Optimizing Edge AI for Tomato Leaf Disease Identification

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ABSTRACT

This study addresses the critical challenge of real-time identification of tomato leaf diseases using edge computing. Traditional plant disease detection methods rely on centralized cloud-based solutions that suffer from latency issues and require substantial bandwidth, making them less viable for real-time applications in remote or bandwidth-constrained environments. In response to these limitations, this study proposes an on-the-edge processing framework employing Convolutional Neural Networks (CNNs) to identify tomato diseases. This approach brings computation closer to the data source, reducing latency and conserving bandwidth. This study evaluates various pre-trained models, including MobileNetV2, InceptionV3, ResNet50, and VGG19 against a custom CNN, training and validating them on a comprehensive dataset of tomato leaf images. MobileNetV2 demonstrated exceptional performance, achieving an accuracy of 98.99%. The results highlight the potential of edge AI to revolutionize disease detection in agricultural settings, offering a scalable, efficient, and responsive solution that can be integrated into broader smart farming systems. This approach not only improves disease detection accuracy but can also provide actionable insights and timely alerts to farmers, ultimately contributing to increased crop yields and food security.

Keywords-smart agriculture; plant disease; edge AI; CNN; MobileNet; inception; VGG19

I. INTRODUCTION

Optimizing agricultural yields has been a crucial goal since the inception of farming. Historically, the success of crops such as tomatoes has depended on variables such as weather, soil fertility, and disease management. Epidemics have periodically devastated crops, resulting in significant economic losses [1]. This ongoing battle against agricultural diseases has driven the evolution of farming techniques and technologies. In recent years, the integration of technology into agriculture has transformed tomato farming. Advanced Artificial Intelligence (AI) and Machine Learning (ML) models have been increasingly employed to predict and manage crop diseases, leading to significant yield improvements. Countries such as Germany, France, and Sweden have extensively adopted such technologies, demonstrating higher agricultural production compared to those with less technological integration [2]. Current research in AI-driven agricultural technology has made significant strides in disease detection. In [3], an image-based automatic diagnostic system was proposed for tomato plants, using CNNs to analyze tomato fruit and leaf images and achieving high accuracy in identifying disease patterns often missed by human inspectors. In [4], custom CNN models were used for reliable leaf disease detection. Further advances include the application of DL for automatic blight disease detection in tomato and potato plants, significantly reducing potential crop losses through early detection and intervention [5]. Reviews on AI applications in tomato leaf disease detection discuss various algorithms used for disease identification and classification, highlighting the evolution of ML techniques to improve diagnostic accuracy [6].

The use of drones equipped with sensors and AI models has been explored for precision farming, using transfer learning to adapt pre-trained models to local conditions and enhance the efficiency and accuracy of disease detection [7]. In [8], a U-Net model was employed for image segmentation, and CNNs were used to classify segmented tomato leaf images into ten disease categories, achieving 98.12% accuracy. CNNs have been used to identify different classes of tomato leaf diseases with 94% accuracy, demonstrating their efficacy in disease detection and management [9]. Despite these advances, the challenge remains to further optimize these technologies for real-time on-site applications. Using edge AI, which enables data processing directly on devices within the agricultural setting, latency issues can be minimized, and bandwidth requirements can be reduced. This approach holds promise in enhancing the practical applicability of AI in agriculture, particularly in resource-constrained environments. This study aims to demonstrate the efficacy of edge AI in detecting tomato plant diseases, positioning it as a critical technology for future agricultural yield optimization.

II. LITERATURE SURVEY

The bacterial canker of the 1910s, the tomato spotted wilt virus in the 1930s, and more recent fungal infestations underscore the vulnerability of tomato crops to diseases [11-12]. Historically, these outbreaks decimate entire fields before the cause could be identified, let alone contained. With advances in AI and ML, the possibility of early detection and rapid response has become a reality. Agricultural technology, especially AI, offers many algorithms capable of identifying patterns and anomalies in crop health that would otherwise go unnoticed by the human eye [13]. DL models such as CNNs have been successfully applied to detect plant diseases from images with remarkable accuracy [14]. Alongside CNNs, other AI models, such as SVMs and Random Forests (RFs), have been used for plant disease diagnosis. However, the true revolution is happening at the edge. By enabling real-time processing of data on devices within the agricultural setting, edge computing is set to transform crop management [15]. Imagine drones, equipped with sensors and edge AI models, patrolling the skies above tomato fields, scanning the crops below and processing terabytes of data on the fly to identify signs of disease or stress in plants. Edge AI models not only herald a new era of precision agriculture but also signify a shift from reactive to preventive farming practices [17]. By leveraging this technology, countries with expansive agricultural land, such as India, China, and Russia, could substantially increase their tomato yields, narrowing the productivity gap with smaller but technologically advanced countries. In this context, this study aims to demonstrate the efficacy of edge AI in detecting tomato plant diseases, positing it as a keystone technology for the future of agricultural yield optimization.

In [18], an image-based automatic diagnosis system was presented for tomato plants utilizing DL techniques. CNNs were used to analyze tomato fruit and leaf images for disease diagnosis. This system achieved high accuracy in identifying disease patterns that human inspectors often overlook. In [19], DL methods, specifically tailored CNN models, were used to improve disease management in tomato crops. In [20], deep neural networks were used to achieve early detection of blight disease in tomato and potato plants, enabling intervention to significantly reduce potential crop losses. In [21], a comprehensive review of AI applications in tomato leaf disease detection was presented. Various AI algorithms used for disease identification and classification were discussed, highlighting the evolution of ML techniques in improving diagnostic accuracy in the agricultural domain. In [22], drones equipped with sensors and AI models were used to detect diseases in tomato crops. This study used transfer learning techniques to adapt pre-trained models to local conditions, enhancing the efficiency and accuracy of disease detection. In [23], a U-Net model was used for image segmentation and CNNs were used to classify segmented images of tomato leaves into ten disease categories, achieving 98.12% accuracy. This demonstrates a high potential for automated disease detection to improve production and reduce crop losses. In [24], CNNs were used to identify eight different classes of tomato leaf diseases with an accuracy of 94.17%. This approach also included feature extraction techniques and demonstrated the efficacy of CNNs in disease detection and management. In [25], a mobile app was developed, which used YOLOv5 to detect tomato diseases and suggest remedies. The app demonstrated a mean average precision of 0.76, showing promise in providing accessible disease management solutions for farmers. In [26], a comprehensive review of the role of AI in sustainable tomato disease management was provided, highlighting several ML and DL techniques for effective disease classification.

Transfer learning models can be used to reduce data and computational costs in the detection of tomato diseases. In [27], the Resnet50 and Xception models were used, with Densenet_Xception achieving the highest accuracy of 97.1%. In [28], the need for automated, accurate, and cost-effective machine vision systems for tomato disease detection was highlighted, reflecting the shift towards automating diagnostic processes in agriculture. In [29], a hybrid approach was proposed using a modified VGG model integrated with an InceptionV3 block for tomato leaf disease classification. This approach achieved a high accuracy of 99.27% and demonstrated improved computational efficiency over traditional models. In [30], a comparative study evaluated the effectiveness of VGG16, ResNet50, and MobileNetV2 in classifying tomato leaf diseases. The highest accuracies were achieved for VGG16 and MobileNetV2, both exceeding 90%, indicating that shallow models can effectively classify tomato diseases. In [31], an optimized MobileNetV2 was used to achieve a classification accuracy of 98.3% and a recall rate of 94.9% for tomato leaf diseases, outperforming other architectures such as Xception and Inception. In [32], a basic CNN model was compared with VGG16, MobileNet, and InceptionV3, showing that MobileNet was the most efficient

due to its lightweight structure and high accuracy, making it ideal for mobile deployment. In [33], transfer learning was used with ResNet110 for tomato leaf disease detection, achieving a remarkable accuracy of 99.7%. This showcases the potential of advanced ResNet models in precise disease identification. In [34], MobileNetV3 models demonstrated exceptional performance, with MobileNetV3-Small achieving an accuracy of 98.99% and MobileNetV3-Large achieving 99.81%. These models were also tested on a workstation and a Raspberry Pi 4, showing promising latency results for practical IoT applications in agriculture [34].

In [35], specific ML and DL methods were explored to classify agricultural images with high accuracy. The results showed that the combination of Gaussian blur and Gaussian noise filters with RGB to CMYK color conversion yielded the highest accuracies: 98.27% for VGG-19, 94.98% for MobileNet-V2, and 99.53% for ResNet-50. The increasing global food demand, driven by population growth, underscores the need to increase agricultural yield and quality for sustainable development. In [36], MobileNet emerged as a highly effective model with an accuracy of 97.35% for multiclass classification and an even higher accuracy of 99.39% for binary classification. A web-based application facilitated prompt disease detection and alerts, to improve crop productivity and economic outcomes through timely interventions. Modified VGG-InceptionV3 and MobileNetV2 have shown particularly high accuracy rates, achieving up to 99.27% and 98.3%, respectively. These models demonstrate the potential of hybrid optimized architectures to reduce computational demands while maintaining high performance. Transfer learning models, such as ResNet and MobileNet, are adaptable to different datasets and local conditions, enhancing both the efficiency and generalizability of disease detection. Mobile applications that use architectures such as MobileNet and YOLOv5 indicate a move toward more user-friendly and accessible disease detection methods. These applications facilitate real-time data processing and disease management recommendations directly to farmers. While deeper networks such as VGG16 and ResNet50 offer high precision, lighter models such as MobileNet provide a balance of accuracy and computational efficiency, making them suitable for real-time and on-device applications.

Future research should focus on integrating advanced CNN architectures, such as InceptionV3 and DenseNet, with traditional models to explore hybrid approaches that could offer even better accuracy and processing times. Increasing the size and diversity of training datasets can further improve robustness and accuracy. Datasets covering a wider range of disease stages and environmental conditions are particularly valuable. There is substantial potential to deploy these models in real-time environments using IoT devices. Research can explore embedding optimized CNN models in drones or handheld devices for in-field disease detection. Ensuring that these advanced models are scalable and accessible to farmers worldwide, especially in developing countries, should be a priority. Simplifying user interfaces and reducing the cost of technology deployment is key. Future developments could focus on creating cross-compatible platforms that integrate different CNN models for comprehensive disease detection,

allowing users to select the most effective model based on their specific conditions and requirements. Building on these findings and focusing on the outlined future directions, researchers can significantly advance the field of agricultural AI, making effective and efficient disease detection more accessible to farmers around the world, thereby enhancing crop management and productivity.

III. METHOD

This study used the Plant Village dataset, specifically focusing on tomato leaf images [37]. This dataset contains a comprehensive collection of images representing various plant diseases. The images in the dataset vary in size, but all were resized to a uniform dimension of 256×256 pixels to maintain consistency during preprocessing and model training. The dataset includes images of tomato leaves categorized into ten distinct classes. The specific disease categories are bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, spider mites (two-spotted spider mites), target spot, yellow leaf curl virus, mosaic virus, and healthy. The tomato leaf subset comprises a total of 18,160 images. The dataset was split into training, validation, and testing sets. The training set consisted of 70% of the images (12,712 images), the validation set comprised 15% (2,724 images), and the testing set also included 15% (2,724 images). This split ensured a balanced representation of all disease categories across the different phases, promoting effective learning and accurate performance assessment. The dataset's diversity in disease representation and image conditions provided a solid foundation for training CNNs to accurately identify and classify tomato leaf diseases.

A. Data Preparation and Preprocessing

The images were preprocessed using TensorFlow and TensorFlow addons. ImageDataGenerator was employed to facilitate real-time data augmentation during model training, enhancing the variety of data. To further enhance the model's ability to generalize and improve its robustness against overfitting, the following data augmentation techniques were applied: rotation (images were randomly rotated by angles within the range of -40° to 40°), translation (images were randomly shifted horizontally and vertically by up to 20% of the total width and height), zoom (images were randomly zoomed in and out by up to 20%), horizontal flip (images were randomly flipped horizontally), and shear (images were sheared by up to 20%). These transformations were applied randomly to each image in the training set, creating a diverse set to train the models. As a result, the effective size of the training dataset was increased significantly. Specifically, the data augmentation process added approximately threefold the number of images to the original training dataset, resulting in an increased training set size of approximately 38,136 images. This increase in data diversity helps improve model performance and its ability to generalize to unseen data.

B. Model Architectures

This study used several well-known CNN architectures, including MobileNetV2, InceptionV3, VGG19, and ResNet50. A custom CNN model was designed as a baseline to benchmark the efficacy of transfer learning against a model trained from scratch. This architecture includes an input layer

for 256×256 RGB images, a first convolutional layer with 32 filters, 3×3 kernel, and ReLU activation followed by max pooling, a second convolutional layer with 64 filters, 3×3 kernel, and a ReLU activation followed by max pooling, a third convolutional layer 3 with 128 filters, 3×3 kernel, and ReLU activation followed by max pooling, a fully connected layer with 256 neurons with ReLU activation, and an output layer with 11 neurons (for the 10 disease categories and healthy class) and softmax activation.

MobileNetV2 is a lightweight and efficient DL model designed for mobile and edge devices. It employs depth-wise separable convolutions, significantly reducing the number of parameters and computational complexity without compromising performance. The architecture includes input layers, convolutional layers, inverted residual blocks, global average pooling layers, dense layers, and an output layer with softmax activation. InceptionV3 is known for its inception modules that perform convolutions of different sizes concurrently. The architecture includes input layers, convolutional layers, inception modules, auxiliary classifiers, global average pooling layers, dense layers, and an output layer with softmax activation. VGG19 is characterized by its deep architecture with 19 layers, primarily using 3×3 convolutional layers. The architecture includes input layers, convolutional layers, max-pooling layers, fully connected layers, and an output layer with softmax activation. ResNet50 employs residual connections to mitigate the vanishing gradient problem in deep networks. This architecture includes input layers, convolutional layers, residual blocks, global average pooling layers, dense layers, and an output layer with softmax activation.

C. Model Construction

The proposed transfer learning approach harnesses the power of MobileNet and Inception pre-trained networks to detect diseases in tomato plants through orchard imagery. Figure 2 shows the algorithm's architecture, which is designed to accommodate the intricacies of disease patterns on leaves.
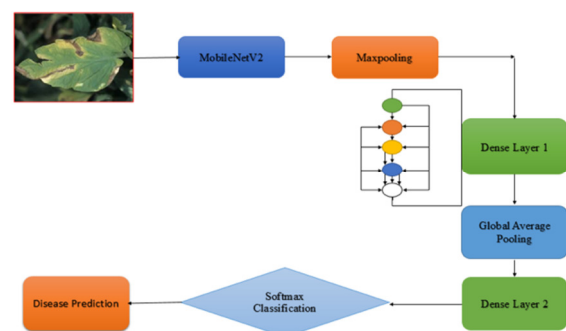

Fig. 1.   Transfer learning architecture representation of adapted MobileNetV2.

1) Step 1: Feature Extraction Using Pre-Trained Networks

The first step involves using pre-trained networks MobileNetV2, InceptionV3, VGG19, and ResNet50 as feature extractors. Each network is truncated to exclude its final classification layers, thus serving as feature extractors that

leverage the extensive feature representation learned from large datasets. Initially, the orchard image is input into a modified version of MobileNet or Inception networks, customized to function as the backbone network.

a) MobileNet as Backbone

The lightweight nature of MobileNet makes it particularly well-suited for edge devices. It employs depth-wise separable convolutions that significantly reduce the number of parameters without compromising the quality of features, which is a crucial aspect for deployment in resource-constrained environments. Table I shows a summary of the MobileNetV2 model.

TABLE I.   SUMMARY OF THE MOBILENETV2 MODEL

Layer Type	Output Shape	Parameters trained
MobileNetV2	(8,8,1024)	3228864
Global Average Pooling	1024	0
Dense	10	10250

For a given input feature map F and a depth-wise convolutional kernel K, the output feature map F' for depth-wise convolution can be described as:

$$Fk'(x,y) = \sum i,j Fk(x+i, y+j) \cdot Kk(i,j) \qquad (1)$$

where k indexes the channel, and i and j are the coordinates in the kernel. After depth-wise convolution, a point-wise convolution is applied to create a linear combination of the output of the depthwise filters:

$$F''(x,y) = \sum k Fk'(x,y) \cdot K'(k) \qquad (2)$$

where K is the point-wise convolutional kernel. The output of the inverted residual block, which consists of an expansion layer, depth-wise convolution, and a projection layer, can be represented as:

$$F'''=H(F+PointwiseConv(ReLU6(BatchNorm(DepthwiseConv($$
$$ReLU6(BatchNorm(PointwiseConv(F \cdot \alpha)))))))) \qquad (3)$$

where F is the input feature map, α is the expansion factor, and H is the hard-sigmoid function applied in the projection layer for non-linearity. The stride s and filter size f for each layer can be introduced to describe how the spatial dimensions of the feature map are transformed:

$$W' = [(W - F + 2P)/S] + 1 \qquad (4)$$

$$H' = [(H - F + 2P)/S] + 1 \qquad (5)$$

b) Inception as Backbone

Alternatively, the Inception model, known for its inception blocks that perform convolutions of different sizes concurrently, allows the model to capture information at various scales. This property is particularly beneficial when dealing with the multiscale nature of leaf disease manifestations.

2) Step 2: Deep and Shallow Feature Fusion Module

Following feature extraction, the algorithm transitions to the fusion module. This step integrates the extracted features at various depths through a dual attention mechanism. The dual attention mechanism serves a similar purpose as described in the reference structure, enhancing salient features and suppressing irrelevant ones across the scales. This enriched feature set is more representative of the nuanced patterns associated with different diseases. This process involves deep features extracted from the later layers of the pre-trained networks, capturing complex patterns and high-level representations, and shallow features extracted from the earlier layers, capturing basic patterns such as edges and textures. The fusion mechanism combines deep and shallow features using concatenation and attention mechanisms to form a comprehensive feature set.

3) Step 3: Disease Detection Branches

The fused feature maps are then used to deploy three specialized detection branches, each operating at distinct scales corresponding to the nature of the detected features. The fine-grained branch focuses on early-stage or minor symptoms, using a shallow network with smaller filters and higher resolution. The medium-grained branch targets intermediate disease stages, using a balanced network depth and filter size. The coarse-grained branch detects well-developed disease signs, using deeper layers and larger filters. Each branch employs the Non-Maximum Suppression (NMS) algorithm to refine detections by eliminating redundancy and focusing on the most relevant disease indicators. The final result is a robust detection system capable of identifying various stages and types of disease in tomato plants.

IV. RESULTS AND DISCUSSION

An exhaustive comparative study was performed between the different CNN architectures to identify tomato leaf diseases.

A. Custom CNN Model

The Custom CNN model was applied independently as a baseline model. It demonstrated progressive improvement in training accuracy over epochs, reaching modest levels. However, it displayed a marked disparity in performance on the validation set with significantly lower accuracy, which could be attributed to overfitting or limited capacity.

B. MobileNet

The MobileNet model consistently outperformed the other models in terms of accuracy and loss metrics. The accuracy of the MobileNet model for the training dataset quickly stabilized at a high level, maintaining close to 1.0 after the initial epoch, indicating a strong ability to generalize from the training data. Similar results were observed in the validation dataset, where MobileNet achieved an accuracy that consistently exceeded 0.95 after the initial epoch, significantly outperforming other models as shown in Figure 2. The loss analysis also supported the superior performance of the MobileNet model. In the validation dataset, MobileNet demonstrated a rapid decline in loss, stabilizing at significantly lower values than the other models. This trend was evident from the first epoch and continued throughout the testing period, suggesting that MobileNet was more effective in minimizing error in classification tasks relative to its counterparts, as shown in Figure 3.
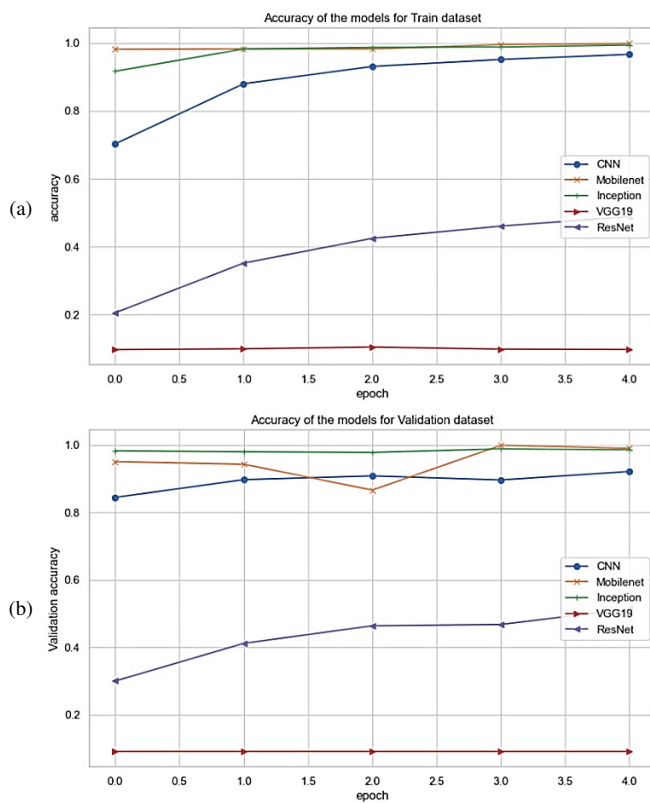
(a)

(b)

Fig. 2.   Overall accuracy, averaged across all classes (a) comparative performance of training accuracy for all models, (b) validation accuracy for all trained models.

C. Inception

Inception, with its intricate design of modules that allow for multi-scale feature extraction, performed admirably, registering high training accuracy that was close to that of MobileNet. Validation accuracy plateaued at high levels, indicative of a strong generalization capability. The losses for both training and validation datasets exhibited a steady decrease, settling at low values that correspond to high accuracy, underscoring the model's effectiveness at learning and generalizing from the dataset.

D. VGG19

VGG19, characterized by its deep architecture and repeated stacking of convolution layers, did not perform as expected. Training accuracy was low and did not improve significantly over time, suggesting that the model may not be as adept at transferring knowledge to this particular task or that it might require more training time or data augmentation to reach its potential. The validation accuracy was also low, further confirming its challenges in adapting to this specific problem. Similarly, the loss metrics for VGG19 remained high for both training and validation, indicating a struggle to minimize prediction errors.

E. ResNet

ResNet, renowned for its residual connections that help against the vanishing gradient problem in deep networks, showed excellent performance on the training set. However,

the validation results were less impressive, as the accuracy improved only marginally over epochs. This discrepancy suggests that while ResNet could learn the training data, it may not have been as effective in generalizing these learnings to the validation set, potentially due to overfitting. The loss metrics mirrored this, with training loss decreasing significantly and validation loss showing minimal improvement.
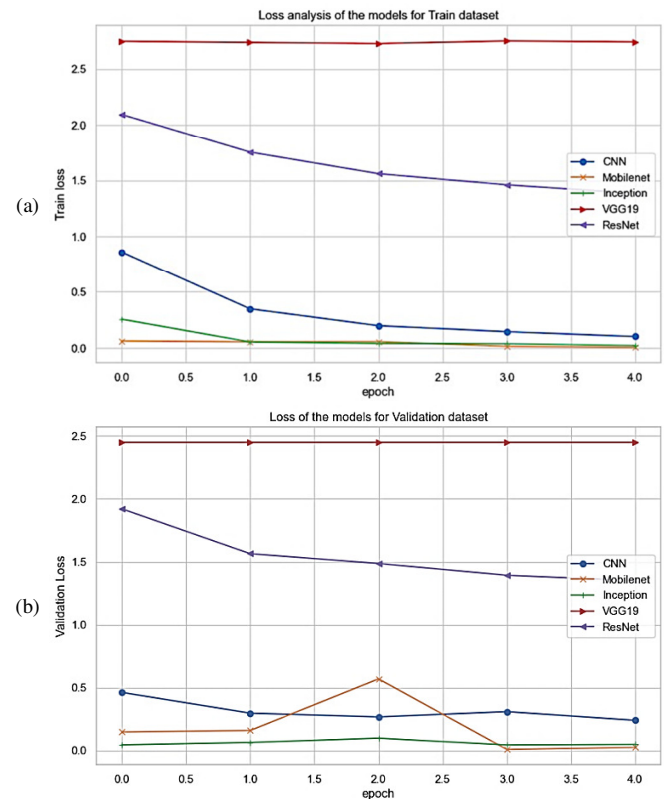

(a)

(b)

Fig. 3.   (a) Comparison analysis for training loss across the models, (b) comparison analysis of validation loss across the models.

F. Model Comparison and Summary

In some models, validation accuracy initially dropped and then increased again. This phenomenon could be due to the model learning to generalize better after initially fitting the training data too closely. This finding indicates the importance of early stopping and regularization techniques in preventing overfitting. In addition, the accuracy was not uniform across all classes. Certain disease categories, such as early blight and bacterial spot, had higher accuracy due to more distinct visual patterns, whereas categories such as leaf mold and target spot had lower accuracy due to more subtle differences. The loss was calculated using categorical cross-entropy, which is suitable for multiclass classification problems. This metric measures the difference between the predicted probability distribution and the actual distribution, providing a comprehensive evaluation of the model's performance.

A comparative analysis of metrics across models on the test dataset revealed that both MobileNet and Inception outperformed their counterparts in terms of accuracy, precision,

recall, and AUC. This proves their ability to effectively transfer learned features from large datasets to the task of identifying tomato leaf diseases. In particular, MobileNet's balance of efficiency and performance, as shown in Figure 3, makes it highly suitable for deployment on edge devices where computational resources are at a premium. The results suggest that when it comes to edge AI and the task of detecting tomato leaf diseases, compact but powerful models such as MobileNet and Inception are preferable, as they not only achieve high accuracy but also maintain this performance across training and validation phases, which is crucial for real-world applications. VGG19's underperformance could be rectified with further tuning, but its larger architecture makes it less ideal for edge deployment. ResNet's ability to learn the training data did not translate as effectively to unseen data, indicating a need for improved regularization or data augmentation techniques. These results underscore the importance of selecting the right architecture and fine-tuning transfer learning approaches to suit the specific nuances of the task, especially when computational efficiency is as important as predictive accuracy.
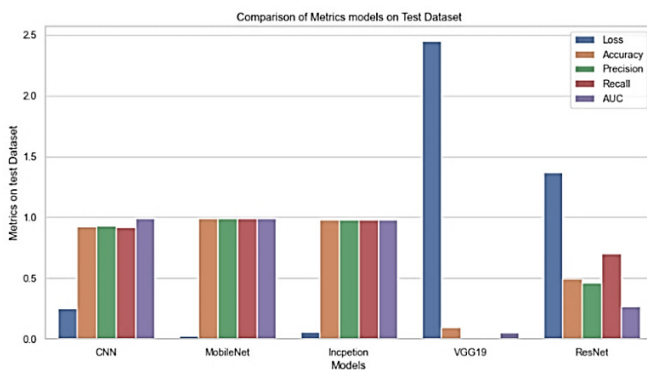

Fig. 4.   Metrics comparison on all trained models.

V.   CONCLUSION AND FUTURE WORK

This study made significant strides in addressing the urgent need for efficient real-time detection of tomato leaf diseases using edge computing. The deployment of CNNs at the edge, particularly with lightweight models such as MobileNet and Inception, can revolutionize disease detection in agricultural settings. These models have showcased not only their accuracy and speed but also their aptitude for generalization, which is vital for reliable deployment in varied and unpredictable real-world conditions. The results confirmed that the computational efficiency and rapid inference times of these models make them exceptionally well-suited for integration into mobile devices and edge-based systems, which are becoming increasingly prevalent in precision agriculture. This marks a substantial advancement from traditional cloud-based systems, plagued by latency and bandwidth limitations, toward more autonomous, responsive, and sustainable agricultural technology practices.

Looking to the future, this study opens several avenues for advancement. These models can be further refined through extensive hyperparameter tuning and incorporate novel neural network architectures that could offer even greater efficiency and accuracy. Research could also benefit from expanding the dataset to include a wider variety of disease manifestations, as well as exploring the effects of various environmental factors on disease development and detection. An important future direction involves the integration of these AI models into a broader suite of smart farming tools. By combining edge AI with IoT sensors for real-time monitoring of plant health, soil conditions, and environmental factors, a comprehensive AI-driven decision support system could be developed for farmers. Such a system would not only detect and diagnose diseases but also recommend optimal interventions based on a holistic view of the crop's health and environmental conditions. Additionally, advanced data augmentation techniques and synthetic data generation could enhance model robustness and generalization, especially in scenarios with limited labeled data. Investigating and implementing advanced model optimization techniques, such as pruning, quantization, and Neural Architecture Search (NAS), can further reduce computational requirements while improving performance on edge devices. Lastly, exploring a collaborative edge-cloud framework can balance the benefits of low latency and high computational power, ensuring scalable and efficient disease management solutions. These advances have the potential to significantly improve the precision and efficacy of agricultural AI applications, making them more accessible and impactful for farmers around the world.

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