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# Transforming Apple Disease Detection with Advanced Deep Learning: A Hybrid Approach Using Mobilenetv3 Small and Res MLP

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***Abstract: The identification of plant diseases through image analysis is crucial in precision agriculture. Traditional methods rely on extensive manual inspection, which is time-consuming and prone to error. Deep learning approaches, particularly convolutional neural networks (CNNs), offer a promising solution for automating this process. This research focuses on preprocessing, augmenting, and analyzing image data to build a robust model capable of distinguishing between healthy and diseased apple leaves. The proposed hybrid model combines MobileNetV3Small and Res MLP architectures, achieving a balance between accuracy and computational efficiency. The novelty of this research lies in the integration of advanced preprocessing techniques and a hybrid deep learning model specifically designed for apple disease detection.***

***Keywords: Apple Disease Detection, Deep Learning, Convolutional Neural Networks, Mobile Netv3small, Res MLP, Precision Agriculture.***

## 1. INTRODUCTION

The significance of early disease detection in crops cannot be overstated, particularly for apple orchards where timely intervention can prevent significant losses [1-4]. Traditional disease detection relies heavily on the expertise of agricultural professionals who manually inspect the leaves, often leading to delays and inaccuracies. This problem is exacerbated in large-scale operations where the volume of plants makes manual inspection impractical [5-8]. Deep learning has emerged as a powerful tool in image analysis, offering a way to automate the detection process. Convolutional Neural Networks (CNNs) have shown remarkable performance in image classification tasks due to their ability to learn hierarchical features from

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raw pixel data [9]. This research leverages CNNs to develop an automated apple disease detection system. The focus is on the preprocessing, augmentation, and analysis of image data to create a robust model that can accurately classify apple leaves as healthy or diseased [10]. The hybrid model proposed in this research integrates MobileNetV3Small with ResMLP architectures. MobileNetV3Small, known for its efficiency in feature extraction, is combined with ResMLP, which refines the extracted features for classification. This hybrid approach aims to strike a balance between accuracy and computational efficiency, making it suitable for real-world applications in precision agriculture [11].

## 2. RELATED WORKS

Data augmentation is crucial for enhancing the generalization capabilities of a model. It artificially enlarges the dataset by creating variations of the images [12], which helps the model learn to recognize features in different conditions. Key augmentation techniques used in this research include:

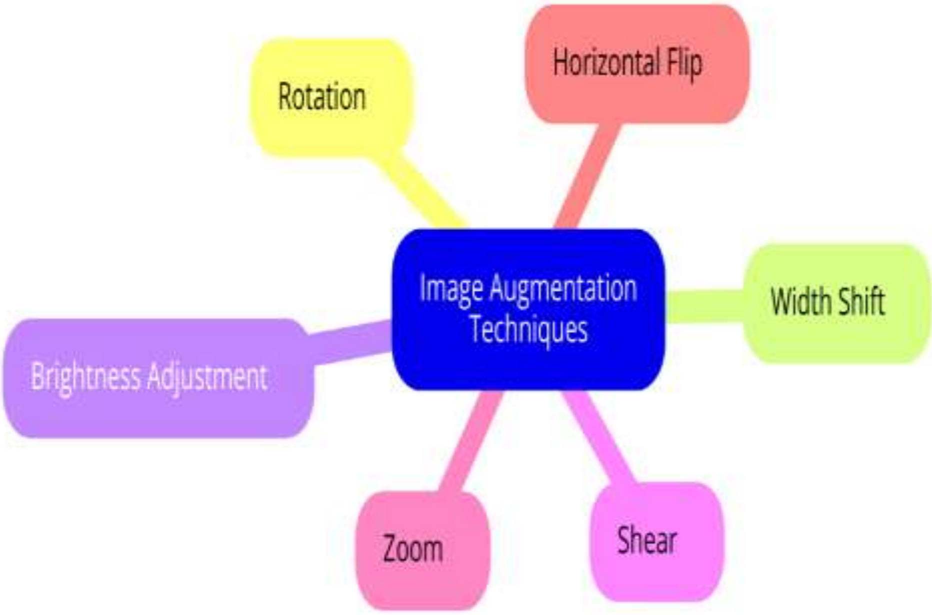


Fig 1: Image Augmentation Techniques

Introduces variability in image orientation by rotating images up to 5 degrees. This helps the model become invariant to slight changes in the leaf's angle. Shifts images horizontally by up to 20% of their width, simulating variations in camera positioning. Alters the brightness of images randomly between 20% decrease and 20% increase, helping the model handle different lighting conditions [13]. Applies shear transformations, which distorts the image along one axis. This helps the model become more robust to distortions in leaf appearance. Zooms in or out of images by up to 20%, providing variability in leaf size and helping the model handle different magnifications. Flips images horizontally, which is particularly useful for balancing the dataset if the leaf orientation is not consistent [14-15].

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## 3. METHODOLOGY

Splitting the dataset into training and validation sets is essential for evaluating model performance. In this research, 60% of the data is allocated to training, while 40% is reserved for validation. This split ensures that the model's ability to generalize to unseen data is tested, which is critical for assessing its practical effectiveness.

### Data Splitting

1. **Training Set (60%)**: Used to train the model and adjust its parameters.
2. **Validation Set (40%)**: Used to evaluate the model's performance during training and fine-tune hyperparameters.

### Importance of Data Splitting

1. **Performance Evaluation**: Ensures that the model is tested on data it hasn't seen during training.
2. **Hyperparameter Tuning**: Allows for tuning of model parameters based on performance metrics from the validation set.
3. **Avoiding Overfitting**: Helps detect and mitigate overfitting by evaluating the model on a separate dataset.

### Preprocessing and Data Augmentation

### Rescaling Pixel Values

Rescaling pixel values is a fundamental preprocessing step in deep learning image classification tasks. By normalizing the pixel values to a range between 0 and 1 (using the formula rescale=1. /255), the numerical stability of the learning algorithm is improved. This normalization ensures that gradients and weight updates during training are consistent, which leads to faster convergence and more reliable model performance.

### Importance of Normalization

1. **Numerical Stability**: Normalized inputs prevent large gradients, which can cause instability in training.
2. **Improved Convergence**: Consistent gradient magnitudes result in smoother and faster convergence.
3. **Better Generalization**: Normalized data can lead to models that generalize better to unseen data.

### Image Analysis and Resizing

Resizing images to a standard size (290x578 pixels) ensures that all images fed into the model are uniform in dimensions. This consistency is crucial for deep learning models, which typically require fixed input sizes.

### Resizing Process

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1. **Standard Size**: Images are resized to 290x578 pixels to match the input requirements of the model.
2. **Preserving Aspect Ratio**: Care is taken to maintain the aspect ratio of the images during resizing to avoid distortion.

**Impact of Resizing**
1. **Consistent Input Size**: Ensures that the model processes all images in the same manner.
2. **Improved Model Efficiency**: Standardized input sizes help in optimizing model performance and computational efficiency.

**Color and Intensity Analysis**
**Color Channel Histograms**
Analyzing color channel histograms involves examining the distribution of pixel intensities within each color channel (Red, Green, and Blue). This analysis helps understand the color composition of the images and informs preprocessing decisions.

**Histogram Analysis**
1. **Red, Green, and Blue Channels**: Histograms for each channel reveal the intensity distribution.
2. **Color Balance**: Helps in identifying if any color channel is dominant or lacking.

**Applications**
1. **Adjusting Preprocessing Techniques**: Histograms inform decisions on color normalization and adjustments.
2. **Feature Enhancement**: Provides insights into feature extraction methods based on color distributions.

**Grayscale Conversion and Histogram Equalization**
Converting images to grayscale simplifies the data by focusing on intensity rather than color. Histogram equalization enhances contrast by redistributing pixel intensities, making features more distinct.

**Grayscale Conversion**
1. **Simplification**: Reduces the complexity of the image by removing color information.
2. **Focus on Intensity**: Highlights features based on lightness and darkness.

**Histogram Equalization**
1. **Contrast Enhancement**: Improves visibility of features by stretching the intensity range.
2. **Feature Distinction**: Makes it easier for the model to detect and classify features.

**Edge Detection Techniques**
Edge detection techniques identify significant changes in pixel intensity, which correspond to the boundaries of objects within the image. Techniques such as Sobel, Prewitt, and Canny are used to enhance edges and aid in feature extraction.

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**Edge Detection Methods**

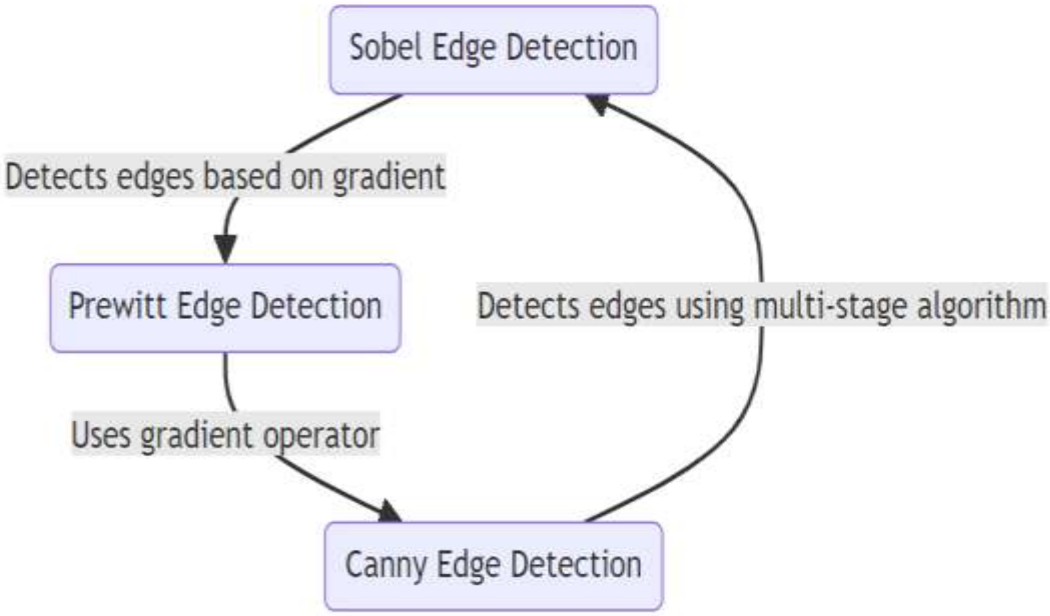


Fig: Edge Detection Methods

1. **Sobel Operator**: Detects edges by calculating gradient magnitude in both horizontal and vertical directions.
2. **Prewitt Operator**: Similar to Sobel, but with a different gradient calculation method.
3. **Canny Edge Detection**: Uses a multi-stage algorithm to detect a wide range of edges with high precision.

**Benefits**
1. **Feature Extraction**: Highlights boundaries and structures within the image.
2. **Enhanced Analysis**: Improves the model's ability to identify and classify edges and features.

**Image Denoising**
**Non-Local Means Denoising**
Non-Local Means (NLM) denoising is an advanced technique that reduces noise while preserving image details. It works by averaging similar patches of the image, which helps maintain textures and important features.

**NLM Denoising Process**
1. **Patch Similarity**: Finds and averages similar patches to reduce noise.
2. **Detail Preservation**: Maintains textures and fine details by considering similar patches.

**Advantages**

1. **Noise Reduction**: Effectively removes noise while preserving important image details.
2. **Enhanced Feature Clarity**: Helps the model focus on relevant features for classification.

**Feature Extraction**

Feature extraction involves identifying and extracting relevant features from images that are crucial for classification. Techniques such as histogram equalization and non-local means denoising enhance the quality of features extracted.

**Feature Extraction Techniques**

1. **Histogram Equalization**: Enhances contrast and highlights important features.
2. **Denoising**: Reduces noise, improving the clarity of features.

**Importance**

1. **Improved Classification**: Extracted features are used for training the model and making predictions.
2. **Enhanced Model Performance**: High-quality features lead to better classification accuracy.

**Contrast Enhancement and ROI Analysis**

**Contrast Enhancement**

Contrast enhancement techniques, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), improve the visibility of details in low-contrast regions by adjusting the contrast adaptively.

**Clahe Process**

1. **Adaptive Equalization**: Applies histogram equalization to small regions of the image, improving local contrast.
2. **Luminance Channel**: Enhances contrast in the Y channel of the YCbCr color space.

**Benefits**

1. **Improved Detail Visibility**: Enhances details in areas with low contrast.
2. **Better Feature Detection**: Helps the model detect and classify subtle features.

**Region of Interest (ROI) Analysis**

Analyzing the Region of Interest (ROI) involves focusing on specific parts of the image that are most relevant for disease detection. Contrast enhancement and ROI analysis improve the model's ability to detect diseases in targeted areas.

**Roi Process**

1. **Segmentation**: Identifies and isolates regions of interest within the image.
2. **Enhanced Focus**: Improves model accuracy by focusing on relevant regions.

**Histogram Equalization and Thresholding**

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Histogram equalization enhances the contrast of the ROI image, making features more distinguishable. Otsu's thresholding creates a binary image by segmenting foreground objects based on intensity levels.

**Histogram Equalization**

1. **Contrast Improvement**: Enhances contrast across the entire ROI.
2. **Feature Clarity**: Makes features more prominent for analysis.

**Otsu's Thresholding**

1. **Binary Segmentation**: Creates a binary image by selecting an optimal threshold based on intensity distribution.
2. **Foreground Detection**: Segments potential foreground objects, aiding in feature extraction.

**Applications**

1. **Improved Segmentation**: Helps in distinguishing between healthy and diseased regions.
2. **Enhanced Visualization**: Provides clear, binary images for further analysis.

**Model Architecture**

Model architecture plays a crucial role in the effectiveness of deep learning applications. In the context of apple disease detection, the architecture of the model significantly impacts the accuracy and efficiency of the system. This section elaborates on the MobileNetV3Small and Res MLP architectures, their integration, and the benefits of this hybrid approach.

**Mobile Net V3small**

MobileNetV3Small is a variant of the MobileNetV3 architecture designed specifically for efficiency in mobile and embedded devices. It balances computational resources with performance, making it well-suited for real-time applications like plant disease detection.
Architecture Details

**Convolutional Layers**

- **Depthwise Separable Convolutions**: MobileNetV3Small utilizes depthwise separable convolutions, which consist of a depthwise convolution followed by a pointwise convolution. This approach reduces the computational complexity and the number of parameters compared to traditional convolutions.
- **Depthwise Convolution**: Applies a single convolutional filter per input channel. This reduces the number of computations significantly.
- **Pointwise Convolution**: Uses 1x1 convolutions to combine the output of depthwise convolutions, enabling the learning of complex feature combinations.
- **Advantages**: Reduces computational cost and model size while maintaining high performance. This is particularly beneficial for mobile and edge devices where resources are constrained.

**Squeeze-And-Excitation (SE) Blocks**

 

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Attention Mechanisms: SE blocks are used to recalibrate channel-wise feature responses. They work by first squeezing the spatial dimensions of the feature map into a channel descriptor and then using a fully connected layer to compute channel-wise weights.

**Process**

- **Squeeze**: Aggregates global spatial information into channel descriptors using global average pooling.
- **Excitation**: Uses a fully connected layer with sigmoid activation to compute channel-wise weights, which are then applied to the feature map.

Advantages: Enhances important features while suppressing less useful ones, improving the representational capacity of the model.

**Efficient Processing**

Optimization for Mobile Devices: MobileNetV3Small is designed to operate efficiently on mobile and embedded devices, making it ideal for applications requiring low latency and minimal computational overhead.

**Efficiency Measures**: Incorporates optimizations like linear bottleneck layers and reduced parameter sizes to achieve high performance with low computational cost.

**Advantages**

1. **Efficiency**: MobileNetV3Small achieves efficient feature extraction with reduced computational and memory requirements. This makes it suitable for deployment on resource-constrained devices.
2. **Performance**: Despite its lightweight design, MobileNetV3Small maintains high accuracy, providing a good balance between performance and resource utilization.

**Residual Multi-Layer Perceptron**

Res MLP is a dense neural network architecture that incorporates residual connections. It is designed to enhance the representation of features extracted by preceding networks, such as MobileNetV3Small, by refining these features through a series of dense layers.
Architecture Details

**Dense Layers**

Layer Structure: Res MLP consists of multiple dense (fully connected) layers that transform the features extracted by the preceding network. These layers perform complex transformations to capture intricate patterns and relationships in the data.

**Function**: Each dense layer applies a linear transformation followed by a non-linear activation function (e.g., ReLU). This process allows the network to learn and represent complex feature interactions.

**Residual Connections**

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Purpose: Residual connections (or skip connections) allow the output of a layer to bypass one or more intermediate layers and be added directly to the output of a subsequent layer. This helps in mitigating the vanishing gradient problem and facilitates the training of deeper networks.
**Implementation**: In Res MLP, residual connections are optional but beneficial. They allow the model to maintain performance and stability even as the depth of the network increases.

**Advantages**
**Flexibility**: Res MLP's architecture can be adapted to various classification tasks by adjusting the number of layers and units in the dense layers. This makes it a versatile choice for refining features in different contexts.
**Improved Accuracy**: The residual connections in ResMLP enhance the learning capacity of the model, leading to improved classification accuracy through refined feature processing.

**Combined Model: MobileNetV3Small and Res MLP**
The hybrid approach integrates MobileNetV3Small and Res MLP to leverage their respective strengths. MobileNetV3Small provides efficient and effective feature extraction, while Res MLP refines these features for accurate classification.
Hybrid Approach

**Feature Extraction**
**Role of MobileNetV3Small**: The initial stage of the model focuses on extracting features from input images using MobileNetV3Small. This stage captures essential visual information and patterns relevant to apple disease detection.

**Feature Refinement**
**Role of Res MLP**: The features extracted by MobileNetV3Small are passed to Res MLP, which further refines these features through dense layers and residual connections. This stage enhances the discriminative power of the model and improves classification performance.

**Benefits**
**Balanced Performance**: The combination of MobileNetV3Small and Res MLP achieves a balance between accuracy and computational efficiency. MobileNetV3Small's lightweight design complements Res MLP's powerful feature refinement, resulting in a model that performs well across different criteria.
**Enhanced Detection**: The hybrid model improves the ability to detect and classify apple diseases by leveraging the strengths of both architectures. MobileNetV3Small captures essential features, while Res MLP refines these features for precise classification.
Detailed Explanation

**Mobilenetv3small**
- **Depthwise Separable Convolutions**: By separating the convolution operation into depthwise and pointwise convolutions, MobileNetV3Small reduces the computational cost

 

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while maintaining high performance. This approach is particularly effective for mobile and embedded devices where computational resources are limited.

- **Squeeze-and-Excitation Blocks**: SE blocks improve the representational power of the network by recalibrating channel-wise feature responses. This helps the model focus on the most informative features, enhancing its ability to detect subtle patterns and anomalies in apple leaves.

**Res MLP**

**Dense Layers**: These layers perform complex transformations on the features extracted by MobileNetV3Small. The use of dense layers allows the network to learn intricate patterns and relationships, improving its ability to classify images accurately.

Residual Connections: By incorporating residual connections, Res MLP addresses the challenges associated with training deep networks. These connections enable the model to learn more effectively, reducing the risk of vanishing gradients and improving overall performance.

**Combined Model**

Integration: The combined model leverages the strengths of both MobileNetV3Small and Res MLP. MobileNetV3Small efficiently extracts features from input images, while Res MLP refines these features for accurate classification. This hybrid approach achieves a balance between computational efficiency and classification accuracy.

- **Performance**: The integration of MobileNetV3Small and Res MLP results in a model that performs well in real-world scenarios. The efficiency of MobileNetV3Small ensures that the model can be deployed on resource-constrained devices, while the feature refinement provided by Res MLP enhances classification accuracy.

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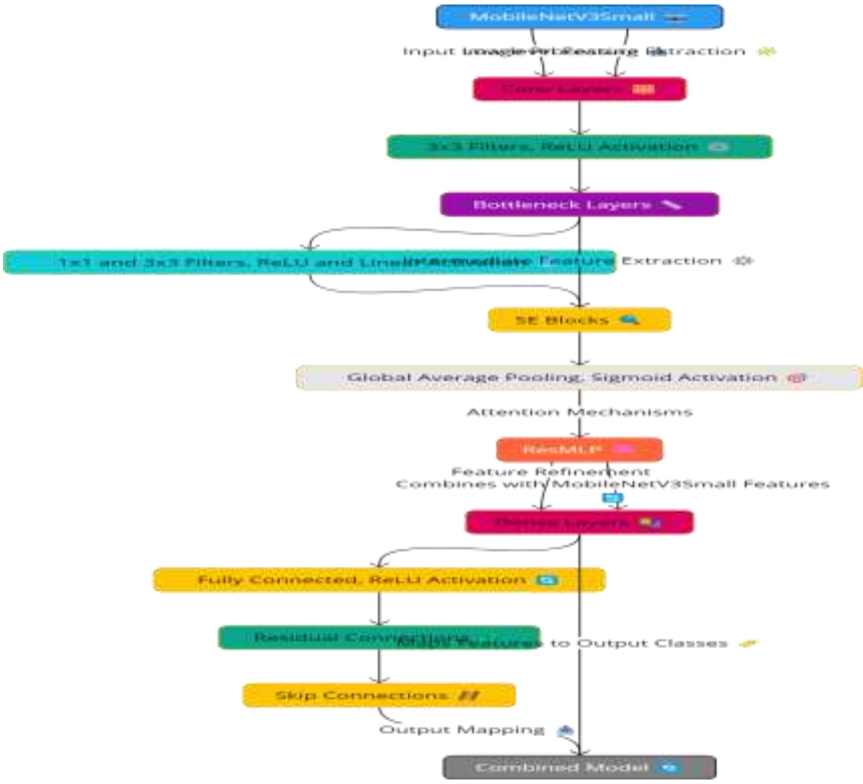
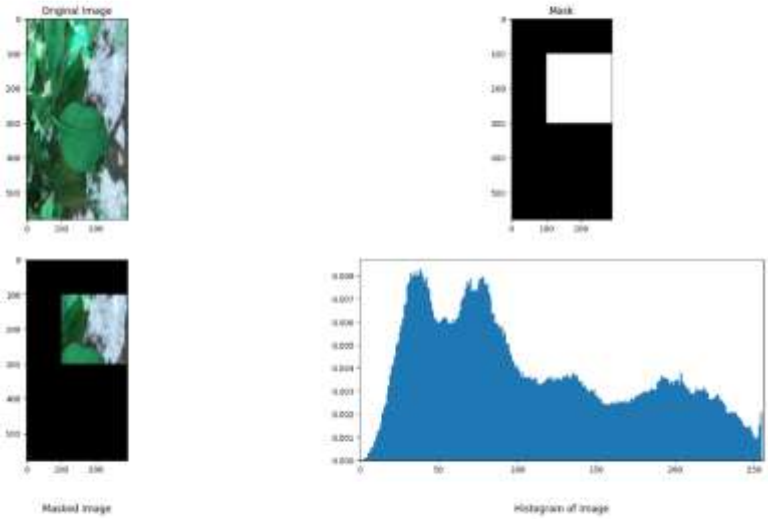



Fig 2: overall Architecture

## 4. RESULTS AND DISCUSSION

Applying masks to images and visualizing histograms help in understanding how masking affects image features and comparing histograms before and after masking.

**Mask Application**:



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1. **Creation and Application**: Masks are created to isolate specific regions and applied to the image to focus on areas of interest.
2. **Impact Analysis**: Examines how masking influences feature visibility and model performance.
3. **Histogram Visualization**:
4. **Comparison**: Compares histograms of original and masked images to assess changes in pixel intensity distribution.
5. **Analysis**: Helps understand the effects of masking on image features.

**Data Augmentation with Keras Image Data Generator**

The Keras Image Data Generator class provides a way to apply various augmentation techniques to training images. This helps create multiple versions of the same image, improving the model's robustness.

**Image Data Generator Techniques**

1. **Rotation**: Randomly rotates images to introduce variability in orientation.
2. **Horizontal Shift**: Shifts images horizontally to simulate different camera angles.
3. **Zoom**: Applies zoom transformations to vary image magnification.
4. **Horizontal Flip**: Flips images horizontally to balance dataset orientation.


**Benefits**:

**Enhanced Data Variety**: Generates diverse images from original data, improving model generalization.

**Reduced Overfitting**: Helps prevent overfitting by providing more training examples

## 5. CONCLUSION

In summary, the proposed hybrid model represents a significant advancement in apple disease detection, combining the strengths of MobileNetV3Small and ResMLP with advanced preprocessing techniques. Its ability to balance accuracy and computational efficiency makes it a valuable tool for precision agriculture, with potential applications extending beyond apple disease detection. The model's innovative approach and practical implications highlight its contributions to the field and set the stage for future developments in agricultural diagnostics. This detailed and comprehensive conclusion underscores the novel aspects of the hybrid model, its impact on the field, and its potential for future advancements. The integration of efficient feature extraction and refined classification, along with advanced preprocessing techniques, establishes a new benchmark for apple disease detection and offers valuable insights for future research and applications.

**Key Contributions**

1. **Advanced Preprocessing**: Utilizes cutting-edge techniques for image enhancement and feature extraction.
2. **Hybrid Model**: Combines efficient feature extraction with refined classification for superior performance.
3. **Future Work**:
4. **Model Optimization**: Further refine the model to improve performance and reduce computational requirements.
5. **Real-World Testing**: Evaluate the model in practical agricultural settings to assess its effectiveness in diverse conditions.

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