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Real-Time Pomegranate Leaf Disease Detection Using Deep Learning Models

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Abstract: *Pomegranate is a commercially valuable horticulture crop whose productivity is significantly affected by leaf diseases, particularly Bacterial Blight caused by Xanthomonas axonopodis pv. punicae. Early detection is crucial for preventing widespread infection and minimizing economic losses. Conventional diagnostic methods rely on visual examination by experts, which is subjective, labour-intensive and prone to delays. This paper presents a Convolutional Neural Network (CNN)–based deep learning approach for automated detection of pomegranate leaf diseases from image datasets. The proposed architecture processes raw leaf images, performs feature extraction and classifies them into healthy or diseased categories. Data augmentation, normalization and regularization techniques are applied to enhance model robustness and reduce overfitting. Experimental results demonstrate high classification accuracy and improved precision compared to traditional machine learning models. The trained model is further integrated into a web-based interface for real-time prediction, enabling farmers and agricultural practitioners to upload leaf images using low-cost devices. The system supports rapid decision-making and contributes to precision agriculture by providing a scalable, reliable and automated disease identification solution.*

Keywords: Convolutional Neural Network, Deep Learning, Pomegranate, Bacterial Blight, Image Classification, Precision Agriculture.

I. INTRODUCTION

India is one of the top 15 exporters of agricultural goods worldwide. According to the Ministry of Finance (2021), India's contribution of global exports of fruits and vegetables is just 1.4%. In recent years, the fruit trade has grown in importance. The variety of fruits available in the worldwide market has expanded due to lower costs, a year-round supply of production, and higher income. Although India is the world's largest pomegranate grower, exports from the country in 2021–2022 accounted for less than 5% of total production, while exports from Spain and Iran accounted for 65–75% and 15%, respectively [1].

Pomegranates are frequently referred to as "superfoods" due to their great nutritional value. They include important vitamins including C, E, and folic acid. Pomegranates are widely used around the world to treat a number of ailments, such as diabetes, heart disease, high blood pressure and sports performance. With a pomegranate output volume of over 31.87 lakh metric tons, India is ranked sixth in the world. Maharashtra leads the world in pomegranate production, accounting for more than half of the total. Gujarat and Karnataka are also important producers. Andhra Pradesh, Madhya Pradesh, Rajasthan, Telangana and Chhattisgarh are the other top pomegranate-producing states in India [2]. Improving quality at every stage—from production, postharvest, processing and handling, storage and until it reaches the customers—is essential to boosting exports. Studying pomegranate export success in Gujarat and India has become crucial in this era of global competition [3].

However, a number of illnesses, including Alternaria and bacterial blight, have an impact on pomegranate farming in India. Farmers may lose a lot of money as a result of these illnesses; bacterial blight alone can reduce output by 20% to 80%. Therefore, it is crucial to protect pomegranates from numerous diseases in their early stages.

II. LITERATURE REVIEW

4] P. Sajitha and et.al described "A deep learning approach to detect diseases in pomegranate fruits via hybrid optimal attention capsule network". This study presents a trustworthy deep learning model for automated pomegranate fruit illness diagnosis. Shape features have qualities like area, perimeter, and MER, while RGB is used to determine colour properties and the GLCM and GLRLM schemes are used to extract texture features from the images. These characteristics improve the classification system, which accurately classifies pomegranate fruit disorders using the Hybrid OACaps Net technology. The suggested model improves classification accuracy, precision, recall, specificity, and recall (98.41%, 98.45%, 99.45%, and 98.43, respectively).

5] Prashant b. Wakhare and et.al presented, "Development of Automated Leaf Disease Detection in Pomegranate Using Alexnet Algorithm". In order to identify pomegranate plant leaf disease, the author of this work created an image classification model. In order to create this system, the Alexnet algorithm was investigated for its ability to automatically identify and categorize plant illnesses from photos of leaves.The entire process involved gathering the photos needed for algorithm validation and training, then pre-processing and augmenting the images before training the model and fine-tuning it. A total accuracy of 97.60% is attained.

6] Sameera P & Abhay A Deshpande presented "Disease detection and classification in pomegranate fruit using hybrid convolutional neural network with honey badger optimization algorithm". This study presented a novel and automatic classification of pomegranate diseases using a hybrid CNN-HBOA approach. In this research, a CNN is combined with the HBOA technique, which optimizes the performance of the CNN by selecting optimal features. The necessary features were extracted through the ResNet-50 architecture, and features related to different types of diseases were extracted. The proposed approach employs a feature extraction method along with an image segmentation process to achieve an enhanced classification performance. The proposed hybrid CNN – HBOA model accuracy was found to be 99.58%, precision of 100%, recall of 98.75%, and F1 score was 99.71% in comparison to other existing models.

7] B. Pakruddin and et.al presented, "Development of a Pomegranate Fruit Disease Detection and Classification Model using Deep Learning". The PomeNetV2 Convolutional Neural Network (CNN) architecture is used in this paper to analyze four pomegranate fruit diseases: Alternaria, Anthracnose, Bacterial Blight, Cercospora, and Healthy. They made use of a suggested dataset that included 5099 photos of pomegranate fruit illness. Additionally, the outcomes of the suggested pomegranate fruit illness categorization approach were contrasted with those of previous studies. According to experimental results, the proposed framework identifies healthy and diseased pomegranate fruit with an accuracy of 99.02% for 75 epochs, outperforming all previous state-of-the-art models.

8]Pushya K D and et.al described, "A novel approach for detecting Pomegranate leaf pathologies using deep learning". In this work, deep learning algorithms are used to create an extremely precise and effective method for early pomegranate crop disease diagnosis. Convolutional neural networks (CNNs), transfer learning, and data augmentation methods including rotation, flipping, and scaling are used to automatically identify and categorize illnesses associated with pomegranate plant leaves. The effectiveness of the CNN models is shown by thorough testing and assessment utilizing performance indicators like accuracy, precision, recall, and F1 score. The main assumption is that, utilizing the Inception v3 CNN model, AI technologies may effectively identify all BLB disorders linked to pomegranates with a 96.33 % accuracy rate.

9] Bashdar Abdalrahman Mohammed and et.al presented, "Pomegranate disease detection and classification dataset for deep learning applications: A case study from Halabja city". The Halabja Pomegranate Fruit Disease Image Dataset, a methodically assembled collection of images from orchards in one of Iraq's principal pomegranate-producing regions, is introduced in this paper. Images were taken in natural outdoor settings to guarantee significant class variation and create an ecological setting. To increase the adaptability and resilience of machine learning models, a common pre-

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processing phase was used, which included scaling all images to 512 × 512 pixels and using various image augmentation techniques. This dataset's distinctive features make it ideal for creating machine learning and deep learning models for precision agricultural computer vision tasks like plant disease detection. It is useful for creating an efficient diagnostic tool that can operate in actual field situations due to its contextual relevance and content diversity.

Problem Statement

There are numerous plant diseases that can cause societal and financial harm because their symptoms are often undetectable in the early stages. Image processing, which includes stages like image segmentation, is used to make things easier and help overcome these kinds of difficulties by isolating the aspects of the leaves where diseases may be easily spotted. A new picture recognition system is suggested based on multiple linear regressions. There is no novelty in image segmentation. The recognition system is created via feature extraction.

The primary goal of this research is to develop a reliable, automated system that uses deep learning to detect leaf diseases in pomegranate plants. The goal of the suggested system is to accurately identify the kind of disease afflicting the leaf. The goal of the study is to evaluate and validate the suggested system's effectiveness in identifying and categorizing pomegranate leaf diseases. By accomplishing these goals, the study hopes to significantly contribute to the creation of efficient plant disease detection systems, which will lessen the detrimental effects of plant diseases on crop quality and output.

III. METHODOLOGY

The purpose of this study was to use images to identify and categorise leaf diseases in pomegranate fruits. A MobileNet framework was integrated into the stated study technique. A lightweight CNN architecture, MobileNet, based on deep learning, was employed for the efficient categorisation of damaged and healthy leaf images. Convolutional neural networks are optimized for effective picture classification in MobileNet. MobileNet's classification performance is improved by optimising the CNN architecture's parameters (model design). Fig.1 depicts the steps involved in putting the suggested technique into practice and the next subsections go over each of them.

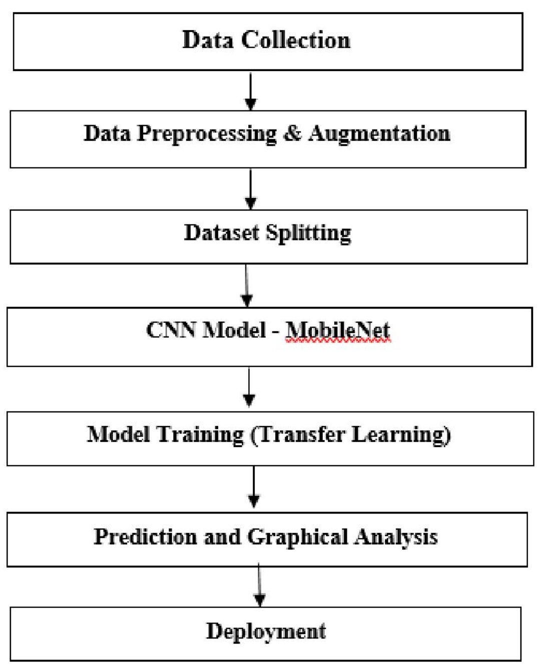

Fig. 1 Proposed Methodology

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Data Collection

A dataset of pomegranate leaf images was collected from field sources and supplemented with publicly available datasets like Kaggle. Total 558 images of pomegranate leaf were collected from the said sources. The images were classified into two groups healthy and bacterial blight. The collected images were labelled as healthy and bacterial blight. The images of both classes were stored in .jpg form and for model training the images were organized into two folders as healthy and bacterial blight.

Data pre-processing

For improving model performance and data uniformity the image data was pre-processed.In this pre-processing step the input images were resized to a fixed size of 256x256 pixel. The pixel values of the images were normalized to [0,1]. Data augmentation step was carried out to increase the diversity of images by the process like rotation, flipping, zoom, brightness adjustment etc.

Dataset Splitting

A dataset including 558 pomegranate leaf images was compiled from several sources, including real-time photography, the Kaggle Dataset, and web resources. 80% of the dataset was used for training, and the remaining 20% was used for testing. The following categories of photos are included in the dataset that was used to train the algorithm.

Healthy leaves - These leaves have no diseases and are green.

Leaves infected with bacterial blight: These pictures show leaves with bright green patches that eventually look wet because of a bacterial infection.

Another popular method for splitting a dataset into training, validation, and testing sets is the split ratio (80-10-10) employed in this study. The network is trained using the training set, and its hyperparameters are adjusted and overfitting is avoided using the validation set. The training algorithm's performance on fresh, untested data is assessed using the testing set. Next, use an 80-10-10 split ratio to divide the dataset into training, validation and testing sets.

Model Design CNN Architecture – MobileNet

The algorithm for training and using MobileNet involves the following steps

MobileNet is a convolutional neural network architecture designed for efficient image classification, especially for mobile and embedded devices. It reduces computational cost by replacing standard convolution with **depth wise separable convolution,** which consists of two operations: depth wise convolution and pointwise convolution.

The CNN model was designed with the following layers:

1. **Input Layer:** Receives pre-processed images of shape (height, width, channels).
2. **Convolutional Layers:** Extract spatial features using filters (Conv2D) followed by ReLU activation.
3. **Pooling Layers:** MaxPooling layers reduce dimensionality and computation.
4. **Flatten Layer:** Converts 2D feature maps into 1D vector.
5. **Dense Layers:** Fully connected layers for classification.
6. **Output Layer:Binary classification:** 1 neuron with sigmoid activation.

Hyperparameters:

1. Optimizer: Adam
2. Loss: Binary cross entropy (for healthy vs diseased)
3. Metrics: Accuracy, Precision, Recall

Model Training

The dataset is divided into 80% for training and 20% for validation. Training data is used to learn patterns, while validation checks how well the model generalizes to unseen data. Batch size is the Number of images processed before

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updating model weights and for this study batch size is 32. Epoch is the model sees the entire training dataset once. Multiple epochs allow the model to gradually improve performance. In this study epoch is 20. For this model Python programming language is used to write the code, TensorFlow/ used to train the model and Kerasused to build layers likeDense and GlobalAveragePooling2D.

Prediction and Graphical Analysis

1. The trained model predicts the class of a new leaf image:
2. The uploaded image is resized, normalized and flattened if necessary.
3. Prediction probabilities are computed.

The class with the highest probability is selected as the predicted label.

Deployment

The model was deployed using **Gradio interface**, providing:

- **Input:** Leaf image upload
- **Output:** Predicted class with confidence
- Real-time predictions accessible via web interface.

IV. RESULT AND DISCUSSION

Confusion Matrix: A **confusion matrix** is a table used to **evaluate the performance of a classification model**. It shows how many predictions were correct and where the model made mistakes.

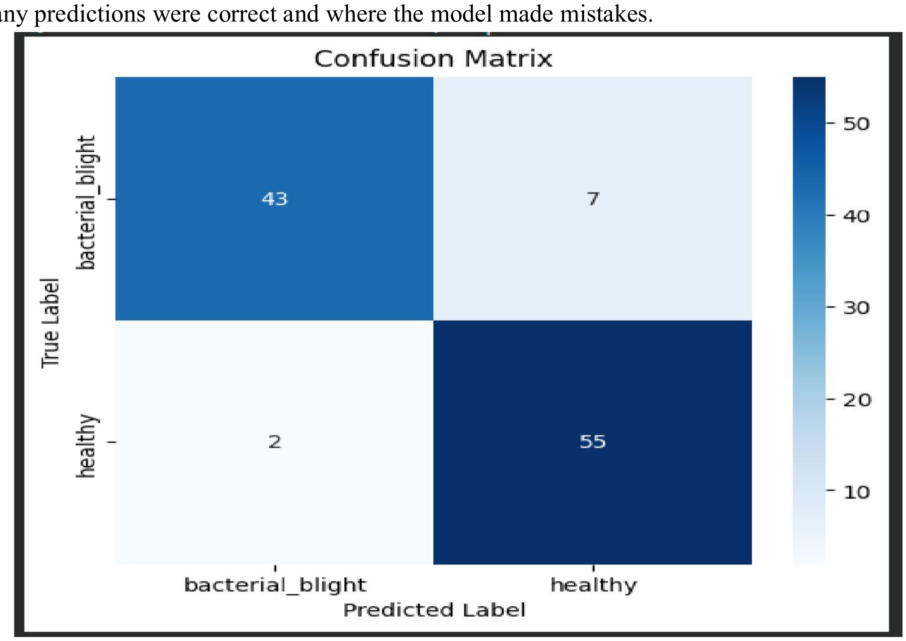

Fig. 2 Confusion Matrix of the model

The graph in Fig. 2 shows the details of the confusion matrix. It shows the TP (True Positive) is 43 that means the model predicted correctly positive. FN (False Negative) is 7 it means that the model missed some positive. FP (False Positive) is 2, it indicates the Model wrongly predicted positive and TN (True Negative) is 55 i.e. Model correctly predicted negative.

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Model Accuracy

Accuracy can be calculated as

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}}$$

Correct predictions = True Positives (TP) + True Negatives (TN)

Total predictions = TP + TN + FP + FN

By the above formula, the Model Accuracy for this model is 91.6%.

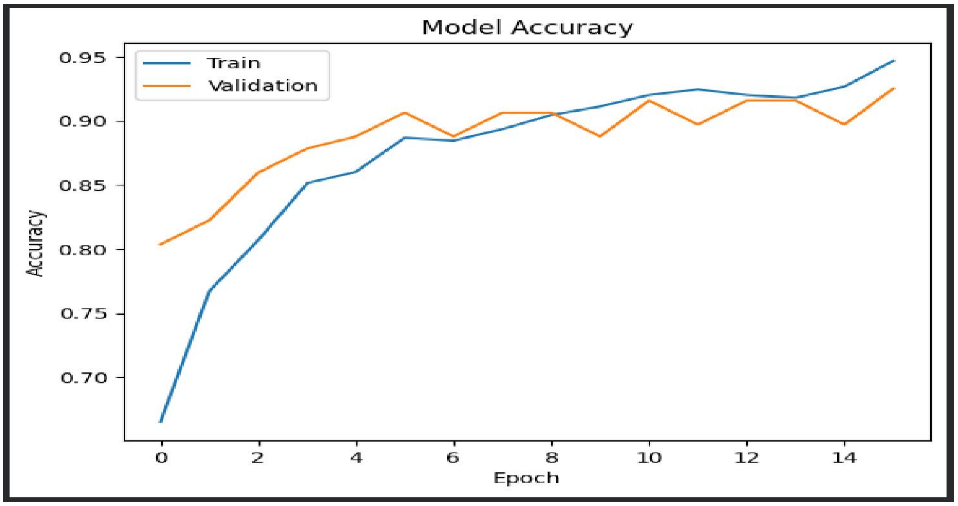

Fig. 3 Model Accuracy

The Fig.3 shows the model accuracy graph. **Model accuracy**shows **how well the model predicts correctly overall.** The graph shows train and validation graph. The graph shows the train and validation lines are nearly close to each other it means there is neither overfitting nor under fitting and it generalising well. From graph it shows both lines are high it means that the model shows the excellent performance.

V. CONCLUSION

In the present research Real-Time Pomegranate Leaf Disease Detection model was developed. The CNN architecture with MobileNet was employed for classification of pomegranate leaf. Early detection of diseases in any fruit is very useful regarding the financial as well as health issues. The developed model in this research successfully classified the healthy and bacterial blight leaf in real time. The confusion matrix graph shows the performance of the classification of the model. It shows that very few images were wrongly predicted or missed by the model. The accuracy graph is also high it is about 91.6%. The present research successfully detects Pomegranate Leaf Disease Detection in real-time.

REFERENCES

[1] https://www.seair.co.in/blog/pomegranate-export-from-india.aspx
[2] https://www.exportimportdata.in/blogs/pomegranate-export-from-india.aspx
[3] Rachana Bansal 1, A. S. Shaikh,Export Status of Pomegranate in India and Gujarat**,** Journal of Agriculture Research and Technology, vol. *49 (1) : 172-178 (2024)*
[4] P. Sajitha a, A. Diana Andrushia a, N. Anand b, M.Z. Naser c, Eva Lubloy, Ecological Informatics 84 (2024) 102859, https://doi.org/10.1016/j.ecoinf.2024.102859

[5] Prashant b. Wakhare, jayash a. kandalkar, rushikesh s.kawtikwar, sonali a. kalme, rutvija v. patil, Development of Automated Leaf Disease Detection in Pomegranate Using Alexnet Algorithm, Current Agriculture Research Journal, Vol. 11, No. (1) 2023, pg. 177-185, ISSN: 2347-4688, Doi: http://dx.doi.org/10.12944/CARJ.11.1.15

[6] Sameera P & Abhay A Deshpande (2024) Disease detection and classification in pomegranate fruit using hybrid convolutional neural network with honey badger optimization algorithm, International Journal of Food Properties, 27:1, 815-837, DOI: 10.1080/10942912.2024.2365927

[7] 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.

[8] Pushya K D, Girish C, Durga Prakash, Manikantan R, A novel approach for detecting Pomegranate leaf pathologies using deep learning, International Journal of Science and Research Archive, 2024, 13(01), 1206–1218, https://doi.org/10.30574/ijsra.2024.13.1.1735

[9] Bashdar Abdalrahman Mohammed a,Peshraw Ahmed Abdalla a, Sirwan M Aziz b, Hiwa Omer Hassan, Pomegranate disease detection and classification dataset for deep learning applications: A case study from Halabja city, Data in Brief 63 (2025) 112298, https://doi.org/10.1016/j.dib.2025.112298