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Fruit Plant Recognition and Classification from Plant Leaves using Deep Learning, CNN Models

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***Abstract:** Plants are an integral part of human life, and the ability to identify a fruit plant from its leaf image is both fascinating and challenging. Advances in image processing and pattern recognition have enabled plant identification using digital images. Machine learning (ML) and convolutional neural network (CNN) models have demonstrated strong capabilities in handling texture-related features in image processing tasks, including segmentation. In this Paper, we present an approach that utilises ML and CNN models, including AlexNet, Inception, ResNet, LeNet, VGG Net, MobileNet, DenseNet, and GoogLeNet. These models are used to classify fruit plants from leaf images, achieving promising performance on leaf image datasets. Among the evaluated CNN models, MobileNet achieved the highest performance with 94.81% training, 99.57% validation, and 99.44% test accuracy, outperforming all others. LeNet, AlexNet, and ResNet also showed strong results above 93%, while DenseNet, GoogLeNet, and VGGNet achieved moderate accuracy. Inception performed the worst, confirming that MobileNet is the most efficient and reliable model for fruit plant leaf classification.*

***Keywords:** Fruit Recognition, Fruit Classification, Feature Extraction, and Texture Extraction.*

Nomenclature:
ANN: Artificial Neural Network
CCD: Centroid-Contour Distance
CNN: Convolutional Neural Network
DL: Deep Learning
GLCM: Grey Level Co-occurrence Matrix
k-NN: k-Nearest Neighbour
LBP: Local Binary Patterns
ML: Machine Learning
MLP: Multi-layer Perceptron
PNN: Probabilistic Neural Network
SVM: Support Vector Machine
VGG: Visual Geometry Group
CNN: Convolutional Neural Network

I. INTRODUCTION

Fruits and vegetables are among the most nutrient-rich agricultural commodities, providing essential vitamins, minerals, fibre, and antioxidants necessary for human health. They are also considered high-value cash crops in global markets, contributing significantly to food security, trade, and rural livelihoods. Due to their high demand and economic importance, fruits and vegetables play a crucial role not only in improving dietary quality but also in generating income for farmers and supporting sustainable agricultural development. Conventional plant classification relies primarily on manual observation, which is often time-consuming, prone to human bias, and limited in accuracy, making it unsuitable for fast and reliable identification. As a result, developing efficient and accurate plant recognition methods has become both challenging and significant. Research on plant identification has been ongoing since the early 20th century, with fruit plants holding a vital place in human life. Over the past few decades, numerous studies have explored image processing and pattern recognition techniques, with particular focus on utilising leaf images for plant recognition. Leaves serve as one of the key features for plant identification, and the majority of image processing-based plant recognition techniques make use of leaf images. In essence, recognizing plant species is primarily achieved through the analysis of leaf characteristics [1].

In pattern recognition, classification is commonly performed using features such as shape, texture, and colour. Kristin et al. [2] highlighted the role of pattern recognition and computer vision in plant identification, emphasising the usefulness of texture features in this domain. However, relying solely on colour features presents several challenges. In many cases, the variation in colour between different plant species is minimal. In contrast, within the same species, leaves may exhibit significant colour differences due to factors such as maturity, disease, or environmental conditions [3]. Furthermore, in natural settings, inconsistent lighting and shadows can distort colour information, leading to reduced recognition accuracy. To address these issues, the proposed approach focuses on shape and texture descriptors, as these features are generally more stable and less sensitive to lighting changes, making them more reliable for plant leaf classification.

Leaf recognition commonly relies on both shape and texture features to achieve accurate classification. Kumar et al. developed Leafsnap, a mobile application designed for automatic plant identification. The system employed HoCS, a shape-based descriptor that captures curvature distributions along leaf boundaries at multiple scales, enabling robust recognition of plant species. In addition to HoCS, several other shape-based methods have been investigated for leaf recognition. For instance, the CCD [4] technique measures the distance between the leaf centroid and points along its contour, producing a signature that

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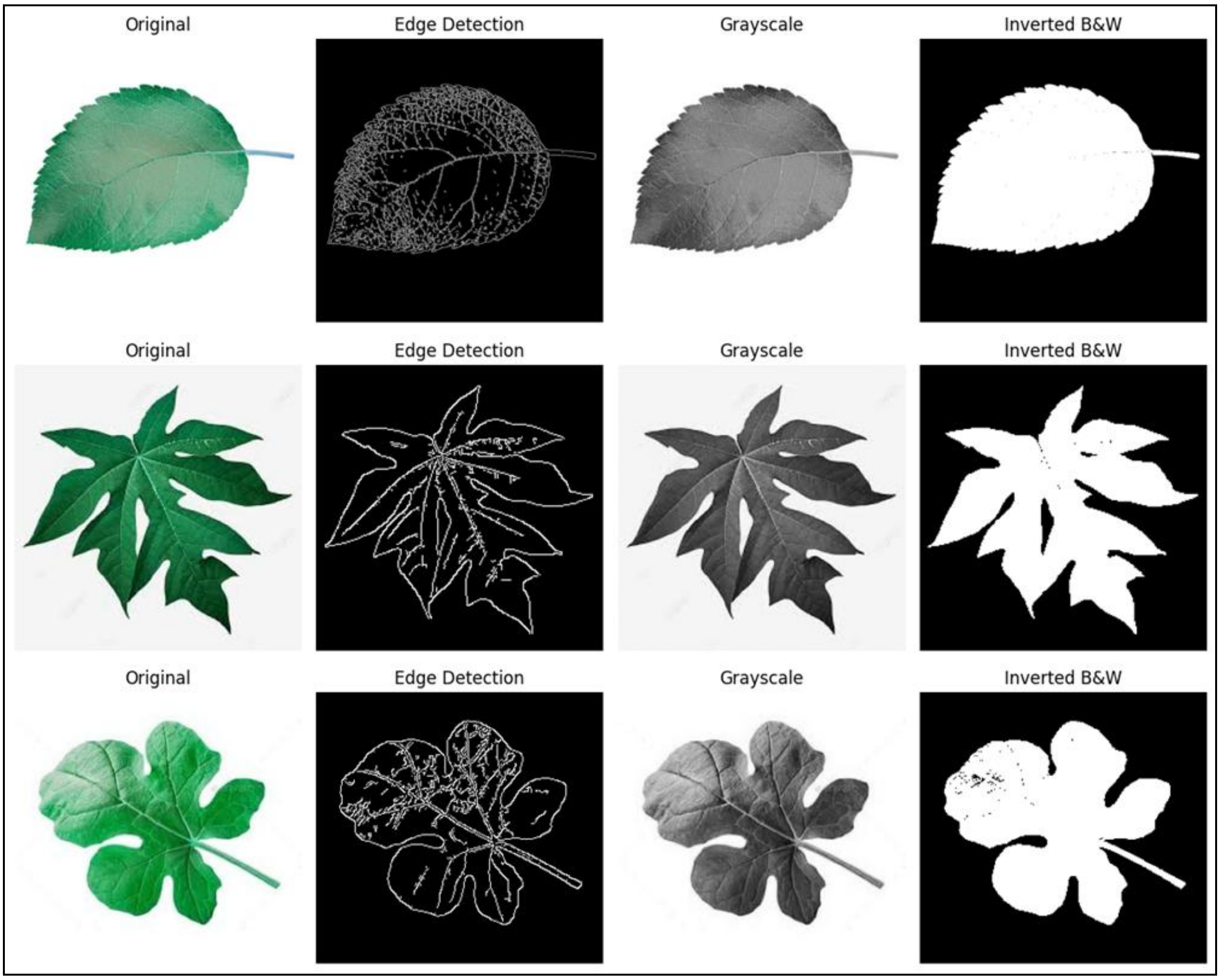
effectively represents the leaf's overall shape. These shape descriptors, when combined with texture analysis, enhance recognition systems' ability to distinguish between visually similar species. In many cases, leaves from different plant species exhibit very similar shapes, making it difficult to distinguish them, even to the human eye. This limitation suggests that relying solely on shape descriptors may not provide sufficient accuracy in plant classification. Therefore, combining shape and texture features provides a more reliable solution for leaf recognition. Texture features, in particular, can capture fine surface details —such as venation patterns, roughness, and pixel-intensity variations —that are often overlooked in shape analysis. Genitha H. et al. (2019) integrate Principal Component Analysis-based feature extraction with Linear SVM classification, demonstrating a robust method for tomato leaf disease detection [5]. The proposed system improves precision and computational efficiency compared to traditional visual inspection methods.

Mohammadreza et al [6] developed a multi-label confusion matrix and applied it to two multi-label datasets, viz, a 12-lead ECG dataset with nine classes and a movie poster dataset with 18 classes. Additionally, the approach incorporated Fourier descriptors, morphological attributes, and mass-shaping characteristics to enhance the discrimination of plant species. A comparison was made between the multi-label confusion matrix and other well-known methods to prove its effectiveness.



[Fig.1: Image Processing for Shape, Texture, Colour, and Veins Feature Extraction: (Row 1) Apple Leaf, (Row 2) Papaya Leaf, and (Row 3) Watermelon Leaf]

II. THEORY OF PLANT RECOGNITION

A. Shape Feature Extraction

In this section, geometric features are employed for the plant identification system. In the proposed system, shape feature extraction plays a crucial role in representing leaf structural characteristics [0]. Several geometric descriptors are employed, including leaf length and leaf width, which provide basic dimensional measurements, while leaf area and leaf perimeter capture the overall size and boundary information. Rectangularity evaluates how closely the leaf shape resembles a rectangle, and diameter represents the maximum distance across the leaf surface. The aspect ratio, defined as the ratio of length to width, helps in distinguishing elongated leaves from broader ones. Solidity measures the compactness of the leaf by comparing its area to the area of its convex hull. In contrast, roundness describes how close the leaf is to a perfect circular shape, as depicted in Figure 1.

B. Texture Feature Extraction

Texture feature extraction captures surface patterns and spatial variations in leaf images, often providing critical information for distinguishing between plant species. These features describe the distribution of pixel intensities, local variations, and repetitive structures within the image. Commonly used statistical measures such as correlation, contrast, energy, and homogeneity are derived from the GLCM to represent texture properties. In addition, methods like LBP are applied to analyse fine-grained surface details by encoding relationships between neighbouring pixels. Other descriptors, including entropy, variance, and lacunarity, are also used to characterise the complexity and irregularity of leaf venation and surface structure [14]. By combining these texture descriptors, the system achieves a more robust representation of leaf characteristics, which significantly enhances the accuracy of plant classification.

C. Colour Feature Extraction

This section focuses on extracting colour-based features. The process is carried out in the RGB colour space, as it is more effective for leaf analysis compared to other colour models [8]. For each of the R, G, and B channels, statistical measures such as the mean, standard deviation, skewness, and kurtosis are computed, forming the set of colour features used for classification.

D. Veins Feature Extraction

Vein characteristics are obtained through a morphological opening process. This operation is applied to the grayscale image using a flat, disk-shaped structuring element with a defined radius. The resulting image is then subtracted from the original to isolate the vein patterns along the leaf margins [7].

III. RELATED WORK

In 2020, Keivani M., Mazloum J.E., and Tavakoli M.B. increasingly focused on applying image processing methods for plant recognition in agriculture. This field has not been as extensively studied as other areas of computer vision. Conventional identification techniques, which rely on manual observation of leaves and fruits, are often subjective, inefficient, and time-consuming. Automated systems have been developed that integrate a variety of feature descriptors, including GIST, LBP, geometric measurements, colour moments, vein structures, and lacunarity-based texture features. Once the features are extracted and normalized, Pbest-guided Binary Particle Swarm Optimization is employed to reduce dimensionality. The optimized features are then classified using ML algorithms such as k-NN, Decision Tree, Naïve Bayes, and multi-class SVM. Testing on the Flavia and Folio datasets revealed that the Decision Tree classifier achieved the highest accuracy, with results of 98.58% and 90.02%, respectively. These outcomes demonstrate that combining diverse feature descriptors with optimization techniques can significantly enhance the accuracy of plant leaf classification systems [9].

While identifying leaf types can be relatively straightforward for a trained botanist, it is a challenging, computationally demanding task for machines. To address this, Shivadekar, S et al. [10] propose a hybrid approach combining DCNNs and the ResNet-50 architecture to enhance diagnostic accuracy. The study uses a publicly available dataset of chest radiographs categorised as COVID-19-positive, viral pneumonia, and typical cases. Data augmentation and transfer learning techniques are applied to improve model performance and generalization. Experimental results demonstrate that the proposed model achieves classification accuracy of 97.81%, sensitivity of 97.22%, and specificity of 97.67%, outperforming several existing models, including SARS-Net and DeTraC. The research highlights the potential of deep learning, particularly ResNet-based architectures, to support radiologists in rapid, reliable COVID-19 screening. It also suggests future work involving larger datasets and the inclusion of CT imaging for enhanced diagnostic precision. Similarly, Kadir et al. [11] conducted a study that integrated texture, colour, and additional texture descriptors, employing the PNN approach to improve classification performance.

Yasin, Elham & Koklu, Murat. (2023) study on the Pudina Leaf Dataset: Freshness Analysis focuses on classifying mint leaves into fresh, dried, and spoiled categories using advanced DL techniques. Feature extraction was performed using CNNs, such as InceptionV3 and VGG19, followed by classification with the Random Forest algorithm. The results demonstrated high accuracy, with InceptionV3 achieving 94.8% and VGG19 reaching 96.8%, indicating the models' strong capability. The integration of DL feature extraction with ensemble-based classification highlights a practical framework for plant leaf quality assessment. It offers potential directions for enhancing automated freshness detection in agricultural applications [12].

Islam et al. [13] employed synthetic texture features for plant species identification using leaf images. The study utilized LBP and HOG to extract texture information. These features were then classified using an SVM. When using HOG features with SVM, classification accuracies were 77.5%, 81.25%, and 85.31% for cell sizes of 2×2, 4×4, and 8×8, respectively. Using LBP features alone with SVM yielded an accuracy of 40.6%. However, combining HOG and LBP features with SVM significantly improved performance, achieving an accuracy of 91.25%. These results indicate that integrating HOG and LBP provides a more robust and accurate feature representation for leaf-based plant identification than using either method alone.

Plant leaves are essential in fields such as biology, Ayurveda, and agriculture, and their classification is based on morphological features, including margins, shapes, and textures. Several ML classifiers—such as Linear Regression, K-NN, SVM, and Random Forest—have been applied to leaf classification across multiple datasets. In a recent study, three datasets were collected, preprocessed, and used to train different classifiers. Random Forest achieved the highest accuracy, signifying superior performance compared to other methods for leaf image classification.
[15].

A. K. Hrithik and V. Kumar in 2022 [16], Automatic plant identification has become increasingly important, particularly for fruit plants,

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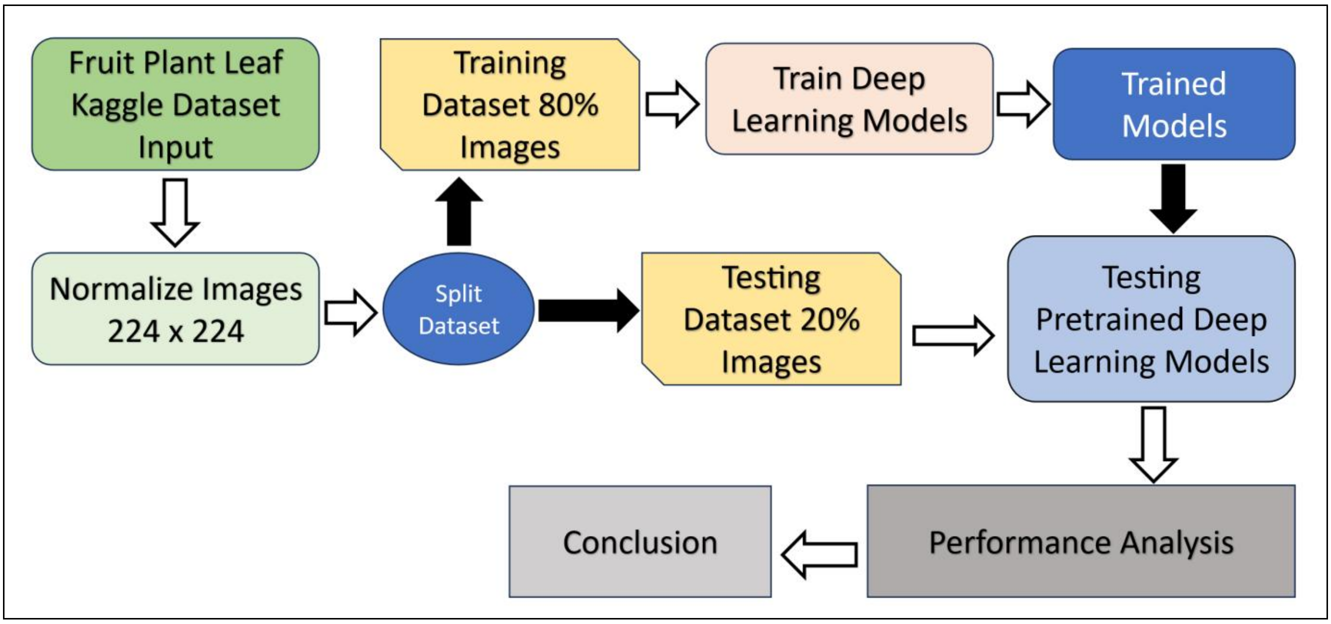
which are vital for nutrition. Leaf images provide key features for classification, but manual identification requires expertise. A recent study collected 11,321 RGB leaf images from 30 fruit plant species using a smartphone and compared multiple ML algorithms, including Logistic Regression, K-NN, SVM, Decision Tree, MLP, and Naive Bayes. Among these, MLP achieved the highest accuracy of 93.18%. The study also evaluated several DL models, including ResNet, AlexNet, VGGNet, SqueezeNet, ShuffleNet, GoogLeNet, ResNeXt50, and DenseNet. It found that ShuffleNet outperformed the others with 99.96% accuracy, demonstrating the effectiveness of DL approaches for leaf-based classification of fruit plants.

In 2024, S. A. Naqvi et al. [17] employed a shallow vast neural network to classify leaf diseases in apple and cucumber plants, using selected features for accurate identification. The models were further interpreted using explainable AI (LIME) to understand their decision-making processes. Experiments on both datasets achieved accuracies of 94.8% for apple and 94.9% for cucumber leaves. Comparisons with several state-of-the-art methods demonstrated that the proposed framework outperformed existing techniques, highlighting its effectiveness for leaf disease classification.

Earlier research has faced several challenges. For example, some approaches, such as PNN-based classification, rely on a limited set of features —such as shape and vein structure —which limits overall accuracy. Similarly, Fourier-based models struggle to capture suitable characteristics for leaves with sharp edges because they rely on sinusoidal smoothing. Moreover, many existing methods fail to comprehensively extract diverse features, leading to incomplete representations of leaf properties. The proposed method incorporates a broader range of descriptors — shape, colour, texture, and vein features — to improve classification performance.



[Fig.2: Research Method Flow Chart]

IV. PROPOSED METHODOLOGY

A. Method

In this study, fruit plant leaves were classified using a range of ML models. The process involved data preprocessing, feature extraction, and the application of multiple classifiers to generate predictions. The performance of each model was assessed using classification accuracy, and the overall methodology was summarised in a flowchart (Figure 2).

B. Dataset

The Fruit Plant Leaf dataset on Kaggle comprises 10 categories of fruit plant leaves, with 291 samples of varying sizes [19]. All images were resized and normalized to a fixed resolution of 224 × 224 pixels before being divided into two subsets: first 80% for training and the second 20% for testing [20], [21]. As depicted in Table I, Figure 3 presents a sample image from each category. Where a pair of images is taken from each class. The same evaluation procedure used in our experiments was applied to this dataset for performance comparison [27].

Table - I: Dataset Image Distribution

Class	Images	Training	Testing
Apple	20	16	4
Banana	27	22	5
Grape	33	26	7
Guava	26	21	5
Jujube	33	26	7
Mango	53	41	12
Grape	21	17	4
Papaya	29	23	6
Pineapple	25	20	5
Watermelon	24	19	5
Total	**291**	**231**	**60**

The dataset class distribution, management, and image count for each class, along with the image count for the training and testing sets, are equally represented in Table I.

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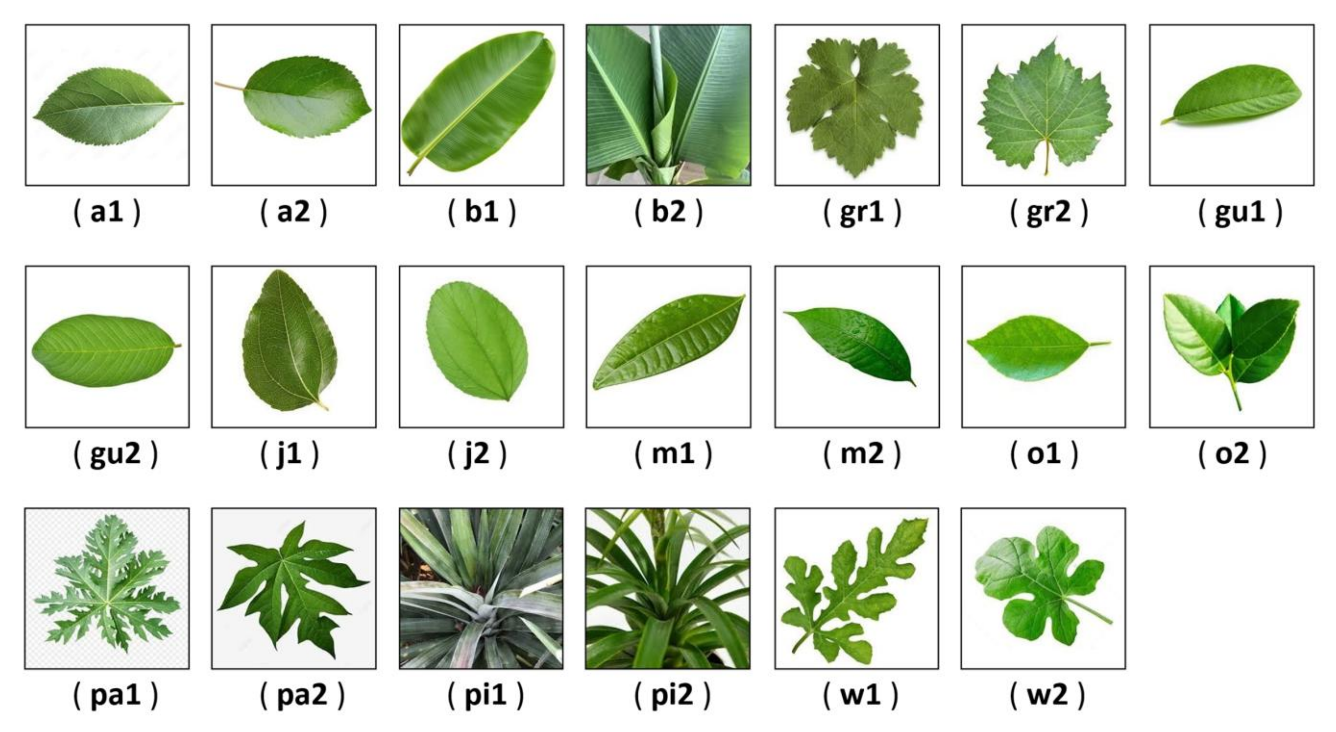

[Fig.3: Randomly Image Examples: (a1) (a2) Apple Leaves, (b1) (b2) Banana Leaves, (gr1) (gr2) Grape Leaves, (gu1) (gu2) Guava Leaves, (j1) (j2) Jujube Leaves, (m1) (m2) Mango Leaves, (o1) (o2) Orange Leaves, (pa1) (pa2) Papaya Leaves, (pi1) (pi2) Pineapple Leaves, and (w1) (w2) Watermelon Leaves]

C. Deep Learning CNN Models

CNNs are among the most widely used models for image recognition and classification. A key advantage of CNNs is their ability to minimize the need for extensive preprocessing compared to many traditional algorithms. They enhance the classification process by automatically learning significant patterns from input data during training, extracting essential information without manual feature engineering. The core objective of a CNN is to organize raw data into a structured representation while preserving critical features, enabling the model to interpret the data effectively. This characteristic makes CNNs particularly well-suited for handling large-scale datasets. In this work, the performance of the proposed CNN model is assessed through a comparative analysis with several established DL architectures [18]. The models selected for evaluation are as follows.

i. AlexNet

AlexNet, introduced by Krizhevsky et al. in 2012, is one of the most influential convolutional neural network architectures, widely studied for its balance between computational efficiency and accuracy. The network consists of eight learnable layers: five convolutional layers followed by three fully connected layers, all with trainable weights. To minimize over fitting, the model incorporates data augmentation and dropout techniques. AlexNet processes input images of size 227 × 227 × 3, and applies the ReLU activation function after each convolutional and fully connected layer to enhance non-linearity. The final fully connected layer contains 1,000 neurons, which are passed through a classifier to categorise images into 1,000 distinct classes [22].

ii. Inception

Inception V3, developed by Google, is the third version in the Inception family of DL architectures. At the same time, batch normalisation was introduced in Inception V2, and Inception V3 further improved performance by incorporating factorisation, which reduces the number of parameters and connections without compromising accuracy. The architecture combines multiple techniques, such as pooling, max pooling, dropout, and fully connected layers. Its final layer uses a classifier to predict the output. Overall, the model consists of 42 layers and accepts input of size 299 × 299 pixels, making it both deep and computationally efficient [23].

iii. ResNet

ResNet50 represents a breakthrough in DL, particularly for tasks such as plant leaf disease detection. One of the key challenges in deep networks is the vanishing gradient problem, which leads to performance degradation as more nonlinear layers are added. Unlike traditional architectures that struggle with learning effective identity mappings when stacked too deeply, ResNet50 introduces the concept of residual connections. These connections enable the network to bypass specific layers, allowing it to learn identity mappings more efficiently and maintain stability during training. The architecture is built around residual blocks, which ensure smooth flow during back-propagation [24].

iv. LeNet

LeNet-5, introduced by Yann LeCun and colleagues in 1998, is considered one of the earliest and most influential convolutional neural network models for image classification. Its popularity stems from its simple yet effective architecture, which consists of seven layers, five of which contain trainable parameters, hence the name LeNet-5. The design

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incorporates three convolutional layers, two subsampling pooling layers, and two fully connected layers, followed by a classifier. Unlike modern CNNs, LeNet-5 uses average pooling in its subsampling layers. The convolutional layers use relatively small 3 × 3 filters, and some are followed by 2 × 2 max pooling operations to reduce the spatial dimensions [22].

v. VGG Net

The VGG architecture, introduced by Simonyan and Zisserman in 2014, highlighted the significance of network depth in the design of convolutional neural networks. The two widely used variants, VGG-16 and VGG-19, are named according to the total number of layers they contain-16 and 19, respectively. A key design principle of VGG is the use of small convolutional filters (3×3) stacked in depth to build a powerful representation. The architecture consists of multiple convolutional layers (depending on the version), followed by five max-pooling layers, three fully connected layers, and a final classifier for output prediction [22].

vi. MobileNet

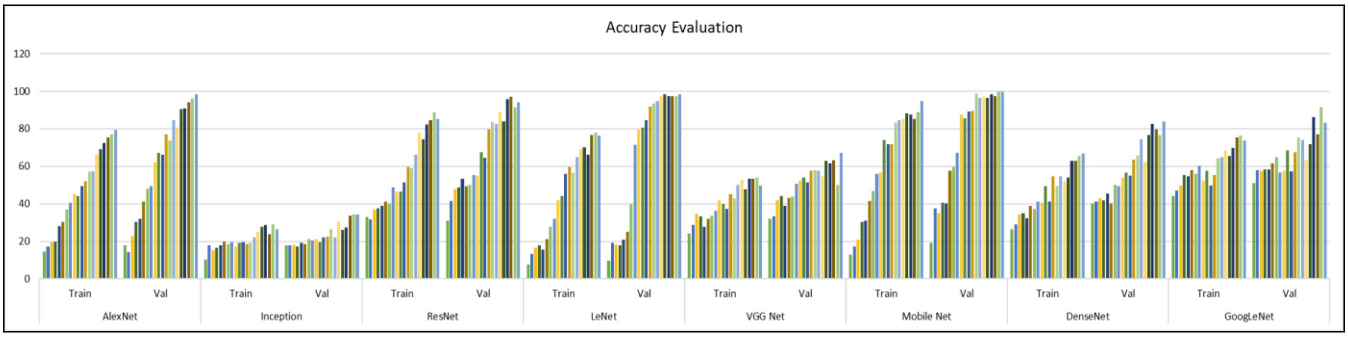
MobileNetV2 is specifically designed to be efficient on mobile and embedded devices, offering strong performance while keeping parameter counts and computational costs low. The architecture is built around three main convolutional layers. The first is the expansion layer, which increases the input data's dimensionality before passing it to the depthwise convolution stage. In this layer, the number of output channels is significantly higher than the number of input channels, effectively expanding the feature space. In contrast, the projection layer reduces the dimensionality back to a smaller number of channels. Typically, an expansion factor of six is used; for example, an input tensor with 10 channels would be expanded to 60 channels [24].

vii. DenseNet

The Dense Convolutional Network, proposed by Huang et al., introduces direct connections from each layer to all subsequent layers. This design offers several benefits, including reducing the vanishing gradient problem, enhancing feature propagation, reassuring feature reuse, and lowering the overall number of parameters [25]. In fruit classification tasks, where species like apples and peaches share highly similar characteristics, distinguishing between them can become challenging after multiple convolutional layers. Traditional deep networks risk losing essential details due to the long path between input and output layers. DenseNet addresses this issue by ensuring stronger gradient flow and better information transfer, ultimately improving classification accuracy in very deep architectures [26].

viii. GoogLeNet

GoogLeNet, introduced by Szegedy et al., is a pre-trained DL model designed to classify images into 1,000 categories. The network is 22 layers deep and begins with a series of convolutional layers (C1–C4), with pooling applied after C1 and C4. Following these initial stages, the architecture incorporates multiple Inception modules, which combine 1×1, 3×3, and 5×5 convolutions in parallel to capture a wide range of feature representations. While max-pooling layers reduce spatial dimensions, they also help manage computational complexity [28]. Although training GoogLeNet can be computationally intensive, the model is known for delivering high classification accuracy.



[Fig.4: Accuracy Estimation Chart of Training and Testing for all CNN Models]

V. EXPERIMENTS AND RESULTS

To compare all the models, we implemented them using Python and executed them on Google Colab. Then, conduct training and testing of each model one by one on the same dataset with fixed-size normalized images; the results of all models are shown in Table II, Comparison through line chart in Figure 5, and Estimation chart of training and testing in Figure 6, are highlights the training and validation performance of several DL models across 20 epochs for plant leaf classification. Among the models, MobileNet, DenseNet, VGGNet, and GoogLeNet show rapid improvement in validation accuracy, consistently exceeding 90% by later epochs, with MobileNet and VGGNet reaching nearly perfect accuracy (above 99%). ResNet and AlexNet demonstrate steady growth, but their validation accuracy plateaus at lower levels than that of more advanced architectures. LeNet, being a simpler model, shows moderate gains but lags behind modern networks. Inception exhibits slower improvement, achieving validation accuracy of only around 34% by the final epoch. Overall, the results indicate that lightweight and deeper architectures such as MobileNet, DenseNet, and VGGNet outperform traditional networks in both convergence speed and classification accuracy.

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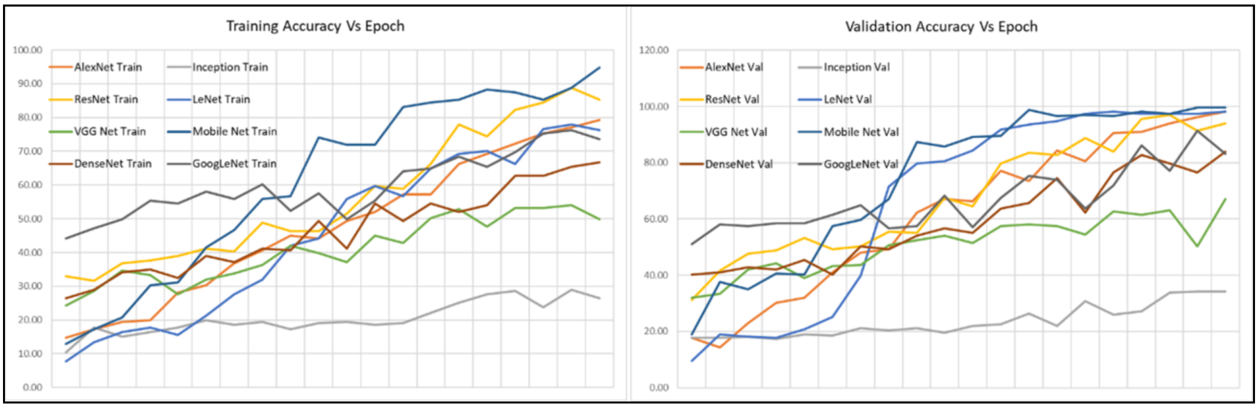
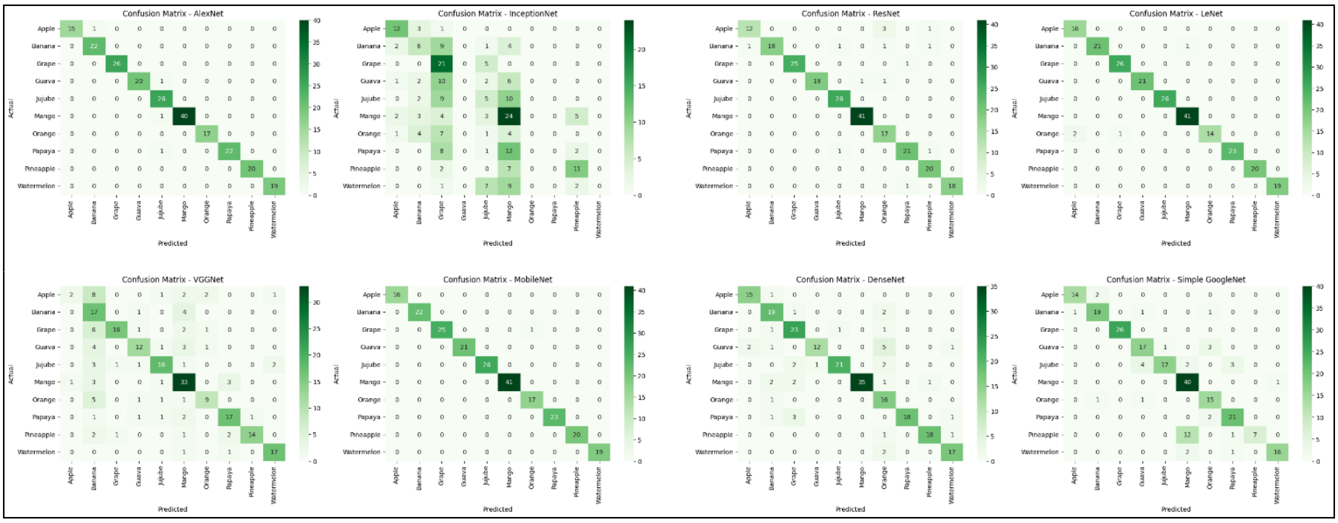
Table II: Training and Validation Results Performance Comparison

Epoch	AlexNet		Inception		ResNet		LeNet		VGG Net		Mobile Net		DenseNet		GoogLeNet	
	Train Accu (%)	Val Accu (%)	Train Accu (%)	Val Accu (%)	Train Accu (%)	Val Accu (%)	Train Accu (%)	Val Accu (%)	Train Accu (%)	Val Accu (%)	Train Accu (%)	Val Accu (%)	Train Accu (%)	Val Accu (%)	Train Accu (%)	Val Accu (%)
01	14.72	17.75	10.39	17.75	32.90	31.17	07.79	09.52	24.24	32.03	12.99	19.05	26.41	40.26	44.16	51.08
02	17.32	14.29	17.75	17.75	31.60	41.56	13.42	19.05	28.57	33.33	17.32	37.66	29.00	41.13	47.19	58.01
03	19.48	22.94	15.15	18.18	36.80	47.62	16.45	18.18	34.63	41.99	20.78	35.06	34.20	42.86	49.78	57.58
04	19.91	30.30	16.45	17.32	37.66	48.92	17.75	17.75	33.33	44.16	30.30	40.69	35.06	41.99	55.41	58.44
05	28.14	32.03	17.75	19.05	38.96	53.25	15.58	20.78	27.71	38.96	31.17	40.26	32.47	45.45	54.55	58.44
06	30.30	41.13	19.91	18.61	41.13	49.35	21.21	25.11	32.03	43.29	41.56	57.58	38.96	40.26	58.01	61.47
07	36.80	48.05	18.61	21.21	40.26	50.22	27.71	39.83	33.77	43.72	46.75	59.74	37.23	50.22	55.84	64.94
08	40.69	49.35	19.48	20.35	48.92	55.41	32.03	71.43	36.36	50.65	55.84	67.10	41.13	49.35	60.17	56.71
09	45.02	62.34	17.32	21.21	46.32	54.98	41.99	79.65	41.99	52.38	56.71	87.45	40.69	54.11	52.38	57.58
10	44.16	67.10	19.05	19.48	46.32	67.53	44.16	80.52	39.83	54.11	74.03	85.71	49.35	56.71	57.58	68.40
11	49.35	66.23	19.48	22.08	51.52	64.50	55.84	84.42	37.23	51.52	71.86	89.18	41.13	54.98	49.78	57.14
12	51.95	77.06	18.61	22.51	59.74	79.65	59.74	91.77	45.02	57.58	71.86	89.61	54.55	63.64	55.41	67.53
13	57.14	73.59	19.05	26.41	58.87	83.55	56.71	93.51	42.86	58.01	83.12	98.70	49.35	65.80	64.07	75.32
14	57.14	84.42	22.08	22.08	66.23	82.68	64.94	94.81	50.22	57.58	84.42	96.54	54.55	74.46	64.94	74.03
15	66.23	80.52	25.11	30.74	77.92	88.74	69.26	97.40	52.81	54.55	85.28	96.97	51.95	62.34	68.40	63.64
16	69.26	90.48	27.71	25.97	74.46	83.98	70.13	98.27	47.62	62.77	88.31	96.54	54.11	76.62	65.37	71.86
17	72.29	90.91	28.57	27.27	82.25	95.67	66.23	97.40	53.25	61.47	87.45	98.27	62.77	82.68	69.70	86.15
18	75.32	93.94	23.81	33.77	84.42	96.97	76.62	97.40	53.25	63.20	85.28	97.40	62.77	79.65	75.32	77.06
19	77.06	96.10	29.00	34.20	88.74	91.34	77.92	97.40	54.11	50.22	88.74	99.57	65.37	76.62	76.19	91.34
20	79.22	98.27	26.41	34.20	85.28	93.94	76.19	98.27	49.78	67.10	94.81	99.57	66.67	83.98	73.59	83.12

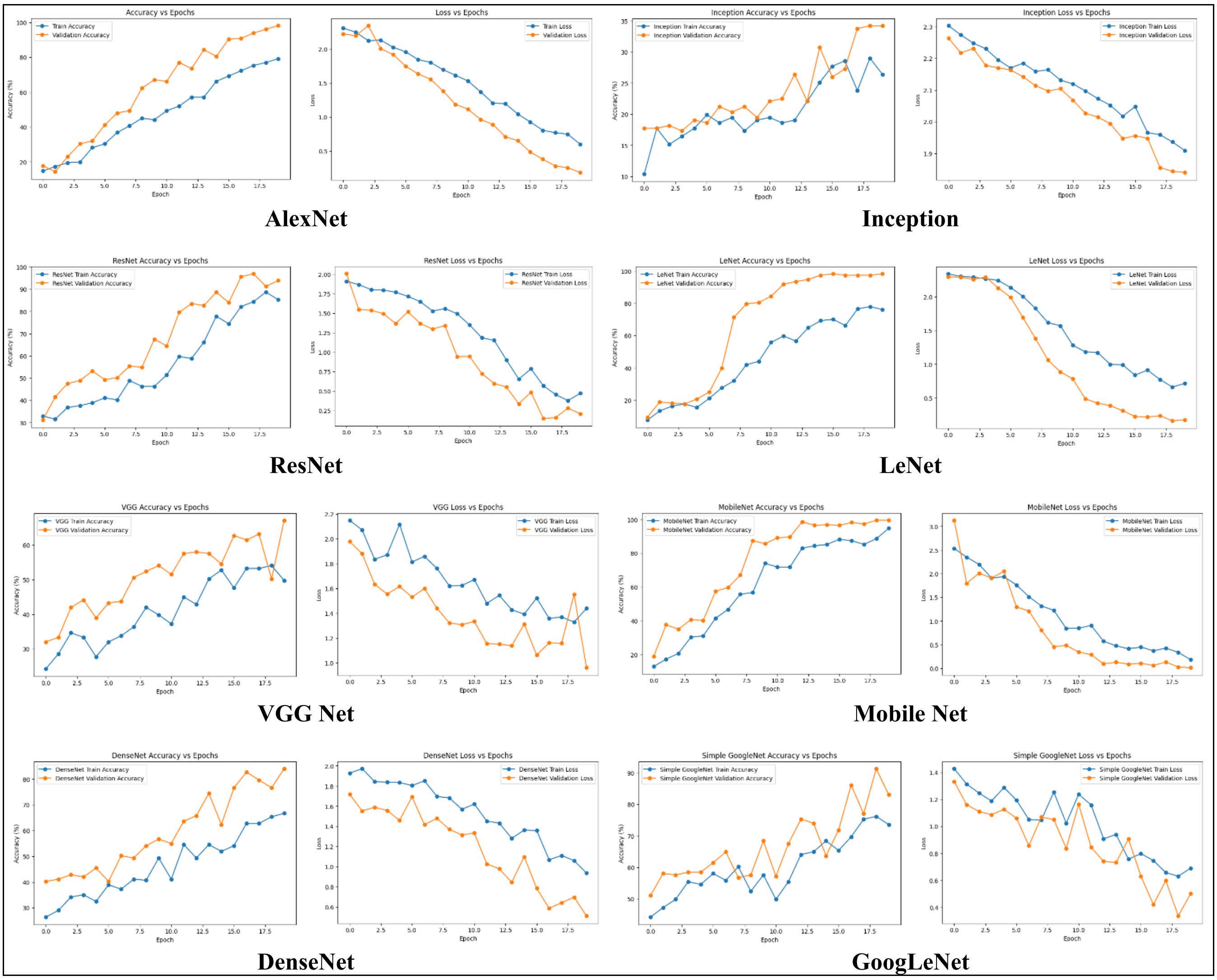


[Fig.5: Training and Validation Accuracy Curves of CNN Models Over Epochs]



[Fig.6: Confusion Matrix of Deep Learning CNN Models]

Figure 5. illustrates the training and validation performance of different CNN models across multiple epochs. They highlight the accuracy trends, convergence rates, and comparative effectiveness of each architecture, providing a clear visual representation of the experimental outcomes. Figures 6 and 7 present experimental results illustrating the performance metrics of CNN models, including accuracy and loss, during training and validation. They offer a comparative view that supports the analysis and highlights the differences in model efficiency.



[Fig.7: Plot of Accuracy and Loss Over the Epoch of Deep Learning CNN Models]

Table III: Performance Comparison and Test Data

No.	CNN Model	Epoch	Accuracy		Prec	Rec	F1
			Train	Val	Test Data		
1	AlexNet	20	79.22	98.28	98.53	98.22	98.32
2	Inception	19	28.57	34.2	23.24	31.58	25.77
3	ResNet	17	88.75	95.67	93.83	92.95	92.97
4	LeNet	16	77.92	98.27	98.28	97.78	97.8
5	VGG Net	20	54.11	67.1	72.66	64.45	65.19
6	Mobile Net	19	94.81	99.57	99.44	99.62	99.52
7	DenseNet	20	66.67	83.98	85.63	84.37	83.63
8	GoogLeNet	19	76.19	91.34	86.58	81.65	81.91

The performance comparison of different CNN architectures reveals notable differences in accuracy and evaluation metrics, as shown in Table III. MobileNet achieved the highest results, with nearly perfect training, validation, and test scores (above 99%), demonstrating excellent generalisation. LeNet and AlexNet also performed strongly, both exceeding 98% accuracy on test data. ResNet closely matched balanced precision, recall, and F1 Scores above 92%, confirming its robustness. DenseNet and GoogLeNet showed moderate performance, with test accuracies around 84% and 82%, respectively. In contrast, VGGNet delivered lower validation and test scores (around 65%), while Inception lagged significantly behind all other models, with the weakest test accuracy (25.77% F1-score). Overall, modern lightweight models like MobileNet outperformed traditional and deeper networks, demonstrating greater effectiveness for this classification task.

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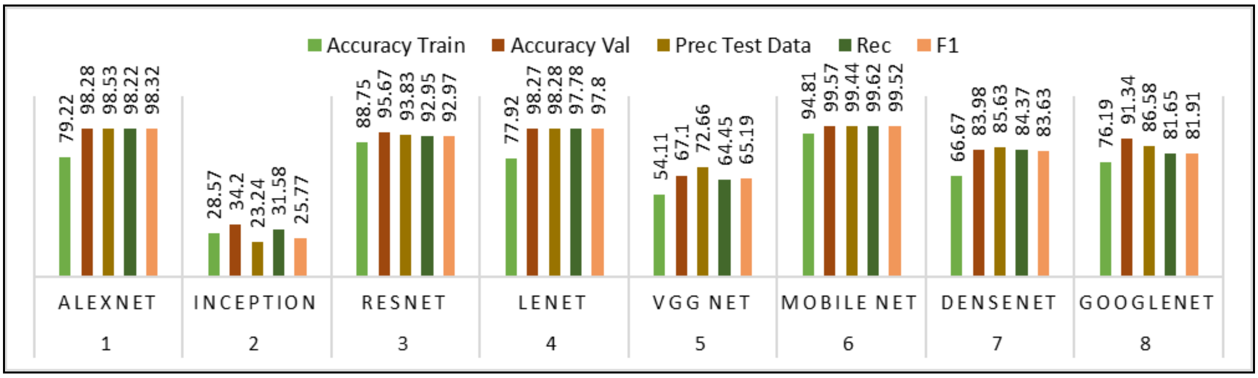

[Fig.8: Performance Comparison Chart for Training and Testing of CNN Models]

The experimental results are demonstrated in Figure 8. A bar chart provides a detailed analysis, showing that MobileNet achieved the best performance with 94.81% training accuracy, 99.57% validation accuracy, and 99.44% test accuracy. LeNet and AlexNet also performed strongly, reaching test accuracies of 98.28% and 98.53%, respectively. ResNet provided balanced outcomes with 88.75% training accuracy, 95.67% validation accuracy, and 93.83% test accuracy. DenseNet and GoogLeNet achieved moderate results, with test accuracies of 85.63% and 86.58%, while VGGNet showed comparatively lower accuracy of 72.66%. Inception performed the weakest, with only 34.20% validation accuracy and 23.24% precision on test data.

VI. CONCLUSION

In this paper, we propose a new approach for fruit plant leaf identification that integrates shape, texture, colour, and vein features, followed by leaf classification using pretrained DL and CNN models. MobileNet achieved the best results with 94.81% training accuracy, 99.57% validation accuracy, and 99.44% test accuracy, along with precision, recall, and F1-scores above 99%, confirming its reliability. LeNet achieved 77.92% training accuracy, 98.27% validation accuracy, and 98.28% test accuracy, while AlexNet achieved 79.22% training accuracy, 98.28% validation accuracy, and 98.53% test accuracy, both demonstrating strong generalisation. ResNet performed consistently well with 88.75% training accuracy, 95.67% validation accuracy, and 93.83% test accuracy, maintaining over 92% across all evaluation metrics. DenseNet (66.67% training, 83.98% validation, 85.63% test) and GoogLeNet (76.19% training, 91.34% validation, 86.58% test) showed moderate effectiveness, whereas VGGNet produced lower performance with 54.11% training, 67.10% validation, and 72.66% test accuracy. The weakest results were from Inception, with 28.57% training accuracy, 34.20% validation accuracy, and only 23.24% precision on test data. Overall, the findings confirm that MobileNet is the most effective model, offering the highest classification accuracy and making it the most suitable choice for real-world agricultural applications.

FUTURE SCOPE

Future research can focus on creating an automated system capable of handling more fruit categories, which would greatly benefit fruit growers. Additionally, a mobile app could be developed to capture fruit images and automatically classify them as fresh or spoiled, providing farmers with a practical, easy-to-use tool.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
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- **Data Access Statement and Material Availability:** The dataset is available for open access on Kaggle. Fruits Plant Leaf (Original Data) *https://www.kaggle.com/datasets/pathanajahar/fruits-plant-leaf*
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