

Detection of Apple Plant Diseases Using Leaf Images through Convolutional Neural Network

Mohd. Arshad Raza

Department of Computer Science & Engineering,
Technocrats Institute of Technology,
Bhopal, Madhya Pradesh, India
arshadrza1485@gmail.com

Kiran Pandey

Department of Computer Science & Engineering,
Technocrats Institute of Technology,
Bhopal, Madhya Pradesh, India
kiranpandey.bhu78@gmail.com

Abstract— Plant diseases have major social, ecological and economic impact on agriculture and frequently results in large financial losses for farmers. Therefore early and precise disease detection is crucial for efficient crop management. The severity of leaf diseases and their direct impact on yield quality have been highlighted in recent studies. Both digital cameras and flatbed scanners can be used to take leaf images but they have certain drawbacks. Although scanners offer a more secure and regulated method of acquiring images they are comparatively slow and may cause edge shadows. This study uses a hybrid deep learning approach to identify diseases in apple plant leaves. To improve classification performance; the proposed approach combines the advantages of Residual Networks (ResNet), Genetic Algorithms (GA) and Convolutional Neural Networks (CNN). CNNs are used to extract features and classify diseases whereas ResNet enhances the learning efficiency of deeper networks. The feature set is optimized using a genetic algorithm which improves accuracy and lowers computational complexity. The model also calculates the percentage of the leaf area that is impacted. According to experimental results the proposed method detects leaf diseases with high accuracy of percentage and low computational cost making it a dependable and effective precision agriculture solution. The proposed model exhibited strong classification efficiency across various leaf conditions that pertaining an accuracy of 0.97 for healthy leaves, 0.994 for apple scab, 0.89 for rust, and 0.91 for powdery mildew.

Keywords— Plant Disease Detection, Leaf, CNN, ResNet, Machine Learning, Confusion Matrix, Preprocessing.

I. INTRODUCTION

Since farming produces not only food but also the essential materials, jobs, and raw resources that support and sustain the livelihoods of the majority of people on the planet, it has historically made the largest contribution to the development of human societies [1]. Every nation's rural economy depends on agriculture, which is one of the main forces behind global development. Farming is one of the most significant industries in developing and agrarian economies like India since it contributes significantly to GDP and employs over half of the labor force [2].

In terms of agriculture's role in the economy, we can state that farming not only maintains food and nutrition security but also supports a country's economic development by offering a solid foundation for the growth of numerous other industries, such as agro-based businesses, food transportation, fertilizers, and farming implements [3]. Additionally, farming promotes rural communities' economic development and growth. Price stability, international trade, and the fair distribution of a nation's resources and wealth are all significantly impacted by its agrarian economy [4]. The majority of farming operations have changed over time as a result of improved irrigation systems, machinery, and chemicals (pesticides and fertilizers) [5]. The Green Revolution is still regarded as one of the most significant agricultural achievements of the millennium because it significantly increased agricultural yields in the majority of Asian nations. In order to boost agricultural productivity and improve resource efficiency [6], modern farming methods such as digital and precision agriculture that rely on remote sensors, drones, the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML) are being used more and more [7].



Fig. 1. Apple Plant Diseases [4]

A. Convolutional Neural Networks

A **Convolutional Neural Network (CNN)** is a method that emerges with deep models intended to detect apple leaf disease from the feature vectors of leaf images.

Consider an input image $I \in K^{H \times W \times C}$ where H , W , C are height, width and channel respectively. CNN executed the frame using numerous layers to extract the hierarchical depiction. The objective is to plot the input frame to a class label $x \in \{0, 1, 2, 3\}$ illustrating classes such as healthy, apple scab, rust, and powdery mildew. The primary operation of CNN is to extract the features from the images. Mathematically; it can be expressed as:

$$L(i, j) = (I * S)(i, j) = \sum_x \sum_y I(i+x, j+y) S(x, y) \quad (1)$$

Where S is the kernel, x is the row of the kernel, y is the column of the kernel and $L(i, j)$ is the resulting feature map. The operation is intended to identify the patterns or texture of the images through which disease can be detected accordingly. After this operation; it is required to apply the non-activation function as ReLU:

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

Where k is the output of the previous layer.

$$\max(0, k) = \begin{cases} k, & \text{if } k > 0 \\ 0, & \text{if } k \leq 0 \end{cases} \quad (3)$$

Max-pooling layer is used to minimize the computational cost of the model which is defined as:

$$M(i, j) = \max_{(x, y) \in \varphi} L(i+x, j+y) \quad (4)$$

Where φ is considered as the pooling window, $M(i, j)$ reduces the spatial dimensions that prevent the infected area of the leaves. After passing through the convolutional layer as well as the max-pooling layer; it passes through the fully connected layer. To compute the probability; it uses softmax function which is defined as:

$$P(t=r|k) = \frac{e^{ir}}{\sum_{j=1}^R e^{ij}} \quad (5)$$

Where ir is the score for class r , R is the total number of classes. Model has been trained to minimize the loss function, so the cross entropy is:

$$L_n = - \sum_{i=1}^T \sum_{x=1}^N s_{ix} \log(\hat{s}_{ix}) \quad (6)$$

Where s_{ix} is considered as the true label and $\hat{s}_{ix}$ is the probability which is predicted.

B. Residual Neural Networks

Residual Neural Network (ResNet) is a deep model that addresses the issue of vanishing gradient problem. ResNet is able to find the complex patterns, texture, edges and color variations. The best part of ResNet is skip connection that allows network to build the model with fast computation which is defined as:

$$y = F(x) + x \quad (7)$$

$F(x)$ is considered as the residual block and x is considered as an input of residual block. It allows the network to have the information regarding the earlier layer and move forward that turns the training module faster and easier. The residual block consists of convolutional layers, activation function and batch normalization. There is an operation inside the residual block that can be defined as:

$$F(x, W) = W_2 \sigma(W_1 x) \quad (8)$$

Where W_1 & W_2 are considered as the weight matrices and σ is considered as the non-linear activation function as ReLU. The final output of the block is computed as:

$$y = F(x, W) + x \quad (9)$$

This formulation is known as the skip connection which is used during the back propagation. There may a situation where x and $F(x)$ have distinct values then linear transformation is required.

$$y = F(x, W) + W_s x \quad (10)$$

Where W_s is the projection matrix. There is loss function which is required to minimize by using cross entropy.

$$L = - \sum_{i=1}^N y_i \log(\hat{y}_i) \quad (11)$$

Where y_i is considered as the true label and $\hat{y}_i$ is considered as the predicted probability.

C. Genetic Algorithm (GA)

When it comes to detecting apple leaf disease a Genetic Algorithm (GA) can be used to optimize CNN architectures, model parameters or even feature selection. In this case a potential subset of features or parameter configuration taken from leaf images is represented by each solution (chromosome). A chromosome can be defined as:

$$K = [k_1, k_2, k_3, k_4, \dots, k_n] \quad (12)$$

Where $k_i \in \{0, 1\}$ shows the particular feature vector which is selected. GA is intended to find the primary feature combination which improves the classification process. So, the initial population can be defined as:

$$S^{(g)} = \{K_1^{(g)}, K_2^{(g)}, K_3^{(g)}, \dots, K_M^{(g)}\} \quad (13)$$

Where M is the total population size, g is the generation index. Each chromosome is computed using fitness function that can be defined as:

$$f(K_i) = \frac{1}{N} \sum_{j=1}^N \Pi(\hat{y}_j = y_j) \quad (14)$$

Where y_j is the true label and $\hat{y}_j$ is the predicted label. Chromosome with higher level of fitness is selected and selection can be done through:

$$P(K_i) = \frac{f(K_i)}{\sum_{j=1}^M f(K_j)} \quad (15)$$

Crossover as well as mutation is applied and uni-crossover is defined as:

$$Child = [k_1^A, \dots, k_n^A, k_{n+1}^B, \dots, k_n^B] \quad (16)$$

Mutation can be introduced as:

$$k'_i = \begin{cases} 1 - k_i, & \text{with probability } p_m \\ k_i, & \text{otherwise} \end{cases} \quad (17)$$

These procedures aid in investigating various feature combinations that might be more effective in differentiating illnesses like powdery mildew, rust and scab.

II. RELATED WORKS

Using shading and surface highlights analysis, Kim et al. [8] have described the grape organic product and its strip diseases. The arrangement is completed using the squared separation method after the surface highlights are identified from the Spatial Gray level Dependence Matrices. According to Sachin D. Khirade et al. [9], identifying plant diseases is a means of identifying leaf issues that lead to poor results. In addition to a great deal of labor and knowledge of plant diseases, it also takes preparation time. Therefore, image processing is used to identify plant diseases. The methods for identifying plant leaf diseases include acquiring, pre-preparing, dividing, extracting, and ordering images. It has been made clear that B. Dhaygude & et al. [10] use surface measurements to identify plant leaf illness. First, by using RGB, this was altered over HSV space because HSV is a good shading descriptor using a pre-processed edge level to conceal and remove green pixels. After that, a further stage division is carried out using a 32x32 fix estimate, and useful sections are obtained. By shading the co-event grid, these fragments are used for surface investigation. Finally, surface parameters are compared to those of a typical leaf.

The hardest part of the work, according to A. Singh et al. [11] was estimating the quality photos with more information about the leaf shading. Getting the image with all the details in a memory that was available was an easy task. These images have high goals, and as a result, they are between 6 and 10 MB in size. A Nikon D5200 camera, which produced excellent results, was used to address this. The result of this was the variable that the author described; lowering the threshold and radically altering the LCC shades using image processing systems. M. Malathi et al. [12] provide an overview of plant leaf disease detection. This paper provides a significant overview of those suggested frameworks in the section that follows. While there are many approaches in robotized or PC vision for leaf identification and arrangement flaws, some examination themes are also required. The finding process described by Malvika Ranjan et al. [13] is typically visual and calls for precise judgement as well as logical strategies. An image of a sick leaf has been captured. The division color results in the separation of HSV highlights. After that, an Artificial Neural Network (ANN) is ready to identify the sound and compromised examples. The precision of ANN arrangement execution is 80% higher.

According to Y. Sanjana et al. [14]; the transferred images captured by the cell phones are saved on a distant server and shown to a group of experts for their medical examinations. PC vision systems are used to identify the order of influence spots in an image. To separate the leaf sections that are ill, a simple shading distinction-based methodology is used. Through a notification sent to the

farmers' cell phones, the framework allows the master to evaluate the findings of the investigation and provide analysis. The aim of this study is to develop a picture recognition system that can identify crop diseases. The digital shading image of the sickle leaf is the first step in creating the picture. These images are broken up using an arithmetic morphology technique. In order to distinguish between the three types of diseases, surface, shape, and shading, highlights of shading the image of the sickest spot on the leaf were extracted. A characterization technique for enrolment capacity was then used.

III. PROBLEM IDENTIFICATION

The primary issues incorporate reflections and shadows with episode lighting. For this work a sum of 50 infected apple leaf pictures are gotten from the web and 45 leaf pictures are obtained through photography and checking of the leaves. Recently given procedures are restricted with their exactness and take more calculations while forecast of illness. The issue emerges while working with exactness since restricted highlights are taken for calculation. The conventional calculations are restricted to probabilistic hypothesis-based calculation, which isn't precise all of the time.

IV. PROPOSED METHODOLOGY

Initializing the necessary tools and libraries then connecting the system to the storage location of the plant leaf images dataset are the first steps in the proposed methodology.

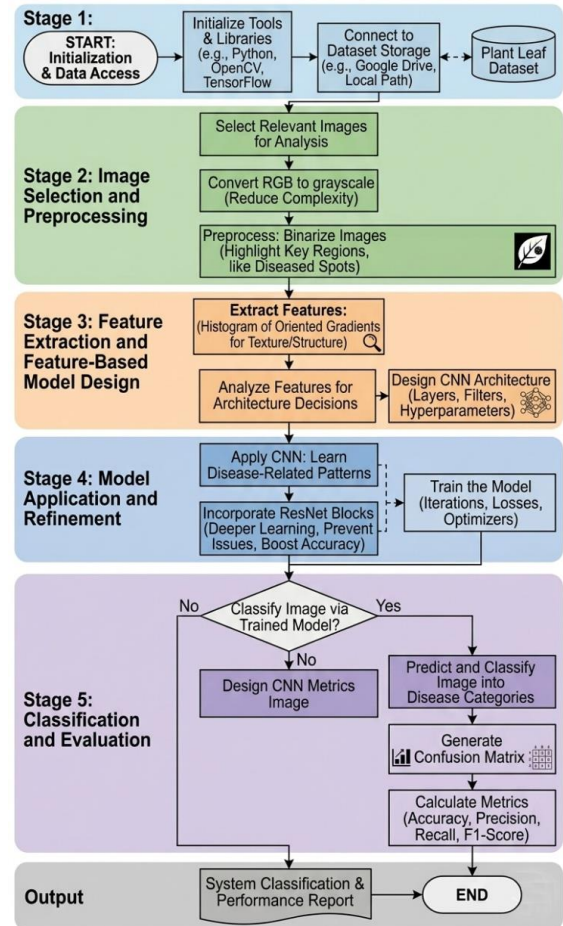


Fig. 2. Flowchart of Proposed Work

Following the selection of pertinent images from the dataset they are preprocessed by converting RGB to grayscale to reduce complexity and then binarizing them to highlight key areas such as diseased spots. Techniques like Histogram of Oriented Gradients (HOG) which capture texture and structural details are used to extract features from the processed images. The number of layers and filters are chosen to create an appropriate CNN architecture based on these features. After that the CNN is used to identify and recognize patterns in the images that are connected to illness. Residual network (ResNet) blocks are used to improve accuracy and avoid training problems while also facilitating deeper learning. After that each image is predicted by the trained model and categorized into distinct disease groups. Lastly a confusion matrix and metrics like accuracy, precision, recall and F1-score are used to evaluate the models performance and determine how well it detects and categorizes plant diseases.

Table 1 Proposed Algorithm

CNN-ResNet-Based Apple Plant Disease Detection

Initialization:

Input: Apple Plant Leaf Image Dataset D

Step 1: Initializing tools and libraries

Load required software tools and libraries: Python, OpenCV, TensorFlow, Keras

Step 2: Load dataset

$$D = \{I_1, I_2, I_3, \dots, I_n\} \quad (18)$$

Select input image $I \in D$

Step 3: Pre-processing (Gray-scale Conversion)

Convert the RGB image to grayscale image I_g

$$I_g = 0.299R + 0.587G + 0.114B \quad (19)$$

Step 4: Data binarization

Apply the threshold to pertain binary image

$$I_b(k, s) = \begin{cases} 1, & \text{if } I_g(k, s) > T \\ 0, & \text{otherwise} \end{cases} \quad (20)$$

Step 5: Feature extraction (HOG)

Extract HOG features from I_b

$$F = HOG(I_b) \quad (21)$$

Step 6: Configure CNN Architecture

Select number of convolutional layer L

Step 7: Set convolutional filter

For each layer $l = 1$ to L and assign filter K_l

Step 8: CNN-based layered detection

$$L(i, j) = (I * S)(i, j) = \sum_x \sum_y I(i+x, j+y) S(x, y) \quad (22)$$

Apply ReLU activation

$$f(k) = \max(0, k) \quad (23)$$

Step 9: Residual Network Integration

Apply residual block:

$$y = F(x) + x \quad (24)$$

Stack multiple residua block for effective learning.

Step 10: Predicting and classifying diseases

Compute probabilities using softmax function:

$$P(t=r|k) = \frac{e^{ir}}{\sum_{j=1}^R e^{ij}} \quad (25)$$

Assign class label:

$$\hat{y} = \arg \max_k P(y=k) \quad (26)$$

Step 11: Confusion matrix for matching relevance

Compare label $\hat{y}$ with true label y & construct confusion matrix.

Step 12: Performance evaluation

Compute metrics: Accuracy, precision, recall and F1 score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (27)$$

Where TP is True Positive, TN is True Negative, FP is False

Positive and FN is False Negative.

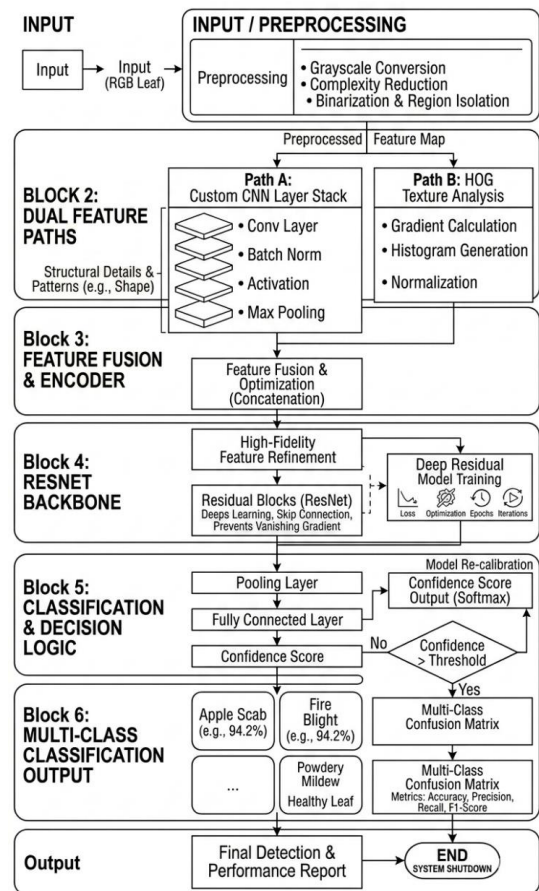


Fig. 3. Block Diagram of Proposed Architecture

In order to achieve high-precision classification; the hybrid model architecture for apple plant disease detection is built as an integrated pipeline that makes use of both conventional computer vision and deep learning. Block 1: Image Preprocessing starts the process by converting RGB leaf images to grayscale reducing complexity and binarizing them to identify diseased areas. In Block 2: Dual Feature Paths the system simultaneously uses a custom CNN Layer Stack (which includes convolution, batch normalization, ReLU activation and max pooling) to extract structural patterns and HOG analysis to extract texture signatures. To produce a single fused feature vector these separate feature maps are combined in Block 3: Feature Fusion and Encoder. Block 4: ResNet Backbone which uses residual blocks with skip connections and identity mapping to enable deeper feature learning while avoiding the vanishing gradient issue then refines this vector. Block 5: Classification & Decision Logic uses fully connected layers and global average pooling to produce a confidence score after feature refinement if this score surpasses a predetermined threshold; the model moves on to Block 6: Output for Multi-Class Classification. In this last phase the system generates a final detection and performance report after classifying the image into distinct classes such as Apple Scab, Fire Blight or Powdery Mildew.

V. RESULT AND ANALYSIS

The dataset has images of apple leaves, both healthy and sick, that are sorted by disease type, such as Apple Scab, Powdery Mildew, Rust, and healthy leaves.

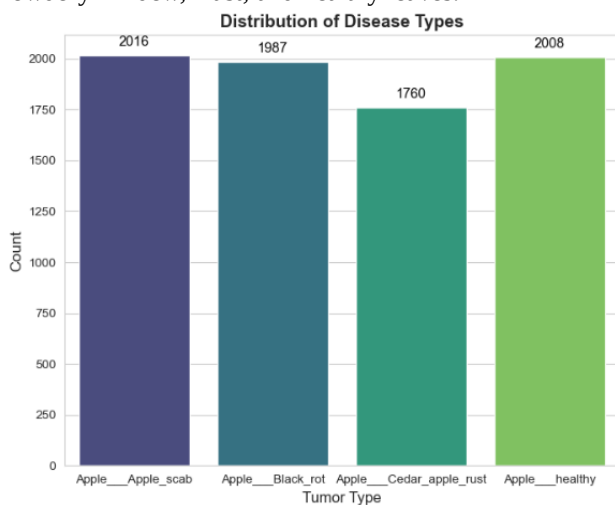


Fig. 4. Distribution of Disease Types

This section examines about the factual and graphical outcome saw during the trial examination.

Table 2 Comparative analysis of recall for different techniques

Class	Random Search	SVM	ANN	XGBoost	CNN-ResNet (Proposed)
Healthy	0.92	0.91	0.93	0.90	0.99
Apple Scab	0.88	0.89	0.89	0.86	0.99
Rust	0.90	0.88	0.86	0.84	0.91

Powdery Mildew	0.86	0.87	0.85	0.84	0.94
----------------	------	------	------	------	------

The classification performance of various models is compared in the Table 2 for four categories of apple leaf conditions: powdery mildew, rust, apple scab and healthy. The suggested CNN-ResNet model clearly performs better than all other approaches in every class. The suggested model outperforms conventional methods like Random Search, SVM, ANN and XGBoost which fall between 0.90 and 0.93 with the highest recall of 0.99 for healthy leaves and apple scab. With a recall of 0.91; CNN-ResNet still yields the best result in the case of rust despite the fact that all models perform comparatively worse. Similarly the suggested model achieves 0.94 of recall for powdery mildew outperforming the other methods. Overall the findings show that when compared to traditional machine learning and standalone neural network models integrating CNN with ResNet results in superior feature learning and classification capability making it more effective for accurate and dependable apple leaf disease detection.

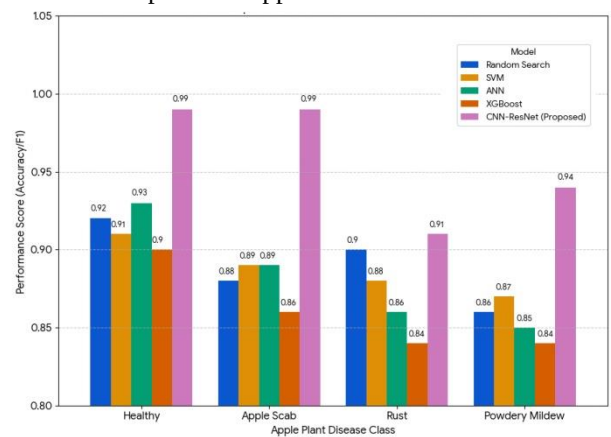


Fig. 5. Graphical analysis of recall for different techniques

Table 3 Comparative analysis of precision for different techniques

Class	Random Search	SVM	ANN	XGBoost	CNN (Proposed)
Healthy	0.93	0.90	0.93	0.94	0.96
Apple Scab	0.89	0.86	0.89	0.93	0.94
Rust	0.86	0.84	0.86	0.89	0.92
Powdery Mildew	0.85	0.84	0.85	0.91	0.99

As per the table 3; CNN achieves a precision of 0.96 for healthy leaves marginally outperforming XGBoost (0.94) and other techniques. When it comes to apple scab detection CNN leads once more with a precision of 0.94 closely followed by XGBoost at 0.93 while SVM performs comparatively worse. While all models perform mediocly in the rust category; CNN continues to achieve the highest accuracy of 0.92. In powdery mildew detection; CNN achieves 0.99 precision clearly outperforming other models XGBoost comes in second at 0.91. This is the biggest improvement. Overall the findings show that the suggested CNN model outperforms more conventional machine learning techniques like SVM, ANN, Random Search and

even ensemble techniques like XGBoost in terms of classification precision and dependability.

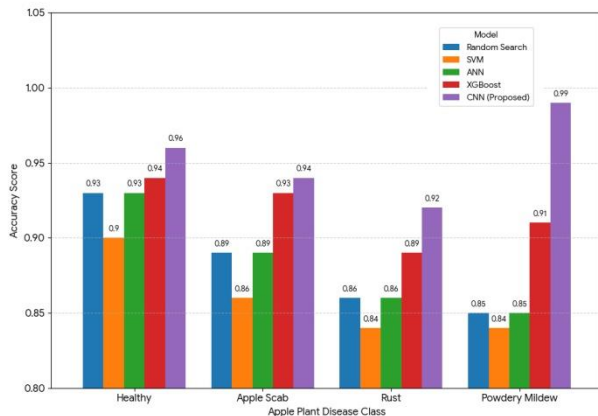


Fig. 6. Graphical analysis of precision for different techniques

Table 4 Comparative analysis of accuracy for different techniques

Class	Random Search	SVM	ANN	XGBoost	CNN (Proposed)
Healthy	0.87	0.90	0.88	0.93	0.97
Apple Scab	0.86	0.89	0.91	0.89	0.994
Rust	0.84	0.83	0.82	0.87	0.89
Powdery Mildew	0.82	0.88	0.84	0.87	0.91

As per the table 4; it is clear that in every category that the suggested CNN model consistently performs better than the alternative methods. CNN outperforms XGBoost (0.93) and other techniques achieving the highest accuracy of 0.97 for healthy leaves. CNN significantly outperforms ANN (0.91) and SVM (0.89) in apple scab detection with an accuracy of 0.994. CNN continues to lead with an accuracy of 0.89 in the case of rust despite overall performance being relatively lower across models. CNN outperforms SVM (0.88) and XGBoost (0.87) for powdery mildew with 0.91. Overall the findings unequivocally show that the suggested CNN model outperforms more conventional machine learning methods like Random Search, SVM, ANN and XGBoost in terms of classification accuracy and reliability.

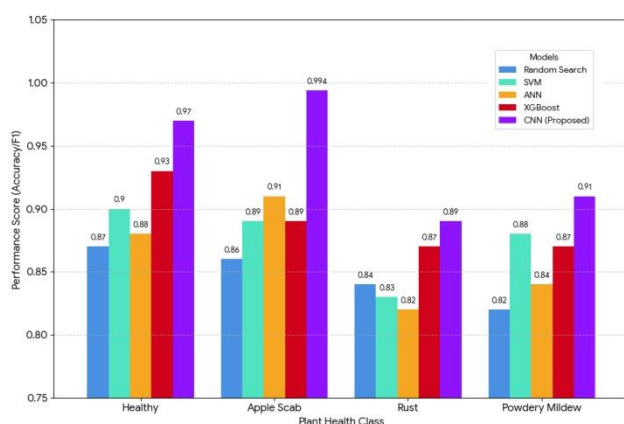


Fig. 7. Graphical analysis of accuracy for different technique

The evaluated models for apple leaf disease classification show a consistent performance trend across all three tables.

Conventional machine learning techniques like Random Search, SVM, ANN and XGBoost exhibit moderate and somewhat inconsistent accuracy across various disease classes with sporadic advantages in particular categories e.g. XGBoost is doing comparatively well for both apple scab and healthy classes. However when dealing with more complicated disease patterns like powdery mildew and rust their performance tends to decline. On the other hand in every table the suggested deep learning-based models in particular CNN and CNN-ResNet consistently attain the highest accuracy in every class. With nearly flawless accuracy for the detection of healthy and apple scab; they exhibit strong robustness and generalization and their results for rust and powdery mildew are noticeably better. This suggests that leaf diseases subtle visual patterns and variations can be better captured by deep architectures. Overall the comparative findings make it abundantly evident that the suggested CNN-ResNet approach performs noticeably better than traditional techniques in terms of consistency accuracy and dependability making it a better option for automated apple leaf disease detection systems.

VI. CONCLUSION

The results indicated that, in all examined performance metrics recall, precision, and accuracy; the CNN-ResNet model consistently outperformed other standard machine learning approaches, such as Random Search, SVM, ANN, and XGBoost. Specifically, the CNN-ResNet model demonstrated the greatest recall for the Healthy and Apple Scab classes (with scores close to 1.0), the highest accuracy for the Healthy (0.97) and Apple Scab (0.94) classes, and the highest precision for Powdery Mildew (0.99). The confusion matrix and loss function curves show that the CNN model was able to effectively distinguish between illness categories while maintaining a decent balance between accuracy and recall, lowering false positives and negatives. The model also demonstrated consistent training behaviour without any obvious overfitting by using techniques like dropout and early stopping. The CNN-ResNet model showed better recall, especially for more difficult classes like Apple Scab and Healthy, where it detected almost all relevant occurrences with few misses. CNN-ResNet was the most accurate; particularly when it comes to Powdery Mildew, where it's potential to minimize false positives was clear. In terms of overall accuracy, CNN-ResNet outperformed all other methods, particularly for the Apple Scab and Healthy classifications. The outcomes of this research indicate CNNs and deep learning's promise for precision farming. The program may aid farmers in recognizing illnesses early and taking preventive measures by automating the identification of apple leaf diseases. This might increase agricultural production overall, increase crop yields, and reduce the demand for pesticides. For plant disease control, which is vital to the sustainability of current agriculture, the system offers an automated, scalable solution. By providing a helpful tool for the early diagnosis of plant diseases, the CNN-ResNet based model exhibits potential as a practical application in agricultural technology. The improved accuracy and performance when compared to traditional models show the advantages of integrating deep learning

into precision farming techniques. Future research might focus on integrating this technology into mobile platforms for wide agricultural usage and deploying it in real-time applications for farmers.

REFERENCES

- [1] H. Williams, "Agriculture: The backbone of global economy and sustainability," *British Journal of Research*, 2024, doi: 10.35841/2394-3718-11.11.101.
- [2] S. Kumar *et al.*, "Multi-sensor fusion for plant disease detection in precision agriculture," *Sensors and Actuators B: Chemical*, vol. 380, p. 131581, 2023.
- [3] P. Kumar *et al.*, "Improving apple disease detection with CNN and data augmentation," *Journal of Plant Pathology*, vol. 109, no. 2, pp. 359–370, 2023.
- [4] A. Kumar *et al.*, "Texture and shape-based image processing techniques for plant disease classification," *Plant Disease Journal*, vol. 109, no. 5, pp. 657–664, 2024.
- [5] J. Li *et al.*, "Hyperspectral and multispectral imaging for early detection of plant diseases," *Precision Agriculture*, vol. 25, no. 4, pp. 738–758, 2024.
- [6] J. Li *et al.*, "Hyperspectral imaging for detecting plant diseases in precision agriculture," *Agronomy*, vol. 14, no. 2, p. 227, 2024.
- [7] Z. Li *et al.*, "Hyperspectral image analysis for early detection of plant diseases," *Frontiers in Plant Science*, vol. 14, pp. 2167–2178, 2023.
- [8] D. G. Kim, K. S. Lee, and W. J. Lee, "Classification of grapefruit peel diseases using color texture features," *International Journal of Image, Graphics and Signal Processing*, vol. 1, no. 1, pp. 11–19, 2009.
- [9] S. D. Khirade and A. B. Patil, "Plant disease detection using image processing," in *Proc. International Conference on Computing Communication Control and Automation (ICCUBE)*, 2015, pp. 768–771.
- [10] S. B. Dhaygude and N. P. Kumbhar, "Agricultural plant leaf disease detection using image processing," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 2, no. 1, pp. 599–602, 2013.
- [11] A. Singh and M. L. Singh, "Automated color prediction of paddy crop leaf using image processing," in *Proc. International Conference on Technological Innovations in ICT for Agriculture and Rural Development (TIAR)*, 2015.
- [12] M. Malathi, K. Aruli, S. Mohamed Nizar, and A. Sagaya Selvaraj, "A survey on plant leaf disease detection using image processing techniques," *International Research Journal of Engineering and Technology*, vol. 2, no. 9, Dec. 2015.
- [13] M. Ranjan, M. R. Weginwar, N. Joshi, and A. B. Ingole, "Detection and classification of leaf disease using artificial neural network," *International Journal of Technical Research and Applications*, vol. 3, no. 3, 2015.
- [14] Y. Sanjana, A. Sivasamy, and S. Jayanth, "Plant disease detection using image processing techniques," *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 4, Special Issue 6, 2015.
- [15] M. Riaz *et al.*, "Hybrid machine learning models for resource management in agriculture," *Precision Agriculture*, vol. 25, no. 3, pp. 559–572, 2023.
- [16] M. Riaz *et al.*, "Deep reinforcement learning for irrigation management in precision agriculture," *Agricultural Systems*, vol. 185, p. 102877, 2024.
- [17] M. Riaz *et al.*, "Reinforcement learning for optimized irrigation in precision agriculture," *Agricultural Systems*, vol. 185, p. 102879, 2024.
- [18] A. Sharma *et al.*, "Challenges in deep learning for agricultural applications," *Precision Agriculture*, vol. 24, no. 2, pp. 251–270, 2023.
- [19] A. Sharma *et al.*, "Unsupervised learning techniques in crop management and disease detection," *International Journal of Agricultural Science*, vol. 8, no. 1, pp. 35–45, 2023.
- [20] A. Sharma *et al.*, "Mobile app-based apple disease detection using CNN," *Sensors and Actuators B: Chemical*, vol. 267, pp. 574–585, 2024.
- [21] R. Sharma *et al.*, "AI and mobile applications for plant disease diagnosis," *Smart Agriculture*, vol. 3, no. 1, pp. 52–63, 2024.
- [22] J. Shin *et al.*, "Deep learning for plant disease classification using leaf images: A comprehensive review," *Agricultural Systems*, vol. 190, p. 103085, 2023.
- [23] J. Shin *et al.*, "Real-time pest monitoring system using deep learning for agricultural drones," *Sensors*, vol. 24, no. 1, pp. 12–27, 2024.
- [1]. S. Shin *et al.*, "Transfer learning for plant disease identification: A case study using convolutional neural networks," *International Journal of Agricultural and Biological Engineering*, vol. 16, no. 2, pp. 20–31, 2023.