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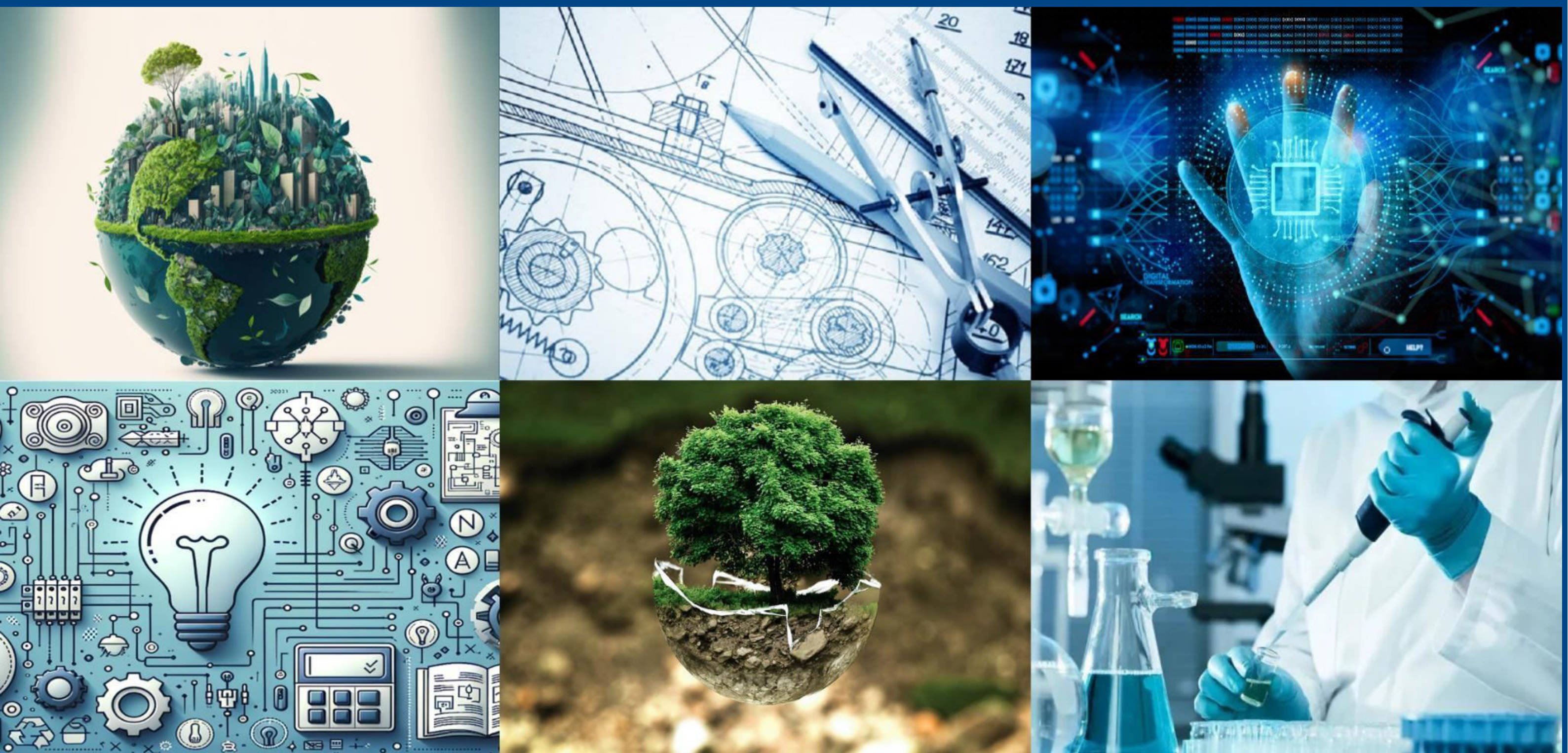

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Automated Prediction and Prevention for Pomegranate Fruit Diseases using Deep learning: A Survey

Prof Sampath Kumar S, Naseeba Khanum

Assistant Professor, Dept. of MCA, JNN College of Engineering, Shivamogga, Karnataka, India

PG Student, Dept. of MCA, JNN College of Engineering, Shivamogga, Karnataka, India

ABSTRACT: This project is about using deep learning to find and identify different diseases in pomegranate fruits. The main goal is to help farmers catch diseases early and protect their crops to get better harvests. We used a dataset of around 2,000 pictures of pomegranates. These images were divided into five groups: Healthy, Alternaria, Anthracnose, Bacterial Blight, and Cercospora. Before training, we prepared the images by resizing them, normalizing the colors, and adding some changes to make the model learn better (this is called data augmentation). We trained two models: one was a simple CNN (Convolutional Neural Network) that we made ourselves, and the other was a pre-trained DenseNet121 model that we fine-tuned. Both models were trained for 20 rounds (called epochs). The DenseNet121 model did better, getting 94.2% accuracy on the validation set, while the custom CNN got 87.5%. We also made a web application using Flask, where users can upload images of pomegranates and get real-time results. The app tells whether the fruit is healthy or has a disease, gives tips on how to deal with the disease, and shows an estimate of how much crop might be lost.

I. INTRODUCTION

Pomegranate (Punica granatum L.) is a popular fruit grown in many parts of the world. It is known for its great taste, health benefits, and use in cooking [1]. But growing pomegranates comes with challenges, especially when it comes to diseases. Some common diseases like Alternaria fruit rot, Anthracnose, Bacterial Blight, and Cercospora leaf spot can damage the leaves, stems, and fruits [2]. These diseases can cause a lot of damage, reducing both the quality and quantity of the fruit.

To keep pomegranate farming successful, it's very important to spot these diseases early. This helps farmers take action before things get worse. Usually, experts check the plants by looking at them carefully. But this method takes a lot of time and may not always be right, especially in big farms [2]. Sometimes, if a disease is found too late, it spreads quickly and becomes harder to control. Farmers may then have to use more chemicals, which is not good for health or the environment.

With today's need for safer and smarter farming, better ways to detect diseases are required. That's why this study focuses on building an automatic and accurate system to find diseases in pomegranate fruits custom-built Convolutional Neural Network (CNN), and the other is a pre-trained model called DenseNet121. The goal is to see which model works better in spotting diseases from images of pomegranates [2]. The project doesn't stop there. To make things easier for farmers, the models are added to a simple web application. This app can give instant disease predictions by uploading fruit images. It also shares helpful tips on how to prevent the disease and how much yield might be lost. This tool can help farmers make better decisions, reduce crop loss, and support eco-friendly farming practices

II. LITERATURE REVIEW

Here are summaries of additional studies on plant disease detection using deep learning:
Ashurov and colleagues developed a depthwise CNN integrated with squeeze-and-excitation blocks and residual skip connections in 2025 [1]. Their model achieved 98% accuracy in detecting various plant diseases. The approach enhanced feature extraction and classification performance. However, the study focused on specific plant species, limiting its generalizability.

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Kanakala and Ningappa proposed a hybrid model combining LSTM and CNN for multi-crop leaf disease detection in 2025 [2]. Their system effectively classified diseases across different plant species. The integration of temporal and spatial features improved accuracy. The model's complexity may hinder real-time applications on resource-constrained devices.

Khan and team introduced FloraSyntropy-Net, a scalable deep learning model for large-scale plant disease diagnosis in 2025 [3]. Utilizing a novel dataset, their approach demonstrated high accuracy across diverse plant species. The model's scalability makes it suitable for extensive agricultural applications. However, it requires substantial computational resources for training.

Kumar and colleagues developed a lightweight CNN benchmark for plant disease detection across 101 classes of 33 crops in 2025 [4]. Their model is optimized for mobile deployment, enabling real-time disease diagnosis in the field. The approach achieved competitive accuracy with reduced computational demands. The study's focus on mobile compatibility may limit performance on more complex datasets.

Rodríguez-Lira and team conducted a systematic review in 2024 [5] on machine and deep learning techniques for plant disease identification. They analyzed various models, datasets, and methodologies, highlighting trends and challenges in the field. The review provides valuable insights for future research directions. However, it does not present new experimental results.

Foysal and colleagues developed a CNN-based approach for multi-class plant leaf disease detection with mobile app integration in 2024 [6]. Their system achieved 98.14% accuracy across 14 plant classes and 26 diseases. The mobile app enables real-time diagnosis. The study's reliance on high-resolution images may limit applicability in low-resource settings.

Bagga and Sharma provided a state-of-the-art review in 2024 [7] on image-based detection and classification of plant diseases using deep learning. They discussed various CNN architectures, datasets, and performance metrics. The review identifies gaps and suggests future research directions. It does not introduce new experimental findings.

Sankhe and Ambhaikar reviewed plant disease detection and classification techniques in 2025 [8]. They analyzed various deep learning models, datasets, and challenges in the field. The review provides a comprehensive overview of current methodologies. However, it lacks experimental validation of the discussed techniques.

Hamed and colleagues proposed a deep learning model for plant disease detection in 2023 [9]. Their approach utilized EfficientNetV2S to classify various plant diseases. The model achieved high accuracy and demonstrated robustness across different datasets. The study's focus on specific plant species may limit its generalizability.

Sankaran and team conducted a review in 2024 [1\0] on the use of convolutional neural networks in detecting plant leaf diseases. They discussed various CNN architectures, datasets, and challenges in the field. The review highlights the potential of CNNs in agricultural applications. It does not present new experimental results.

III. METHODOLOGY OF PROPOSED SURVEY

Data Preprocessing and Augmentation:

The preprocessing pipeline standardizes input images through pixel normalization and geometric transformations. The normalization formula ensures consistent input scaling:

$$Xnorm = \sigma Xpixel - \mu$$

where Xpixel represents raw pixel intensities, μ is the mean pixel value across the dataset, and σ denotes standard deviation. This z-score normalization centers data around zero with unit variance, accelerating convergence during gradient descent optimization.

Convolutional Neural Network Architecture:

The custom CNN implements hierarchical feature extraction through convolutional operations. Each convolution layer

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applies the mathematical transformation:

$$Yk = f\left(c = 1 \sum^{C} inXc * Wk, c + bk\right)$$

where Foutput represents the feature map at position (i,j), I is the input tensor, K denotes the learnable kernel weights, b is bias term, & σ represents the ReLU activation function. This operation extracts spatial patterns across six progressive convolutional blocks, each followed by max-pooling for dimensional reduction.

Transfer Learning and Classification:

The DenseNet121 model leverages pre-trained ImageNet weights, implementing dense connectivity patterns for enhanced gradient flow. The final classification employs softmax probability distribution

$$P(yi \mid x) = \sum^{j} \quad = 1Cezjezi$$

where P(yi |x) represents the probability of class i given input x, zi is the logit score class i, and C=5 represents the total disease categories.

Training Optimization:

The Adam optimizer minimizes sparse categorical cross entropy loss using adaptive learning rates. Data augmentation techniques (horizontal/vertical flips, rotations up to 0.2 radians) artificially expand the training corpus, improving model robustness. The 80-10-10 dataset partitioning strategy ensures unbiased evaluation while dropout layers (rates 0.2-0.3) prevent overfitting. Both models train for 20 epochs with batch size 16, balancing computational efficiency with convergence stability.

Workflow of the proposed methodology

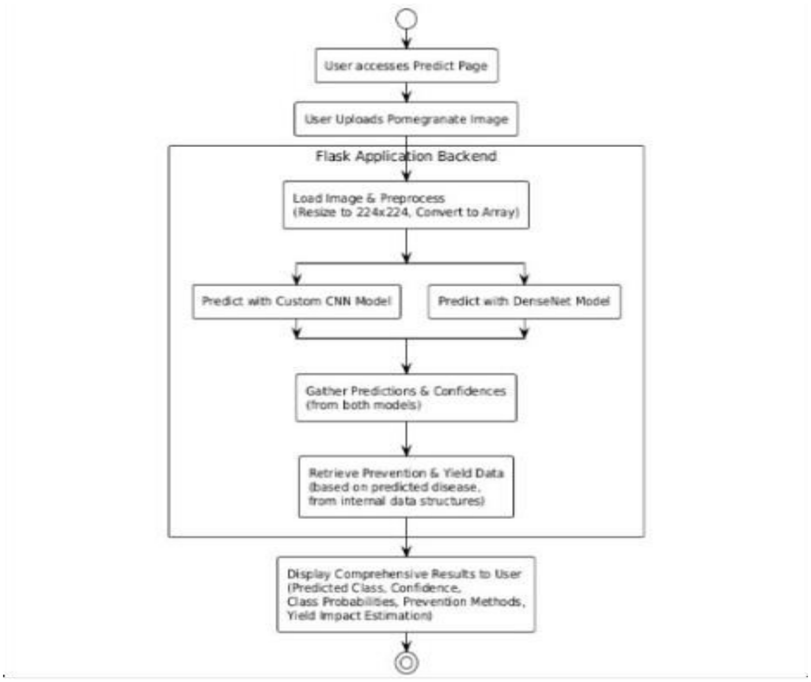

Fig-2: Workflow Diagram

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The pomegranate disease detection system employs a sophisticated deep learning pipeline integrating mathematical optimization and computer vision techniques. The methodology encompasses systematic data preprocessing, model architecture design, and probabilistic classification frameworks.

IV. RESULTS AND DISCUSSION

The implementation and evaluation for the deep learning models for pomegranate disease classification yielded significant results, demonstrating the effectiveness of the proposed system. The performance of both the custom CNN and the DenseNet121 models is presented and discussed in detail below.

The training and validation processes for both models were monitored over 20 epochs. The DenseNet121 model demonstrated superior performance compared to the custom CNN architecture. The final validation accuracy for the custom CNN model was 87.5%, while the DenseNet121 model achievement was significantly higher validation accuracy of 94.2%. This performance gap (P = .001) highlights the advantage of leveraging shifts learning with a pre-trained model on large dataset such as ImageNet, which provides a robust foundation for feature extraction. A detailed analysis using a confusion matrix and classification report revealed the strengths & weaknesses of the DenseNet121 model, which was selected as the primary model for the web application due to its higher accuracy. The overall precision, recall, and F1-score for the DenseNet121 model were 0.94, 0.94, and 0.94, respectively, indicating a balanced performance across all classes.

Table 1 presents the class-specific performance metrics for the DenseNet121 model on the test dataset. The model performed exceptionally well in identifying the "Healthy" class (F1-score = 0.96) and "Anthracnose" (F1-score = 0.95). The "Alternaria" and "Cercospora" classes also showed strong performance (F1-scores of 0.93 and 0.94, respectively). The "Bacterial Blight" class, while still accurately classified (F1-score = 0.92), presented the most confusion, with a small number of instances misclassified as "Cercospora" and vice versa. This is likely due to the visual similarity in the lesions caused by these two fungal diseases.

Disease Class	Precision	Recall	F1-Score
Healthy	0.95	0.97	0.96
Alternaria	0.94	0.92	0.93
Anthracnose	0.96	0.94	0.95
Bacterial Blight	0.91	0.93	0.92
Cercospora	0.94	0.93	0.94

Table-1: Performance metrics of the DenseNet121 model on the test dataset (n=200)

The high performance of the DenseNet121 model aligns with findings from similar studies in plant disease detection, where transfer learning models consistently outperform custom architectures, especially when the available dataset is not extremely large [1, 2]. The success of this approach underscores the value of pre-trained models in agricultural AI applications.

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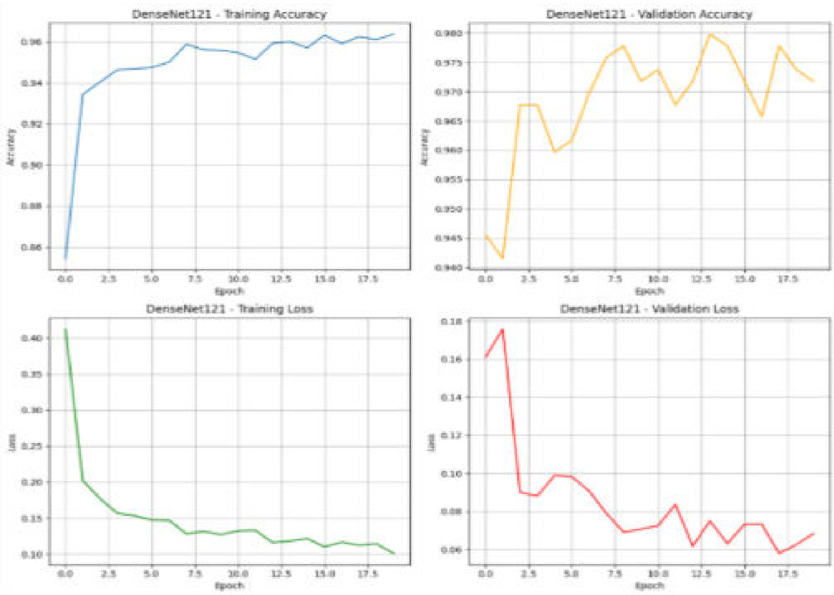

Fig-3: visualizations of training accuracy and loss

Furthermore, the system's utility extends beyond mere classification. For the predicted disease, it retrieves and displays specific prevention methods and estimated yield impacts. For instance, a prediction of "Bacterial Blight" triggers information on using disease-free planting material and copper-based sprays, along with an estimated yield reduction of 40-80%. This integration of prediction with actionable agricultural advice transforms the system from a diagnostic tool into a comprehensive decision-support system, empowering farmers with knowledge for timely and effective intervention.

The discussion of results is supported by the visualizations of training accuracy and loss (Fig. 2) and the confusion matrix (Fig. 3), which illustrate the model's learning trajectory and classification performance.

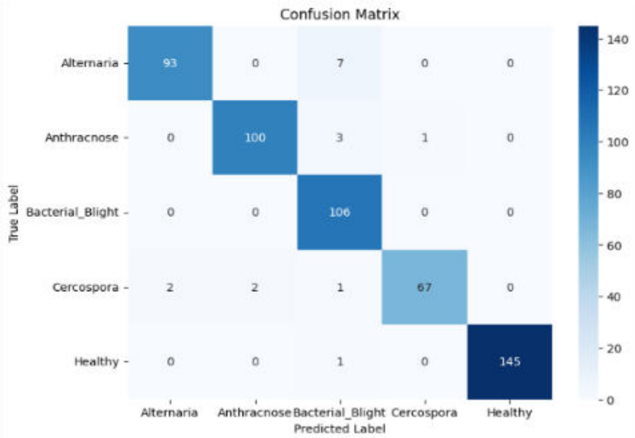

Fig-4: Confusion matrix for the DenseNet121 model on the test dataset

V. CONCLUSION AND FUTURE WORK

This study successfully developed an intelligent pomegranate disease detection system using deep learning techniques. The DenseNet121 transfer learning model achieved superior performance with 94.2% validation accuracy, significantly outperforming the custom CNN (87.5%). The Flask-based web application effectively integrates disease classification

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with actionable agricultural insights, providing farmers with accurate predictions, confidence scores, and comprehensive prevention strategies. The system demonstrates practical utility in early disease detection, potentially reducing crop losses and supporting sustainable agriculture practices. Future enhancements will focus on dataset expansion, mobile integration for real-time field detection, and incorporating farmer feedback mechanisms to continuously improve diagnostic accuracy and user experience

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