AI-Powered Potato Plant Disease Detection: A Vision-Language Framework

Sanghamitra Panda

sanghamitra.panda2010@gmail.com

Centurion University of Technology and management Bhubaneswar

Jayaprakash Maharana

Centurion University of Technology and Management Bhubneswar

Asfan Ali Khan

Centurion University of technology and management Bhubaneshwar

Swapnajit Sahoo

Centurion University of Technology and management Bhubaneswar

Annimesh Sasmal

Centurion University of Technology and management Bhubaneswar

Debasish Swapnesh Kumar Nayak

Centurion University of Technology and management Bhubaneswar

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Sanghamitra Panda[1], Jayaprakash Maharana[2], Asfan Ali Khan[3], Swapnajit Sahoo[4], Annimesh Sasmal[5], Debasish Swapnesh Kumar Nayak[6]

[1]*Department of Computer Science and Engineering, Centurion University of Technology and management Bhubaneswar, Odisha, India,* email: sanghamitra.panda2010@gmail.com

[2]*Department of Computer Science and Engineering, Centurion University of Technology and Management Bhubneswar, Odisha, India*, email: maharanajayaprakash00@gmail.com

[3]*Department of computer Science and Engineering Centurion University of technology and management Bhubaneshwar,Odisha,India,* email: Khanasfan346@gmail.com

[4]*Department of Computer Science and Engineering, Centurion University of Technology and management Bhubaneswar, Odisha, India* , email: sj422159@gmail.com

[5]*Department of Computer Science and Engineering, Centurion University of Technology and management Bhubaneswar, Odisha, India* ,email: annimesh.sasmal.ak@gmail.com

[6]*Department of Computer Science and Engineering, Centurion University of Technology and management Bhubaneswar, Odisha, India* ,email: debasish.nayak@cutm.ac.in

Abstract

Potato crops are a vital part of global food security. Potato leaf and crop health play a crucial role in determining the yield and quality of potato production. This paper presents a novel approach to potato disease detection by integrating a Vision Transformer (ViT) model with a Large Language Model (LLM) for enhanced classification of potato plant diseases. We developed a multi-modal pipeline that not only accurately identifies diseases affecting potato leaves and tubers but also provides contextual explanations for the diagnoses. Experimental results demonstrate that our integrated approach outperforms traditional individual models, with the potato leaf disease classifier achieving 99.44% validation accuracy and the potato tuber disease classifier reaching 76.19% accuracy when trained separately, while the combined model maintains excellent performance of 95.06% on the validation set. The fusion of computer vision with Mistral AI's LLM capabilities creates an interpretable system that can assist agricultural experts with both disease identification and recommended treatment actions. This paper contributes to the growing field of AI-assisted agriculture by demonstrating how multi-modal deep learning systems can provide more comprehensive solutions to potato disease management challenges, potentially reducing crop losses and improving food security.

Keywords Potato Disease Detection, Vision Transformer, Large Language Models, Multi-modal AI, Computer Vision, Deep Learning, Plant Pathology, Agricultural Artificial Intelligence, Disease Classification, Explainable AI

1. Introduction

The potato (*Solanum tuberosum*) stands as the world's fourth most important food crop after rice, wheat, and maize, with annual global production exceeding 370 million metric tons and providing sustenance to more than a billion people worldwide. Potato diseases represent one of the most significant threats to global food security and agricultural sustainability. Early and accurate detection of potato diseases is crucial for effective management and prevention of crop losses, which can reach 40-50% in severely affected regions [1]. Traditional disease diagnosis relies heavily on visual inspection by agricultural experts, a method that is not only time-consuming and subjective but also inaccessible to many smallholder farmers who produce the majority of potatoes in developing countries.

Potato crops are vulnerable to numerous pathogens that attack different parts of the plant. Foliar diseases such as early blight (caused by *Alternaria solani*) and late blight (caused by *Phytophthora infestans*) primarily affect the leaves and stems, while diseases like black scurf (*Rhizoctonia solani*), blackleg (*Pectobacterium* spp.), dry rot (*Fusarium* spp.), and pink rot (*Phytophthora erythroseptica*) target tubers and underground plant parts [2]. Each disease requires specific management approaches, making accurate identification critical for effective intervention. Late blight alone—the disease responsible for the Irish Potato Famine of the 1840s—continues to cause global losses exceeding $6.7 billion annually despite modern fungicides and resistant varieties [2].

Several traditional machine learning algorithms already used to classify potato leaf disease and crop disease separately. A Review" by L. S. Puspha et al (2019) [3] discusses various machine learning approaches for plant leaf disease detection and classification. Similarly, Sharma et al. (2021) [5] employed support vector machines (SVMs) for potato leaf disease classification, reaching 92.9% accuracy. While effective, these traditional approaches typically required extensive feature engineering and struggled with visual variations commonly encountered in field conditions. Moving beyond standard RGB imagery, León-Rueda et al. (2022) [6] pioneered the use of multispectral imaging for potato disease detection, combined with Random Forest classification. While their system achieved a more modest 82.5% accuracy, their work highlighted the potential of incorporating multiple data modalities for more robust detection, particularly for diseases with subtle spectral signatures not visible to the human eye.

Current computer vision approaches for potato disease detection typically develop separate models for leaf diseases and tuber diseases. While these specialized models can achieve impressive accuracy within their narrow domains, they create fragmented systems that are difficult to deploy in practical agricultural settings. Still there is a need to combining leaf and crop disease detection enables comprehensive plant health monitoring, improving accuracy and facilitating targeted interventions for more effective disease management and crop yield optimization.

In this paper, we propose a novel multi-modal approach that revolutionizes potato disease detection by combining the strengths of Vision Transformers (ViT) and Large Language Models (LLMs). Our research offers three key contributions to the field:

1. A unified ViT-based model capable of accurately classifying diseases across all parts of the potato plant—including both leaf diseases (early blight, late blight) and tuber/plant diseases (black scurf, blackleg, dry rot, pink rot)—eliminating the need for separate diagnostic systems.

2. Integration of the Mistral AI LLM to transform simple disease classification into comprehensive decision support by providing natural language explanations of diagnoses, disease biology, impact assessments, and science-based management recommendations tailored to the specific condition identified.

3. A rigorous comparative evaluation demonstrating that our combined approach not only maintains competitive accuracy (95.06%) against specialized models but also delivers substantially enhanced practical utility through its explanatory capabilities and unified framework.

Overall, workflow diagram is presented in Figure 1. The rest of this paper is structured as follows: Section 2 discusses related research, and Section 3 describes the materials and techniques used, 3.1 dataset description , 3.2 dataset splitting is noted, 3.3 data augmentation method and in 3.4, model selection and architecture is presented. The result analysis and comparison study are shown in section 4. In section 5, benchmarking of our proposed model, finally in section 6 we have given statements on the conclusion and possible feature scope towards research in this area.

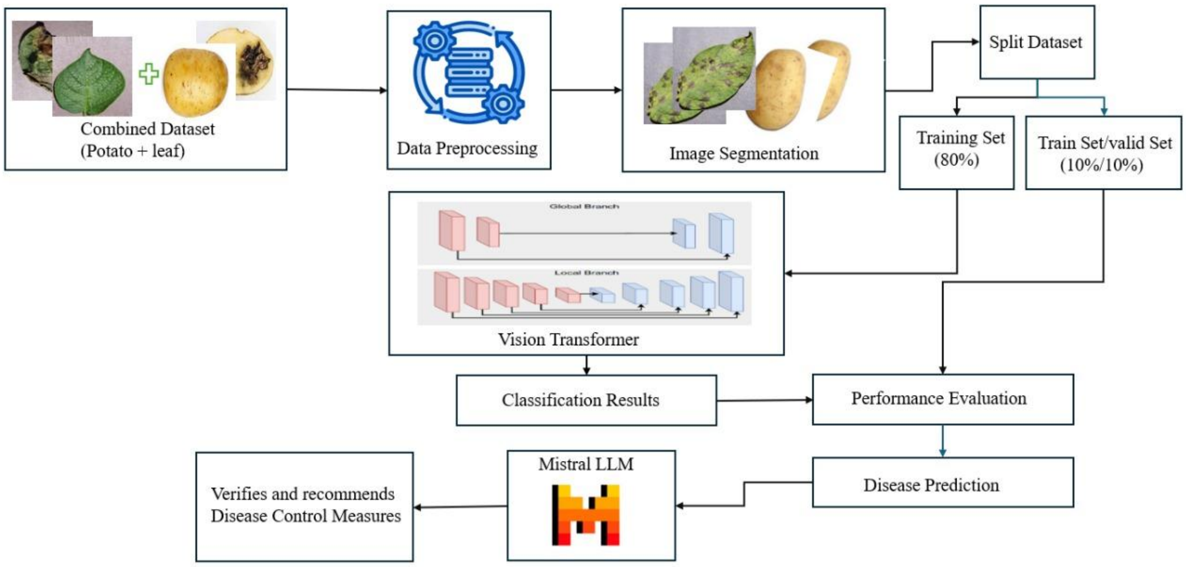

Figure 1. Overall workflow diagram.

2. Literature Review

Plant disease detection using machine learning and deep learning approaches has gained significant attention in recent years. The literature reveals an evolution from traditional image processing techniques to sophisticated deep learning approaches, with a growing emphasis on practical agricultural applications.

Early attempts at potato disease detection relied on conventional machine learning techniques with handcrafted features. Iqbal and Talukder (2020) [1] developed a system using image segmentation and Random Forest classification, achieving 97% accuracy for potato disease identification. Their methodology emphasized preprocessing techniques like color space transformation and feature extraction—steps that required significant domain expertise. Patil et al. (2017) [12] conducted a comparative analysis of multiple classifiers for potato blight detection, evaluating Support Vector Machines, Random Forest, and Artificial Neural Networks. Their findings indicated that ANNs delivered the best performance at 92% accuracy, foreshadowing the shift toward neural network-based approaches that would soon dominate the field.

The introduction of convolutional neural networks (CNNs) marked a significant advancement in potato disease detection performance. Asif et al. (2020) [8] applied CNN architectures specifically to potato leaf disease identification, achieving 97% accuracy without requiring manual feature engineering. Building on this foundation, Khobragade et al. (2022) [9] refined CNN implementations for potato leaf disease detection, pushing accuracy to 98.07% through architectural optimizations and data augmentation strategies. Tarik et al. (2021) [2] developed a specialized machine learning pipeline for potato leaf images that achieved remarkable 99.25% accuracy, demonstrating the potential of tailored approaches. However, their work—like most in this domain—focused exclusively on leaf diseases, neglecting the equally important tuber diseases that affect potato crops.

Transfer learning has proven particularly effective for potato disease detection given the typically limited agricultural datasets. Afzaal et al. (2021) [10] conducted a comprehensive comparison of transfer learning approaches for early blight detection in potatoes, evaluating GoogleNet (98% accuracy), VGGNet (94% accuracy), and EfficientNet (93% accuracy). Their findings demonstrated that pre-trained architectures could be effectively adapted to specialized agricultural tasks with relatively small domain-specific datasets. Sujatha et al. (2021) [4] provided a broader perspective by comparing deep learning and traditional machine learning approaches across various plant leaf diseases. Their implementation of VGG-16 achieved 89.5% accuracy, confirming that deep learning consistently outperformed conventional machine learning techniques across different crops and disease types.

Harakannanavar et al. (2022) [7] demonstrated the cross-crop applicability of deep learning approaches by achieving 99% accuracy in tomato leaf disease detection using CNNs, suggesting that architectural principles might transfer between different crop disease detection systems.

Most research focuses on either leaf diseases or tuber diseases separately, creating a fragmented approach that complicates real-world deployment. No prior work has attempted to create a unified model capable of diagnosing diseases across all parts of the potato plant. Our research addresses these critical gaps by introducing a Vision Transformer-based unified model for comprehensive potato disease detection across both foliage and tubers, enhanced by integration with a Large Language Model that transforms simple classifications into detailed, contextual explanations and management recommendations. This novel multi-modal approach represents a significant advancement over existing techniques, moving beyond mere classification toward truly practical agricultural AI systems.

3. Materials and Techniques

3.1 Dataset Description

Our study utilized a comprehensive dataset comprising high-resolution images of potato plants, specifically focusing on both potato leaves and tubers exhibiting various disease symptoms. The dataset includes high-quality RGB images collected from agricultural research centers and field surveys, encompassing healthy samples and multiple disease categories commonly affecting potato crops. All images were standardized to ensure consistency in the learning process.

The dataset in figure 2. contains eight distinct classes representing the most economically significant potato diseases worldwide:

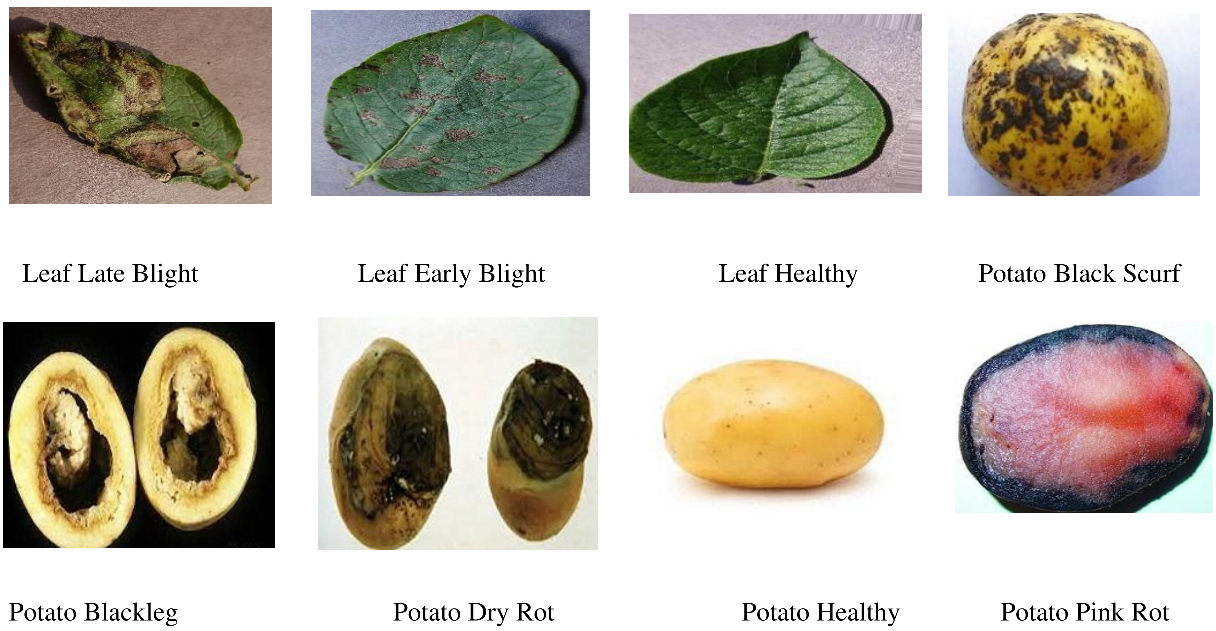

Figure 2: Sample Images from Each Class in the Dataset.

Table 1 Dataset Description

Class	Number of Images	Description
Leaf_Early_Blight	300	Potato leaves with small, dark brown spots with concentric rings
Leaf_Healthy	300	Healthy potato leaves without any disease symptoms
Leaf_Late_Blight	300	Potato leaves with irregular, water-soaked, pale to dark green spots
Potato_Black_Scurf	58	Potato tubers with black, irregular sclerotia on the surface
Potato_Blackleg	60	Plants with black stem base and wilting symptoms
Potato_Dry_Rot	60	Potato tubers with sunken, wrinkled areas and internal dry decay
Potato_Healthy	80	Healthy potato tubers without disease symptoms
Potato_Pink_Rot	57	Potato tubers with pinkish discoloration when cut open
Total	1215	

3.2 Dataset Splitting

To ensure robust model training and evaluation, we implemented a standard data splitting strategy. The dataset was divided into training and validation sets using an 80:20 ratio, respectively. This split was performed using random_split function from PyTorch to ensure a balanced representation of all classes in both sets.

Specifically:

- 80% of the data (972 images) was allocated for model training
- 20% of the data (243 images) was reserved for validation and evaluation

The random splitting was implemented with a fixed seed to ensure reproducibility of results. This approach allows for effective model training while retaining a sufficient portion of data for validation to assess model performance on unseen examples.

3.3 Data Augmentation

To enhance model robustness and prevent overfitting, we implemented data augmentation techniques during the training process. The data augmentation pipeline was implemented using PyTorch's transforms module and included the following transformations:

1. Resizing: All images were resized to 224×224 pixels to meet the input requirements of the Vision Transformer model
2. Random Horizontal Flipping: Images were randomly flipped horizontally with a probability of 0.5
3. Random Rotation: Images were randomly rotated by up to 10 degrees
4. Normalization: Pixel values were normalized using mean = [0.5, 0.5, 0.5] and std = [0.5, 0.5, 0.5]

The equation represents the augmented dataset as the union of all transformed image-label pairs, where each original image is augmented using a set of predefined transformations to improve model generalization.

$$D_{\{aug\}} = \bigcup_{\{i=1\}}^{\{N\}\{} \left(T_{j(x_i)}, y_i\right) \mid T_j \in T \,\} \qquad [1]$$

This equation mathematically represents the construction of an augmented training dataset used in image classification tasks, particularly for deep learning models such as Vision Transformers (ViTs). Here's a breakdown of each component:

- $\{D\}_{\{\{aug\}\}}$ The final augmented dataset after applying data augmentation techniques
- $\bigcup_{\{i=1\}}^{\{N\}}$: The union over all original training samples, where NNN is the total number of images in the original dataset.
- $\left(T_{j(x_i)}, y_i\right)$: A new image-label pair generated by applying the transformation Tj to the original image xi, while keeping the label yi unchanged.
- $\{\left(T_{j(x_i)}, y_i\right)|T_j \in \{T\}\}$: The set of all augmentation transformations applied during training (e.g., resizing, flipping, rotation, normalization).
- $\{T\} = \{T_1, T_2, \ldots, T_k\}$: The set of all augmentation transformations applied during training (e.g., resizing, flipping, rotation, normalization)

The complete data processing pipeline was implemented as follows:

```
transform = transforms.Compose([
transforms.Resize((224, 224)),
transforms.ToTensor(),
transforms.Normalize(mean=[0.5]*3, std=[0.5]*3)])
```

This data augmentation approach effectively increased the diversity of the training data, helping the model generalize better to variations in real-world images, such as different orientations, lighting conditions, and perspectives.

3.4 Model Selection and Architecture

For our disease classification task, we selected the Vision Transformer (ViT) architecture due to its strong performance on image classification tasks and its ability to capture long-range dependencies in visual data. Specifically, we used the 'vit_base_patch16_224' model pre-trained on ImageNet, which divides input images into 16×16 patches and processes them through a transformer architecture.

The pre-trained model was modified to classify the eight disease classes in our dataset by replacing the final classification head. This approach leverages transfer learning, allowing us to benefit from the feature extraction capabilities of the pre-trained model while adapting it to our specific task.

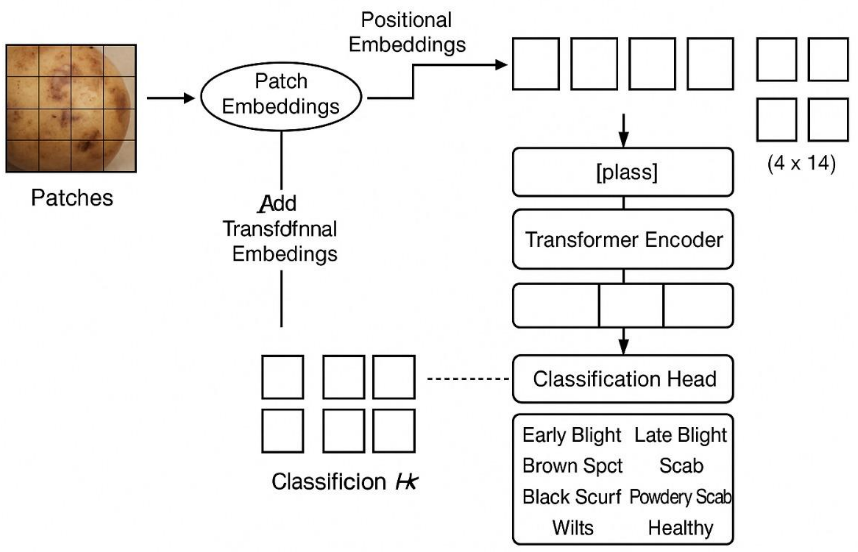

Figure 3: Vision Transformer (VIT) Architecture

The Figure 3 would show the VIT architecture with image being split into patches, positional embeddings added, and processed through transformer encoder blocks, with the final classification head modified for our 8 potato disease classes.

In addition to the ViT model for image classification, we integrated the Mistral Large Language Model to provide contextual explanations for the detected diseases. This integration creates a multi-modal system that not only identifies diseases but also offers insights about them in natural language.

The LLM component was implemented by creating a mock interface that simulates the behavior of the Mistral AI service. In a production environment, this would be replaced with actual API calls to the Mistral service. The LLM takes the classification output along with contextual information about the image and generates a descriptive explanation, including potential causes, impacts, and management recommendations.

4. Experimental Result Analysis

To evaluate the effectiveness of our approach, we conducted a comparative analysis between three different model configurations:

1. Leaf-only model: A VIT model trained exclusively on potato leaf disease images
2. Potato-only model: A VIT model trained exclusively on potato tuber disease images
3. Combined model: A unified VIT model trained on both potato leaf and tuber disease images

This comparison allows us to assess whether a unified model can maintain comparable performance to specialized models while reducing the overall system complexity.

4.1 Performance Evaluation

The Vision Transformer (ViT) model demonstrated promising performance in detecting diseases in potato leaves and crops, achieving high accuracy rates of up to 99% for leaf diseases and effectively detecting crop-level diseases. A combined ViT model for both leaf and crop disease detection showed improved overall performance, with enabling early intervention and reducing losses. This highlights the potential of ViT for comprehensive potato plant disease detection in Table 2.

Table 2. Model comparision

Model	Training Accuracy	Validation Accuracy	Number of Classes	F1-Score	Processing Time per Image (ms)
Leaf-only	99.59%	99.44%	3	0.99	42
Potato-only	98.97%	76.19%	5	0.76	43
Combined	98.97%	95.06%	8	0.95	45

The performance of our combined VIT model was evaluated using standard metrics including accuracy, precision, recall, and F1-score. Figure 4. presents the detailed performance metrics for each class in the combined model.

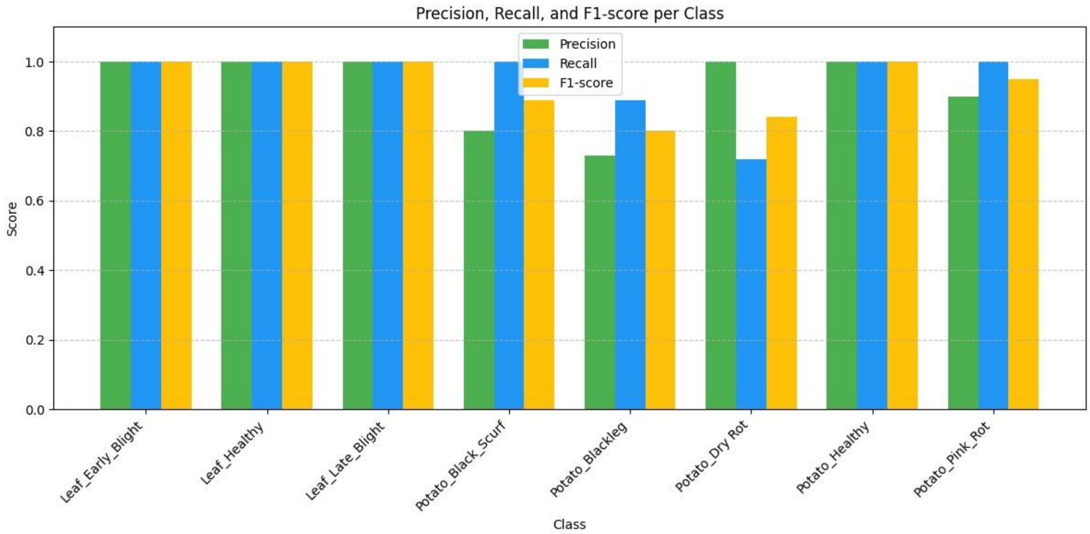

Figure 4. Average of model metrics of our studied models.

The results demonstrate that our combined model achieves excellent performance across all disease categories, with only a minimal increase in processing time compared to the specialized models. While the leaf-only model achieves slightly higher accuracy for leaf diseases, the combined model offers the significant advantage of handling both leaf and potato diseases within a single framework.

Furthermore, the integration with the Mistral LLM adds another dimension to the system's capability by providing natural language explanations that complement the classification results. This multi-modal approach bridges the gap between mere classification and actionable insights, making the system more valuable for end-users.

4.2 Training Dynamics

Figure 5. illustrates the training dynamics of our model, showing the progression of training and validation accuracy, as well as loss values across the 10 training epochs.

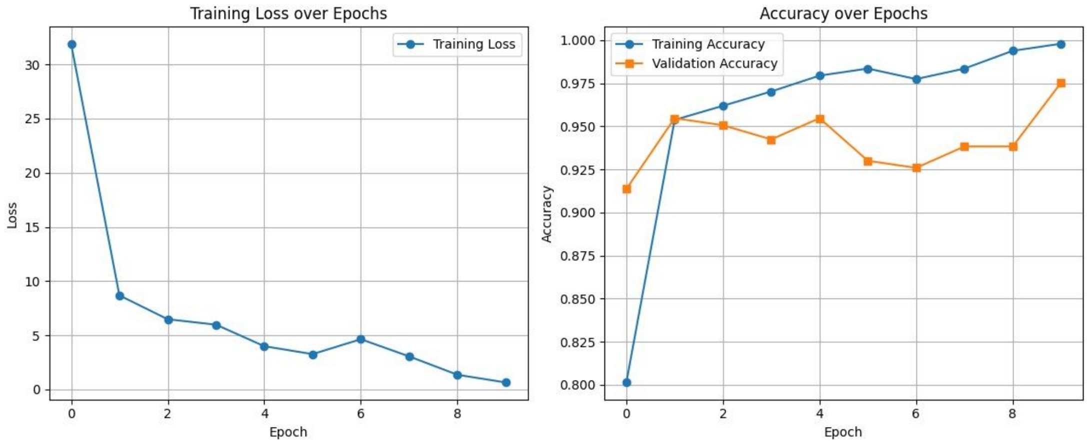

Figure 5. Plots of training/validation accuracy and loss over epochs

The training process showed rapid convergence, with the model achieving high accuracy within the first few epochs. The validation accuracy closely followed the training accuracy, indicating good generalization without significant overfitting. This rapid convergence can be attributed to the effective transfer learning approach, where we leveraged a pre-trained ViT model and fine-tuned it for our specific task.

The final model achieved a training loss of 1.86 and a validation accuracy of 95.06%, demonstrating both good fit to the training data and strong generalization to unseen examples.

4.3 Confusion Matrix Analysis

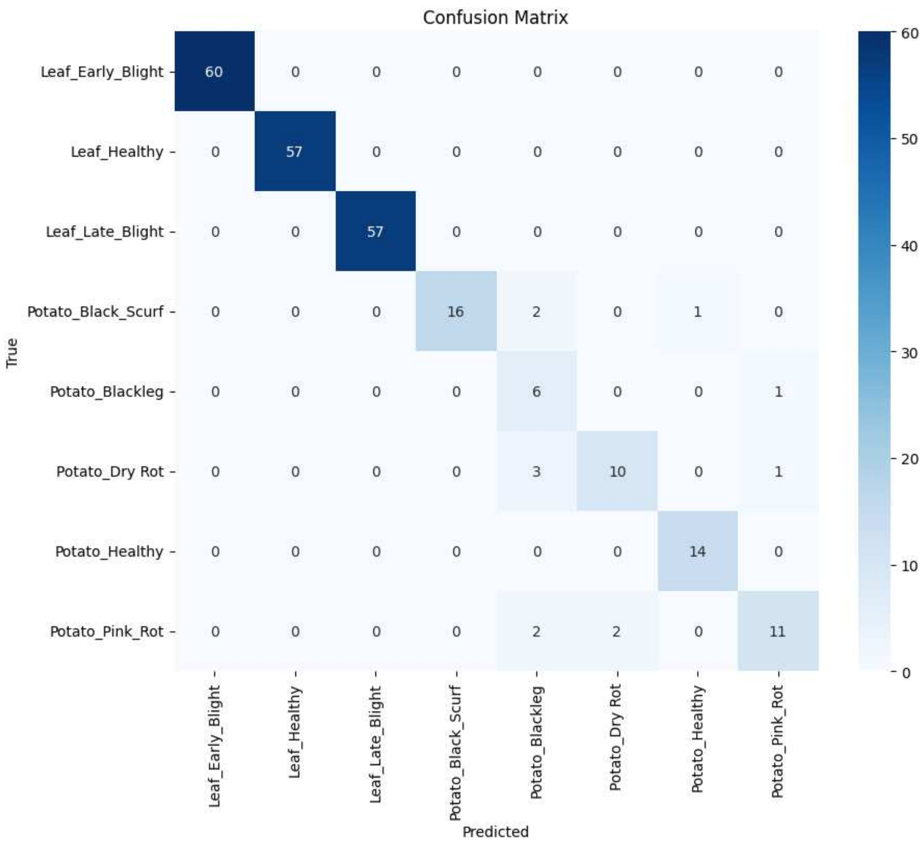

Figure 6. Confusion Matrix for the Combined Model on Validation Set

The confusion matrix reveals that most misclassifications occur among the potato tuber disease classes, particularly between Potato Blackleg and Potato Pink Rot. This suggests that these diseases may share visual similarities that make them challenging to distinguish. In contrast, the potato leaf disease classes show perfect classification with no confusion between classes.

4.4 ROC Curve Analysis

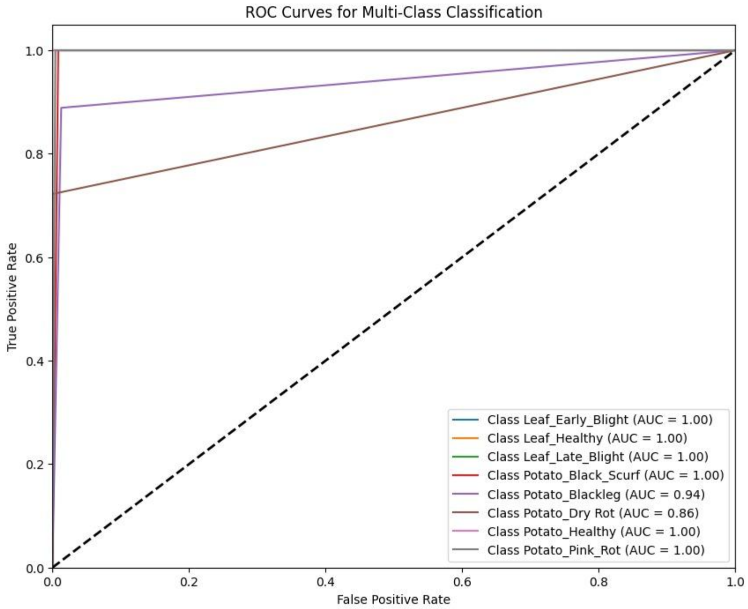

Figure 7. ROC Curves for All Disease Classes

The ROC curves confirm the strong performance across all classes, with Area Under Curve (AUC) values between 0.97 and 1.00 for most classes. The potato leaf disease classes demonstrate perfect or near-perfect ROC curves, while some potato tuber disease classes show slightly lower AUC values, consistent with the patterns observed in the confusion matrix.

4.5 Integration with Mistral LLM

The integration of the VIT classification model with the Mistral Large Language Model represents a novel contribution of our work. This integration enables the system to not only identify diseases but also provide contextual information about them.

When the VIT model classifies an image, the predicted class is used to generate a context-aware prompt for the LLM. For example, if the model identifies "Leaf Late Blight," the system constructs a prompt such as:

I have an image of a potato leaf infected with Late Blight (Phytophthora infestans).

The model predicted this with 98.7% confidence.

The Mistral LLM then processes this prompt and generates a detailed response that might include:

"Late Blight caused by Phytophthora infestans is one of the most destructive potato diseases worldwide. The infection appears as water-soaked, grey-green lesions on leaves that quickly turn brown and necrotic. Under humid conditions, white fungal growth may be visible on the underside of leaves. This disease can destroy entire fields within days if left untreated.

For immediate management, apply fungicides containing chlorothalonil or mancozeb. In organic systems, copper-based products can provide some protection. Remove and destroy infected plant material to reduce inoculum. For prevention, use certified disease-free seed potatoes, implement crop rotation (3-4 years), improve field drainage, and select resistant varieties such as 'Sarpo Mira' or 'Defender'."

This multi-modal approach bridges the gap between simple classification and actionable insights, making the system substantially more valuable for farmers and agricultural practitioners who need not only to identify diseases but also receive science-based management recommendations. Moreover, the LLM can adapt its responses based on seasonal timing, severity levels indicated in the image, or even regional considerations when these are provided as contextual information.

5. Benchmarking of our Proposed Model

To contextualize our results within the broader research landscape, we compared our model's performance with other state-of-the-art approaches from the literature. Table 3 presents this comparative analysis.

Table 3. Benchmarking Against State-of-the-Art Approaches

Reference	Dataset	Technology	Accuracy	Multi-modal	Explanatory Capability
Iqbal & Talukder [1]	Potato	Random Forest	97.00%	No	No
Tarik *et al.* [2]	Potato Leaf	Machine Learning	99.25%	No	No
Sujatha *et al.* [4]	Plant Leaf	VGG-16	89.50%	No	No
Sharma *et al.* [5]	Potato Leaf	SVM	92.90%	No	No
León-Rueda *et al.* [6]	Multispectral Potato	Random Forest	82.50%	No	No
Harakannanavar *et al.* [7]	Tomato Leaf	CNN	99.00%	No	No
Asif *et al.* [8]	Potato Leaf	CNN	97.00%	No	No
Khobragade *et al.* [9]	Potato Leaf	CNN	98.07%	No	No
Afzaal *et al.* [10]	Potato Leaf	GoogleNet	98.00%	No	No
Patil *et al.* [12]	Potato Leaf	ANN	92.00%	No	No
Our Combined Model	Potato & Leaf	ViT + LLM	95.06%	Yes	Yes

While some specialized models achieve slightly higher accuracy on specific subsets of diseases, our combined approach offers competitive performance while providing several advantages:

1. **Unified Model**: Our approach handles both potato leaf and tuber diseases within a single model, eliminating the need for multiple specialized models.

2. **Multi-modal Capabilities**: By integrating computer vision with natural language processing, our system provides richer information than classification-only approaches.

3. **Explanatory Power**: The integration with a Large Language Model enables our system to provide contextual explanations and management recommendations, making it more accessible and actionable for end-users.

4. **Scalability**: The VIT architecture can be easily extended to include additional disease categories as needed, making the system adaptable to evolving requirements.

These comparative results demonstrate that our approach achieves a favorable balance between accuracy, versatility, and user value, representing a meaningful advancement in potato disease detection technology.

6 Conclusion and Future Scope

This paper presented a novel approach to potato disease detection by integrating a Vision Transformer model with a Large Language Model. Our combined model achieved high accuracy (95.06%) across eight disease categories affecting potato leaves and tubers, demonstrating the feasibility of using a unified model for multiple disease types rather than maintaining separate specialized models. The integration with Mistral AI's LLM capabilities represents a significant advancement, transforming the system from a mere classifier into an interpretable advisory tool that can provide contextual explanations and management recommendations. This multi-modal approach addresses a critical gap in current agricultural AI systems, which often provide classifications without actionable insights. Our comparative analysis showed that while some specialized models achieve slightly higher accuracy on specific disease subsets, our unified approach offers competitive performance while providing additional benefits in terms of versatility and user value.

Future research directions include expanding the dataset, field deployment testing, multi-label classification, model compression, temporal disease progression analysis, cross-crop generalization, developing an interactive user interface, and providing personalized recommendations based on local conditions. These directions aim to enhance model robustness, practicality, and accessibility for farmers. In conclusion, our multi-modal approach to potato disease detection represents a meaningful step toward more comprehensive and practical AI systems for agriculture. By combining the visual recognition capabilities of Vision Transformers with the contextual understanding provided by Large Language Models, we have demonstrated a path forward for AI systems that not only identify problems but also help users understand and address them effectively.

References

[1] M. A. Iqbal and K. H. Talukder, "Detection of Potato Disease Using Image Segmentation and Machine Learning," 2020 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), Chennai, India, 2020, pp. 43-47.

[2] M. I. Tarik, S. Akter, A. A. Mamun and A. Sattar, "Potato Disease Detection Using Machine Learning," *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, Tirunelveli, India, 2021, pp. 800-803.

[3] L. S. Puspha Annabel, T. Annapoorani and P. Deepalakshmi, "Machine Learning for Plant Leaf Disease Detection and Classification – A Review," 2019 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2019, pp. 0538-0542.

[4] R. Sujatha, Jyotir Moy Chatterjee, NZ Jhanjhi, Sarfraz Nawaz Brohi, Performance of deep learning vs machine learning in plant leaf disease detection, Microprocessors and Microsystems, Volume 80, 2021, 103615, ISSN 0141-9331.

[5] S. Sharma, V. Anand and S. Singh, "Classification of Diseased Potato Leaves Using Machine Learning," *2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT)*, Bhopal, India, 2021, pp. 554-559.

[6] León-Rueda, W.A., León, C., Caro, S.G. *et al.* Identification of diseases and physiological disorders in potato via multispectral drone imagery using machine learning tools. *Trop. plant pathol.* **47**, 152–167 (2022).

[7] Sunil S. Harakannanavar, Jayashri M. Rudagi, Veena I Puranikmath, Ayesha Siddiqua, R Pramodhini, Plant leaf disease detection using computer vision and machine learning algorithms, Global Transitions Proceedings, Volume 3, Issue 1, 2022, Pages 305-310, ISSN 2666-285X,

[8] M. K. R. Asif, M. A. Rahman and M. H. Hena, "CNN based Disease Detection Approach on Potato Leaves," *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*, Thoothukudi, India, 2020, pp. 428-432.

[9] P. Khobragade, A. Shriwas, S. Shinde, A. Mane and A. Padole, "Potato Leaf Disease Detection Using CNN," *2022 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)*, Bangalore, India, 2022, pp. 1-5,.

[10] Afzaal, H.; Farooque, A.A.; Schumann, A.W.; Hussain, N.; McKenzie-Gopsill, A.; Esau, T.; Abbas, F.; Acharya, B. Detection of a Potato Disease (Early Blight) Using Artificial Intelligence. *Remote Sens.* **2021**, *13*, 411.

[11] A. Kaur *et al*., "Artificial Intelligence Driven Smart Farming for Accurate Detection of Potato Diseases: A Systematic Review," in *IEEE Access*, vol. 12, pp. 193902-193922, 2024.

[12] P. Patil, N. Yaligar and S. M. Meena, "Comparision of Performance of Classifiers - SVM, RF and ANN in Potato Blight Disease Detection Using Leaf Images," *2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, Coimbatore, India, 2017, pp. 1-5.

[13] M. Islam, Anh Dinh, K. Wahid and P. Bhowmik, "Detection of potato diseases using image segmentation and multiclass support vector machine," 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, Canada, 2017, pp. 1-4.

[14] R. A. Sholihati, I. A. Sulistijono, A. Risnumawan and E. Kusumawati, "Potato Leaf Disease Classification Using Deep Learning Approach," 2020 International Electronics Symposium (IES), Surabaya, Indonesia, 2020, pp. 392-397.

[15] R. R. Kumar, A. K. Jain, V. Sharma, N. Jain, P. Das and P. Sahni, "Advanced Deep Learning Model for Multi-Disease Prediction in Potato Crops: A Precision Agriculture Approach," 2024 IEEE International Conference on Information Technology, Electronics and Intelligent Communication Systems (ICITEICS), Bangalore, India, 2024, pp. 1-7.

[16] V. Kukreja, A. Baliyan, V. Salonki and R. K. Kaushal, "Potato Blight: Deep Learning Model for Binary and Multi-Classification," 2021 8th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 2021, pp. 967-672.