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# Advancements in Agricultural Technology: Vision Transformer-Based Potato Leaf Disease Classification

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**Abstract**

Potato (Solanum tuberosum) is an essential global food crop that is susceptible to various leaf diseases, which can drastically reduce agricultural productivity. Accurate and timely detection of these diseases is crucial for effective management and ensuring food security. This research investigates the application of Vision Transformer (ViT) models, particularly the ViT_B_16 architecture, for detecting and classifying potato leaf diseases such as early blight, late blight, and healthy leaves. Utilizing a comprehensive dataset from Kaggle, which includes 2,152 images across three categories, along with an additional custom dataset, the ViT model is fine-tuned and evaluated using separate training, testing, and validation sets. The findings reveal an impressive accuracy of 99.55%, underscoring the efficacy of ViT-based methods for precise and dependable detection of potato leaf diseases. This study enhances agricultural technological practices by providing a robust tool for early disease diagnosis and strategic agricultural planning.

**Keywords:** Potato leaf diseases, Vision Transformer, Disease detection and Classification, Agricultural productivity.


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## 1. Introduction

Potatoes are one of the most significant agricultural products in the world, supplying a substantial portion of the dietary requirements of the global population. However, various diseases, particularly leaf diseases, often affect this important crop's agricultural productivity. Implementing efficient disease management measures is important to reduce output losses.

Ensuring healthy, sustainable, and inclusive food systems is imperative for global development goals. Agricultural development is a powerful tool to eradicate extreme poverty, promote shared prosperity, and provide sustenance for an anticipated 10 billion people by 2050. With the agriculture sector contributing 4% to global GDP and up to 25% in some of the least developed countries, its growth significantly uplifts incomes, particularly among the impoverished. However, multiple challenges, such as disruptions from COVID-19, extreme weather, pests, conflicts, and the recent global food crisis triggered by events like Russia's invasion of Ukraine, threaten progress. Climate change exacerbates these issues, impacting crop yields, while current food systems contribute to 30% of greenhouse gas emissions. Moreover, unsustainable practices lead to one-third of globally produced food being lost or wasted, endangering food and nutrition security. Poor diets, a major global health risk, contribute to the leading causes of death worldwide, affecting millions who either lack adequate nutrition or face health issues due to an imbalance in food consumption. Addressing these multifaceted challenges is essential for global well-being and sustainable development [16].

Potatoes play a crucial role in Nepal's agriculture, serving as a major vegetable crop in mid-hills and terai, and a staple in high hills. Despite ranking fifth in area coverage, fourth in total production, and first in productivity, potatoes contribute significantly to cash generation and food production for smallholder farmers. The National Potato Research Program (NPRP) and National Potato Development Program (NPDP) were established to enhance livelihoods through research and development. The outlook highlights the potential of potatoes in addressing food security and poverty, emphasizing the need to address production constraints. Challenges include clean seed management, disease control, and processing. The conclusion stresses the importance of collective efforts in research and development, urging support for improved control of diseases, sustainable practices, and marketing system enhancements to benefit farmers, intermediaries, and consumers [7]. In recent years, advancements in technology, particularly in the field of image processing and machine learning, have provided innovative solutions for plant disease detection. The ability to harness the power of these technologies in agriculture holds great promise for improving crop health monitoring.

### 1.2 Problem Statement

There's been extensive prior research on employing machine learning for disease detection and classification. However, a notable research gap exists in utilizing the ViT architecture specifically for detecting diseases in potato leaves.

### 1.3 Objective

This study aims to leverage the capabilities of the Vision Transformer (ViT) model to develop an advanced, accurate, and efficient disease detection system that can significantly contribute to sustainable agricultural practices and food security.

### 1.4 Contribution

The research makes a significant contribution to the field of agriculture by introducing an innovative approach to potato leaf disease detection using ViT architecture fine-tuned with custom data set. This approach surpasses the limitations of traditional machine learning algorithms in terms of accuracy, precision, and recall.

The model undergoes fine-tuning on a diverse dataset comprising images of potato leaves affected by different diseases, including early blight, late blight, and healthy leaves. Subsequently, the fine-tuned model undergoes evaluation on distinct training, testing, and validation datasets to assess its ability to generalize across varied scenarios.

## 2. Related Work

The study proposes an innovative approach for detecting and classifying potato late blight, focusing on the ShuffleNetV2 2× model within the realm of deep learning. Late blight, a severe threat to potato production caused by phytophthora infestation, motivated the researchers to construct a diverse dataset encompassing seven categories of potato leaf diseases, considering both single and complex backgrounds. Data augmentation techniques were employed to expand the dataset for robust training. The study systematically enhances the

ShuffleNetV2 2× model by introducing an attention module, reducing network depth, and minimizing 1 × 1 convolutions, resulting in a significant reduction in parameters, FLOPs, and model size. The optimized model not only improves classification accuracy but also demonstrates enhanced CPU inference speed when deployed on an embedded device, emphasizing the importance of balancing model complexity, accuracy, and inference speed in practical applications. Comparative analysis with other pre-trained models, such as MobileNet, GhostNet, and SqueezeNet, further underscores the suitability of the ShuffleNetV2 2× model for the specific task of potato late blight identification [2].

The growth and productivity of potato plants are significantly impeded by various diseases, with Early Blight (EB) and Late Blight (LB) being common and impactful leaf diseases. Identifying these diseases at an early stage is crucial for optimizing crop production. The dataset, comprising healthy and diseased potato leaves from a publicly available plant village database, undergoes image segmentation. Seven classifier algorithms are utilized, and an impressive accuracy of 97% is demonstrated by the Random Forest classifier. Detection of early blight and late blight is the focus of the study. As recommended by the author, the integration of additional plant species in future iterations serves to underscore the system's adaptability, showcasing its potential to make a more significant impact on agriculture at a broader scale [4].

This research introduces a Convolutional Neural Network (CNN) for the classification of potato leaf diseases, with a particular focus on early blight and late blight. The proposed method achieves an overall accuracy of 99.18%, showcasing the CNN model's effectiveness in accurate disease identification. The study emphasizes the scalability of the method to other plant species and its advantages over traditional manual inspection, highlighting the potential for real-time monitoring and disease management. Even though the study shows that it is exceptionally good at recognizing potato leaf diseases, more investigation is advised to examine how well it works with various species of plants and environmental circumstances [11].

Declining potato production in India due to various disease is addressed in this study, which proposes an automated disease detection system utilizing Convolutional Neural Network (CNN) algorithms. Image processing and machine learning techniques are applied to a dataset comprising over 2000 images of healthy and unhealthy potato leaves, resulting in a commendable accuracy of 91.41% in testing for the CNN model. The potential of deep learning, specifically CNN, for accurately classifying late blight, early blight, and healthy leaf images is emphasized in the conclusion. The study envisions significant implications for the agriculture sector in India, particularly for non-literate farmers, and plans for future work, including the development of an Android application for widespread disease detection, expanding the database for improved accuracy, creating an internet-connected interface for accessible use by farmers, and exploring applications beyond potato leaf disease recognition. The proposed system aims to empower farmers with instant solutions and advice, transforming disease management in agriculture [1].

The research contributes to the classification of potato diseases using a CNN approach with a dataset comprising an extensive 10,000 pictures of potato leaves images from diverse sources, including Kaggle, Google, and raw data from potato fields. The dataset consists of distinct categories that correspond to potato healthy leaves, potato late blight, and potato early blight. The four main components of the research approach are data collection, data pre-processing, data augmentation, and image categorization. The findings show that the model reaches its highest performance after 40 epochs, exhibiting excellent precision rates for 30 and 50 epochs, respectively, and flawless accuracy during testing. The envisioned future research involves the development of a web-based or Android application aimed at benefiting potato farmers, thereby aligning with broader goals of enhancing agricultural practices and global food security. This work builds upon the growing body of literature advocating for the integration of deep learning techniques in agricultural systems, emphasizing their potential impact on crop disease management and sustainable food production and an original dimension to the research, providing valuable insights for enhancing disease classification models in the agricultural sector [3].

Utilizing over 2000 leaf images from Kaggle's "Plant Village" dataset, the study achieves an impressive 91.41% accuracy. The work aligns with existing literature highlighting the significance of advanced technologies, such as deep learning, in streamlining disease identification in agriculture. The proposed multi-level deep learning model integrated with ChatGPT provides farmers with a user-friendly tool for swift disease identification and remedy suggestions, contributing to improved crop yield and overall agricultural productivity. This research underscores the potential of advanced technologies to revolutionize disease management in agriculture [5].

The proposed methodology uses K-means for image segmentation, gray level co-occurrence matrix for feature extraction, and multi-class support vector machine for classification, achieved a notable accuracy of 95.99%. However, the author suggests the potential for further improvement, recommending the exploration of convolutional neural networks (CNNs) to enhance accuracy. The importance of key components in CNN architectures, such as activation functions, batch normalizations, and various layers, is highlighted for optimizing disease detection in agricultural settings [10].

Deep learning algorithms, namely VGG16, VGG19, and ResNet50, are employed in this study for the recognition and division of diseases on potato leaves. The VGG16 model, which uses K-means clustering segmentation and other data augmentation approaches, achieves the greatest accuracy of 97% among the three networks. Future work involves the creation of a tool for early identification of leaf diseases, incorporation of additional algorithms to enhance model performance, diversification of dataset types, and the development of a more effective application for agricultural fields [8].

This study focused on extracting relevant features from the dataset by fine-tuning transfer learning-trained models, like VGG19 and various classifier performance is measured. Among them, logistic regression performed better than the others, obtaining a significant classification accuracy of 97.8% across the test dataset. The concept of transfer learning is employed to develop an automated system for diagnosing and classifying diseases in potato leaves, including early blight, late blight, and healthy states, reaching a 97.8% classification accuracy on the test dataset, can facilitate early disease detection for farmers, contributing to enhanced crop yields [12].

A system utilizing deep learning, specifically GoogleNet, Resnet50, and VGG16 convolutional neural network architectures, is presented in this study for classifying diseases in potato plants based on leaf conditions. The experiment, conducted for the first 40 CNN epochs, achieved a noteworthy 97% accuracy, affirming the viability of the deep neural network approach. The model, developed based on the concept of CNN, accurately classifies disease conditions of various categories. The research suggest that the performance can be improved by using Generative Adversarial Networks (GANs) for data creation and Transfer Learning to enhance accuracy [6].

An efficient methodology for identifying healthy and diseased plant leaves is outlined in the paper, employing image processing and machine learning techniques. Diseases, causing chlorophyll damage and visible spots on leaves, are detected through a process involving image preprocessing, segmentation, feature extraction, and classification using machine learning algorithms. The dataset for disease detection is sourced from a Kaggle website, containing over 12,949 images of healthy and unhealthy crop leaves. Support Vector Machines (SVM) achieve recognition accuracy of 80% through the grayscale co-occurrence matrix (GLCM) for feature extraction. Convolutional Neural Networks (CNNs) further enhance accuracy, reaching 97.71%, surpassing the results obtained with hard coding technology and contributing to automatic plant leaf disease identification [9].

Recent advances in artificial intelligence have significantly improved early detection of potato leaf diseases such as early and late blight. Traditional methods struggle with variability in crop species, symptoms, and environmental factors. Deep learning techniques, particularly Convolutional Neural Networks (CNNs) and models like YOLOv5 for image segmentation, have shown high accuracy. These models, tested on datasets such as PlantVillage and region-specific collections, achieve near-perfect accuracy with data augmentation and transfer learning. Despite their success, generalizing across regions remains a challenge. Future directions include developing real-time monitoring systems and mobile applications to enhance accessibility for farmers, thereby improving crop management and productivity [13].

Artificial intelligence has enhanced early detection of potato diseases, with Convolutional Neural Networks (CNNs) like Inception V3 proving effective. Traditional methods struggle with variability in crop diseases, while deep learning models achieve high accuracy through advanced architectures and optimizers. Studies show CNNs can accurately classify diseases like early and late blight, improving crop management. Future research focuses on integrating these models into practical tools for real-time monitoring and early intervention [14].

Recent advancements in machine learning, particularly Convolutional Neural Networks (CNNs), have significantly improved the detection of potato diseases such as early and late blight. Traditional methods face challenges due to variability in disease symptoms and environmental factors, while CNNs, optimized with techniques like Adam and cross-entropy analysis, offer high accuracy and efficiency. Studies demonstrate that CNN models can achieve over 99% accuracy in disease detection, reducing agricultural losses and enhancing productivity. These models are increasingly being integrated into smart farming practices for real-time monitoring and early intervention [15].

## 3. Methodology

To detect and classify the potato leaf disease Vision Transformer (ViT) is used. The methodology of the proposed workflow is shown in Figure 1 below.

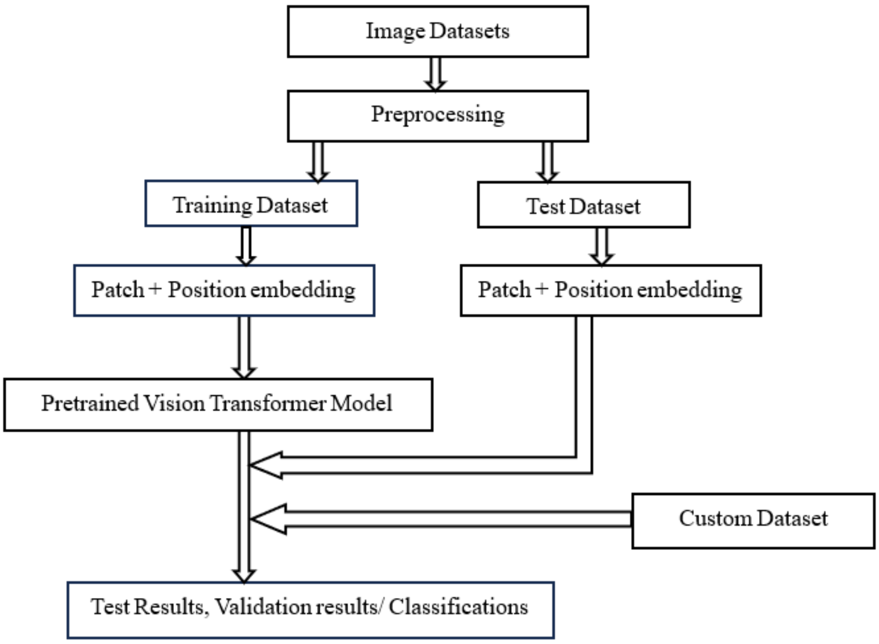


**Figure 1.** Workflow for Potato Leaf Disease Classification

### 3.1 Image Datasets

The primary dataset acquired from Kaggle [16] comprises 2,152 images categorically labeled into three distinct classes: Potato Early Blight, Potato Late Blight, and Potato Healthy. This dataset is intended for research in the domain of plant pathology, specifically focusing on the identification and classification of potato diseases. It includes 1,000 images for both Potato

Early Blight and Potato Late Blight classes, along with 152 images depicting healthy potato plants. The dataset encompasses visual variations that may arise from diverse environmental conditions, plant growth stages, and disease manifestations.

In addition to the Kaggle dataset, a custom dataset was also employed, which was meticulously curated from local agricultural sources to ensure a broad representation of real-world conditions. The sample of custom datasets is shown in Figure 2. This custom dataset includes images of potato leaves under various stages of disease progression and different environmental impacts, providing a robust validation set for the fine-tuned Vision Transformer (ViT) model. This custom dataset comprises of 150 images which includes 50 images for each class: Potato Early Blight, Potato Late Blight, and Potato Healthy. The custom dataset was subjected to the same preprocessing steps as the Kaggle dataset to maintain consistency in model training and validation. The inclusion of this custom dataset is crucial as it introduces real-world variability and challenges, ensuring that the model's performance is not only theoretically sound but also practically viable.

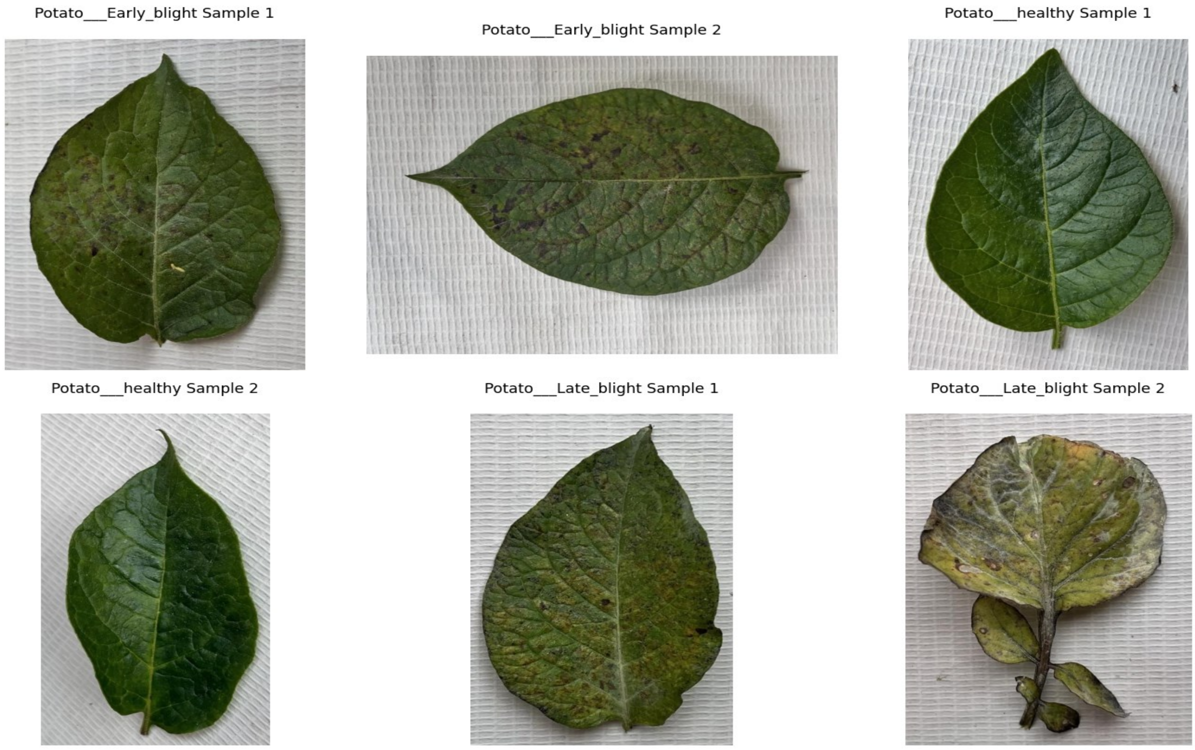


**Figure 2.** Sample Images from Custom Dataset

### 3.2 Preprocessing

To enhance image quality, a Gaussian filter was applied to the images to eliminate Gaussian noise. Subsequently, the filtered images are resized into a standardized size of 224x224 pixels to achieve uniformity. This resizing is essential for the creation of 16x16 patches from each image, contributing to a consistent input size for further processing. The dataset underwent division into various test-train ratios for comprehensive model evaluation. The train and test ratio is taken as 80 and 20 percent. Each image was then subdivided into patches of size 16x16, resulting in a total of 196 patches per image (14x14 grid). This systematic preprocessing ensures noise reduction, standardizes image dimensions, and facilitates the creation of patches, thereby optimizing the dataset for subsequent analysis and model performance assessment.

### 3.3 Vision Transformer

The ViT model is initialized with pretrained weights, such as the ViT_B_16 architecture, and further fine-tuned on a custom dataset comprising potato images. To adapt the model for the specific task, the base parameters are frozen, and the classifier head is modified to align with the three classes in the dataset. Positional encodings are added to retain spatial information. The sequence of patch embeddings, along with positional embeddings, is fed into a Transformer encoder composed of multiple layers. Each layer contains multi-head self-attention mechanisms for calculating attention weights and multi-layer perceptron (MLP) blocks. Layer normalization ensures stability, and during training, an optimizer adjusts hyperparameters in response to computed loss. The training process spans 10 epochs, during which the model's parameters remain static due to the freezing mechanism. The evolution of the model is visualized through loss curves, showcasing a progressive reduction in both training and validation losses over the epochs. The custom dataset was taken from local sources, preprocessed it, patch and position embedding is done and given to the trained ViT model for further validation process.

The implementation and evaluation of the Vision Transformer (ViT) model were conducted using the following libraries as shown in table 1 :

- torch (PyTorch): A deep learning framework used for implementing the ViT model.

- torchvision: Provides datasets, transforms, and models specific to computer vision.
- matplotlib: A plotting library used for visualizing the loss curves.

### 3.3.1 Fine-Tuned Parameters in ViT

The following Table.1 details the parameters that were fine-tuned in the ViT model for the custom dataset:

**Table 1.** Details of the Fine- Tuned Parameters

| Parameter | Description | Initial Value | Fine-Tuned Value |
|---|---|---|---|
| Learning Rate | Rate at which the model updates the parameters during training | 0.001 | 0.0001 |
| Batch Size | Number of samples processed before the model updates | 32 | 16 |
| Epochs | Number of complete passes through the training dataset | 10 | 10 |
| Optimizer | Algorithm used to adjust the learning rate and model parameters | Adam | Adam |
| Loss Function | Function to compute the loss during training | Cross-Entropy Loss | Cross-Entropy Loss |
| Dropout Rate | Probability of dropping out units in the MLP blocks during training to prevent overfitting | 0.1 | 0.1 |
| Classifier Head | Final layer modified to align with the three classes in the dataset | Pretrained Head | Custom 3-class Head |
| Patch Size | Size of the patches the image is divided into | 16x16 | 16x16 |
| Positional Encoding | Encodings to retain spatial information of patches | Pretrained Encoding | Fine-Tuned Encoding |
| Multi-Head Attention | Mechanisms to compute attention weights | Pretrained Weights | Fine-Tuned Weights |

## 4. Experiment Result and Analysis

### 4.1 Confusion Matrix

After training, testing was performed on the test dataset for potato leaf disease detection. During the testing phase, notable outcomes were encapsulated within the confusion matrix as shown in Figure 3. The model exhibited remarkable efficiency in identifying instances of Potato Early Blight, achieving a true positive count of 198 with minimal false negatives (2 instances) and no false positives. Likewise, for Potato Late Blight, the model displayed robust performance with a true positive count of 200, although two instances of false positives were noted. In the case of Potato Healthy, the model demonstrated impeccable precision, accurately classifying all instances with zero false positives and false negatives. Various performance metrices are calculated using formula given as in Eq. (1, 2, 3, 4)

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{1}$$

$$Precision = TP \;/\; (TP + FP) \tag{2}$$

$$Recall = TP \;/\; (TP + FN) \tag{3}$$

$$F1\,score = 2 \times ((precision \times recall) \;/\; (precision + recall)) \tag{4}$$

where TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

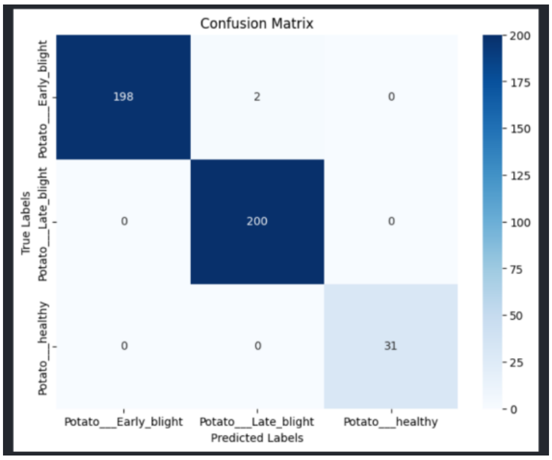


**Figure 3.** Confusion Matrix During Model Testing

The model achieved a training accuracy of 99.54% and a test accuracy of 99.55%. It demonstrated high performance in predicting potato diseases with minimal training and testing loss. The F1 scores, which consider both precision and recall, were recalculated to ensure accuracy in the presence of false positives and negatives, particularly emphasizing the balance between sensitivity and precision.

### 4.2 Performance Observations Using the Confusion Matrix

The performance of the proposed model was evaluated using the confusion matrix, revealing the following insights:

- **Potato Early Blight**: The model identified 198 true positive cases with only 2 false negatives and no false positives, indicating high sensitivity and precision in detecting this class.
- **Potato Late Blight**: The model showed a true positive count of 200, with 2 false positives. This reflects strong classification capability, although a few instances were misclassified as Potato Late Blight.
- **Potato Healthy**: The model perfectly classified all healthy potato instances with zero false positives and false negatives, demonstrating excellent specificity and precision.

These observations indicate that the model is highly effective at classifying potato leaf diseases, with minimal errors as shown in Figure 4. The high accuracy, precision, recall, and

F1 scores across all classes underscore the model's robustness and reliability in real-world applications.

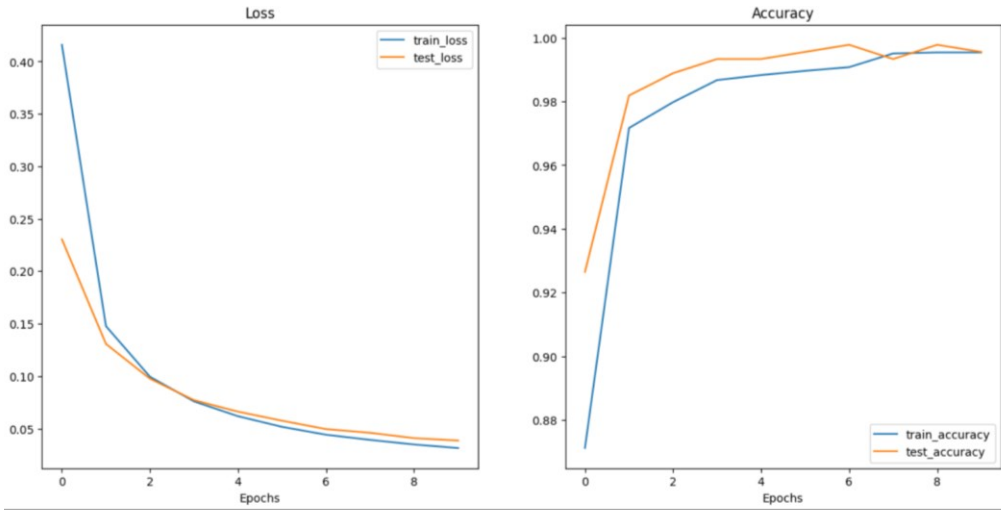


**Figure 4.** Loss and Accuracy Curve during Testing

The calculated F1 score, considering the minimal false positives and false negatives, is 0.997, indicating a very high level of model precision and reliability.

For validating the work, the ViT model was tested using custom datasets comprising three categories taken from local resources. These datasets were meticulously verified through manual inspection to ensure their relevance and accuracy. During the validation phase, the model achieved a validation accuracy of 99.15%. This high level of accuracy underscores the model's robust discriminative capability across various categories of potato diseases, demonstrating its substantial potential for practical implementation in agricultural disease management. The validation results are crucial as they confirm the model's effectiveness in real-world scenarios, providing a strong foundation for its deployment in the field.

## 5. Conclusion

This research explored potato leaf disease detection employing Vision Transformer (ViT) models, augmented with custom datasets, and has yielded remarkable results, showcasing an impressive accuracy of 99.55%. The utilization of ViT, with its transformer architecture originally designed for natural language processing, demonstrates its effectiveness in image classification tasks within the domain of agriculture and plant pathology. The high accuracy achieved not only underscores the potential of ViT-based approaches for precise and reliable potato disease detection but also connects back to the discussions in previous sections about the need for advanced technological solutions in agriculture. These findings hold significant implications for agricultural practices, offering a powerful tool for early disease diagnosis and informed decision-making, thereby addressing the challenges outlined in the introduction and related work sections.

## 6. Future Work

Future work may involve extending the evaluation to larger and more diverse datasets, exploring model interpretability, and investigating real-world deployment scenarios to further validate the practical applicability of ViT models in the context of plant disease detection. In future by making an application web based or android, which will be available to end user so that farmers can detect the disease at early stage.

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