



Enhanced Approach for Classification of Apple Disease Using Different Deep Learning Models

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ABSTRACT

Farmers typically lack knowledge of diagnosing and controlling different apple diseases. However, some apple diseases have visual symptoms that the eye can diagnose, but their diagnosis is time-consuming and costly. Earlier detection of infections and crop health issues can enable control of fruit diseases through effective management approaches. A proposed solution is to design an automatic disease diagnosis system using image processing techniques. This paper presents a low-cost method for apple disease diagnosis using a neural network and classifying fruit into four classes: scab, bitter rot, black rot, and healthy. This method involves different models (VGG-16, VGG-19, and ViT) and feature extraction to tackle this problem; we introduce the Vision Transformer image detection (ViT) Model to classify apple diseases. Initially, preprocessing was performed using an image processor, feature scaling, feature extraction, feature normalization, data augmentation, and hyperparameter tuning. Finally, the classification section compares ViT with other models, such as the Visual Geometry Group – 16 layers (VGG-16) and the Visual Geometry Group – 19 layers (VGG-19). The average accuracy of VGG-16 for disease classification is 97.03%. The average accuracy of the Visual Geometry Group – 19 layers (VGG-19) for disease classification is 95.5%. The proposed ViT model can significantly improve the accuracy of apple fruit disease classification. The average accuracy of disease classification achieved with the current proposed techniques was 99.17%.

Keywords: Apple Disease, Deep Learning Models, Rot, Scab, Blotch

INTRODUCTION

Apple cultivation takes place in 94 countries worldwide (Kavya et al., 2024). It is among the most widely grown deciduous fruits, with its origin traced to Central Asia, from which it gradually spread to various regions of the world. At present, China is the largest producer of apples, followed by the United States, Italy, and France (Dubey & Jalal, 2012). Due to their nutritional and health benefits, apples are cultivated in nearly all parts of the world. However, variations in climate and economic resources result in uneven production levels across countries (Bhat et al., 2025; Rai et al., 2015). The ten leading apple-producing countries, along with their production (in tons), are as follows: China – 47,573; Turkey – 4,818; United States – 4,429; Poland – 4,265; India – 2,589; Russia – 2,380; Italy – 2,256; Iran – 1,990; France – 1,786; and Chile – 1,480 (Dubey & Jalal, 2012; Muder et al., 2022). Another important measure is apple production per capita, which reflects the efficiency of production relative to population size (Sun et al., 2021). This parameter highlights countries where apple cultivation plays a central role in agriculture and contributes significantly to the economy (Muder et al., 2022). The Republic of Moldova ranks highest globally with 0.168 tons of apples produced per person, followed by New Zealand (0.119 tons), Poland (0.111 tons), North Macedonia (0.079 tons), Chile (0.077 tons), Bosnia and Herzegovina (0.064 tons), Turkey (0.057 tons), Belarus (0.077 tons), Serbia (0.056 tons), and Uzbekistan (0.039 tons) (Kavya et al., 2024). Countries with favorable climatic conditions and long-standing apple-growing traditions dominate this list. Pakistan is ranked 19th globally in terms of apple production. The climatic conditions and fertile soils of the country promote significant variation in apple size, color, shape, and taste (Sugiarti et al., 2021a). Thousands of apple varieties are cultivated worldwide, each with unique features such as size, color, flavor, texture, ripening time, shelf life, and disease resistance (Foong et al., 2021; Szot et al., 2022). These varieties are generally classified into three categories: (a) cider apples, (b) cooking apples, and (c) dessert apples, which differ in color, aroma, crispness, and taste. Popular apple varieties include Red Delicious, Golden

Delicious, Gala, Fuji, Granny Smith, Honeycrisp, Braeburn, McIntosh, Jonagold, and Pink Lady (Brown & Maloney, 2018; Foong et al., 2021).

In Pakistan, apples have been cultivated for centuries, particularly at higher altitudes (around 1,300 m) in regions bordering Afghanistan, Iran, and China (Sugiarti et al., 2021a). Apple cultivation is of major economic significance, with Balochistan contributing about 80% of the national output. Apple plants are susceptible to several diseases that affect both apple leaves and apple fruits. Major apple leaf diseases include Apple Scab, Fire Blight, Powdery Mildew, and Cedar Apple Rust, while fruit diseases include bacterial, fungal, viral, viroid, and miscellaneous disorders (Subha & Kasturi, 2024b). This study specifically focuses on three important fungal apple fruit diseases, including (a) Apple Scab, (b) Apple Rot, and (c) Apple Blotch.

Apple Scab

It is a fungal disease that begins with spores in the soil or air (Sattarova & Soatov, 2024). The disease spreads more in damp weather, when the air is not moving well, or the soil holds too much water (Jamwal et al., 2022). If trees are not pruned or cleaned properly, the problem gets worse. It appears as dark, rough spots on apple leaves and fruit, which lower their quality and marketability (Hasan et al., 2024).

Apple Rot

It is a fruit disease caused by fungal spores found in the soil or air (Jamwal et al., 2022). The problem mostly occurs in wet, humid conditions (Liu et al., 2022). Apples develop soft, brown, and decayed spots that spread quickly, especially when fruits are damaged or not handled and stored properly after harvest (Shewa et al., 2022; Singh & Aravind, 2021).

Apple Blotch

It is a fungal disease that mostly occurs in warm and humid weather. The infection spreads from nearby infected plants and becomes worse when air circulation is poor, the soil stays too wet, or trees are not pruned and cleaned properly (Sattarova & Soatov, 2024). It appears as dark, irregular patches on apple leaves and fruit, reducing their quality and market value (Kviklys et al., 2022). Some apple diseases are illustrated in Figure 1 below.

Earlier research applied various machine learning and deep learning models for the classification of apple diseases, achieving high accuracy rates (Khan et al., 2022). Convolutional Neural Networks (CNNs) such as VGG-16, VGG-19, ResNet50, InceptionV3, DenseNet121, and MobileNet have been applied to identify apple defects, including blotch, scab, and rot. The results showed that VGG-16 achieved an accuracy of 89.50%, VGG-19 achieved 82.60%, ResNet50 achieved 41.10%, InceptionV3 achieved 93.30%, DenseNet121 achieved 93.20%, and MobileNet achieved the highest accuracy of 98.70%, based on evaluation metrics such as precision, recall, and F1-score (Kavya et al., 2024). A Convolutional Neural Network (CNN) achieved an accuracy of 99.17% in detecting apple defects such as blotch, scab, and rot, using a dataset split of 90% for training and 10% for testing, while also evaluating key performance metrics including precision, recall, and F1-score (Dubey & Jalal, 2012). Naive Bayes achieved an accuracy of 96.43% in detecting apple defects such as blotch, rot, and scab using texture-based GLCM feature extraction (Sugiarti et al., 2021a). Another study using a Convolutional Neural Network (CNN) with ResNet-50 achieved 98.89% validation accuracy in detecting and classifying rotten fruits such as bananas, apples, and oranges (Foong et al., 2021). Similarly, a combination of Deep Convolutional Generative Adversarial Network (DCGAN) and Deep Convolutional Neural Network (DCNN) achieved an exceptionally high accuracy of 99.99% in classifying apple blotch, rot, and scab (Ayaz et al., 2021). Furthermore, the Deep Spectral Generative Adversarial Networks (DNRCNN) model attained 94.25% overall accuracy, while the DenseNet recursive Convolutional Neural Network (DSGANs) model achieved 93.5% overall accuracy although regarding sensitivity, specificity, and F1-Score, the proposed models showed higher credibility and performance than the existing algorithmic methods such as DSGANs and DNRCNN yielded 92.5% and 93.14% in sensitivity, 92.9% and 93.21% for specificity, and 93.1% and 94.35% for F1-Score (Tian et al., 2021). The Multi-scale Dense Inception-V4 and Multi-scale Dense Inception-Resnet-V2 achieved overall accuracies of 94.31% and 94.74%, respectively, in the classification of 11 types of apple leaf and fruit images. Different metrics, such as accuracy, precision, sensitivity, and F1-score, were used to compare different models across datasets (Tian et al., 2021). The Deep Spectral Generative Adversarial Networks (DSGAN) model attained 93.5% higher performance accuracy over 40 apples, 92.5% in sensitivity over 40 apples, 92.9% for specificity over 40 apples and 93.1% for F1-Score over 40 apples (Subha & Kasturi, 2024b).

However, previous studies have widely used traditional machine learning and deep learning models, such as CNN-based architectures (VGG-16, VGG-19, ResNet50, InceptionV3, DenseNet121, and MobileNet), achieving high accuracy in detecting apple diseases (Ait Nasser & Akhloufi, 2024). However, most of these works reported



Fig 1: Apple Disease Classification.

results closest to 98% accuracy, leaving little scope to explore commonly used models with relatively lower performance, such as VGG-16 and VGG-19. Moreover, while advanced architectures such as Vision Transformer image detection (ViT) have recently shown promise in plant disease detection, they have been used only for apple leaves, not for apple fruits (Ali et al., 2025; Barman et al., 2024; Nishankar et al., 2025). Importantly, no prior study has reported such experiments in Pakistan, further strengthening the novelty of this research.

Deep learning has become one of the most effective methods for identifying plant and fruit diseases in recent years. CNN-based models used in past research include VGG-16, VGG-19, ResNet50, InceptionV3, DenseNet121, and MobileNet, and most achieve an accuracy of about 98% (Shah et al., 2023). Other architectures, such as VGG-16 and VGG-19 demonstrated comparatively lower performance than others. The Vision Transformer (ViT) model has been of interest for detecting plant diseases, although it has not yet been used on apple fruits; it has been used on apple leaves. To close the gap, the current study uses ViT to detect apple fruit diseases and enhances the accuracy of VGG-16 and VGG-19. Moreover, this study has not been conducted with these models in the context of Pakistan before; thus, it is new and important for creating automated solutions to support local agriculture.

The study aims to identify the presence of apple fruit diseases, including scab, rot, blotch, and normal apple fruits, using deep learning methods. To maintain the reliability of the dataset, Kaggle was used as the source, unlike past studies that used mixed or random datasets. The Vision Transformer (ViT) model has been used for the first time to detect apple fruit disease, achieving better accuracy, F1-score, sensitivity, and specificity. Also, VGG-16 and VGG-19, which had lower accuracy, were optimized to perform better. This paper, therefore, broadens the scope of deep learning by proposing a new model and improving on existing models for the classification of apple fruit diseases.

Related Work

The related work is organized into three sections: Sections A and B provide an overview of apple diseases and the techniques used to detect them, while Section C presents a detailed literature review. Previous researchers classified apple diseases such as apple rot, apple scab, and apple blotch using a Naïve Bayes Classifier (Ahmed & Yadav, 2024; Sugiarti et al., 2021a). Classify fresh and rotten fruit apples, banana and orange (Foong et al., 2021). Classification of apple disease such as apple blotch, apple scab and apple rot (Ayaz et al., 2021). Classification of apple disease such as apple blotch, apple rot and apple scab (Dharm et al., 2019; Singh et al., 2022). Classification and detection of apple diseases such as apple scab, apple blotch, and apple rot (Subha & Kasturi, 2024a). The detection of apple disease such as apple scab, apple bitter rot and apple rust (Azgomi et al., 2023) (Singh et al., 2022). Classification of apple diseases such as apple blotch, apple scab and apple rot [1]. This study focused on the classification of apple scab, apple rot, apple blotch and normal apple. Past studies in this domain have applied Naïve Bayes classifier, Gray level co-occurrence matrix (GLCM) and K-Mean clustering (Sugiarti et al., 2021a), the CNN-based rotten fruit detection using ResNet 50 model (Foong et al., 2021). Non-linear deep features and imposed the DCGAN-DCNN models (Ayaz et al., 2021). Imposed the Resnet50 (Dubey & Jalal, 2016), the DNRCNN and DSGANs models [10], CNN model for the detection of apple disease (apple scab, apple bitter rot and apple rust) and different deep learning models including VGG-16, VGG-19, Resnet50, Inception V3, Densenet-121 and Mobile Net. This study used CV2 to split the data into training and test images. For resizing and feature shape, use global average pooling 2D and ResNet50, then apply the ViT Models VGG-16 and VGG-19, and plot the graphs of training, testing, and loss accuracy, the confusion matrix, Specificity, and Sensitivity.

Convolutional Neural Networks (CNNs) such as VGG-16, VGG-19, ResNet50, InceptionV3, DenseNet121, and MobileNet have been applied to identify apple defects, including blotch, scab, and rot. The results showed that VGG-16 achieved an accuracy of 89.50%, VGG-19 achieved 82.60%, ResNet50 achieved 41.10%, InceptionV3 achieved 93.30%, DenseNet121 achieved 93.20%, and MobileNet achieved the highest accuracy of 98.70%, based on evaluation metrics such as precision, recall, and F1-score (Kavya et al., 2024).

A Convolutional Neural Network (CNN) achieved an accuracy of 99.17% in detecting apple defects such as blotch, scab, and rot, using a dataset split of 90% for training and 10% for testing, while also evaluating key performance metrics including precision, recall, and F1-score (Dubey & Jalal, 2012). Naive Bayes achieved an accuracy of 96.43% in detecting apple defects such as blotch, rot, and scab using texture-based GLCM feature extraction (Sugiarti et al., 2021a). Another study utilizing a Convolutional Neural Network (CNN) with ResNet-50 demonstrated strong performance, achieving 98.89% validation accuracy in detecting and classifying different rotten fruits such as bananas, apples, and oranges (Foong et al., 2021) Similarly, a combination of Deep Convolutional Generative Adversarial Network (DCGAN) and Deep Convolutional Neural Network (DCNN) achieved an exceptionally high accuracy of 99.99% in classifying apple blotch, rot, and scab (Ayaz et al., 2021).

Furthermore, the Deep Spectral Generative Adversarial Networks (DNRCNN) model attained 94.25% overall accuracy. In comparison, the DenseNet recursive Convolutional Neural Network (DSGANs) model achieved 93.5% overall accuracy. However, regarding sensitivity, specificity, and F1-Score, the proposed models showed higher credibility and performance than the existing algorithmic methods, such as DSGANs and DNRCNN, which yielded 92.5% and 93.14% in sensitivity, 92.9% and 93.21% for specificity, and 93.1% and 94.35% for F1-Score (Subha & Kasturi, 2024a). The Multi-scale Dense Inception-V4 and Multi-scale Dense Inception-Resnet-V2 achieved overall accuracies of 94.31% and 94.74%, respectively, in the classification of 11 types of apple leaf and fruit images.

Different metrics, such as accuracy, precision, sensitivity, and F1-score, were used to compare different models across datasets (Tian et al., 2021).

The Deep Spectral Generative Adversarial Networks (DSGAN) model attained 93.5% higher performance accuracy over 40 apples, 92.5% in sensitivity over 40 apples, 92.9% for specificity over 40 apples and 93.1% for F1-Score over 40 apples (Subha & Kasturi, 2024b). Several researchers have proposed different approaches for apple disease detection and classification using both traditional machine learning and modern deep learning techniques. One study applied the Naïve Bayes classifier combined with GLCM and K-Means clustering, achieving an accuracy of over 96.43% for apple rot, scab, and blotch (Subha & Kasturi, 2024a). Deep learning methods showed even stronger performance, such as ResNet-50 with transfer learning, which classified fresh and rotten fruits (apple, banana, and orange) with 98.89% accuracy (Dubey & Jalal, 2012). Another researcher used DCGAN-DCNN models for apple blotch, scab, and rot, obtaining an outstanding accuracy of 99.99% (Manzoor et al., 2024). Similarly, a ResNet-50 model trained on 570 images from Kaggle and Google achieved 95.24% accuracy for blotch, 100% for rot, and 80.95% for scab (Foong et al., 2021). Advanced architectures such as DNRCNN and DSGANs also showed promising results, achieving accuracies of 94.25% and 93.5%, respectively, on a dataset of 2,154 images. However, performance was affected by factors such as image resolution, background noise, and lighting conditions (Subha & Kasturi, 2024a). Another CNN-based model with four convolutional layers achieved 90% accuracy on apple scab, bitter rot, and rust, but using only 570 images led to overfitting and limited disease variation (Foong et al., 2021). A broader comparative study tested VGG-16, VGG-19, ResNet-50, Inception V3, DenseNet-121, and MobileNet on 2,000 manually collected high-resolution images, reporting the best accuracy with MobileNet (98.70%), followed by DenseNet-121 and Inception V3 (93.30%), while VGG-16 (89.50%), VGG-19 (82.60%), and ResNet-50 (41.10%) performed relatively lower. However, frequent misclassification between apple scab and apple rot was noted due to their similar visual characteristics (Sugiarti et al., 2021a; Zhang et al., 2025).

The literature review summarizes that traditional models, such as Naive Bayes performed reasonably well (96%). Deep learning models such as MobileNet, InceptionV3, and DCGAN-DCNN achieved very high performance (up to 99.99%), whereas previous architectures such as VGG-16 and VGG-19 did not achieve high accuracy (Mascarenhas & Agarwal, 2021; Sugiarti et al., 2021b). The Vision Transformer (ViT) model is used in this work, which learns more discriminative features and operates on image patches rather than entire images. Consequently, ViT improves performance over older CNN-based models, especially in comparison with the poorer performance of VGG-16 and VGG-19, and thus proves effective for robust apple disease classification.

MATERIALS AND METHODS

Google Colab was adopted as the main tool of model implementation and training in the proposed workflow (Figure 2). It was through the Kaggle repository (Apple Fruit Disease). The collected images were preprocessed, including augmentation, to enhance sample size and model generalization. The experimental design was designed to answer the research questions on the importance of preprocessing evaluation and the performance of various deep learning models (ViT, VGG-16, and VGG-19) in improving apple disease classification performance.

Dataset

Datasets In this simulation experiment, we used the Apple Fruit Disease dataset collected from the online <https://www.kaggle.com/datasets/kaivalyashah/apple-disease-detection>. Here, this link is used to download the dataset. Figure 2 represents the blotch apple shown in (a), the normal is shown in (b), the rotting apple is represented in (c), and the scab apple is displayed in (d). To maintain a balanced dataset, the images per category are split at a 70:30 ratio.

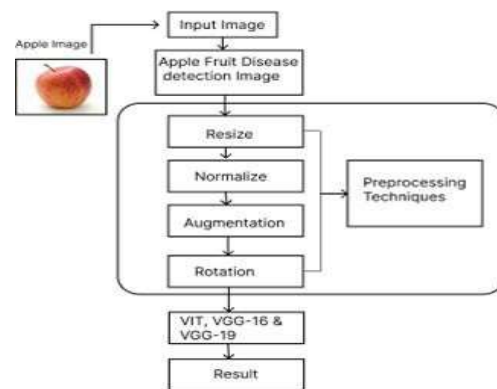


Fig 2: Methodology.

RESULTS AND DISCUSSION

This study classifies apple diseases, specifically apple scab, apple rot, and apple blotch, using different models such as VGG16, VGG19, and ViT. Table 1 shows the overall accuracy of the three models: ViT generates an accuracy of 99.17%, VGG-19 generates an accuracy of 95.05%, and VGG-16 displays an accuracy of 97.03%.

ViT MODEL

The ViT model's training and validation accuracies are shown in figure 3. The training accuracy increases rapidly from 1-4 epochs, indicating that the model is learning the basic pattern in the dataset, while the validation accuracy

Table 1: Overall result

Model	Accuracy
VIT	99.17%
VGG-19	95.05%
VGG-16	97.03%

is better in this phase. During 5-10 epochs, the dataset slowly increases in both validation and training, and by the time it approaches 95%, the gap between them remains small, indicating good generalization. During the 11-15 epochs, training accuracy approached 100% and validation accuracy stabilized around 97%-

98%. The small gap between training and validation accuracy indicates minor overfitting. In figure 4, the training and validation losses over 15 epochs show a rapid reduction in the first 4 epochs, with a higher loss at epoch 1, indicating that the model is initially far from optimal. Both training and validation losses drop sharply, indicating that the model is quickly learning important features from the dataset. Epoch's 5-10 loss continues to decrease, but the rate of reduction slows, suggesting the model is refining its understanding rather than making large adjustments. Epochs 11-15: training loss continues to decrease slowly, and validation loss becomes smoother and slightly increases after the 13th epoch. In figure 5, the training, validation, and test accuracy over 15 epochs show that during 1-4 epochs, both training and validation accuracy grow slowly from 50% to ~80%, indicating the model is in the learning phase and the test accuracy has not been evaluated yet at this stage. During epochs 5-10, the training and validation accuracies approach 95%, indicating that the model's transition from basic recognition patterns to refinement. During 11-15, epochs show that training and validation accuracies approach 99% and ~98%, respectively, and test accuracy approaches 98.33%, indicating excellent generalization.

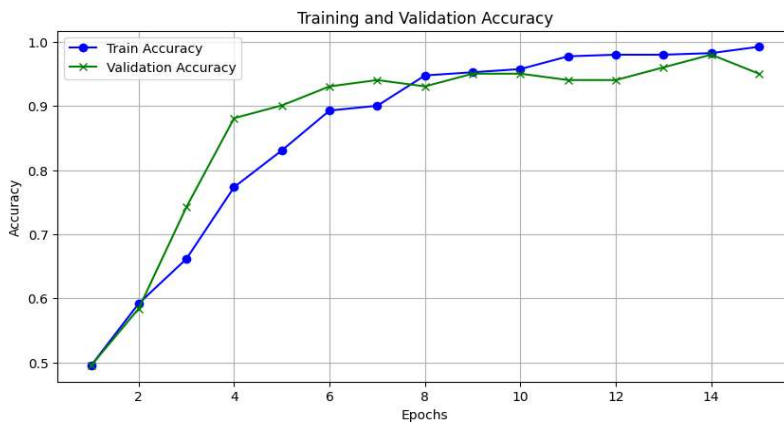


Fig 3: Training validation accuracy.

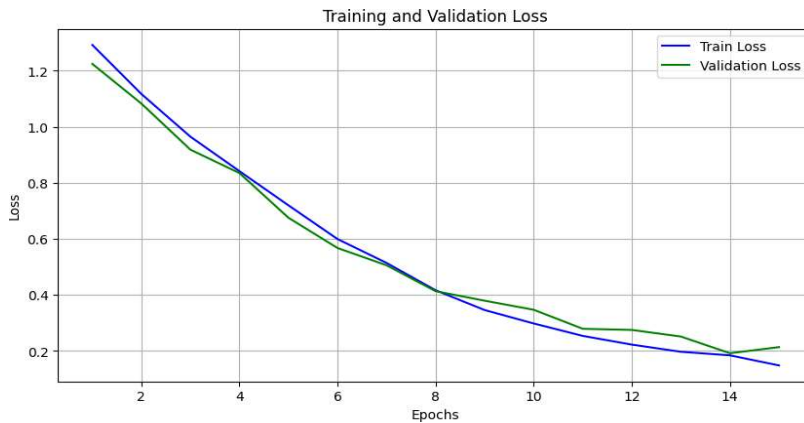


Fig 4: Training and validation loss.

VGG-16

Training accuracy of VGG-16. Figure 6 and 7 show that when the model is trained without overfitting, around 50 epochs, there is still a neck in the center of the 5 range that can be forecasted with a percentile of 100 and above. Conversely, validation accuracy reaches nearly the same level, confirming that the loss, which first increased dramatically, began to improve. Validation loss rose even faster than training loss at the outset. Validation data leads to cycles that a realistic loss function can achieve. The training accuracy blue line always starts low and keeps increasing in parallel with the accumulated data, but never fully, finally remaining at nearly 1.0 at the validation milestone of about 50 epochs. After about the same period, around 60 epochs, true validation v and a wide, constant level of fluctuation can even be expected. Losing both verification and prediction accuracy could lead to hysteria. Training loss blue line smoothly starts high, but low loss (numbers always declining), which is a good sign that the error rate invariably falls. When dealing with excessive validation data, it can be stripped much more efficiently than has been touted throughout.



Fig 5: Training validation and test accuracy.

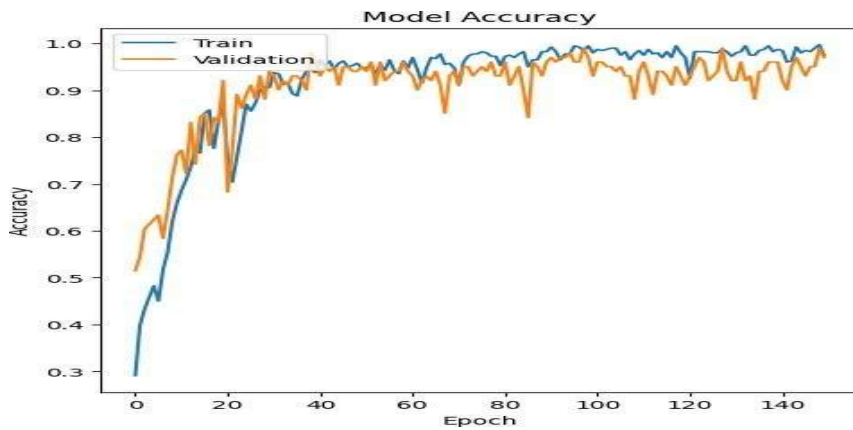


Fig 6: Training and validation accuracy.

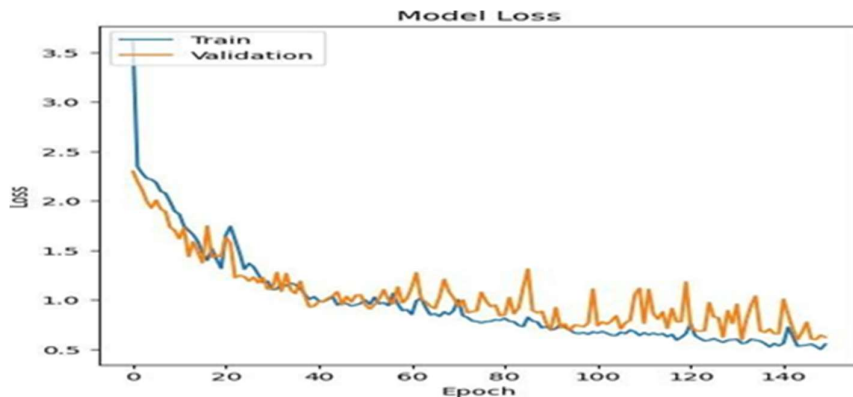


Fig 7: Training and validation loss.

VGG-19

Vgg-19 model figure 8 and 9 train accuracy (blue line) starts low (~0.2) at the beginning of the training process. It increases steadily and approaches 1.0 (100%) by the 40th epoch. After that, the training accuracy stabilizes at around 1.0, indicating that the model fits the training data very well. Validation accuracy (orange line) also starts low but increases rapidly within the first 20 epochs, surpassing 0.8 (80%) After ~20 Epochs, Validation accuracy fluctuates slightly but gradually approaches 1.0, indicating good Generalization performance. Training loss (blue line) starts high (~3.0) and decreases steadily as the model learns, dropping below 0.5 by the end of training.

This steady decrease demonstrates effective learning on the training data. The validation loss (orange line) follows a similar downward trend to the training loss, decreasing rapidly in the first 20 epochs. However, it shows slight fluctuations throughout the training process, indicating varying Vgg-19 model fig 6(a) and (b) train accuracy (blue line) starts low (~0.2) at the beginning of the training process. It increases steadily and approaches 1.0 (100%) by the 40th epoch. After that, the training accuracy stabilizes at around 1.0, indicating that the model fits the training data very well. Validation accuracy (orange line) also starts low but increases rapidly within the first 20 epochs, surpassing 0.8 (80%). After ~20 Epochs, Validation accuracy fluctuates slightly but gradually approaches 1.0, indicating good Generalization performance.

The training loss (blue line) shows a steady decrease, demonstrating effective learning on the training data. The

validation loss (orange line) follows a similar downward trend to the training loss, decreasing rapidly in the first 20 epochs. However, it shows slight fluctuations throughout training, indicating varying performance on unseen data. By the end, the validation loss stabilizes around 0.5, which aligns with the training loss. However, it shows slight fluctuations throughout training, indicating varying performance on unseen data. By the end, the validation loss stabilizes around 0.5, which aligns with the training loss. The model v learns, dropping below 0.5 by the end of training. This steady decrease demonstrates effective learning on the training data. The validation loss (orange line) follows a similar downward trend to the training loss, decreasing rapidly in the first 20 epochs. However, it shows slight fluctuations throughout training, indicating varying performance on unseen data. By the end, the validation loss stabilizes around 0.5, which aligns with the training loss. The model learns, dropping below 0.5 by the end of training. This steady decrease demonstrates effective learning on the training data. The validation loss (orange line) follows a similar downward trend to the training loss, decreasing rapidly in the first 20 epochs. However, it shows slight fluctuations throughout training, indicating varying performance on unseen data. By the end, the validation loss stabilizes around 0.5, which aligns with the training loss.

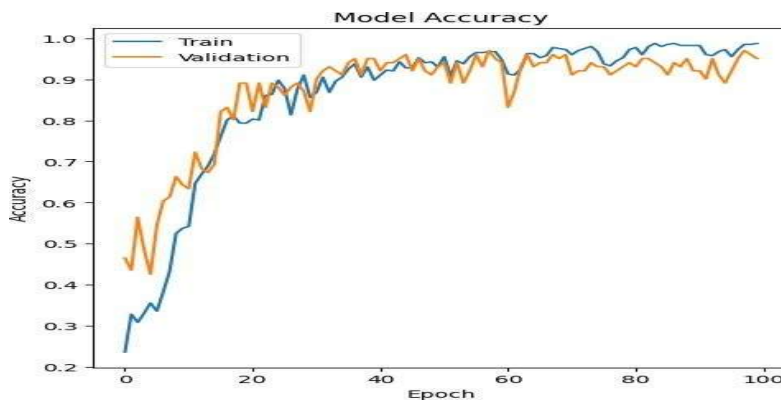


Fig 8: Training and validation accuracy.

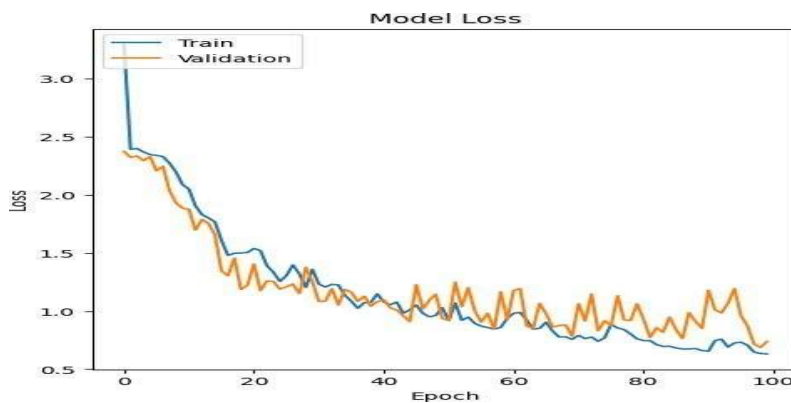


Fig 9: Training and validation loss

Specificity and Sensitivity Result of Vit Model

Figure 10 and 11 show the VIT sensitivity, which represents the model's ability to identify positive cases for each apple class correctly. Blotch apples have 100% sensitivity, meaning all blotch apples were correctly identified. Normal apples have 100% sensitivity, meaning all normal apples were detected accurately. Rot apples approach 100% sensitivity, indicating perfect detection; scab apples approach 925 sensitivity, indicating that a small portion of scab apples are misclassified with other categories. Blotch apples, normal apples, and rot apples approach 100% specificity while scab apples are slightly low to 100%.

Specificity and Sensitivity Result of VGG- 16 Model

Figures 12 and 13 represent VGG-16. The left graph (colored pink) shows Sensitivity (Recall) for each apple class, indicating the degree of correct identification of model samples for each class. The higher the bars, the better the performance. For the majority of classes (Blotch Apple, Rot Apple, Scab Apple), the results are nearly ideal. The only class that falls short is Normal Apple. The right graph (colored green) illustrates another measure, Specificity, which estimates the extent to which the model fails to classify other classes as the class in question. All classes are characterized by very high Specificity, indicating that the model is unlikely to misclassify predictors from other classes. In the general case, the model classifies the majority of classes, with only a moderate deficiency in recognizing Normal Apple.

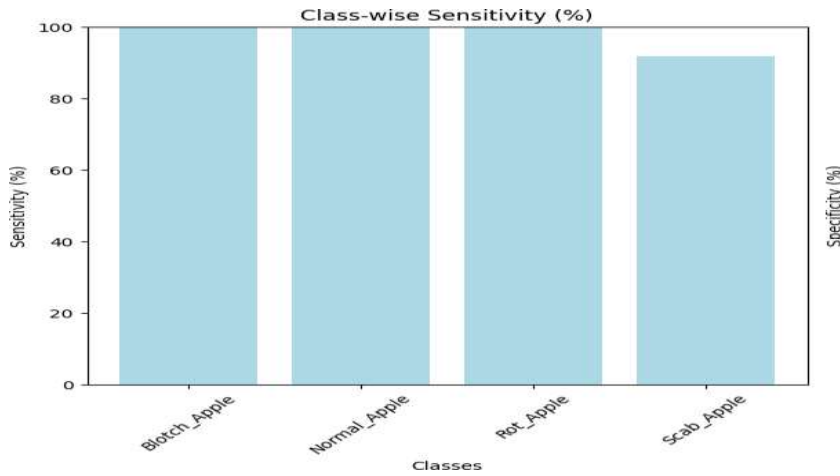


Fig 10: Specificity of ViT Model

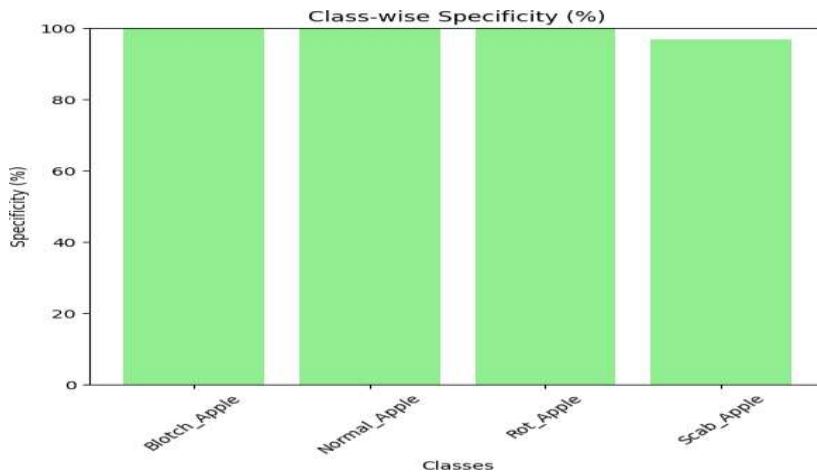


Fig 11: Specificity of ViT Model

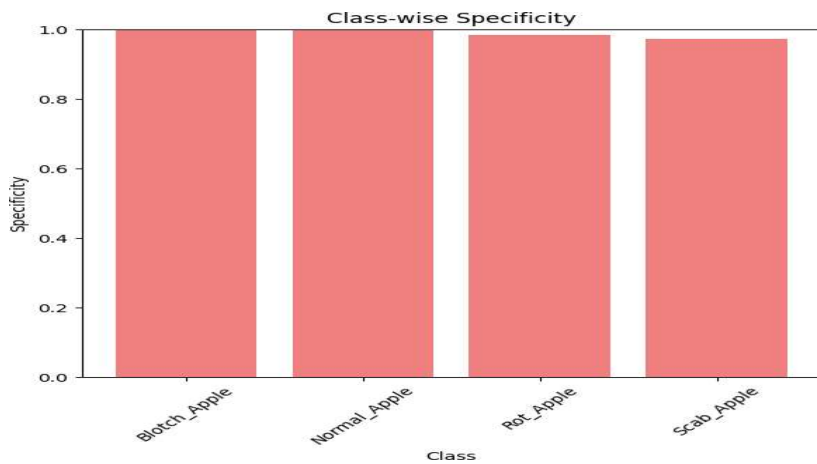


Fig 12: Specificity of VGG-16

Specificity and Sensitivity Result of VGG-19 model

Figures 14 and 15 represent VGG-19. Figure 14 VGG-19 Blotch apple, normal apple, scab apple and Rot apples approach 100% sensitivity, while the Scab apple approaches 92% sensitivity. Specificity Blotch Apple: Achieved 100% specificity, meaning no other apple types were incorrectly classified as Blotch Apple. Normal Apple: The model also exhibits 100% specificity for Normal Apples, showing flawless distinction from other categories. Rot Apple: Specificity is 100%, ensuring no other apples are mislabelled as Rot Apple, while the Scab Apple approach is slightly lower.

Table 2 shows that the blotch, normal, and rot apples achieve 100% precision, recall, sensitivity, specificity, and F1 score, indicating perfect classification for these categories. Scab apple shows 97% precision, 100% recall, and 92% sensitivity, with a specificity of 97%, indicating slight misclassifications compared to other classes. Overall, the model performs excellently with minimal error in identifying scab apple.

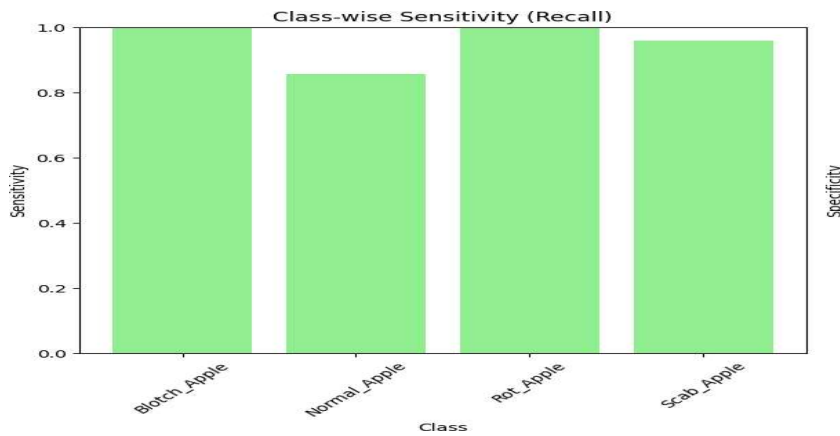


Fig 13: Specificity of VGG-16

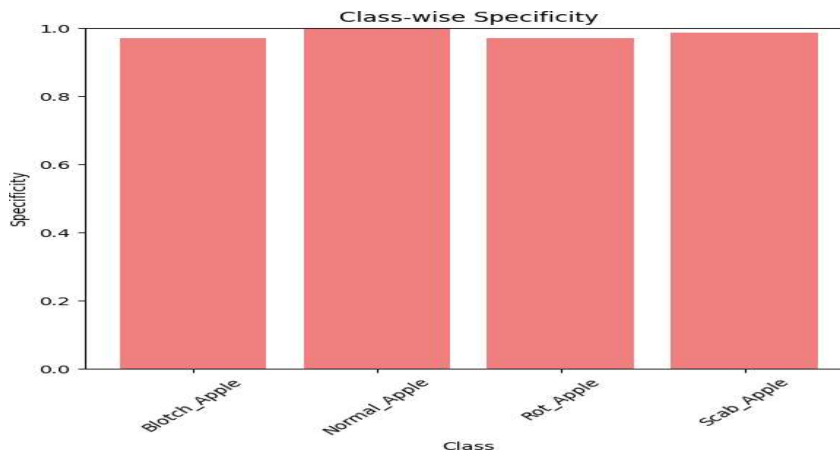


Fig 14: Sensitivity of VGG-19

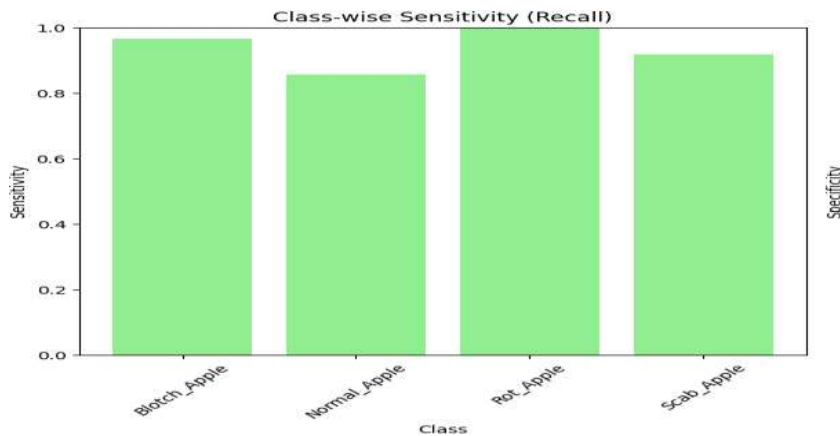


Fig 15: Specificity of VGG-19

Table 2: Result of proposed ViT model

Dataset Classes	Precision %	Recall %	F1-Score %	Sensitivity %	Specificity%
Blotch Apple	1.00	1.00	1.00	100	100
Normal Apple	1.00	1.00	1.00	100	100
Rot Apple	1.00	0.97	0.99	100	100
Scab	0.97	1.00	0.98	92	97

Table 3 shows that the blotch apple achieves 100% precision, recall, F1- score, sensitivity, and specificity. Normal apples achieve 100% precision, 86% Recall, 92% F1-score, 85% sensitivity, and 100% specificity. Rot apple achieves 97% precision, 100% recall & sensitivity, 98% specificity, and 99% F1-score. Scab apple achieves 92% precision, 96% Recall, 94% F1-score, 96% sensitivity, and 97% specificity.

Table 4 represents that blotch apples achieve 93% precision, 97% recall & specificity, 95% F1-score, and 96% sensitivity. Normal apples achieve 100% precision & specificity, 86% recalls 925 F1-score and 85% sensitivity. Rot apple achieves 94% precision, 100% recall & sensitivity, and 97% F1 score. Scab apples achieve 96% precision, 92% recall & sensitivity, 94% F1-score, and 98% specificity

Table 3: Result of proposed VGG-16 model.

Dataset Classes	Precision %	Recall %	F1-Score %	Sensitivity %	Specificity%
Blotch Apple	0.93	0.97	0.95	96	97
Normal Apple	1.00	0.86	0.92	85	100
Rot Apple	0.94	1.00	0.97	100	97
Scab	0.96	0.92	0.94	92	98

Table 4: Result of proposed VGG-19 model

Dataset Classes	Precision %	Recall %	F1-Score %	Sensitivity %	Specificity%
Blotch Apple	1.00	1.00	1.00	1.00	1.00
Normal Apple	1.00	0.86	0.92	0.85	1.00
Rot Apple	0.97	1.00	0.99	1.00	98
Scab	0.92	0.96	0.94	0.96	97

Confusion Matrix VIT MODEL

Figure 16 shows the confusion matrix for the classification of apple diseases, indicating that the model has high predictive ability. Every 30 Blotch_Apple sample, every 24 Normal_Apple sample, and every 38 Rot_Apple sample were misclassified, with no misclassifications, so they are perfectly recognized in each category. In the case of Scab_Apple, the majority of samples (26 of 28) were correctly classified, with 2 samples misclassified as Rot_Apple, with slight overlap between these two related disease types. This low level of confusion indicates that the model is successful in acquiring the unique attributes of most classes. Still, in some cases, similarities between scab and rot apples are not readily apparent, which increases the risk of error. Overall, the confusion matrix indicates high classification accuracy, indicating the model's ability to discriminate between healthy and diseased apples and between the various scab defect types.

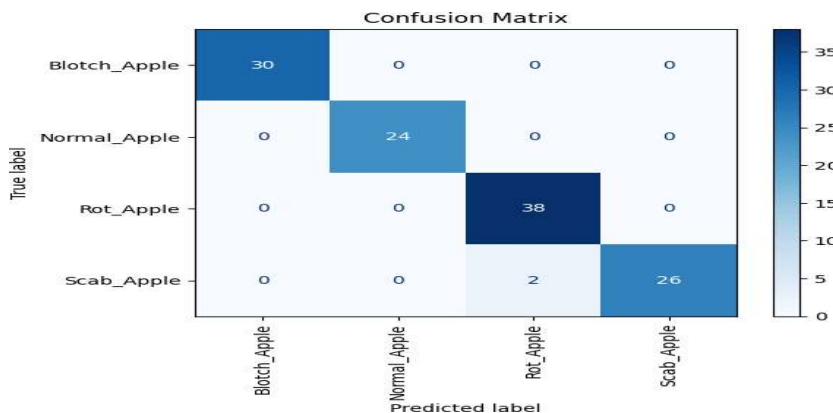


Fig 16: Confusion matrix of VIT model.

Methodology Confusion Matrix VGG-16 Model

A confusion matrix for the second model is presented in Figure 17, further supporting the model's good classification performance. There was no misclassification, and 29 Blotch_Apple samples were correctly identified. In the case of Normal_Apple, the number of correct classifications was 12, whereas 2 samples were wrongly identified as Scab_Apple, indicating that these two categories share a small degree of visual similarity. The model was perfectly classified for Rot_Apple, correctly classifying all 33 samples. In the case of Scab_Apple, 24 samples were correctly classified, whereas 1 sample was misclassified as Rot_Apple. These findings show that the model performs very well overall, with almost perfect accuracy across all categories and only a small amount of confusion between Normal and Scab, or Scab and Rot apples. This illustrates that the model is reliable at distinguishing apple defects and shows where more effort can be made to improve feature extraction, which will reduce misclassification.

Confusion Matrix VGG-19 Model

The confusion matrix of the third model, as shown in Figure 18, shows good classification performance with some minor misclassifications. Among 29 Blotch_Apple samples, 28 were accurately classified, and 1 was mistakenly classified as Scab_Apple. In the case of Normal_Apple, 12 were correctly identified, and 1 sample was falsely identified as Blotch_Apple and another as Rot_Apple, indicating a small amount of overlap between these groups. As illustrated in the case of Rot_Apple, the class's performance was excellent, with all 33 samples correctly classified with no errors. In the case of Scab_Apple, 23 samples were perfectly classified, and one was misclassified as Blotch_Apple, and another as Rot_Apple. Generally, the model would achieve high accuracy across all categories, and there could be slight confusion between similar-looking classes, such as Blotch versus Scab and Normal versus Rot. These findings demonstrate the model's strength and hint at the areas where it can be optimized further to achieve minimal misclassification errors.

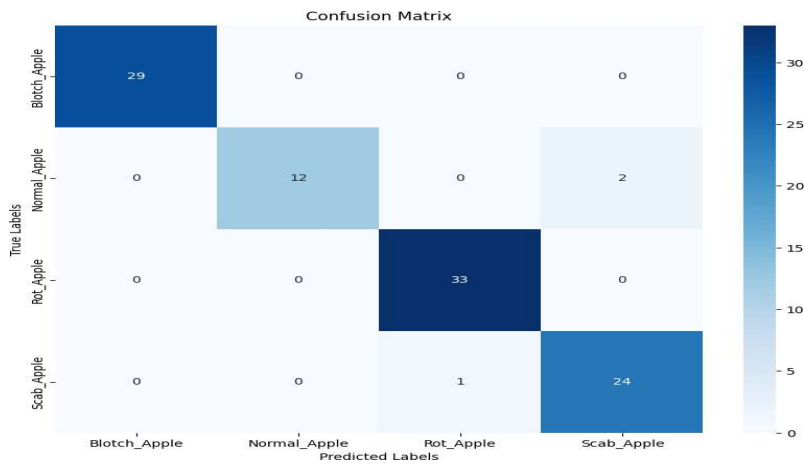


Fig 17: Confusion matrix of VGG-16 model

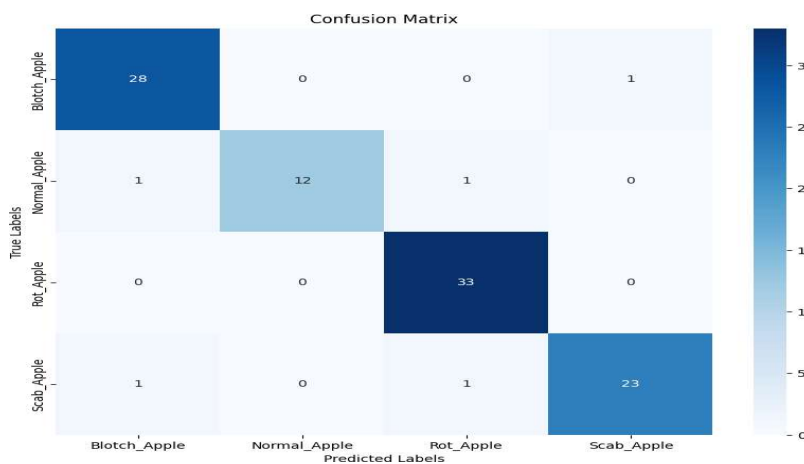


Fig 18: Confusion matrix of VGG-19 model.

Conclusion

This study shows that deep learning models are effective at classifying apple fruit diseases, including blotch, scab, rot, and healthy apples. Although VGG-16 and VGG-19 achieved good accuracies of 97.03% and 95.05%, respectively, the Vision Transformer (ViT) model achieved the best accuracy of 99.17%. These findings suggest that transformer-based architectures have better performance and generalize better than traditional CNN models. The suggested solution will help detect cancer early, minimize crop loss, and enable farmers to enhance the quality of their yields by providing a reliable, automated solution. The research can be further developed in the future by applying the method to larger, more varied datasets and by incorporating it into a real-time system to apply it practically in the field.

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