a 94% F1 score for black-spot disease, 89% for Canker, 92% for fruit greening, 96% for fruit scab, and 89% for healthy images.

Figure No. 10 (b) depicts the disease classification accuracy in leaves using the LSTM model, with leaves with black spots having 92%, Canker having 94%, leaves greening having 93%, health leaves having 93 % and melanose having 92%.

Comparative analysis

This section describes the comparative evaluation of the proposed method with the existing deep learning-based model. The classification accuracy of the models has been compared with the proposed customized CNN model.

Accuracy comparison

The accuracy of our proposed CNN-LSTM approach for detection and classification of the citrus fruit disease is compared with the existing approach such as KNN (Kattak *et al*., 2021b), SVM (Kattak *et al*., 2021b), and CNN (Kattak *et al*., 2021b). Figure No. 11 depicts the proposed approach accuracy as 96% whereas, the existing approach such as KNN (Kattak *et al*., 2021b), SVM (Kattak *et al*., 2021b), and CNN (Kattak *et al*., 2021b) attains the value of 82.75%, 88%, and 94%.

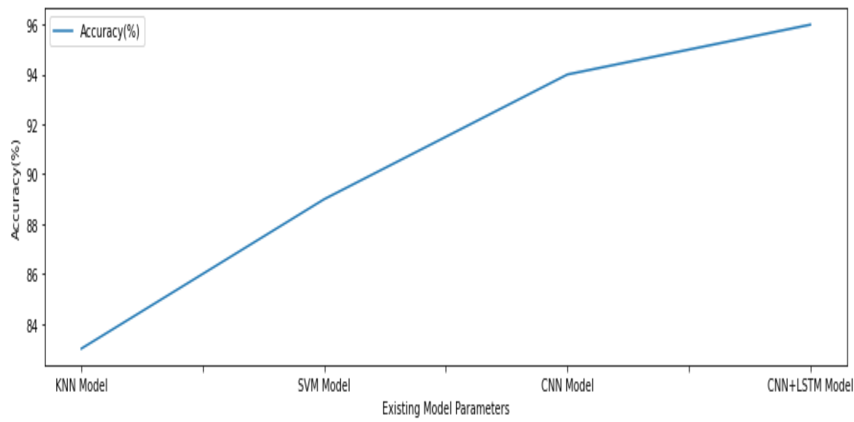


Figure No. 11
Accuracy Comparison in the classification of Citrus fruit and Leaves disease

We can conclude from the following graphical representation of the various parameters that our proposed model provides superior accuracy in automatically categorizing the various diseases in citrus fruits and leaves.

CONCLUSION

Citrus is a well-known fruit widely grown in several regions due to its favourable nutritional and medicinal properties. In general, citrus leaves or fruits provide exceptional nutrients plus minerals for consumer health. Nevertheless, various plant diseases were important considerations that limit the amount, quality of output, and even the economic system. The tough aspect of detecting and diagnosing the citrus leaf and fruit diseases is done manually. Farmers' generalized monitoring approach may also be time-consuming, costly, and incorrect at times. For that reason, a customized CNN-based model is developed in this work which combines CNN and LSTM to identify and categorize the infection in fruits and leaves. This proposed CNN-based model automatically distinguishes healthy fruits and leaves from those affected by infections such as fruit black spots, blight, fruit greening, fruit scab, and Melanoses. In contrast, the CNN is utilized in the research to remove deep features from the given input pictures of fruits and leaves of citrus plants, and LSTM is used to classify the disease using the retrieved feature. As an outcome, the proposed CNN-based model detects diseases in fruits and leaves more accurately. With other superior deep learning methods and imitation, outcomes show that the proposed technique had the classification exactness(accuracy) of 96%, higher than the recent existing works such as KNN, SVM, and CNN.

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