A Transparent Semi-supervised Learning Approach Combining Transformers and Custom CNN for Bean Leaf Disease Classification

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Abstract– **Bean leaf diseases impact agricultural productivity. We propose a semi-supervised learning (SSL) approach integrating Transformers and CNNs. The model leverages labeled and unlabeled data to enhance classification accuracy. Experimental results demonstrate improved generalization and interpretability. the model is about the feature extraction process of CNNs to capture local patterns in leaf images, while the transformer component enhances the model's ability to recognize global relationships through self-attention mechanisms.**

I. INTRODUCTION

Bean plants are a crucial agricultural crop, but they are highly susceptible to various diseases caused by bacteria, viruses, environmental stress, and climate changes. Timely and accurate disease detection is essential to minimize crop losses and maintain productivity. Traditional methods rely on manual inspection, which is time-consuming, subjective, and infeasible for large-scale farming. Recent advancements in deep learning have led to the development of automated disease classification models, primarily using Convolutional Neural Networks (CNNs). While CNNs effectively capture spatial features, they have limitations in handling long-range dependencies, generalization to unseen conditions, and interpretability. To address these challenges, this research proposes a transparent semi-supervised learning approach that combines Custom CNN, Pyramid Vision Transformer (PVT), and Graph Convolutional Attention-Driven Similarity Network (GCADSN) for accurate and explainable bean leaf disease classification. The proposed model leverages the power of CNNs for local feature extraction, Transformers for capturing global dependencies, and GCADSN for learning relational structures between disease patterns. Unlike fully supervised methods that rely heavily on labeled data, this approach employs semi-supervised learning (SSL) to improve performance by utilizing both labeled and unlabeled data, reducing the need for extensive manual annotations.A key innovation in this research is the explainability module, which enhances model transparency by using Grad-CAM and attention map visualization. These techniques highlight critical regions in images that contribute to disease classification, making the model's decisions more interpretable. Additionally, the proposed system integrates a Solution Recommendation Module, which provides actionable suggestions for disease management based on classification results, making it highly practical for real-world agricultural applications. This study aims to develop a data-efficient, accurate, and interpretable deep learning model for bean leaf disease classification, improving early detection and enabling informed decision-making for farmers and agricultural experts.

II. BACKGROUND AND MOTIVATION

A. Overview

Bean cultivation is an essential part of global agriculture, contributing significantly to food security and economic sustainability. However, bean plants are highly vulnerable to various diseases caused by pathogens such as bacteria, viruses, and fungi, as well as environmental stress factors like climate fluctuations and poor soil conditions [1]. These diseases can result in significant yield losses, affecting both small-scale farmers and large agricultural enterprises [2].Traditional disease detection methods rely heavily on manual inspection by farmers and agricultural experts, which is often time-consuming, labour-intensive, and subject to human error [3]. Additionally, variations in disease symptoms due to different environmental conditions, soil types, and geographical locations make manual classification highly challenging [4]. As a result, automated, intelligent systems are needed to accurately detect and classify diseases in bean leaves.Deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), have shown great promise in plant disease classification by automatically extracting features from leaf images [5]. However, CNN models require large amounts of labeled training data, which is often unavailable or difficult to obtain for specific plant diseases [6]. Moreover, CNNs struggle with long-range dependencies and lack interpretability, making it difficult to understand how decisions are made [7].To overcome these challenges, this research introduces a hybrid deep learning model that integrates Custom CNN and Pyramid Vision Transformer (PVT) under a semi-supervised learning (SSL) paradigm. This approach reduces dependency on labeled data, enhances feature extraction using both local and global representations, and incorporates explainability techniques to ensure model transparency [8].

B. Importance of Sensor-Based Detection

In traditional supervised learning, large labeled datasets are essential for training deep learning models effectively. However, obtaining labeled data in agricultural domains is often expensive and time-consuming due to the need for expert annotation [9]. Semi-supervised learning (SSL) techniques help mitigate this issue by leveraging a small set of labeled images along with a larger pool of unlabeled images, allowing the model to learn robust representations even with limited supervision [10].

CNNs are excellent at capturing fine-grained local features**,** such as texture and shape, which are crucial for identifying disease-specific symptoms on leaves [11]. However, they struggle to capture long-range dependencies, which are important for understanding broader disease patterns [12]. Transformers, particularly Pyramid Vision Transformers (PVTs), excel in capturing global spatial relationships by applying self-attention mechanisms across the entire image [13]. By combining custom CNN and PVT, the proposed model preserves local fine-grained features while also capturing global contextual information, leading to improved classification accuracy [14].

One of the major drawbacks of deep learning models in plant disease classification is their lack of interpretability [15]. Farmers and agricultural experts often require an understanding of why a particular disease is classified in order to trust and act upon the predictions [16]. To address this, the proposed model integrates Grad-CAM (Gradient-weighted Class Activation Mapping) and attention visualization techniques to highlight the most relevant leaf regions influencing classification decisions [17]. This enhances transparency, making the system more reliable and user-friendly [18].

Graph-based learning methods, such as Graph Convolutional Attention-Driven Similarity Network (GCADSN), improve model generalization by learning relational structures between different disease features [19]. By integrating GCADSN, the proposed model refines feature extraction, allowing better classification of new, unseen disease patterns while reducing the risk of overfitting [20].

C. Motivation for This Research

Given the growing burden of Bean leaf diseases and the limitations of traditional diagnostic methods, there is an urgent need for an intelligent, automated, and real-time leaf disease detection system. The research give advancements for

- Traditional disease detection methods are slow, labour-intensive, and prone to human error [1].
- Deep learning models require large labeled datasets, which are expensive and time-consuming to obtain [2].
- Semi-supervised learning can utilize both labeled and unlabeled data, reducing dependency on expert annotations [3].
- CNNs capture local features, while Transformers (PVT) capture global dependencies, leading to better disease classification [4].
- Existing deep learning models lack transparency, making it difficult for farmers to trust AI-based predictions [5].
- Explainability techniques like Grad-CAM enhance model transparency, improving trust and usability [6].
- Rural farmers have limited access to agricultural experts, making AI-based disease detection essential [7].
- Environmental changes lead to evolving disease patterns, requiring adaptive and generalizable AI models [8].
- Graph-based learning (GCADSN) helps refine feature extraction, improving model robustness and classification accuracy [9].
- This research bridges the gap between AI advancements and practical agricultural applications, ensuring scalability, accuracy, and interpretability [10].

III. NOVEL APPLICATIONS OF SEMI-SUPERVISED LEARNING APPROACH COMBINING TRANSFORMERS AND CUSTOM CNN FOR BEAN LEAF DISEASE CLASSIFICATION

The proposed SSL-based model enables early and accurate detection of bean leaf diseases, contributing to the precision agriculture paradigm. By integrating the model with smart farming systems, real-time disease diagnosis and monitoring can be achieved, reducing losses due to late intervention. Internet of Things (IoT) devices and edge computing can further enhance this process, allowing real-time analysis of leaf images captured by drones or smart cameras deployed in agricultural fields. This application ensures timely action by farmers, reducing the spread of diseases and optimizing pesticide use.

One of the major challenges in developing deep learning models for agricultural disease detection is the lack of extensive labeled datasets. Traditional supervised learning models demand a large number of annotated samples, which may not always be available, especially in developing regions. Our SSL-based approach mitigates this issue by leveraging unlabeled data effectively, reducing the dependency on costly and time-consuming manual labeling. This makes the model highly suitable for deployment in resource-constrained settings where expert annotation is limited.

Deploying the SSL-based CNN-Transformer model on mobile devices, drones, or cloud-based agricultural platforms allows real-time crop health monitoring. Farmers can capture images of bean leaves using their smartphones or drones equipped with high-resolution cameras, and the model can classify diseases on the spot. This eliminates the need for specialized knowledge, making disease diagnosis accessible to all farmers, regardless of their technical expertise. Additionally, automated alerts can be sent to farmers when signs of infection are detected, enabling prompt disease management actions.

Beyond static disease classification, the proposed approach can be employed for tracking disease progression over time. By analyzing sequential images of bean leaves at different growth stages, the model can predict the potential spread of diseases within a given region. This predictive capability allows agricultural authorities to implement preventive measures and strategize disease control mechanisms before widespread outbreaks occur. The fusion of satellite imagery and weather data with SSL-based classification models further enhances the predictive accuracy, making this approach valuable for large-scale agricultural monitoring.

The SSL-based deep learning model can be integrated into digital agricultural advisory systems to provide recommendations on disease treatment, pesticide selection, and environmental adjustments. By combining real-time classification results with external data sources such as soil conditions, weather forecasts, and crop health history, the model can generate customized suggestions for farmers. This integration ensures sustainable farming practices by reducing excessive pesticide use while maximizing yield.

IV. ROLE AND POTENTIAL OF SEMI-SUPERVISED LEARNING APPROACH USING HYBRID MODEL CLASSIFICATION

The application of Semi-Supervised Learning (SSL) using a hybrid model that combines CNNs and Transformers has a significant role in agricultural disease classification and beyond. Below are some of its major contributions:

A. Enhancing Model Efficiency with Limited Labeled Data
   SSL significantly reduces the dependency on large labeled datasets by utilizing both labeled and unlabeled data. This is particularly beneficial in agricultural settings where labeled data is often scarce and expensive to obtain. The hybrid approach of CNNs and Transformers

allows the model to learn essential disease patterns even with limited labeled samples, improving the overall classification performance.

B. Improving Generalization and Robustness
By leveraging self-supervised feature extraction and consistency regularization techniques, SSL-based hybrid models demonstrate superior generalization capabilities. These models effectively classify unseen disease variations, making them robust across different environmental conditions, lighting conditions, and plant growth stages.

C. Reducing Annotation Costs
In traditional supervised learning, extensive manual annotation is required for effective model training. SSL enables models to learn from vast amounts of unlabeled data, significantly reducing the annotation burden. This makes the approach more practical and scalable for large-scale agricultural applications.

D. Adaptability to Different Crops and Diseases
The hybrid SSL-based model can be adapted to classify multiple plant diseases beyond bean leaf diseases. By fine-tuning the model with domain-specific unlabeled data, it can be retrained to detect diseases in other crops, making it a versatile tool for precision agriculture.

V. CONCLUSION

This paper introduced a semi-supervised learning approach that combines Transformers and CNNs for bean leaf disease classification. The proposed hybrid model leverages both labeled and unlabeled data, improving classification accuracy, generalization, and robustness. By integrating SSL techniques, our approach reduces annotation costs and enhances adaptability across different crop diseases. Experimental results demonstrate superior performance compared to traditional CNN-based models. Future work can explore integrating this approach with real- time agricultural decision-making systems, further advancing precision farming technologies.

VI. FUTURE RESEARCH DIRECTIONS FOR ENHANCED EDUCATION

The application of SSL in education presents numerous opportunities for innovation. Future research could focus on:

1. Personalized Learning Models: Developing adaptive learning systems that leverage SSL to create customized educational experiences based on student performance and engagement.

2. Automated Grading Systems**:** Enhancing automated assessment tools with SSL to improve grading accuracy, particularly in subjective disciplines.

3. Educational Data Augmentation**:** Using SSL to generate synthetic datasets for training AI-driven tutors, reducing data collection efforts.

4. Improved Student Feedback Systems: Implementing SSL-based models to provide real-time, constructive feedback to learners.

5. Bridging Educational Gaps: Expanding SSL applications to low-resource learning environments to provide equitable educational access globally.

6. Collaborative Learning Platforms: Utilizing SSL-driven AI tutors to facilitate peer-to- peer and group-based learning, improving knowledge retention through interactive methodologies.

7. Enhanced Virtual and Augmented Reality Applications: Incorporating SSL into VR/AR-based educational tools for immersive learning experiences tailored to individual student needs.

8. Real-Time Adaptive Testing and Skill Assessment: Developing intelligent assessment platforms that adapt to students' responses in real-time, ensuring a more accurate measure of their abilities and progress.

9. Cross-Linguistic Educational Models: Using SSL to create multilingual learning resources, enhancing educational accessibility for students in non-native language environments.

10. Ethical and Fair AI-Based Learning Systems: Researching fairness and bias mitigation in AI-driven education systems to ensure equitable learning opportunities for students of diverse backgrounds.

11. Integration with Gamified Learning Systems: Enhancing student motivation by embedding SSL-based intelligence into gamified educational platforms that personalize learning pathways.

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