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Optimized Deep Learning Model for Pomegranate Disease Detection: A Convolutional Neural Network Long Short-Term Memory Approach

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ABSTRACT

Pomegranate is a high-value fruit globally recognized for its nutritional benefits and applications in traditional medicine and cosmetics. India is a key player in the global pomegranate market, but the industry faces challenges such as diseases that affect crop productivity and economic losses for farmers. This study proposes a novel approach to pomegranate disease detection using a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model. The proposed model leverages CNNs for effective feature extraction and LSTMs for sequential data handling, achieving superior performance compared to traditional methods and other deep learning techniques. Experimental results demonstrate high accuracy, recall, precision, and F1 score. The Proposed model achieved an accuracy of 98.53% and loss of 0.0677. The study also explores the limitations of transfer learning approaches such as VGG16 and ResNet50, and larger models like AlexNet, which did not perform well in this context. The findings suggest that the hybrid CNN-LSTM model offers a scalable and adaptable solution for agricultural disease detection, with potential applications for various crops.

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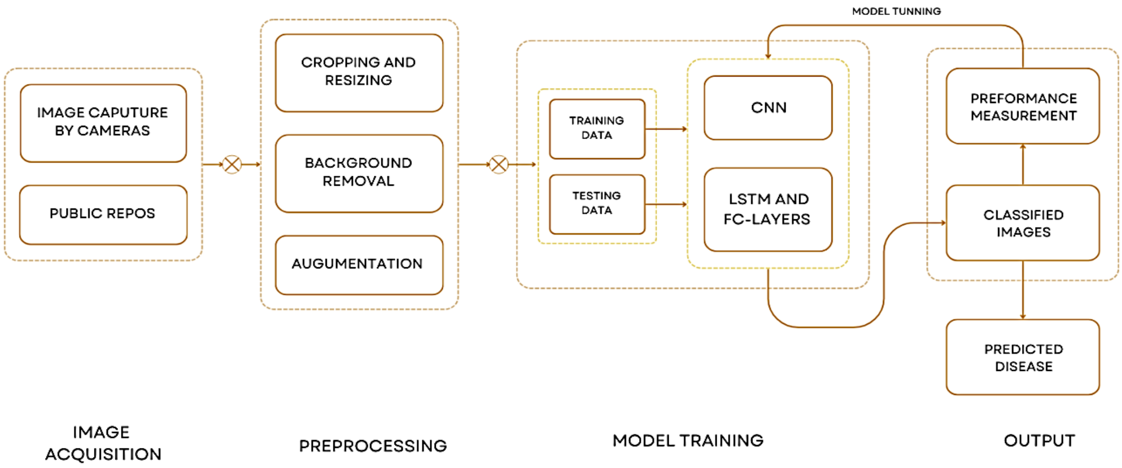
Graphical Abstract



System Architecture of the Proposed CNN-LSTM Model

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NOMENCLATURE			
x_t	Current input	h_t	Hidden state
$\tilde{C}_t$	Candidate cell state	h_{t-1}	Previous hidden state
C_{t-1}	Old cell state	O_t	Output gate's activation
W_i, W_f, and W_o	Weight matrices	b_i, b_f, and b_o	Biases associated with the respective gates

1. INTRODUCTION

Pomegranate (*Punica granatum*) is one of the most valuable fruits available. It is globally recognized as a "Super-food" owing to its nutritious characteristics (1). The leathery red skin encases vibrant, ruby-red arils makes up for a delicious sweet food which also offers a variety of health benefits. Pomegranate fruit is rich in vitamins and dietary fiber (2).

Beyond its use as a food, pomegranate has all found many applications in various sectors, from traditional medicine to cosmetics. The fruit's extracts are utilized in the pharmaceutical industry for their potential in treating various medical conditions, such as cardiovascular diseases and cancer (3). Moreover, the aesthetic and therapeutic properties of pomegranate make it a good ingredient in skincare and beauty products.

India is one of the leading countries in pomegranate production (4). Contributing significantly to the global pomegranate market. India provides a suitable environment for pomegranate cultivation. According to recent statistics, our country has witnessed an increase in pomegranate production, making it a key player in the global supply chain (5).

Pomegranates are grown on more than 500,000 hectares worldwide, with a projected 6.54 million metric tons produced globally as of 2021–2022. The United States, Spain, China, Iran, and Turkey are other important producers. With 3.22 million metric tons, India leads the world in production, mostly from states like Telangana (2.34%), Maharashtra (54.85%), Gujarat (21.28%), Karnataka (9.51), and Andhra Pradesh (8.82%).

However, the thriving pomegranate industry faces many formidable challenges like drought, climate change, etc. With diseases being a major factor contributing to yield losses. Pomegranate orchards are susceptible to various diseases caused by fungi, bacteria, and viruses. These diseases not only affect the fruit's quality but also pose a threat to the overall health of the trees, potentially leading to long-term economic losses for farmers. One of the major disease is the Bacterial blight, which affects all parts of the plant but is more destructive on fruits (6). Other common diseases include Alternaria, Anthracnose, etc. affecting both plant and fruit. The impact of these diseases extends beyond individual crops, affecting the livelihoods of farmers and the overall economy of regions dependent on pomegranate cultivation.

Traditional methods of disease detection in agriculture rely on visual inspection and manual monitoring which are inherently time-consuming and often lack the precision required for early disease detection. Advent of Machine learning techniques, provides us an opportunity to implement the new approaches to disease detection in pomegranate cultivation.

These new machine learning techniques enable us to build automation disease detection systems which are more efficient and accurate. Deep Learning techniques, which a subset of machine learning, is becoming increasingly popular in research as graphics processing technology advances and low-cost GPUs become more widely available. Within the realm of image processing, a deep learning technique known as Convolutional Neural Networks (CNNs) have emerged as a particularly effective deep learning technique.

This research proposes a hybrid model i.e. combining CNN with LSTM layer. This paper also compares other state-of-the-art models to the proposed model.

1. 1. Overview of Pomegranate Fruit Diseases

Pomegranate crop is susceptible to many diseases that pose significant challenges to the health of fruit and crop productivity. Improper Agricultural practices and harsh climate can promote diseases. Figure 1 shows the diseased pomegranate fruits with corresponding disease name below it. Below are few common diseases that affect pomegranate.

1) Bacterial Blight (*Xanthomonas axonopodis*)

Bacterial blight in pomegranates is primarily caused by the bacterium *Xanthomonas axonopodis pv. punicae*. The disease manifests itself as watery lesions on leaves, stems and fruits. These lesions expand and merge, forming large necrotic areas. On fruits, the spots are dark brown to black and can be slightly raised with a cracked appearance. In severe cases, fruits can crack open, leading to secondary infections and significant economic losses. The epidemiology of bacterial blight indicates that it is favored by warm and humid conditions.

Management of bacterial blight involves the use of copper-based bactericides, cultural practices to reduce humidity around plants, and pruning to remove infected plant part.

2) Alternaria Fruit Rot (*Alternaria alternata*)

Alternaria fruit rot disease is caused by the fungus *Alternaria alternata*. This disease is characterized by the appearance of small, black spots on the surface of the fruit, which eventually enlarge and merge, covering large areas of the fruit. Internally, the rot progresses, leading to blackened seeds and a mushy consistency of the arils.

The infection can start at the blossom end or through wounds on the fruit surface.

The development of *Alternaria* disease is typically favored by high humidity and warm temperatures. The fungal spores are spread by wind, rain, and insects, and the disease can be exacerbated by poor orchard hygiene and inadequate ventilation. Effective management includes maintaining good orchard sanitation, ensuring proper spacing and pruning to improve air circulation, and applying fungicides during periods of high risk. Post-harvest handling practices, such as rapid cooling and proper storage, can also help reduce the incidence of *Alternaria* rot.

3) Anthracnose (*Glomerella cingulata*)

Anthracnose of pomegranate is a disease caused by the fungus *Glomerella cingulata*. This disease is distinguished by the presence of dark, sunken lesions on the fruit, which can coalesce to cover larger areas. The affected tissues may exude a pinkish spore mass under humid conditions. Internally, the rot can extend into the fruit, causing decay and making the fruit unmarketable.

Anthracnose thrives in warm, wet conditions, similar to other fungal diseases. The spores are disseminated by rain splash, wind, and contaminated tools. The disease can also spread from infected plant debris. Effective management strategies include the removal and destruction of infected plant material, improving air circulation through pruning, and applying fungicides during critical periods of infection risk. Additionally, avoiding overhead irrigation and ensuring good drainage can help reduce the prevalence of anthracnose.

4) Cercospora (*Cercospora punicae*)

Cercospora fruit spot is caused by the fungus *Cercospora punicae*. Pomegranate fruits that have been infected develop small, circular to irregular spots that range from dark brown to black. As the disease progresses, these spots can grow and coalesce, often resulting in premature fruit drop. The disease can also affect leaves and stems, causing similar spotting and potential defoliation.

The fungus thrives in warm, wet conditions and is spread by rain splash and wind. It can survive on plant debris and in soil, contributing to ongoing infection cycles if not properly managed. Controlling Cercospora fruit spot involves cultural practices such as removing and destroying infected plant debris, improving air circulation through pruning, and applying appropriate fungicides. Crop rotation and avoiding overhead irrigation can also reduce the disease's spread.

Correct Identification of diseases at early stages can help farmers to mitigate the losses.The dataset mentioned in Figure 1 is used from Mendeley Data (7). The proposed system in this project can be used by farmers for accurate detection of diseases. The main advantage of employing a CNN-LSTM hybrid model for pomegranate disease detection lies in its integration of effective spatial feature extraction (CNN) with temporal

Figure 1. Various Diseases Affecting Pomegranate

pattern recognition (LSTM), resulting in enhanced accuracy, improved precision, and more resilient classification of fruit diseases relative to the use of CNN or LSTM independently.The proposed method uses image as input instead of Csv file which will helpful for algorithm to learn and obtain good accuracy.

2. LITERATURE SURVEY

Several studies have explored the use of machine learning and image processing techniques for pomegranate disease detection and classification. This section explores the findings from the literature survey, which summarizes information from 24 research publications (Table 1).

This section is divided into three subsections each following a theme of machine learning like traditional techniques, deep learning techniques and emerging technologies.

2. 1. Traditional Machine Learning Techinques

Earlier attempts to detect pomegranate disease relied heavily on traditional machine learning techniques such as KNN, k-means, and SVM. For example, Tejal Deshpande et al. proposed a system that uses k-means clustering for image segmentation and grades infected areas based on color and size. Color and size of the infected area are not reliable indicators of disease (8). Their system can only detect healthy and bacterial blight. This limits their system's ability to perform multiclass classification tasks.

Several studies used K-means clustering for image segmentation, followed by SVM for classification. Bhange and Hingoliwala (9) proposed a system that uses K-means and SVM to classify pomegranate diseases with accuracy of 82%. Gaikwad et al. (10) applied similar techniques for multi-fruit disease detection. Their system showed remarkable accuracy.

Kantale and Thakare (11) utilized the Ada-Boost Ensemble algorithm to classify pomegranate diseases, leveraging a dataset of 190 images. Their model achieved an impressive accuracy of 92.90%. However, despite its high accuracy, the Ada-Boost algorithm has some drawbacks, such as its sensitivity to noise and high computational demands, especially when training on large datasets. These limitations can hinder its practical application in various agricultural scenarios.

Neural networks have also been applied in pomegranate disease classification. Dhakate and Ingole (12) developed a system that uses Artificial Neural Network as a classifier and showed an accuracy around 90% with a dataset of 500 images. Patil (13) have focused on PNN (Probabilistic neural network) for disease classification and achieved an accuracy of 80.30% with a dataset of 166 images, which is divided into 100 for training and 66 or testing. These systems are in their early stages and require image preprocessing, such as noise reduction to be effective.

Otsu Threshold combined with k-means can be used for image segmentation before Image Classification. This approach was used by Pawar and Jadhav (14) along with multi layer neural network, this system achieved an accuracy of 90% on 40 test images. The study was limited to a small dataset. It suffers similar drawbacks as discussed above.

Reddy et al. (15) developed an ANN based approach for detecting diseases in grapes, apple and pomegranates. The system achieved 93% accuracy. The system uses color texture analysis for feature extraction and employs k-means clustering to segment an image. However, the authors did not provide details on the ANN architecture and hyperparameters.

A simple histogram equalization is applied on extracted ROI to enhance the features. These features are used by Multiclass SVM to classify the leaf disease. Using this approach the authors achieved 98.07% accuracy (16).

2. 2. Deep Learning Methods With the advent of deep learning, field of image processing has significantly elevated the accuracy and efficiency of disease detection.

Sharath et al. (17) have proposed a system for detecting diseases in fruits like pomegranate, orange, grapes, and papaya using convolutional neural networks (CNN). The system achieved around 91% accuracy in detecting diseases like citrus canker, greening, etc in grapes, and bacterial blight, borers, cercospora in pomegranates (18). Pawar et al. (19) have proposed a leaf disease system for multiple plants using 15 layer CNN model. Their system could detect diseases in 10 different plants with upto 93% accuracy. The authors did not report specific accuracy metrics for each plant species.

A newer more complex variant of CNN called Alexnet. AlexNet architecture has 8 layers, this model was employed by Wakhare et al. (20); their model achieved an accuracy of 97.6%. They have used a dataset of 1245 pomegranate leaf images. Their research was limited to detecting only two diseases which are bacterial blight and Alternaria (21).

An advanced region based CNN model called faster-RCNN was used in pomegranate disease, detection and classification in a research by Javeriya (22). Faster R-CNN is 250 times faster than RCNN. The model was designed to identify two common diseases—anthracnose and bacterial blight—using a custom dataset of annotated images. The authors acknowledged that low image resolution could lead to detection failures.

2. 3. Emerging Technologies Newer methods like transfer learning have emerged. In transfer learning, the pretrained models are utilized to fine tune on the pomegranate disease dataset. Commonly used pretrained models are VGG16, Inception-V3, Resnet, DenseNet. These models are the variants of CNN.

Nirgude and Rathi (21) compared three CNN based architectures they are Resnet-18, Resnet-50 and Inception-V3. They collected 1,493 images of the pomegranate fruits and the leaves at different stages of disease development over six months. They acknowledged the need to address the "Black Box" problem often associated with deep learning models. This could be handled by merging the Grad-CAM model. The authors did not provide specific implementation details to recreate the experiment.

Al Ansari (23) used deep learning techniques such as AlexNet and VGG-16 to demonstrate the ability to automatically diagnose diseases in pomegranate plants using leaf images. AlexNet achieved an accuracy of 89.57%, while VGG-16 achieved a higher accuracy of 95.23%. However, there are notable drawbacks to this study. The models were trained for only 12 epochs, which might not be sufficient for them to fully learn the features necessary for accurate disease diagnosis. For example a research paper by Qi et al. (24) used MSRCR defogging algorithm and image normalization techniques to enhance the images. They used Canny SLIC algorithm for precise segmentation of diseased region. A focal loss function was used to improve the DenseNet169 architecture, resulting in an recognition accuracy of 98.98% for three types of grape, outperforming traditional DenseNet's 97.95% accuracy. Additionally, the computational complexity and processing time associated with the proposed model are not discussed, which could be crucial for real-time applications.

Vasumathi and Kamarasan (7) proposed an architecture which combined CNN-LSTM model to classify a set of about 6519 pomegranate fruit images. Features like fruit color, number of spots, shape, size of diseased area, etc where extracted manually into a csv dataset. Their model achieved 98.17% on this dataset. The binary classification of normal or abnormal fruit limits its practical use.

TABLE 1. Literature Survey

Sl.No.	Part	Feature Extraction	Classifier	Accuracy	Critical Analysis
(1)	Both leaf and fruit	K- means clustering	Classification based on color and area	Not Mentioned	This system calculates the percentage of infection based on the size of the infected area. This is better than manual techniques but has lower accuracy (8).
(2)	Fruit	K- means clustering	SVM	82	Bhange and Hingoliwala (9) proposed a web based tool which uses Image processing techniques to determine if a pomegranate fruit is infected with bacterial blight or not. The SVM used here is not suitable for multiclass classification (9).
(3)	Both leaf and fruit	GLCM, PSO	Ada-Boost Ensemble	92.9	Gaikwad et al. (10) used a very small dataset of 190 images of both fruit and leaf. There may be a chance of over fitting.
(4)	Both leaf and fruit	GLCM	Neural Network	90	Kantale and Thakare (11) constructed a classifier from basic Artificial Neural Network(ANN) and uses the basic back-propagation algorithm to train ANN. 500 images of leaf and fruit were used as a dataset .
(5)	Fruit	Standard deviation, entropy, variance, smoothness & skewness.	Probabilistic neural network(PNN)	80.3	PNN is a special class of ANN. This network is not widely used because they are slower than other methods (12).
(6)	leaf	Otsu thresholding, K-means clustering	Multi layer neural network	90	Dhakate and Ingole (12) paper did not provide details of the model.
(7)	Multiple fruits including pomegranate	ANN	ANN	90	Accuracy of model can be improved by better preprocessing and restricting to classification of single fruit type (16).
(8)	Leaf	K- means clustering	Multi-Class SVM	98.07	Simple histogram equalization is applied on extracted ROI to enhance the features . Those features are used by Multiclass SVM to classify the leaf disease (15).
(9)	Both leaf and fruit	Grabcut Segmentation and canny edge detection	CNN	91	Authors used both leaf and fruit images. Dimensions of images were limited to 432x288 to reduce processing time. Morphological processing is also used to clean the image (16).
(10)	Fruit	Statistical Analysis and DWT	CNN, SVM	96.93, 96	Sharath et al. (17)compared segmentation techniques like manual segmentation and k-means using CNN and SVM classifiers, concluding that manual segmentation combined with CNN yielded the highest accuracy.
(11)	Leavesof multiple plants	None	CNN	93	Sánchez et al. (18) trained a CNN with 15 layers to detect diseases in 10 different plants with a dataset size of 50000 images. Their system also suggests pesticide for the detected disease.
(12)	Leaf	None	Alexnet	98.07	Pawar et al. (19) developed a leaf disease detection system using AlexNet, achieving high accuracy. Comparisons with other CNN variants like ResNet50 and VGG16 showed AlexNet performed best.
(13)	Fruit	None	Multiple - ResNet50, ResNet18, InceptionV3	95.26, 98.37, 97	Wakhare et al. (20) compared 3 CNN based models. These models were pretrained on the ImageNet dataset. Authors have mentioned the “Black Box” problem of Deep Learning models, which can be solved by integrating these models with the Grad-CAM model.
(14)	Fruit	None	Faster-RCNN	Not Mentioned	Nirgude and Rathi (21) used a variant of RCNN called Faster-RCNN. Authors collected and annotated the images. They also provided the detailed architecture of the model. Drawback is they have not provided proper metrics.
(15)	Fruit	None	CNN-LSTM	98.19	Javeriya (22) combined two deep learning techniques CNN and LSTM to construct a binary classifier. This model has an accuracy of 92.9%. Authors used a dataset of 6519 images. This system can be further developed to multi-class classification.

Sl.No.	Part	Feature Extraction	Classifier	Accuracy	Critical Analysis
(16)	Fruit - Multiple Fruits	Canny SLIC algorithm	Multi-Scale Improved DenseNet	98.98	Al Ansari (23) used the MSRCR based defogging algorithm and Canny SLIC algorithm for image segmentation. Authors improved the DenseNet algorithm by using Focal loss function, focuses more on processing samples, that are difficult or hard for classification in training process.
(17)	Leaf	None	CNN	98.38	This paper provides the detailed architecture of the model. They did not mention any preprocessing step. Qi et al. (24) provide a detailed explanation of CNN, but fails to provide information on other aspects of the system like preprocessing, data collection, metrics, etc.
(18)	Fruit	None	CNN-LSTM	97.1	Vasumathi and Kamarasan (7) proposed a system combining CNN and LSTM with Dragonfly algorithm optimization, trained on a 6,500-image dataset for multiclass classification.
(19)	Leaf	None	CNN based Architectures	Not Mentioned	Vasumathi and Kamarasan (25) proposed a GAN-based data augmentation technique to expand dataset size, which was then used with transfer learning models to develop a classifier.

Vasumathi and Kamarasan (25) extended their work to a multi-class classification using similar hybrid CNN-LSTM model and used dragonfly optimization algorithm for weight optimization. The same csv dataset was used in training of their model and achieved accuracy of 97.1%. Extracting the features manually is a time consuming task, this also limits its use in automated disease detection.

In the study by Naseer, et al. (26) proposed a model to detect growth stages of pomegranate fruit. They utilized a dataset consisting of 5,857 images classified into five growth stages: Bud stage, Early-Fruit stage, Flower stage, Mid-growth stage and Ripe stage. The study utilized Synthetic Minority Over-sampling Technique (SMOTE) is used to address the class imbalance in the dataset. While the proposed method achieved a high accuracy of 98%, it also faced some drawbacks.

Nirmal et al. (27) studied supervised and unsupervised machine learning approaches for detecting diseases in pomegranate leaves. K-means, an unsupervised technique, to isolate the diseased regions of the leaves. The MobileNet model achieved a superior accuracy of 98.18%, while ResNet achieved 95.53% on the Mendeley database. This high resource demand limits the scalability of the approach, making it less feasible for deployment on large, diverse datasets.

3. RESEARCH GAP

The reviewed literature reveals significant advancements in detection and classification of pomegranate diseases using various machine learning and deep learning techniques. Despite the promising results, several research gaps persist. Many studies utilized relatively small datasets, which limits their ability to generalize, leading to overfitting issues. Larger and more diverse datasets are needed to enhance model robustness and performance. This requires collaborative efforts among researchers and agricultural institutions to collect and share extensive, high-quality image datasets. Moreover, leveraging data augmentation techniques can help mitigate the issue of limited datasets by artificially increasing the size, quality and variability of training data.

Traditional machine learning approaches like SVM and ANN have shown good accuracy with limited datasets, but training these models on large, diverse datasets can be computationally intensive. These approaches also require complex preprocessing techniques; without preprocessing, models deliver poor accuracy and often increase training time. Significant preprocessing, including cropping, noise reduction, and background removal, helps models to focus on the relevant or suitable parts of the fruit rather than the noise present in images. However, some research papers provide vague information on preprocessing techniques, limiting the replication of exact models. To address this, future research should include detailed descriptions of preprocessing steps and consider standardizing these procedures to facilitate replication and comparison across studies.

Many studies have used single deep learning approaches, which, while effective, are time-consuming to implement and train, especially for large models like AlexNet and ResNet. Combining multiple deep learning approaches, such as CNN and LSTM, can potentially reduce model size and training time while maintaining or even enhancing performance. For example, CNNs can be used for feature extraction, and LSTMs can process the extracted features to capture temporal dependencies, if any.

Furthermore, the robustness of these models to varying environmental conditions, such as lighting, occlusions, and background clutter, has not been explicitly addressed, which can significantly impact the accuracy of disease detection in real-world scenarios. Future research should focus on developing models that are resilient to such variations. This can be achieved by training models on datasets that include a wide range of environmental conditions or by employing techniques like data augmentation to simulate these conditions during training.

Finally, some models only provide binary classification, limiting their use in applications where multi-class classification is more appropriate. Developing models that can handle multi-class classification is crucial for practical applications. This involves not only designing appropriate network architectures but also ensuring that the training datasets are sufficiently diverse and well-labeled to cover multiple disease categories.

4. PROPOSED METHODOLOGY

This section discusses the preprocessing of the dataset, developing the model and training the model. For creating model and training model python programming language and many advanced libraries were leveraged. The libraries used are keras, tensorflow, numpy, rembg, pillow.

4. 1. Dataset Preprocessing Pakruddin and Hemavathy (28) have created a standard dataset for training deep learning models which is publicly available. This dataset contains 5099 images divided into 5 classes. The classes are Alternaria, Anthracnose, Bacterial Blight, Cercospora, Healthy. Below Table 2 shows the distribution of images in each class. The dataset contains high quality images collected from areas like Ballari, Bangalore, Bagalkote, etc.

1) Resizing

Fortunately the dataset has all the images in square format. Images are of 3120x3120 pixels. The images were reduced to 512x512 pixels in this step by the resize_images function from the library fastai sublibary vision.

2) Background Removal

Images have fruit in the center and leaves in the background. Removal of background can help the model to focus on the fruit rather than background. It also helps to speed up the machine learning process by reducing the epochs. Figure. 2 shows the output of the process.

For Removing background rembg library was used.

3) Augmentation

Computational techniques like scaling, rotating, shifting were used to generalize the model and reduce overfitting. The ImageDataGenerator class from tensorflow was used to augment only the training dataset. Table 3 shows the parameters used in augmentation.

Figure 2 shows the stages background removal and augmentation of a single image.

4. 2. Proposed Model Vasumathi and Kamarasan (7) proposesd a CNN+LSTM model that utilizes an image dataset for pomegranate fruit disease detection. In this suggested architecture, convolutional neural networks (CNNs) are used here to extract features from input image samples, while long short-term memory networks (LSTMs) utilize these features to model the temporal connections between the data points. This combined approach allows the model to effectively capture both local patterns, such as edges and corners, and global patterns, such as objects and scenes. Moreover, by incorporating LSTMs, the model is capable of understanding the temporal dynamics and dependencies that may exist between different parts of the image over time.

This integrated methodology enables the model to comprehensively understand the data and produce highly accurate predictions. The model can provide precise and reliable classification results by combining CNNs' spatial feature extraction strengths with LSTMs' temporal

TABLE 2. Curated Collection of Labeled Mendeley Dataset Details

Sl. No	Class Name	Image Quantity
1	Alternaria	886
2	Anthracnose	1166
3	Bacterial Blight	966
4	Cercospora	631
5	Healthy	1450

TABLE 3. Different Parameters used in Augmentation

Sl. No	Parameter	Value
1	Rotation range	40
2	Width shift range	0.2
3	Height shift range	0.2
4	Zoom range	0.2
5	Horizontal flip	True
6	Fill mode	Nearest

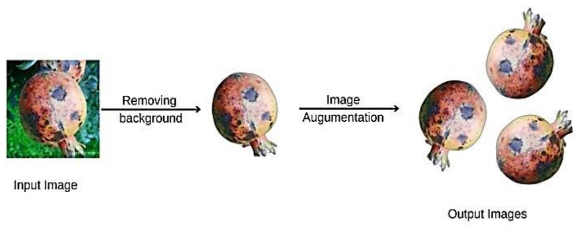

Figure 2. Background Removal and Augmentation

modeling capabilities. Convolutional neural network (CNN) and a long short-term memory (LSTM) network are briefly described as follows.

4. 1. 1. Convolutional Neural Network A simple neural network often lacks the capability to learn complex features required for sophisticated image recognition tasks such as disease classification. Deep learning architectures, such as Convolutional Neural Networks (CNNs), are more suitable for these tasks (23). CNNs are a specific type of multilayer perceptron network that operate on the principle that complex features can be constructed by refining lower-level features at each successive layer (29-31). A CNN typically consists of multiple convolutional layers, multiple pooling layers, and fully connected (FC) layers. An example of a CNN architecture with its layers is illustrated in Figure 3. The *CNN optimal structure* is usually found by optimizing *hyperparameters* like: activation functions, learning rate and fully connected layer size.

Convolution operations apply these filters across the input using a parameter called "stride," which determines the step size for the filter application, ensuring the output dimensions are integer values (32).

Mathematically, the convolution operation is expressed as Equation 1.

$$F(i,j) = (I * K)(i,j) = \sum\sum I(i+m, j+n)K(m,n) \quad (1)$$

where i here is the input matrix, K is a 2D kernel (filter) given by of size m×n, and F is the resulting 2D feature map from the convolution operation denoted by I∗K (33).

To introduce non-linearity into the feature maps, a Rectified Linear Unit (ReLU) layer is used (34). The ReLU activation function computes the output by applying a threshold at zero, which can be mathematically represented as Equation 2.

$$f(x) = max(0, x) \quad (2)$$

The pooling layer, often following convolutional layers, performs downsampling of the input dimensions to reduce the number of parameters and computational load. Max pooling is one of the most common pooling technique used, where the maximum value within a defined region of the input is selected to form the pooled feature map (35). Finally, the fully connected (FC) layer acts as a classifier, making decisions based on features extracted by the convolutional and pooling layers.

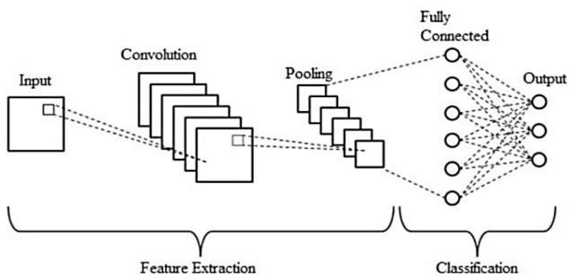

Figure 3. A typical architecture of the CNN

4. 1. 2. Long Short-Term Memory Long Short-Term Memory (LSTM) networks are an advanced type of Recurrent Neural Network (RNN) designed to address the problem vanishing and exploding gradients that are associated with traditional RNNs (36). LSTMs introduce memory blocks that replace conventional RNN units, allowing the network to retain long-term states and effectively connect previous information to current data (37). An LSTM network includes three primary gates: the input gate, forget gate, and output gate, which control the flow of information within the network. Figure 4 shows the internal architecture of LSTM network, depicting how these gates function. Figure 5 illistrates the system architecture of the proposed CNN-LSTM model.

The input gate determines which part of the input to be added to the cell state. This process is defined by the following Equations 3, 4 and 5.

$$i_t = \sigma(W_i \cdot (h_{t-1}, x_t) + b_i) \quad (3)$$

$$\tilde{C}_t = \tanh(W_i \cdot (h_{t-1}, x_t) + b_i) \quad (4)$$

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \quad (5)$$

Here, i_t is calculated by passing the previous hidden state h_{t-1} and the current input x_t through a sigmoid layer to

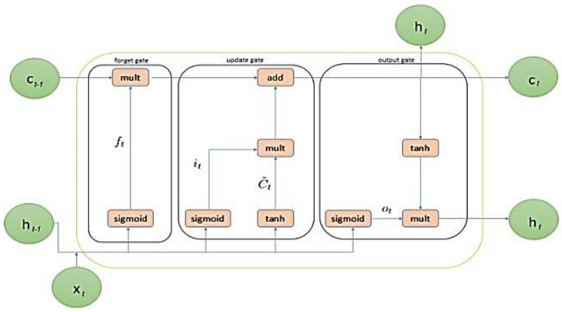

Figure 4. Internal Structure of Long Short-Term Memory

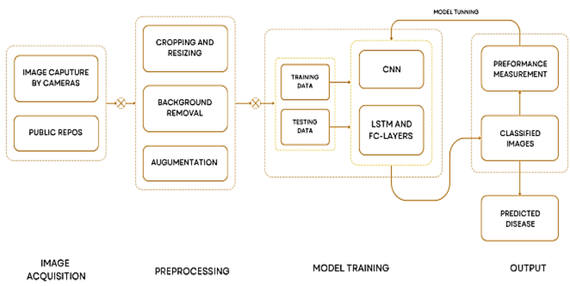

Figure 5. System Architecture of the Proposed CNN-LSTM Model

decide which information to add. The new candidate cell state $\tilde{C}_t$ is obtained by passing h_{t-1} and x_t through a tanh layer. The current cell state C_t is a combination of the old cell state C_{t-1}, modified by the forget gate ft and the new candidate cell state $\tilde{C}_t$.

The forget gate allows selective information passage using a sigmoid function, which can be expressed as Equation 6.

$$f_t = \sigma(W_f \cdot (h_{t-1}, x_t) + b_f) \quad (6)$$

The output gate determines the necessary states for continuation using the inputs h_{t-1} and x_t, as shown in the following Equations 7 and 8.

$$O_t = \sigma(W_o \cdot (h_{t-1}, x_t) + b_o) \quad (7)$$

$$ht = O_t \tanh(C_t) \quad (8)$$

where O_t is the output gate's activation, and h_t is the final hidden state output. W_i, W_f, and W_o represent weight matrices, while b_i, b_f, and b_o are the biases associated with the respective gates.

4. 1. 3. Combined CNN-LSTM Model The convolutional layers here are used to extract spatial features from images. Each layer applies a set of kernels (filters) to the input image, performing an element wise multiplications and summations. This operation is called as convolution which highlights specific features in the input image. The first convolutional layer (Conv2D) is having 32 kernels with a kernel size of 3x3 which uses the ReLU activation function. This layer processes the input images of shape (256, 256, 3). All subsequent convolutional layers all use ReLU activation function with each layer doubling the number of kernels. Number of kernels used in each convolution layer is given in Table 4.

After the convolutional layers, the model incorporates a Long Short-Term Memory (LSTM) layer which captures temporal dependencies and sequence information. This information is useful for understanding the progression of disease symptoms over sequences of image features. Proposed model uses 128 LSTM units, the input to this layer is reshaped by a reshape layer. The reshape layer preceding the LSTM layer ensures that the input is in the correct format, transforming the 2D feature maps into a tensor suitable for LSTM processing. This transformation is critical for leveraging the LSTM's ability to process sequential data, as it enables the model to understand the progression of disease symptoms over a series of images.

The dense layers, also called as Fully Connected (FC) layers, perform the final classification based on the features extracted and processed by the preceding layers. The first dense layer in this model has 1024 units with ReLU activation function, which will introduce non-linearity. The subsequent dropout layer has a dropout value of 0.2 which helps in preventing overfitting by randomly setting a fraction of input units to 0 during training. The final dense layer has 5 units one for each class with softmax activation. The last layer does the classification of input into one of the five disease categories. Detailed Layer information of proposed model is given Table 4.

The model training utilizes 60% of the dataset, with 20% used for validation and the remaining 20% for testing. Training is performed with a batch size of 32 for 210 epochs. The model achieved a training accuracy of

TABLE 4. Layer Information of Proposed CNN-LSTM Model

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 16)	4624
max_pooling2d_1 (MaxPooling 2D)	(None, 62, 62, 16)	0
conv2d_2 (Conv2D)	(None, 60, 60, 32)	4640
max_pooling2d_2 (MaxPooling 2D)	(None, 30, 30, 32)	0
conv2d_3 (Conv2D)	(None, 28, 28, 64)	18496
max_pooling2d_3 (MaxPooling 2D)	(None, 14, 14, 64)	0
conv2d_4 (Conv2D)	(None, 12, 12, 128)	73856
max_pooling2d_4 (MaxPooling 2D)	(None, 6, 6, 128)	0
reshape (Reshape)	(None, 36, 128)	0
lstm (LSTM)	(None, 36, 256)	394240
flatten (Flatten)	(None, 9216)	0
dense (Dense)	(None, 1024)	9438208
dropout (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 5)	5125

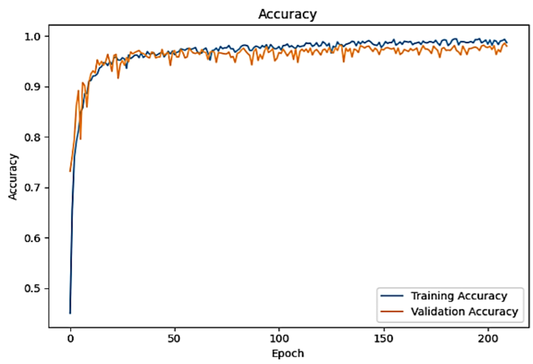

Figure 6. Training and Validation Accuracy through each Epoch

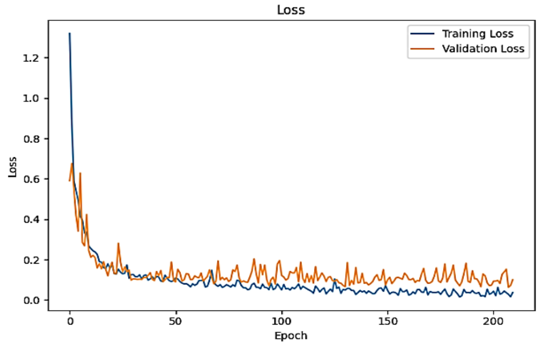

Figure 7. Training and Validation Loss through each Epoch

98.82% with a loss of 0.0430 and a validation accuracy of 98.14% with a loss of 0.0535. The training and validation accuracy and loss for each epoch are depicted in Figures 6 and 7.

4. 3. Other Models Along with the proposed model 4 more models were trained for comparing results. Additional models VGG16, Alexnet, ResNet50. Same data with same ratio was used to train these other models

1) Alexnet

AlexNet marked a significant milestone in the realm of deep learning. Its architecture revolutionized the computer vision field by demonstrating the power of Convolutional Neural Networks (CNNs) on large-scale image classification tasks. With five convolutional layers followed by three dense layers, it achieved remarkable accuracy, winning the ILSVRC in 2012 (38). Table 5 shows the summary of the alexnet model.

This model achieved 99.61% training accuracy 93.03% validation accuracy. The training and validation accuracy and loss for each epoch are shown in Figures 8 and 9.

2) VGG16

The VGG16 model, introduced by the Visual Geometry Group(VGG), University of Oxford, represents another significant advancement in field deep learning, particularly for tasks related to image classification (38). With its 16-layer design, comprising 13 convolutional layers and then 3 Fully Connected (FC) layers, VGG16 demonstrated impressive capabilities in feature extraction and classification.

In many instances, researchers adopted transfer learning techniques, where pretrained VGG16 models were fine-tuned for specific tasks by freezing the weights of the convolutional layers and adding new fully connected layers for task-specific classification (39).

Table 6 shows a summary of the VGG16 model used in this study. It outlines the different layers and how they are organized.

This model achieved 99.80% training accuracy and 95.88 %validation accuracy. The training and validation accuracy for each epoch are shown in Figures 10 and 11.

TABLE 5. Layer Information of AlexNet

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 55, 55, 96)	34944
batch_normalization (Batch Normalization)	(None, 55, 55, 96)	384
max_pooling2d (MaxPooling2D)	(None, 27, 27, 96)	0
conv2d_1 (Conv2D)	(None, 27, 27, 256)	2973952
batch_normalization_1(Batch Normalization)	(None, 27, 27, 256)	1024
conv2d_2 (Conv2D)	(None, 27, 27, 384)	885120
batch_normalization_2 (Batch Normalization)	(None, 27, 27, 384)	1536
conv2d_3 (Conv2D)	(None, 27, 27, 384)	1327488
batch_normalization_3 (Batch Normalization)	(None, 27, 27, 384)	1536
conv2d_4 (Conv2D)	(None, 27, 27, 256)	884992
batch_normalization_4(Batch Normalization)	(None, 27, 27, 256)	1024
max_pooling2d_1 (MaxPooling2D)	(None, 13, 13, 256)	0
flatten (Flatten)	(None, 43264)	0
dense (Dense)	(None, 4096)	177213440
dense_1 (Dense)	(None, 4096)	16781312
dense_2 (Dense)	(None, 5)	20485

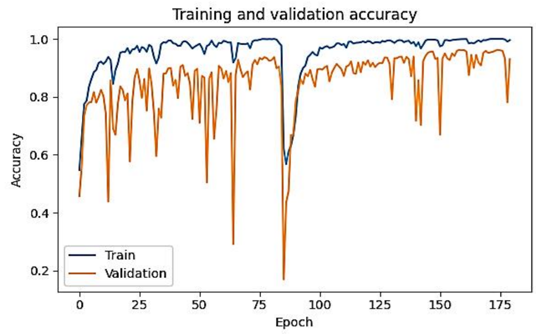

Figure 8. AlexNet Model Accuracy through each Epoch

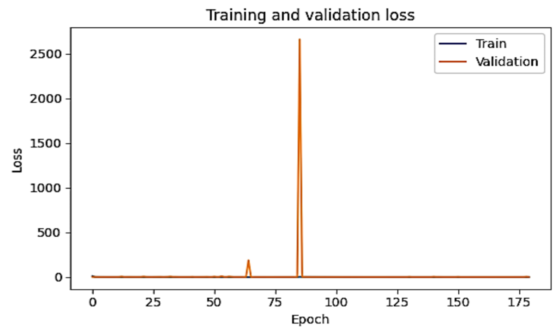

Figure 9. AlexNet Model Loss through each Epoch

3) ResNet50

ResNet50, an advancement of the ResNet architecture pioneered by Microsoft Research, exemplifies the ongoing refinement of deep learning frameworks (38). Distinguished by its 50-layer structure, ResNet50 presents a heightened level of complexity, enabling nuanced feature extraction across diverse datasets and domains.

In the conducted research, a customized version of ResNet50 was utilized, integrating four supplementary layers before the training phase. This augmentation aimed to further enhance the model's capacity to extract and leverage hierarchical features from input data, thereby potentially improving its performance on specific tasks. Table 7 shows the model summary of the ResNet50 model.

This model achieved 99.08% training accuracy and 74.88% validation accuracy. The training and validation accuracy for each epoch are shown in Figures 12 and 13.

TABLE 6. Layer Information of VGG16

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	((None, 224, 224, 3))	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 10)	250890

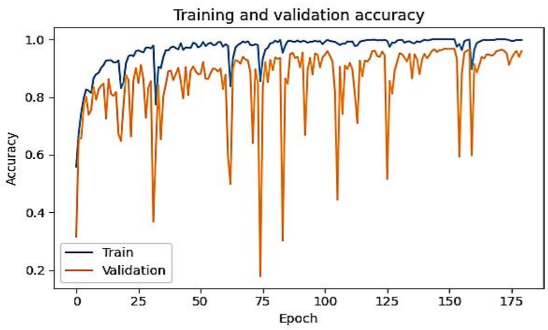

Figure 10. VGG16 Model Accuracy through each Epoch

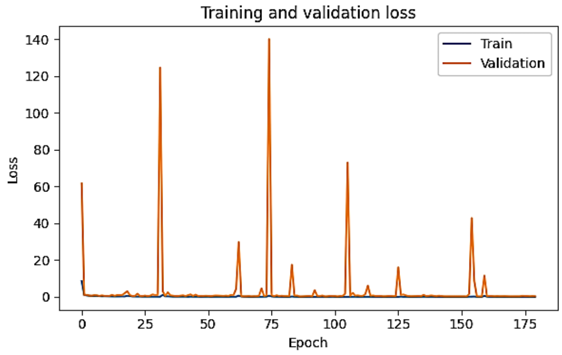

Figure 11. VGG16 Model Loss through each Epoch

5. RESULTS AND DISCUSSION

The proposed CNN+LSTM hybrid model was compared to various models as discussed above using some of the important performance metrics. Metrics used are Classification Accuracy, Precision, Recall, F1-Score and Specificity.

TABLE 7. Layer Information of ResNet50

Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 7, 7, 2048)	23587712
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
batch_normalization (Batch Normalization)	(None, 2048)	8192
dense_2 (Dense)	(None, 256)	524544
batch_normalization_1 (BatchNormalization)	(None, 256)	1024
dense_3 (Dense)	(None, 128)	32896
dropout (Dropout)	(None, 128)	0
batch_normalization_2 (BatchNormalization)	(None, 128)	512
dense_4 (Dense)	(None, 64)	8256
dropout_1 (Dropout)	(None, 64)	0
batch_normalization_3 (BatchNormalization)	(None, 64)	256
dense_5 (Dense)	(None, 5)	325

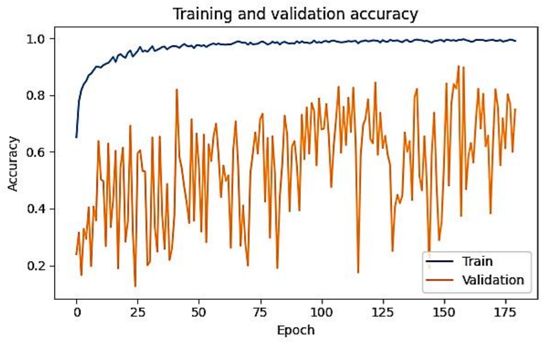

Figure 12. ResNet50 ModelAccuracy through each Epoch

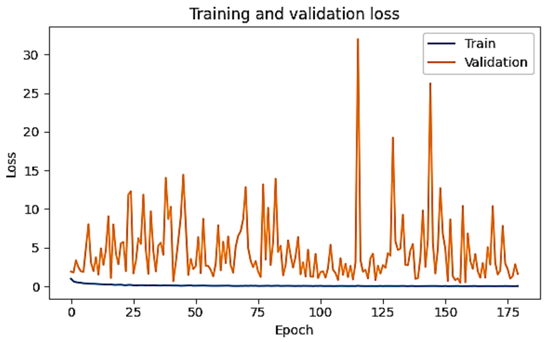

Figure 13. ResNet50 Model Loss through each Epoch

5. 1. Classification Accuracy This is one of the critical metrics for measuring performance. It refers to the percentage of correct predictions made by the classification model. Equation 9 is used for the calculation of this metric.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ Predictions} \tag{9}$$

Figure 14 shows the accuracies of all trained models. The proposed model achieved the highest test accuracy of 98.8% with a test loss of 0.804. Resnet50 performed the worst among all the models.

5. 2. Precision Precision is the ratio of correct predictions(true positives) to total predictions. Equation 10 is used for the calculation of precision.

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)} \tag{10}$$

Figure 15 shows the proposed model achieved precision of 0.99 which is highest compared to other models.

5. 3. Recall Recall is also known as sensitivity. It measures the ratio of true positives correctly classified as Positive to the total number of positive predictions. Equation 11 is used for the calculation of this metric.

$$Recall = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \tag{11}$$

Figure 16 shows the recall values of all trained models. The proposed model has the achieved highest recall value.

5. 4. F1 Score F1 Score is a harmonic mean of precision and recall. Equation 12 is used for the calculation of this metric.

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{12}$$

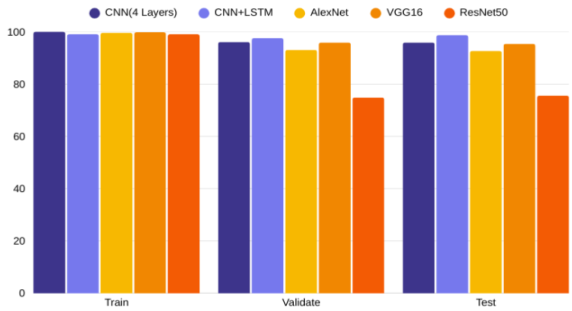

Figure 14. Test Accuracy of all Trained Models

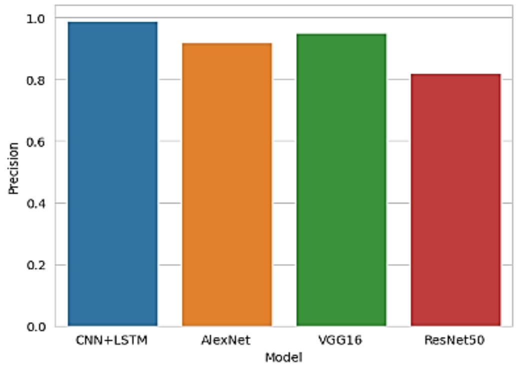

Figure 15. Highest Precision of CNN LSTM Model

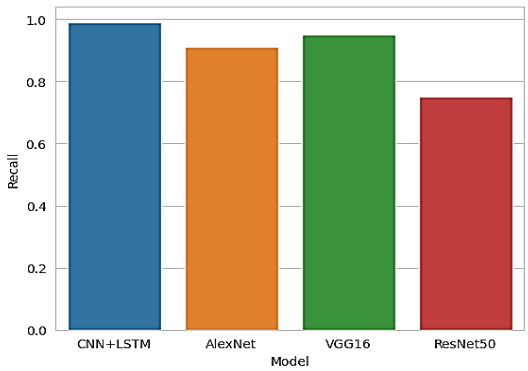

Figure 16. Recall of all Trained Models

Figure 17 shows the F1 Scores of all trained models. It shows that the proposed model has outperformed all other models.

5. 5. Confusion Matrix Confusion Matrix provides a detailed breakdown of the actual versus predicted classification. Figure 18 shows the confusion matrix of Proposed Model.

From the above metrics, it can be observed that the proposed CNN+LSTM model outperformed the other CNN based model Alexnet and state-of-art transfer learning models ResNet and VGG16. Also it is noted that the proposed model uses fewer layers (CNN as well as fully connected) compared to other models.

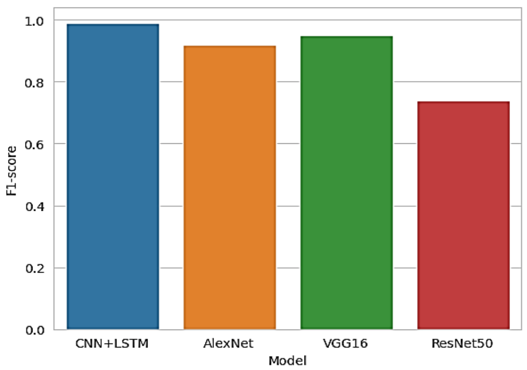

Figure 17. F1-Score of all Trained Models

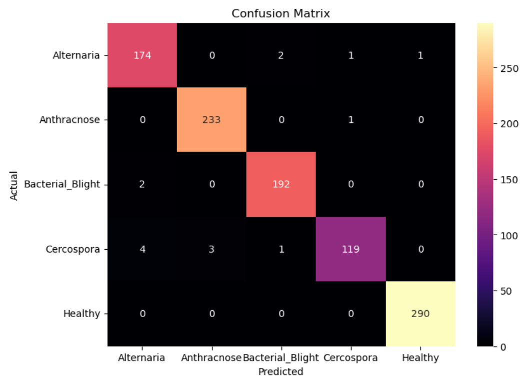

Figure 18. CNN+LSTM Model outperformed the other CNN based model

6. CONCLUSION

This study proposed a novel approach for detecting pomegranate fruit disease detection by using a hybrid model. By combining the feature extraction of CNN with sequential handling of LSTM, the proposed model demonstrates higher performance compared to other models that were considered for this study.

Experiment results show that the proposed model CNN-LSTM archives higher accuracy and precision, significantly improving the disease detection and classification capabilities. This advancement can help the agriculture and food industry in reducing economic costs.The study provides a comprehensive evaluation of various machine learning models, highlighting the efficacy of hybrid models in agricultural disease detection. Similar approaches could benefit other crops which offer scalable and adaptable solutions.

However there are limitations also exist. The dataset, while extensive, is region-specific and limited to few varieties of pomegranate fruit. Expanding the dataset to include other varieties and other locations can increase the robustness of the model. Additionally, integrating advanced image preprocessing techniques and exploring other hybrid combinations may yield better results.

The study also adds the ineffectiveness of transfer learning approaches like VGG16 and ResNet50 and the performance issues of larger models like AlexNet indicating that larger architectures may not always perform better in this context.

In conclusion, the CNN-LSTM hybrid model marks a significant advancement in agricultural disease detection, offering a promising tool for improving the sustainability and productivity of pomegranate cultivation and potentially revolutionizing agricultural practices.

Future Work:The following are some potential avenues for further research, building on the encouraging findings of this study: investigation of further hybrid architectures, such as CNN-GRU, Transformer-based networks, or lightweight attention-based architectures, for use in real-time disease detection in the field using mobile devices or drones.

7. REFERENCES

1. Khan N, Fahad S, Naushad M, Faisal S. Pomegrantes economics and medicinal aspects in the world. Available at SSRN 3597891. 2020. 10.2139/ssrn.3597891
2. Mena P, Gironés-Vilaplana A, Moreno DA, García-Viguera C. Pomegranate fruit for health promotion: Myths and realities. Funct Plant Sci Biotechnol. 2011;5:33-42. http://globalsciencebooks.info/Online/GSBOnline/images/2011/FPSB_5(SI2)/FPSB_5(SI2)33-42o.pdf
3. Ismail T, Sestili P, Akhtar S. Pomegranate peel and fruit extracts: a review of potential anti-inflammatory and anti-infective effects. Journal of ethnopharmacology. 2012;143(2):397-405. https://doi.org/10.1016/j.jep.2012.07.004
4. Ganeshkumar D, Bhattacharyya K, Narsimhaiah L, Yumnam SS. Performance of pomegranate export from India. Economic Affairs. 2016;61(4):575-80. https://www.researchgate.net/publication/329871322
5. Hosamani S, Alur A, editors. Pomegranate-an Indian scenario. III International Symposium on Pomegranate and Minor Mediterranean Fruits 1089; 2013.

6. Heber D. Pomegranate ellagitannins. Herbal Medicine: Biomolecular and Clinical Aspects 2nd edition. 2011. https://pubmed.ncbi.nlm.nih.gov/22593938/
7. Vasumathi M, Kamarasan M. An effective pomegranate fruit classification based on CNN-LSTM deep learning models. Indian Journal of Science and Technology. 2021;14(16):1310-9. https://doi.org/10.17485/IJST/v14i16.432
8. Deshpande T, Sengupta S, Raghuvanshi K. Grading & identification of disease in pomegranate leaf and fruit. International Journal of Computer Science and Information Technologies. 2014;5(3):4638-45. 10.13140/RG.2.2.12639.84643
9. Bhange M, Hingoliwala H. Smart farming: Pomegranate disease detection using image processing. Procedia computer science. 2015;58:280-8. 10.1016/j.procs.2015.08.022
10. Gaikwad SA, Deore KS, Waykar MK, Dudhane PR, Sorate G. Fruit disease detection and classification. International Research Journal of Engineering and Technology. 2017;4:1151-4.
11. Kantale P, Thakare S. Pomegranate disease classification using Ada-Boost ensemble algorithm. Int J Eng Res Technol. 2020;9:612-20. 10.17577/IJERTV9IS090216
12. Dhakate M, Ingole A, editors. Diagnosis of pomegranate plant diseases using neural network. 2015 fifth national conference on computer vision, pattern recognition, image processing and graphics (NCVPRIPG); 2015: IEEE. 10.1109/NCVPRIPG.2015.7490056
13. Patil J. Pomegranate fruit diseases detection using image processing techniques: a review. Information Technology in Industry. 2021;9(2):115-20. https://doi.org/10.17762/itii.v9i2.310
14. Pawar R, Jadhav A, editors. Pomogranite disease detection and classification. 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI); 2017: IEEE. 10.1109/ICPCSI.2017.8392162
15. G. Nagarjuna Reddy LG, P. Eshwar, P. Sarvothama Reddy , K. Madhu Sudhan Reddy. ANN based Fruit Disease Detection using Texture Analysis. International Journal of Emerging Technologies and Innovative Research. 2023;10(4):e187-e93. http://www.jetir.org/papers/JETIR2304425.pdf
16. Madhavan MV, Thanh DNH, Khamparia A, Pande S, Malik R, Gupta D. Recognition and classification of pomegranate leaves diseases by image processing and machine learning techniques. Computers, Materials & Continua. 2021;66(3):2939-55.
17. Sharath D, Kumar SA, Rohan M, Suresh K, Prathap C, editors. Disease detection in plants using convolutional neural network. 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT); 2020: IEEE. 10.1109/ICSSIT48917.2020.9214159
18. Sánchez MG, Miramontes-Varo V, Chocoteco JA, Vidal V, editors. Identification and classification of botrytis disease in pomegranate with machine learning. Science and Information Conference; 2020: Springer.
19. Pawar S, Shedge S, Panigrahi N, Jyoti A, Thorave P, Sayyad S, editors. Leaf disease detection of multiple plants using deep learning. 2022 international conference on machine learning, big data, cloud and parallel computing (COM-IT-CON); 2022: IEEE. 10.1109/COM-IT-CON54601.2022.9850899
20. Wakhare PB, Kandalkar JA, Kawtikwar RS, Kalme SA, Patil RV. Development of automated leaf disease detection in pomegranate using Alexnet algorithm. Curr Agric Res J. 2023;11(1):177-85. http://dx.doi.org/10.12944/CARJ.11.1.15
21. Nirgude V, Rathi S. A robust deep learning approach to enhance the accuracy of pomegranate fruit disease detection under real field condition. Journal of Experimental Biology and Agricultural Sciences. 2021;9(6):863-70. 10.18006/2021.9(6).863.870
22. Javeriya S. Faster-RCNN based deep learning model for pomegranate diseases detection and classification. LC International Journal of STEM (ISSN: 2708-7123). 2021;2(3):114-20. 10.36647/CIML/02.02.A002
23. Al Ansari MS. A Machine Learning Approach to Pomegranate Leaf Disease Identification. International Journal on Recent and Innovation Trends in Computing and Communication ISSN. 2023:2321-8169. 10.17762/ijritcc.v11i9.9597
24. Qi Y, Zhichao C, Lan L, editors. Fruit Disease Identification Based on Improved Densenet Fusion Defogging Algorithm. 2021 18th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP); 2021: IEEE. 10.1109/ICCWAMTIP53232.2021.9674088
25. Vasumathi M, Kamarasan M. An lstm based cnn model for pomegranate fruit classification with weight optimization using dragonfly technique. Indian J Comput Sci Eng. 2021;12(2):371-84. 10.21817/indjcse/2021/v12i2/211202051
26. Naseer A, Amjad M, Raza A, Munir K, Samee NA, Alohali MA. A novel transfer learning approach for detection of pomegranates growth stages. IEEE access. 2024;12:27073-87. 10.1109/ACCESS.2024.3365356
27. Nirmal M, Jadhav PP, Pawar S. Pomegranate leaf disease detection using supervised and unsupervised algorithm techniques. Cybernetics and Systems. 2023:1-12. 10.1080/01969722.2023.2166192
28. Pakruddin B, Hemavathy R. Development of a Pomegranate Fruit Disease Detection and Classification Model using Deep Learning. Indian Journal of Agricultural Research. 2024;58. 10.17632/b6s2rkpmvh.1
29. Gu J, Wang Z, Kuen J, Ma L, Shahroudy A, Shuai B, et al. Recent advances in convolutional neural networks. Pattern recognition. 2018;77:354-77. 10.1016/j.patcog.2017.10.013
30. Hochreiter S. The vanishing gradient problem during learning recurrent neural nets and problem solutions. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems. 1998;6(02):107-16. 10.1142/S0218488598000094
31. Schmidhuber J. Deep learning in neural networks: An overview. Neural networks. 2015;61:85-117. 10.1016/j.neunet.2014.09.003
32. Hassan SM, Maji AK. Plant disease identification using a novel convolutional neural network. IEEE access. 2022;10:5390-401. 10.1109/ACCESS.2022.3141371
33. Devi EA, Gopi S, Padmavathi U, Arumugam SR, Premnath S, Muralitharan D, editors. Plant disease classification using CNN-LSTM techniques. 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT); 2023: IEEE. 10.1109/ICSSIT55814.2023.10061003
34. Shafik W, Tufail A, Liyanage CDS, Apong RAAHM. Using a novel convolutional neural network for plant pests detection and disease classification. Journal of the Science of Food and Agriculture. 2023;103(12):5849-61. https://doi.org/10.1002/jsfa.12700
35. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Communications of the ACM. 2017;60(6):84-90. 10.1145/3065386
36. Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:14091556. 2014. https://www.researchgate.net/publication/265385906
37. Yan Q, Yang B, Wang W, Wang B, Chen P, Zhang J. Apple leaf diseases recognition based on an improved convolutional neural network. Sensors. 2020;20(12):3535. https://doi.org/10.3390/s20123535
38. He K, Zhang X, Ren S, Sun J, editors. Deep residual learning for image recognition. Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. 10.1109/CVPR.2016.90

39. LeCun Y, Boser B, Denker JS, Henderson D, Howard RE, Hubbard W, et al. Backpropagation applied to handwritten zip code recognition. Neural computation. 1989;1(4):541-51. 10.1162/neco.1989.1.4.541

Persian Abstract

چکیده

انار میوه‌ای با ارزش بالا است که به دلیل فواید تغذیه‌ای و کاربردهایش در طب سنتی و لوازم آرایشی، در سطح جهانی شناخته شده است. هند بازیگر کلیدی در بازار جهانی انار است، اما این صنعت با چالش‌هایی مانند بیماری‌هایی که بر بهره‌وری محصول تأثیر می‌گذارند و ضررهای اقتصادی برای کشاورزان روبرو است. این مطالعه رویکرد جدیدی را برای تشخیص بیماری‌های انار با استفاده از یک مدل ترکیبی شبکه عصبی کانولوشن (CNN)و حافظه کوتاه‌مدت بلند (LSTM)ارائه می‌دهد. مدل پیشنهادی از CNNها برای استخراج ویژگی مؤثر و از LSTMها برای مدیریت داده‌های متوالی استفاده می‌کند و در مقایسه با روش‌های سنتی و سایر تکنیک‌های یادگیری عمیق، به عملکرد برتر دست می‌یابد. نتایج تجربی، دقت، یادآوری، دقت و امتیاز F1 بالایی را نشان می‌دهد. مدل پیشنهادی به دقت ۹۸.۵۳٪ و تلفات ۰.۰۶۷۷ دست یافت. این مطالعه همچنین محدودیت‌های رویکردهای یادگیری انتقالی مانند VGG16 و ResNet50 و مدل‌های بزرگ‌تر مانند AlexNet را که در این زمینه عملکرد خوبی نداشتند، بررسی می‌کند. یافته‌ها نشان می‌دهد که مدل ترکیبی CNN-LSTM یک راه‌حل مقیاس‌پذیر و سازگار برای تشخیص بیماری‌های کشاورزی با کاربردهای بالقوه برای محصولات مختلف ارائه می‌دهد.