RESEARCH ARTICLE Indian Journal of Agricultural Research, Volume 58 Special Issue: 1121-1130 (November 2024)

Development of a Pomegranate Fruit Disease Detection and Classification Model using Deep Learning

B. Pakruddin[1,2], R. Hemavathy[1]

10.18805/IJARe.A-6281

ABSTRACT

Background: India's economy heavily relies on agriculture, which provides a living for a significant portion of the nation's population. Agriculture in India faces several challenges, including fruit diseases. Pomegranate cultivation is widespread across various states in India, with Maharashtra, Karnataka andhra Pradesh, Gujarat and Tamil Nadu being major pomegranate-producing states. Fruit disease detection and classification play a significant part in refining crop yield: water scarcity, soil degradation, outdated farming techniques and the impact of climate change. Farmer suicides are a distressing issue, often linked to financial burdens, crop failures and debt. Manual disease detection methods are labor-intensive, time-consuming and prone to errors. Furthermore, understanding the data usually requires the knowledge of qualified specialists. These restrictions may make it more difficult to detect diseases promptly and increase the chance that the disease will spread across the flock, which could have dangerous results.

Methods: In this paper, we use the PomeNetV2 Convolutional Neural Network (CNN) architecture and also examine 4 diseases of pomegranate fruit with names: Alternaria, Anthracnose, Bacterial Blight, Cercospora and Healthy. We used a proposed dataset of 5099 pomegranate fruit disease images. We compared the results of the proposed pomegranate fruit disease classification method with those of existing works.

Result: Based on our experimental findings, the suggested framework outperforms all other state-of-the-art models with an accuracy of 99.02% for 75 epochs in identifying healthy and diseased pomegranate fruit.

Key words: Agriculture, Classification, Convolutional neural networks, Deep learning, Disease detection.

INTRODUCTION

Pomegranates are a nutritious and versatile fruit with significant health benefits, culinary uses and economic importance (Singh *et al*., 2023). Cultivating pomegranates requires specific climate and soil conditions, along with effective pest and water management. Despite challenges, pomegranates remain a valuable crop for farmers and a popular fruit for consumers worldwide (Pakruddin *et al.,* 2024; Gawade *et al.,* 2018). The import and export of pomegranates play a vital role in India's agricultural economy, providing income and employment while contributing to foreign exchange earnings. However, challenges such as quality control, pest management, infrastructure, market access and climate change must be addressed to capitalize on this potential fully. Effective government policies, industry initiatives and investment in infrastructure and technology are crucial to overcoming these challenges and boosting the pomegranate trade Wakhare *et al*. (2023). Pomegranate plants can be affected by a diversity of diseases, which can meaningfully impact yield and fruit quality. These diseases can be classified into fungal, bacterial, viral and other categories.

Fungal disease and its symptoms Alternaria Fruit Rot (*Alternaria alternate*): Dark, sunken lesions on fruits, the internal tissue may become discolored and rot Aloi and Francesco *et al*. (2021). Cercospora Fruit Spot (*Cercospora punicae*): Small, dark spots on leaves and fruit, spots may coalesce to form larger lesions (Gk, Ravichandra *et al*. 2023). Aspergillus Fruit Rot (*Aspergillus niger*): lack mold on the surface of the fruit, affected fruit may shrivel and become hard. Botrytis Fruit Rot (*Botrytis cinerea*): Gray mold on flowers and fruits, can lead to fruit drop and reduced yield. Fusarium Wilt (*Fusarium oxysporum*): Yellowing and wilting of leaves, vascular discoloration and stunted growth (Nirgude *et al*., 2024; AlZubi *et al*., 2024). Bacterial Diseases and its Signs Bacterial Blight (*Xanthomonas axonopodis* pv. Punicae): Fruit cracking can result from water-soaked lesions on leaves, stems and fruits that turn black. (Sharath *et al*., 2019). Viral diseases and its symptoms pomegranate mosaic virus mosaic patterns on leaves, leaf distortion and reduced fruit size and quality. Other Diseases and their Symptoms Heart Rot (*Phomopsis* sp., *Colletotrichum gloeosporioides*): Internal fruit decay, often without external

[1]Department of Computer Science and Engineering, R.V. College of Engineering, Visvesvaraya Technological University, Belagavi-590 018, Karnataka, India.
[2]Department of Computer Science and Engineering, Presidency University, Bengaluru-560 064, Karnataka, India.

Corresponding Author: B. Pakruddin, Department of Computer Science and Engineering, R.V. College of Engineering, Visvesvaraya Technological University, Belagavi-590 018, Karnataka, India.
Email: fakrubasha@gmail.com
Orchid: 0000-0002-7660-0227; 0000-0002-7586-7827.

How to cite this article: Pakruddin, B. and Hemavathy, R. (2024). Development of a Pomegranate Fruit Disease Detection and Classification Model using Deep Learning. Indian Journal of Agricultural Research. 58 (Special Issue): 1121-1130. doi: 10.18805/IJARe.A-6281.

Submitted: 14-07-2024 **Accepted:** 24-08-2024 **Online:** 21-10-2024

symptoms, affected fruits may have a hollow or rotten core. Leaf spot (Myrothecium roridum): Circular, brown spots with a yellow halo on leaves, severe infections can lead to defoliation.

Farmers may efficiently control pomegranate diseases and ensure healthier plants and higher-quality fruit output by putting these methods into practice. Improve air circulation, ensure proper plant spacing, maintain field hygiene and avoid overhead irrigation. Use fungicides and bactericides as necessary, following recommended guidelines for application. Employ beneficial microorganisms that can suppress disease-causing pathogens. Plant disease-resistant varieties whenever possible to reduce the impact of diseases. To stop infections from spreading, remove and destroy any contaminated plant parts. Fruits should be stored cool and dry to avoid postharvest illnesses.

After employing machine learning and deep learning techniques to perform a survey on illness detection and classification for pomegranate fruit, we have concluded that additional study is required to address developing diseases. The proposed model addresses the deficiencies of prior approaches in deep learning-based pomegranate fruit disease detection and classification. The existing model for pomegranate fruit disease was proposed by the authors, but it had several drawbacks, including low accuracy and high processing times. To address these issues, we proposed a PomeNetV2 model that predicts pomegranate diseases much more quickly and accurately than the current system. This paper's major goal is to create a deep learning-based automated system that can reliably identify and categorize pomegranate fruit disorders. The goal of the study is to evaluate and confirm the effectiveness of the system, which will aid in the creation of useful instruments for identifying fruit diseases and lessen the detrimental effects of plant diseases on crop quality and yield.

The researchers (Naseer *et al*., 2024) investigated identifying pomegranate growth stages early on by employing an effective method. According to the results, the random forest model outperformed cutting-edge techniques, achieving a high accuracy of 98%. Farmers that use this strategy can reduce risks and increase crop productivity.

Nirgude *et al*. (2022) suggest a framework for deploying agricultural drones and sensors to collect data in real-time on weather, soil and water characteristics. Random Forest (RF), out of all the machine learning models that were assessed, had the best accuracy (96.53%). By using this method, the pomegranate industry can better diagnose and classify prevalent diseases, leading to improved fruit quality and growth.

A CNN-LSTM deep learning model was created by the authors Vasumathi *et al*. (2021) to divide a dataset of 6519 fruits into categories for normal and pathological conditions. Each dataset entry contains nine features within an Excel file. CNNs perform deep feature extraction and LSTMs use these features for categorization. With an accuracy of 98.17%, sensitivity of 97.77%, specificity of 98.65% and an F1-score of 98.39%, the suggested system performed well. Previous detection methods had lower sensitivity and accuracy due to unresolved faults. Deep learning offers advanced techniques to enhance analytical and predictive accuracy in early illness identification.

The purpose of the study by Aloi *et al*. (2021) was to define the mycotoxigenic characteristics of Alternaria species that cause heart rot in pomegranates in southern Italy. The CNN-based ResNet50 architecture proposed by the authors Nirgude *et al*. (2021) effectively identifies and classifies five distinct illness types with ambiguous symptoms and complex histories. The enhanced ResNet50 model attained a test accuracy of 97.92%, outperforming both Inception-V3 (78.75%) and ResNet18 (87.5%) at a learning rate of 0.001. The multiclass cross-entropy loss function was used to determine the error rate.

Patil *et al*. (2021) explain that their study examines feature extraction, segmentation, preprocessing and classification strategies for pomegranate plant disease detection. It observes the shortcomings of current approaches for detecting fruit diseases and compares them. Vasumathi *et al*. (2021) state that a hybrid CNN-LSTM approach to identify and categorize four different pomegranate fruit illnesses. Discriminant analysis and principal component analysis are used to extract and process features such as color, texture and shape. By adjusting the cost function and optimizing the weight, the dragonfly algorithm raises the initial 92% accuracy of the CNN-LSTM classifier to 97.1%. With a graphical user interface, Mangena *et al*. (2021) suggested MATLAB-based framework successfully classifies damaged and healthy leaves with an accuracy of 98.39%. The findings of experiments also show that it achieves 98.07% accuracy in diagnosing illnesses on pomegranate leaves.

The primary goal of this paper is to develop an effective PomeNetV2 model for accurately detecting pomegranate fruit diseases using advanced deep learning techniques, a specially designed dataset, activation functions and optimization algorithms. The study will assess and validate the model's performance in identifying and classifying these diseases. By accomplishing this, the research seeks to contribute significantly to the creation of efficient tools for detecting fruit diseases, ultimately helping to mitigate their adverse effects on crop yield and quality.

MATERIALS AND METHODS

All the experiments were conducted at the research center named Rashtreeya Vidyalaya College of Engineering Bangalore in the academic year 2023-2024.

Dataset used

In this research, we have leveraged a newly proposed dataset B Pakruddin *et al*. (2024) focusing on the afflictions affecting pomegranate fruits. This dataset is a culmination of diverse samples sourced from various regions such as

Ballari, Bengaluru and Bagalakote, among others, spanning from July to October 2023. Comprising a total of 5099 meticulously curated images, this dataset encompasses a comprehensive array of pomegranate fruit conditions, exactly categorized into five distinct types: Healthy (1450 images), Bacterial blight (966 images), Anthracnose (1166 images), Chavan *et al*. (2017). Cercospora (631 images) and Alternaria (886 images). Each image is accurately labeled and organized into corresponding folders, ensuring seamless access and utilization. Samples of pomegranate fruit disease images are exposed in Fig 1.

Image pre-processing and labelling

Image resizing

Image resizing in the pre-processing step is essential for ensuring uniform input size, reducing computational load, ensuring model compatibility, maintaining consistency and improving overall model performance. These benefits are critical for effective and efficient model training and testing. Each image size in the dataset contains 3120 * 3120, during pre-processing each image size is considered as 220 * 220.

Pixel normalization

We should resize the photographs to the proper size before feeding them into the network. Additionally, to normalize the pixel values and improve the model's performance, we should divide them by 256 and scale them to the range of 0 to 1. Our model can be pre-processed by adding a layer and this normalization should be implemented during both training and inference (Bhange *et al*., 2015).

Noise removal

Noise removal is an essential pre-processing step to improve image quality, reduce irrelevant information and enhance feature extraction. Techniques such as Gaussian blurring, median filtering, bilateral filtering and non-local means denoising are commonly used to effectively remove noise while preserving important image details.

Augmentation

Data augmentation is essential for increasing dataset size, improving model robustness, preventing overfitting and balancing classes.

Mathematical formulation of PomeNetV2 CNN model

Six convolutional layers, six max-pooling layers Thorat *et al*. (2023), one flattened layer and two dense layers make up our PomeNetV2 deep learning model. The mathematical notation for this model is organized as follows:

1. Convolutional and max-pooling layers.

$$P_6 = P(f(W_6 * P(f(W_5 * P(f(W_4 * P(f(W_3 * P(f(W_2 * P(f(W_1 * X + b_1) + b_2) + b_3) + b_4) + b_5) + b_6) \quad ...(1)$$

2. Flatten layer

$$F = \text{flatten}\ (P_6) \quad ...(2)$$

3. Dense layers

$$D_1 = f\ (W_1^d\ F + b_1^d) \quad ...(3)$$

4. Output layer

$$D_2 = f\ (W_2^d\ D_1 + b_2^d) \quad ...(4)$$

$$\text{Output} = \text{softmax}\ (D2\ ) \quad ...(5)$$

Where:

X: Input tensor.

Wi, bi: Weight matrix and bias vector for the *j*-th convolutional layer.

$W_{i,}^d$ b_i^d: Weight matrix and bias vector for the *j*-th dense layer.



Fig 1: Sample of healthy and diseased pomegranate fruit images.

f: Activation function (*e.g.*, ReLU for convolutional layers, softmax for output layer).

P: Max-pooling operation, ⋆: Convolution operation. Akhilesh *et al*. (2020).

Performance metrics

The effectiveness of deep learning models can be measured using metrics such as Accuracy, Precision, Recall, F1 score and Support. These metrics deliver an excellent means of comprehending several facets of the model's performance (Vasumathi *et al*., 2021; Khatawkar *et al*., 2023).

$$\text{Precision} = \frac{TP}{TP+FP} \quad ...(6)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad ...(7)$$

$$\text{F1 - Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision}+\text{Recall}} \quad ...(8)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+FN} \quad ...(9)$$

Support

Support represents the number of occurrences of each class in actual data. It gives an indication of the frequency of each class in the dataset.

Where the confusion matrix is represented by true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) values.

Experimental setup for the proposed model

The research was conducted utilizing Google Colab, utilizing a system with 12.7 GB of RAM and 107.7GB of disk space, employing the Python programming language. This was executed on a Windows 10, 64-bit i3 computer equipped with 8GB of RAM. The performance of the proposed PomeNetV2 Convolutional Neural Network (CNN) model was evaluated against various existing methods across different types of pomegranate fruit diseases. Table 1 Summarizes some common hyperparameters used for the PomeNetV2 model.

In the realm of deep learning, data augmentation is a commonly employed tactic aimed at enhancing model performance and generalization, particularly in scenarios where datasets are limited. The fundamental aim of data augmentation is to introduce diverse transformations to the existing data, thereby expanding the size of the training dataset artificially. This process enhances the model's capability to generalize effectively to unseen data and facilitates the learning of invariant features. Basic data augmentation techniques such as rotation, flipping, zooming and cropping, among others, find widespread application in various deep learning contexts. Table 2 showcases a selection of methods utilized for both pre-trained models and the proposed model.

In this study, we have also used three techniques for data augmentation Cache, Shuffle and Prefetch. Cache involves storing the processed dataset in memory (or on disk) after it has been loaded and possibly pre-processed for the first time. This reduces the overhead of repeated data loading and pre-processing during each epoch.

Table 1: Hyperparameter setting for the experiments.

Hyperparameters	Values
Image input size	220 × 220 × 3
Epoch count	75
Size of batch	32
Learning rate	0.001
Activation function	ReLU
Optimizer	Adam
Loss function	Sparse categorical cross-entropy

Table 2: Data Augmentation for the proposed dataset in the PomeNetV2 model.

Parameters	Values
Resize	220×220
Rescale	1.0/255
Random rotation	0.2
Horizontal flip	True
Vertical flip	True

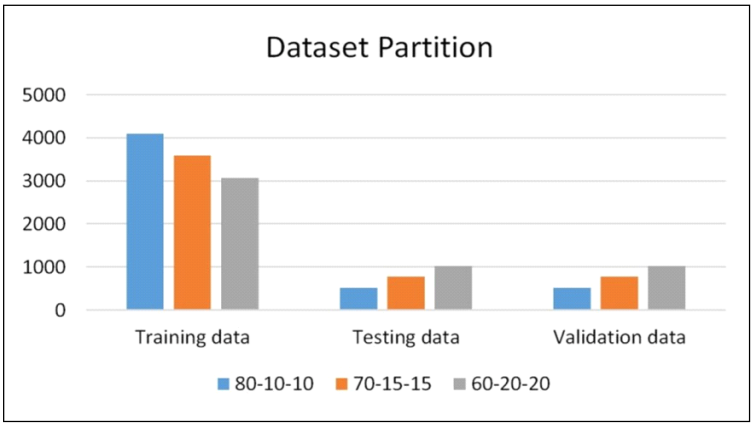


Fig 2: Partitioning the dataset into training, testing and validation.

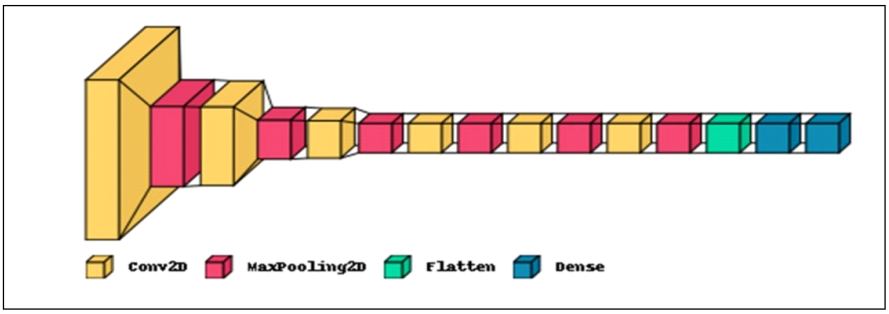


Fig 3: Visualization of the PomeNetV2 framework.

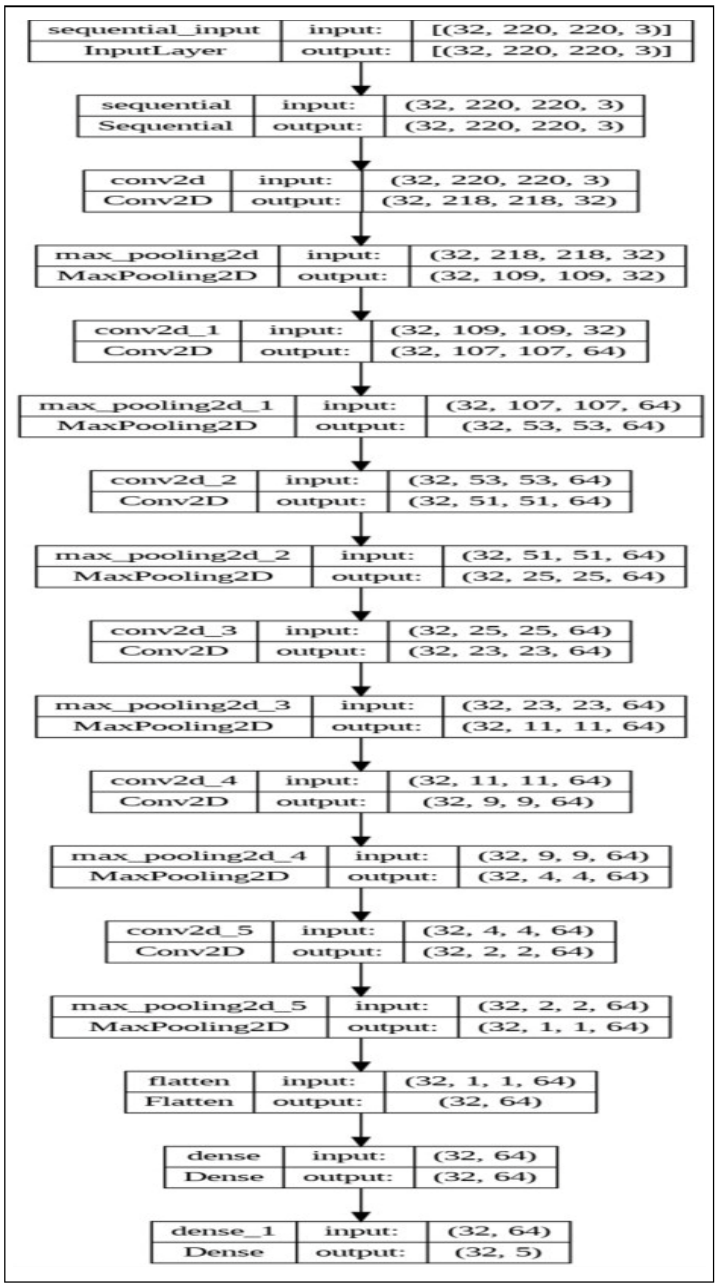


Fig 4: The input and output dimensions of each layer in the suggested PomeNetV2 CNN model are shown in the diagram along with the layer names.

Shuffling (buffer_size = 1000) the dataset ensures that the order of the data is randomized. This is essential to boost generalization and stop the model from picking up any erroneous patterns from the data's order. Prefetching (buffer_size = tf.data.AUTOTUNE) overlaps the data pre-processing and model training by preparing the next batch of data while the current batch is being processed. This is done asynchronously to ensure that the data pipeline can keep up with the training process. Fig 2 describes dataset is separated into 3 subsets, namely training, validation and testing with different percentages.

Proposed model architecture

The author developed PomeNetV2, a lightweight 15-layer CNN model designed to classify healthy images and four disease categories within the proposed dataset. This model, built without using transfer learning, includes 6 convolutional layers with trainable weights and biases, 6 max-pooling layers, 1 flattened layer and 2 fully-connected dense layers. To combat overfitting, the model features a reduced number of layers and fewer filters per layer. Each convolutional layer employs a 3×3 kernel size and each max-pooling layer uses a 2×2 pool size, with 64 filters in each layer, a stride of size 1 and valid padding. Feature extraction occurs in the first 12 layers, while the final 3 layers are used for classification. The model is trained from scratch without any transfer learning. Fig 3 describes the visualization of the PomeNetV2 CNN framework, while the input and output dimensions of each layer in the suggested PomeNetV2 CNN structure are shown in Fig 4.

RESULTS AND DISCUSSION

Table 3 displays the performance outcomes of numerous activation functions and loss functions when paired with the recommended 15-layer PomeNetV2 CNN architecture.

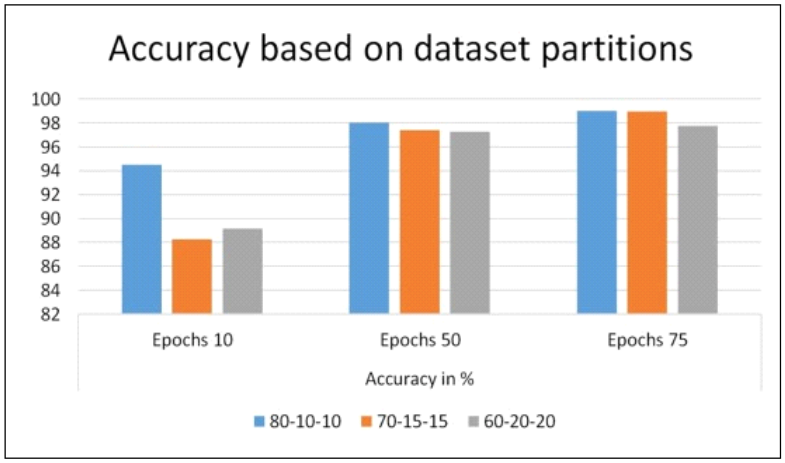


Fig 5: Describes accuracy based on dataset partitions.

Table 3: Analyzing various settings using the given dataset.

Method	Loss function	Activation functions	Accuracy
15-Layer CNN	sparse_categorical_crossentropy	Softmax	99.02%
15-Layer CNN	sparse_categorical_crossentropy	Sigmoid	99.00%
15-Layer CNN	sparse_categorical_crossentropy	Tanh	19.34%

Table 4: Performance of accuracy and loss based on the number of epochs.

Epochs	Training loss	Training accuracy	Validation loss	Validation accuracy
1	1.0735	0.5346	1.0992	0.5859
5	0.2791	0.9089	0.2776	0.8906
10	0.1661	0.9443	0.166	0.9453
15	0.1279	0.9616	0.1629	0.9395
20	0.1069	0.9669	0.0806	0.9785
30	0.0958	0.9718	0.0658	0.9785
40	0.0551	0.9816	0.0573	0.9816
50	0.0738	0.982	0.0616	0.9805
75	0.0495	0.9836	0.0395	0.9902

Sparse categorical cross entropy outperformed the other loss functions that were investigated in terms of performance. Conversely, binary cross-entropy and categorical cross-entropy loss functions are incompatible due to multiclass classification. This discrepancy can be attributed to binary cross entropy's suitability for binary class data, making it less effective for categorizing multiclass pomegranate disease grades. Additionally, three activation functions were tested in this investigation, Softmax and Sigmoid activation functions in conjunction with the sparse categorical cross-entropy loss function achieving accuracy of 99.02% and 99.00% respectively. This setup performed better than every other combination that was looked at. 19.34% accuracy was obtained using the Tanh activation function and the sparse categorical cross-entropy loss function.

The performance metrics of the PomeNetV2 framework-namely training accuracy, training loss, validation accuracy and validation loss-are meticulously detailed across different epoch counts in Table 4. These metrics provide insights into the model's learning process and its ability to generalize from the training data. The dataset used for developing the framework is strategically divided into three subsets: training data, testing data and validation data. This division is visually represented in Fig 5, which also indicates that the images for each subset were selected randomly to ensure unbiased training and evaluation. Fig 5 further illustrates the accuracy achieved

Table 5: A comparison between the current and published work.

Reference	Diseases detected	Method	Accuracy
Proposed work	5	PomeNetV2 CNN	99.02%
Vasumathi *et al.,* 2021	2	CNN+LSTM	98.17%
Mangena *et al.,* 2021	5	K- means,SVM	98.07%
Vasumathi *et al.,* 2021	4	Hybrid CNN+LSTM	97.16%
Wakhare *et al.,* 2023	3	AlexNet	97.60%
Nirgude *et al.,* 2024	5	LSTM and i-Ensemble-MLC	95.82%
Kantale *et al.,* 2020	3	AdaBoost Ensemble Algorithm	92.9%
Akhilesh *et al.,* 2020	3	Neural networks	85%
Manisha Bhange *et al.* 2015	1	SVM	85%

Table 6: Report on diseases-wise classification for the proposed PomeNetV2 model's precision, recall F1-score, and support.

Classes	TP	TN	FP	FN	Precision	Recall	F1-score	Support
Alternaria	176	842	1	0	99.43	100	99.71	177
Anthracnose	232	785	1	1	99.57	99.57	99.57	233
Bacterial_Blight	193	825	0	1	100	99.48	99.73	193
Cercospora	126	893	0	0	100	100	100	126
Healthy	290	729	0	0	100	100	100	290

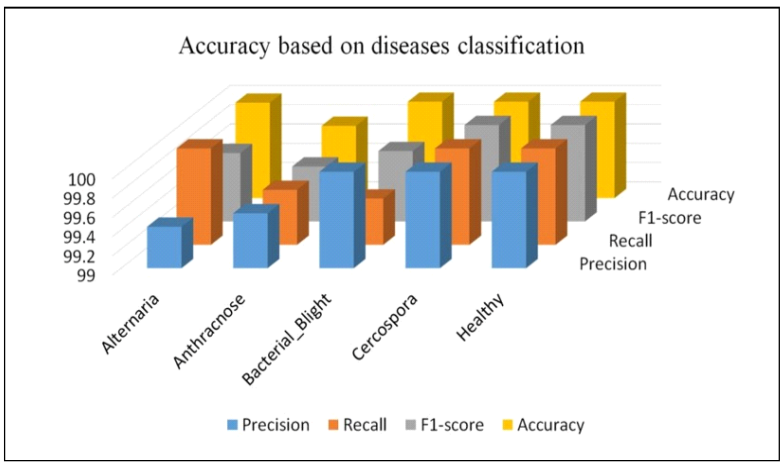


Fig 6: Comparison of accuracy across various diseases.

for each data split. Among various configurations tested, the 80%-10%-10% split-comprising 80% of the data for training, 10% for testing and 10% for validation-proved to be the most effective. This particular split reached a peak accuracy of 99.02% at 75 epochs, demonstrating the framework's exceptional ability to accurately classify pomegranate diseases and healthy fruit under this data distribution. This high level of performance highlights the robustness of the PomeNetV2 framework and its potential for real-world application in agricultural settings, where precise disease detection is crucial for crop management and yield optimization.

The summary indicates that the designed model, PomeNetV2, achieves an overall accuracy of approximately 99.02%. Fig 6 Specifically, for Alternaria, the framework achieves an accuracy of about 99.99%. For Anthracnose, the accuracy is approximately 99.75%. The framework achieves 100% accuracy for Bacterial Blight, Cercospora and Health. The new work must be compared to previously published studies to determine which model can produce

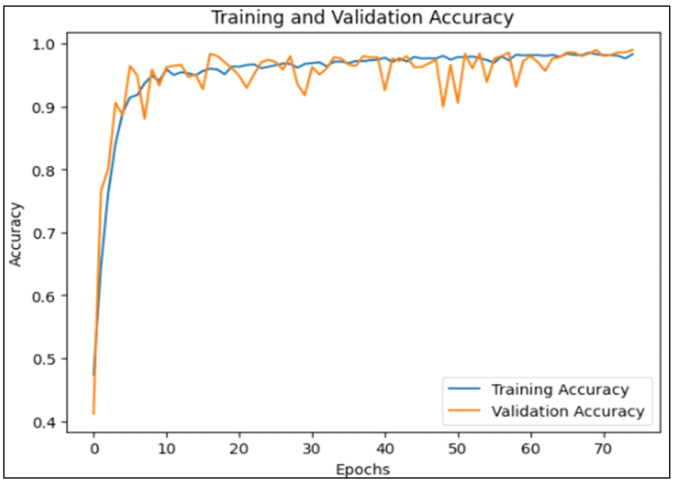


Fig 7: Training and validation accuracy comparison curves for pomenetv2 model.

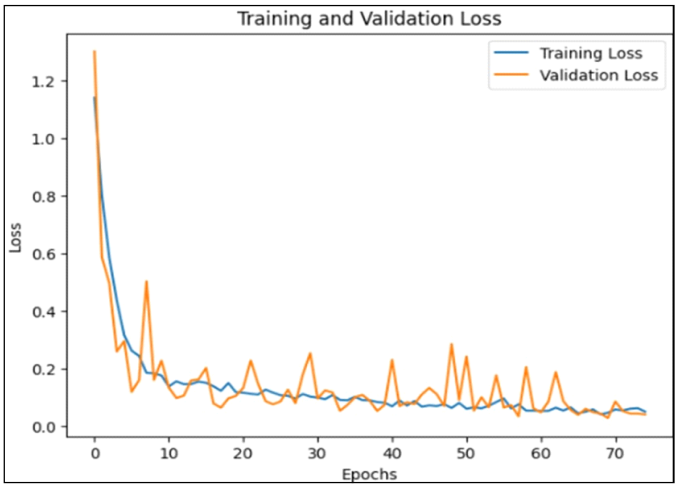


Fig 8: PomeNetV2 model training and validation loss comparison curves.

```
Epoch 70/75
128/128 [==============================] - 27s 208ms/step - loss: 0.0456 - accuracy: 0.9836 - val_loss: 0.0272 - val_accuracy: 0.9902
Epoch 71/75
128/128 [==============================] - 27s 212ms/step - loss: 0.0569 - accuracy: 0.9821 - val_loss: 0.0844 - val_accuracy: 0.9805
Epoch 72/75
128/128 [==============================] - 27s 212ms/step - loss: 0.0535 - accuracy: 0.9818 - val_loss: 0.0515 - val_accuracy: 0.9824
Epoch 73/75
128/128 [==============================] - 27s 210ms/step - loss: 0.0596 - accuracy: 0.9811 - val_loss: 0.0428 - val_accuracy: 0.9863
Epoch 74/75
128/128 [==============================] - 28s 220ms/step - loss: 0.0495 - accuracy: 0.9836 - val_loss: 0.0395 - val_accuracy: 0.9902
```

Fig 9: Validation and Training Based on epochs, accuracy.

greater accuracy. The outcomes are displayed in Table 5. Table 6 displays the additional performance parameters, which include recall, accuracy, precision, F1-score and support. Fig 7 and 8 describe loss and accuracy for training and testing. Fig 9 Shows accuracy achieved 99.02% for 75 epochs.

CONCLUSION

The article introduces the PomeNetV2 framework, a sophisticated system designed for the automatic identification and classification of pomegranate diseases through the analysis of fruit images. This innovative framework integrates several advanced techniques, including image pre-processing, augmentation, feature extraction, max pooling and image classification, to accurately diagnose pomegranate conditions. PomeNetV2 specifically targets four types of pomegranate diseases: Alternaria, Anthracnose, Bacterial Blight and Cercospora fruit spot, in addition to identifying healthy fruit. The framework demonstrates impressive performance, achieving an accuracy of approximately 99.99% for Alternaria, 99.75% for Anthracnose and 100% accuracy for both Bacterial Blight nd Cercospora fruit spot, as well as healthy pomegranates. Overall, PomeNetV2 maintains a remarkable accuracy rate of about 99.02% across all categories. Looking ahead, we have planned to create an Android application to further support farmers. This app will enable efficient detection and classification of pomegranate diseases in real-time and provide actionable remedy suggestions, enhancing the overall management and health of pomegranate crops.

ACKNOWLEDGEMENT

Public, commercial, or nonprofit funding agencies did not provide a particular grant for this study.

Data availability

Pomegranate Fruit Diseases Dataset for Deep Learning Models (Original data) (Mendeley Data). https://data.mendeley.com/datasets/b6s2rkpmvh/1

Credit author statement

Pakruddin B: Conceptualization, Formal analysis, Methodology, Investigation and Writing-original draft, Writing -review and editing; Dr. Hemavathy R: Supervision, Validation, Writing-review and editing.

Declaration of competing interests

The authors state that none of their known financial conflicts or interpersonal connections might have had an impact on the work presented in this paper.

REFERENCES

Akhilesh, R.G.S.M., Kumar, S.A. and Prathap, C. (2020). Disease Detection in Pomegranate using Image Processing. 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184), Tirunelveli, India, 2020, pp. 994-999, doi: 10.1109/ICOEI48184.2020.9142972.

Aloi, F., Riolo, M., Sanzani, S., Mincuzzi, A., Ippolito, A., Siciliano, I., Pane, A., Gullino, M. and Cacciola, S.O. (2021). Characterization of alternaria species associated with heart rot of pomegranate fruit. Journal of Fungi. 7. 172. 10.3390/jof7030172.

AlZubi, A.A., Raghuramapatruni, R., Kumari, P. (2024). Classification and severity level assessment of fusarium wilt disease in chickpeas using convolutional neural network. Legume Research-An International Journal. https://doi.org/10.18805/lrf-807.

Bhange, M. and Hingoliwala, H.A. (2015). Smart farming: Pomegranate Disease detection using image processing. Procedia Computer Science. 58: 280-288.

Chavan, A.A., Dhutraj, D.N. (2017). Survey on pomegranate anthracnose caused by *Colletotrichum gloeosporioides* (Penz.) In Marathwada region. Indian Journal of Agricultural Research. 51(2): 155-160. doi: 10.18805/ijare.v0iOF.7644.

Gawade S.N., Kale A.P., Shaikh J.A., Sharma R.C. (2018). Study on nutrient package for pomegranate (Punica granatum L.). Indian Journal of Agricultural Research. 52(2): 199-202. doi: 10.18805/IJARe.A-4861.

Kantale, P., Thakare, S. (2020). Pomegranate disease classification using ada-boost ensemble algorithm. International Journal of Engineering Research and Technology (IJERT). 9: 9. doi: 092020.

Khatawkar S., Jadhav S., Sapate S., Patil P., Shinde A. (2023). Disease detection on pomegranate fruits using machine learning approach. AIP Conference Proceedings. 2717, art. no. 020004. doi: 10.1063/5.0130455.

Mangena, V., Thanh, D., Khamparia, A., Pande, S., Malik, R. and Gupta, D. (2021). Recognition and Classification of Pomegranate Leaves Diseases by Image Processing and Machine Learning Techniques. Computers, Materials and Continua. 66: 2939-2955. 10.32604/cmc.2021.012466.

Naseer, A., Amjad, M., Raza, A., Munir, K., Abdelsamee, N., Alohali, M. (2024). A novel transfer learning approach for detection of pomegranates growth stages. IEEE Access. 10.1109/ACCESS.2024.3365356.

Nirgude, V., Rathi, S. (2021). 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. 9(6): 863-870. https://doi.org/10.18006/2021.9(6).863.870.

Nirgude, V., Rathi, S. (2022). Exploratory data analysis and optimal feature selection on pomegranate dataset for enhancing the performance of pomegranate disease prediction. Annals of Forest Research. 65(1): 746-764.

Nirgude, V., Rathi, S. (2024). i-PomDiagnoser: A real-time pomegranate disease management system. Indian Journal of Science and Technology. 17(14): 1391-1401. https://doi.org/10.17485/IJST/v17i14.57.

Pakruddin, B., Hemavathy, R. (2024). A comprehensive standardized dataset of numerous pomegranate fruit diseases for deep learning. Data in Brief. 54: 110284, ISSN 2352-3409. https://doi.org/10.1016/j.dib.2024.110284.

Pakruddin, B., Hemavathy, R. (2024). A Systematic Review of Pomegranate Fruit Disease Detection and Classification Using Machine Learning and Deep Learning Techniques. In: ICT: Innovation and Computing. [Joshi, A., Mahmud, M., Ragel, R.G., Karthik, S. (eds)] ICTCS 2023. Lecture Notes in Networks and Systems, Springer, Singapore. 879. https://doi.org/10.1007/978-981-99-9486-1_13.

Patil, Et. (2021). Pomegranate fruit diseases detection using image processing techniques: A review. Information Technology in Industry. 9. 115-120. 10.17762/itii.v9i2.310.

Ravichandran, G.K., Somasekhara, Y., Shilpa, M., Mahesh, M., Shalini, M. (2023). Pomegranate Cercospora Leaf Spot as an Emerging Problem, Tackle through Biological, Botanical and Fungicidal Approach, both *in-vitro* and Field Conditions. Biological Forum-An International Journal. 15: 553-563.

Sharath, D.M., Akhilesh, Kumar, S.A., Rohan, M.G. and Prathap, C. (2019). Image-based plant disease detection in pomegranate plant for bacterial blight. International Conference on Communication and Signal Processing (ICCSP), Chennai, India. pp: 0645-0649. doi: 10.1109/ICCSP.2019.8698007.

Sharath, M.D., Akhilesh, K., Arun, S., Rohan, G.M. and Prathap, C. (2019). Image-based Plant Disease Detection in Pomegranate Plant for Bacterial Blight. International Conference on Communication and Signal Processing (ICCSP). Chennai, India. pp. 0645-0649. doi: 10.1109/ICCSP.2019.8698007.

Singh, P., Sharma, M. and Didwania, N. (2023). Effect of processing techniques on nutritional parameters of antioxidant rich Pomegranate Flowers. Agricultural Science Digest. doi: 10.18805/ag.D-5776.

Thorat, A., Kulkarni, A., Chavan, D., Joshi, M., Jarali, A. (2023). Classification of pomegranate fruit disease using CNN, ICT infrastructure and computing. ICT4SD 2023. Lecture Notes in Networks and Systems, Springer, Singapore. vol 754. https://doi.org/10.1007/978-981-99-4932-8_6.

Vasumathi, M.T, Mari, K. (2021). An effective pomegranate fruit classification based On CNN-LSTM Deep learning models. Indian Journal of Science and Technology. 14(16): 1310-1319.

Vasumathi, M. and Mari, K. (2021). An lstm-based cnn model for pomegranate fruit classification with weight optimization using dragonfly technique. Indian Journal of Computer Science and Engineering. 12: 371-384. 10.21817/indjcse/2021/v12i2/211202051.

Wakhare, P.B., Kandalkar, J.A., Kawtikwar, R.S., Kalme, S.A., Patil, R.V. (2023). Development of automated leaf disease detection in pomegranate using alexn*et al*gorithm. Curr Agri Res. 11(1). doi: http://dx.doi.org/10.12944/CARJ.11.1.15.