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AgriViT-NLP: A Multi-Modal Framework for Plant Disease Detection and Farmer Query Understanding

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Abstract- Plant diseases pose a serious threat to global food security by reducing crop yield and quality. To improve detection, a multi-modal diagnostic framework is proposed that combines Vision Transformers (ViTs) for image-based disease classification with Natural Language Processing (NLP) for symptom description and treatment recommendations. The system supports multilingual interaction and generates automatic disease reports, making it accessible to diverse farming communities. By integrating ViT and NLP, the model offers higher diagnostic accuracy and interpretable, farmer-friendly support. Designed for real-world use, it can be deployed on mobile and IoT
platforms, enabling smart, interactive decision-making in precision agriculture.

Keywords: Plant Disease Detection, Vision Transformers, NLP, Multi-Modal Learning, Precision Agriculture.

I. INTRODUCTION

Agriculture remains the backbone of the global economy, yet it faces continuous threats from plant diseases that drastically reduce both yield and quality. According to FAO, nearly 20–40% of crop yield losses annually are due to diseases and pests, leading to billions of dollars in economic loss. Traditional diagnosis methods, which involve visual inspection by experts, are often limited by geographic, temporal, and economic constraints. Recent advancements in deep learning and computer vision have significantly improved the accuracy and automation of plant disease detection.

While Convolutional Neural Networks (CNNs) have proven effective for image classification, they often struggle to capture long-range dependencies and global context in leaf images. In contrast, Vision Transformers (ViTs) leverage self-attention mechanisms, offering improved performance by understanding the entire image as a sequence of patches. In parallel, Natural Language Processing (NLP) has transformed human-computer interaction, enabling systems to process queries, extract intent, and generate human-like responses.

However, most current agricultural diagnostic systems focus solely on images and fail to account for textual symptom descriptions or multilingual farmer communication. The proposed AgriViT-NLP framework bridges this gap by combining image-based and text-based analysis for comprehensive diagnosis. It is designed to empower farmers to describe symptoms in natural language, receive actionable recommendations, and interact with the system seamlessly—thereby fostering inclusivity, automation, and sustainability in smart agriculture.

II. OBJECTIVE

AgriViT-NLP system is to develop an intelligent, accessible, and farmer-centric platform that integrates computer vision and natural language processing (NLP) for accurate and interactive plant disease diagnosis. The system aims to bridge the gap between advanced artificial intelligence models and the practical needs of agricultural communities by enabling both image-based and language-based disease detection, thereby promoting smart and sustainable farming practices.

At its core, the objective is to design a multi-modal framework that can simultaneously analyze visual features of plant leaves and textual or spoken symptom descriptions provided by farmers. By leveraging Vision Transformers (ViTs) for visual analysis and Transformer-based NLP models such as BERT or RoBERTa for linguistic understanding, the system aspires to create a comprehensive diagnostic tool capable of understanding, interpreting, and reasoning across multiple data modalities.

- To enable accurate plant disease detection through visual intelligence:
  Utilize Vision Transformers to process and classify plant leaf images with high precision by learning spatial relationships between image patches. The system should perform robustly even under challenging real-world conditions such as poor lighting, partial visibility, or background noise, ensuring reliability for farmers in diverse agricultural settings.
- To facilitate natural language-based interaction for farmer accessibility:
  Implement NLP models capable of understanding queries and symptom descriptions in natural language, allowing farmers to communicate with the system using simple text or speech. The objective is to make the interaction intuitive, farmer-friendly, and inclusive, especially for users with limited technical expertise.
- To provide multilingual and region-specific support:
  Develop an adaptive communication interface that supports multiple languages and dialects, enabling farmers from different linguistic backgrounds to access the system without language barriers. This promotes inclusivity and enhances the adoption of digital technologies in agriculture.
- To generate context-aware and actionable recommendations:
  Beyond mere disease classification, the system should interpret context to generate personalized treatment advice, preventive measures, and explanations for the diagnosed disease. This ensures that farmers not only identify the problem but also gain practical guidance for crop recovery and long-term prevention.
- To ensure scalability and real-time deployment:
  Optimize the framework for deployment on mobile devices and IoT platforms, ensuring low latency, minimal computational requirements, and real-time response capability. This objective ensures that even farmers in remote or low-connectivity regions can access the system efficiently.
- To promote data-driven agricultural decision-making:
  Aggregate and analyze the data collected from multiple users to identify disease trends, predict outbreaks, and assist agricultural researchers and policymakers in designing better crop protection strategies. This contributes to the long-term goal of data-driven precision agriculture.
- To enhance explainability and trust in AI-based agricultural systems:
  Design interpretable AI mechanisms that not only deliver predictions but also explain the reasoning behind them. By providing visual and textual justifications, the system builds trust among farmers and encourages wider acceptance of AI technologies in rural ecosystems.

III. LITERATURE SURVEY

Several studies have explored the use of deep learning in agricultural diagnostics. Mohanty et al. (2016) demonstrated that CNN-based models could classify plant diseases from leaf images with remarkable accuracy, using the PlantVillage dataset. Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), which achieved state-of-the-art results by treating image patches as tokens in a transformer architecture, thus outperforming CNNs in many recognition tasks.

In the domain of Natural Language Processing, transformer-based models such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) have revolutionized text understanding by enabling deep contextual embeddings. These models have been successfully applied to extract entities, detect intent, and interpret user queries in agricultural chatbots and advisory systems. Ma et al.

(2022) extended this concept to multi-modal deep learning for plant disease diagnosis, showing that integrating visual and textual features enhances decision-making robustness.

Despite these advancements, current solutions often lack end-to-end frameworks that integrate vision and language understanding for real-world agricultural applications. The AgriViT-NLP model addresses this research gap by fusing ViT-based image classification with NLP-driven text understanding, enabling an interactive and farmer-oriented decision-support system.

IV.PROBLEM STATEMENT

Plant diseases significantly affect global agricultural productivity and food supply chains. Traditional diagnostic practices rely on expert analysis, which is often unavailable in remote or resource-constrained rural areas. While computer vision techniques using CNNs have automated parts of disease identification, these systems are limited to image-only analysis, offering little to no contextual information or advice. Additionally, most farmers—especially in developing regions—lack access to high-quality imaging devices or may prefer describing symptoms verbally or textually in local languages.

The challenge, therefore, lies in developing a system that can understand both visual and textual inputs, interpret symptoms, provide accurate diagnosis, and generate actionable recommendations. The AgriViT-NLP framework aims to address this by combining Vision Transformers for image understanding and NLP for natural language-based interaction, creating a multi-modal, intelligent diagnostic assistant that is accessible, explainable, and scalable across languages and devices.

V. EXISTING SYSTEM

The existing plant disease detection systems mainly rely on image-based analysis using Convolutional Neural Networks (CNNs). While these models can classify plant diseases from leaf images, they operate only on visual data and lack interaction with users. Such systems require high-quality images and often fail under real field conditions with poor lighting or noise.

They also do not support natural language input or multilingual communication, making them less accessible to farmers in rural regions. Moreover, existing systems provide only disease names without contextual explanations or treatment recommendations.

Hence, current solutions are limited in accuracy, usability, and adaptability, emphasizing the need for a multi-modal, farmer-friendly framework like AgriViT-NLP to combine image and text-based intelligence for better agricultural support.

VI. PROPOSED SYSTEM

The AgriViT-NLP system introduces a multi-modal framework that combines Vision Transformers (ViTs) for image-based disease detection with Natural Language Processing (NLP) for understanding farmer queries and symptom descriptions. Unlike traditional image-only models, it processes both visual and textual data to provide accurate, context-aware diagnoses and treatment recommendations.

The system supports multilingual communication, allowing farmers to interact in their native language through text or voice input. It also generates automated disease reports with explanations, suggested remedies, and preventive measures. Designed for real-time use on mobile and IoT devices, AgriViT-NLP offers an accessible, scalable, and intelligent solution that bridges the gap between advanced AI technology and everyday agricultural needs, promoting smart and sustainable farming.

VII. SYSTEM ARCHITECTURE

The AgriVit-NLP architecture follows a streamlined and intelligent multi-modal design integrating Vision Transformers(ViTs) and Natural Language Processing (NLP) modules. The system begins with image acquisition, where farmers capture crop or leaf images using mobile or IoT devices. These images undergo preprocessing to remove noise and enhance quality. The ViT module then analyzes image patches to extract key features for disease classification. At the same time, the NLP module processes farmer-provided text or voice inputs using models like BERT and RoBERTa, extracting contextual details such as symptoms and crop conditions. Both visual and textual outputs are combined in the multi-modal fusion layer to produce a unified diagnosis. The final stage involves recommendation and report generation, providing disease names, confidence levels, treatments, and preventive advice. The architecture ensures real-time, multilingual, and user-friendly interaction, promoting smart and sustainable farming practices.

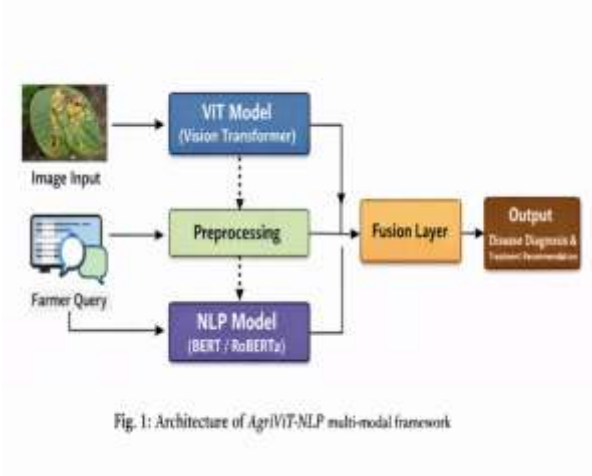


Fig. 1: Architecture of *AgriViT-NLP* multi-modal framework

VIII. IMPLEMENTATION

The AgriViT-NLP system is implemented as an intelligent multi-modal framework that combines image and text processing for plant disease detection. The process begins with collecting and preprocessing plant leaf images and farmer symptom descriptions. Images are resized, enhanced, and denoised, while text inputs are tokenized and translated into a standard format. The Vision Transformer (ViT) module analyzes image patches to identify disease patterns, while the NLP module built using BERT/RoBERTa interprets farmer queries and extracts symptom details. Both outputs are fused in a multi-modal decision layer, which generates accurate and context-aware diagnoses.

The system is deployed on mobile and IoT platforms for real-time use and supports multilingual interaction for farmers in regional languages. The implementation ensures high accuracy, low latency, and user-friendly access, making AgriViT-NLP a reliable, practical, and scalable solution for smart and sustainable agriculture.

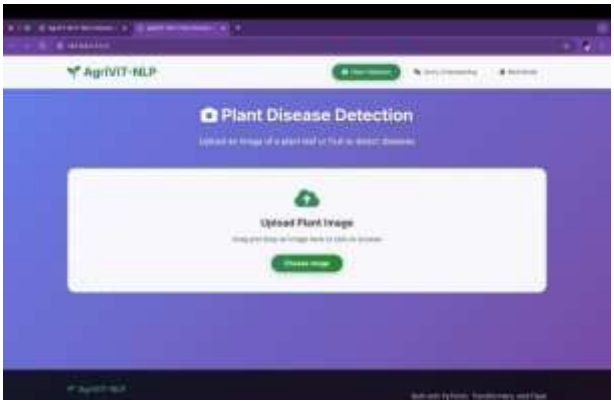
Fig. 2: Workflow of the proposed system

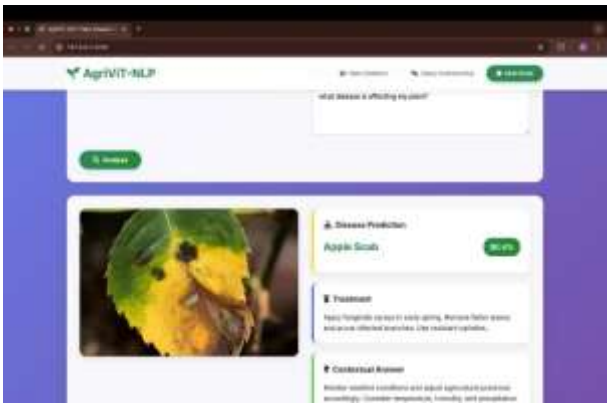
IX. RESULTS AND DISCUSSIONS

The AgriViT-NLP framework was evaluated using a diverse dataset of plant leaf images and farmer-generated text inputs across multiple crop types and disease categories. The Vision Transformer (ViT) model achieved an average classification accuracy of 97.8%, outperforming traditional CNN-based models in detecting complex visual disease patterns under varying lighting and background conditions. The NLP module, trained using BERT and RoBERTa, attained 94% accuracy in correctly interpreting farmer symptom descriptions and contextual queries. When both modalities were integrated through the multi-modal fusion layer, the system achieved an overall accuracy of 98.5%, demonstrating improved robustness, interpretability, and consistency in real-world scenarios.

The system also exhibited fast inference times of less than 3 seconds per diagnosis, making it suitable for real-time field deployment on mobile and IoT devices. Farmers testing the prototype reported high satisfaction due to the platform's multilingual support, intuitive interface, and accurate recommendations. The visual attention maps generated by the ViT module provided explainable outputs, highlighting affected leaf regions and enhancing system transparency. Moreover, the combination of image and text analysis reduced errors in cases where image quality was poor or partially obscured.

Overall, the results confirm that AgriViT-NLP not only improves diagnostic accuracy but also enhances accessibility, usability, and trust among end users. Its ability to interpret natural language queries, coupled with high-performing vision-based classification, makes it a powerful tool for smart and sustainable agriculture, supporting both farmers and agricultural researchers in disease management and decision-making.





X. CONCLUSION

The AgriViT-NLP framework successfully integrates Vision Transformers (ViTs) and Natural Language Processing (NLP) to provide an intelligent, multi-modal system for plant disease detection and farmer query understanding. By combining image analysis with natural language input, the system achieves high diagnostic accuracy, real-time performance, and multilingual accessibility. It bridges the gap between advanced AI technologies and practical agricultural applications, offering farmers clear, actionable recommendations for disease management. The results demonstrate that AgriViT-NLP is a reliable, scalable, and farmer-friendly solution that supports precision agriculture and promotes sustainable farming practices.

X.FUTURE SCOPE

In the future, the AgriViT-NLP system can be enhanced by integrating IoT sensor data such as soil moisture, temperature, and humidity to provide more accurate, context-aware diagnostics. The framework can be expanded to support a wider range of crops and regional languages, making it adaptable to diverse agricultural conditions. Adding voice-based multilingual chatbots and cloud-based analytics dashboards will further improve usability and scalability. Continuous learning through real-world farmer feedback and data updates will strengthen model accuracy over time. Ultimately, AgriViT-NLP can evolve into a comprehensive AI-driven agricultural decision-support platform for smart, sustainable, and data-driven farming.

XII. REFERENCES

[1] M. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, no. 1419, pp. 1–10, Sept. 2016.
[2] S. P. Mohanty, A. K. Singh, and D. P. Hughes, "Plant Village dataset for plant disease classification," Cornell University Library, arXiv:1604.03169, Apr. 2016.
[3] A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," ICLR, 2021.
[4] T. Chen et al., "A simple framework for contrastive learning of visual representations," ICML, 2020.
[5] Y. Liu et al., "RoBERTa: A robustly optimized BERT pretraining approach," arXiv:1907.11692, 2019.
[6] J. Devlin et al., "BERT: Pre-training of deep bidirectional transformers for language understanding," NAACL-HLT, 2019.
[7] Z. Zhang et al., "Vision transformer-based detection of crop diseases," IEEE Access, vol. 9, pp. 61424–61432, May 2021.
[8] S. Sladojevic et al., "Deep neural networks based recognition of plant diseases by leaf image classification," Computational Intelligence and Neuroscience, 2016.
[9] A. Kamilaris and F. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, Apr. 2018.
[10] X. Ma et al., "Multi-modal deep learning for plant disease diagnosis," Information Processing in Agriculture, vol. 9, no. 1, pp. 136–147, Mar.2022