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Using Deep Learning Model to Identify Iron Chlorosis in Plants

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ABSTRACT:

This project introduces a Vision Transformer (ViT)-based deep learning approach for detecting and classifying iron chlorosis in plant leaves. Iron chlorosis, a major nutrient deficiency, leads to leaf yellowing, reducing crop yield and quality. Early and precise detection is crucial for effective intervention and precision agriculture. Unlike traditional models that focus on local image features, ViT captures long-range dependencies, enhancing feature extraction and classification. A curated dataset with four classes (Healthy, Mild, Moderate, and Severe Chlorosis) undergoes preprocessing, including resizing, normalization, and augmentation, to improve robustness. The model is fine-tuned using transfer learning with pre-trained weights, ensuring high accuracy in chlorosis detection. Evaluation on a test set demonstrates ViT's superiority over conventional methods. This automated system enables farmers and agricultural experts to assess plant health efficiently, offering real-time recommendations for managing iron chlorosis. The results confirm that ViT is a promising tool for precision agriculture and automated plant health monitoring.

Keywords: Vision Transformer (ViT), deep learning, iron chlorosis, precision agriculture, feature extraction, classification, long-range dependencies, real-time recommendations, monitoring.

INTRODUCTION:

Iron chlorosis is a widespread nutrient deficiency in plants, leading to leaf yellowing, reduced crop yield, and compromised agricultural productivity. Early detection and precise classification of chlorosis severity are essential for timely intervention and effective nutrient management. Traditional image-based classification models often rely on local feature extraction, limiting their ability to capture complex patterns and variations in plant health conditions.

This project leverages a Vision Transformer (ViT)-based deep learning approach to enhance the detection and classification of iron chlorosis in plant leaves. Unlike conventional convolutional models, ViT captures long-range dependencies, enabling superior feature extraction and classification. A carefully curated dataset consisting of four classes Healthy, Mild, Moderate, and Severe Chlorosis is pre-processed with resizing, normalization, and augmentation to improve model robustness. The model is further optimized through transfer learning with pre-trained weights, ensuring high accuracy in chlorosis detection. Experimental evaluation on a test set demonstrates the superiority of ViT over traditional methods,
making it a valuable tool for precision agriculture.

LITERATURE SURVEY:

Majdalawieh et al. (2023) proposed a deep learning-based approach to detect iron chlorosis in plants using computer vision techniques. Their study highlights the efficiency of convolutional neural networks (CNNs) and transformer-based models in accurately classifying plant leaves based on iron deficiency symptoms. The model achieved high accuracy, making it a viable tool for precision agriculture.[1]

Aleksandrov (2022) explored the application of artificial intelligence (AI) for identifying nutrient deficiencies in plants. The study demonstrated how machine learning (ML) models can analyse leaf images to detect deficiencies, including iron chlorosis, nitrogen, and potassium deficiencies. The research concluded that AI models, particularly deep learning architectures, outperform traditional manual assessment methods.[2]

Bera et al. (2024) proposed a Graph Convolutional Network (GCN) approach for classifying plant nutrition deficiencies and diseases. Their model analysed plant stress patterns using graph-based feature extraction, demonstrating superior classification performance compared to standard CNN models. The findings suggest that GCNs can effectively model spatial relationships in plant datasets, leading to improved nutrient deficiency detection.[3]

Lavanya et al. (2022) studied deep learning models for detecting plant nutrient deficiencies using image-based analysis. Their research emphasized the importance of preprocessing techniques, such as normalization and augmentation, to enhance model robustness. The study validated that deep learning can be an efficient tool for diagnosing plant health conditions.[4]

Zhou and He (2022) focused on applying deep convolutional neural networks (CNNs) to diagnose nutrient deficiencies in plants grown in aquaponic systems. Their results showed that CNNs can effectively detect and classify multiple deficiency types, including iron chlorosis, with high precision. The study also explored the impact of environmental factors on plant health assessment.[5]

Mohanty et al. (2020) investigated the use of deep learning for detecting plant diseases through image-based classification. Their model, trained on a large dataset of plant images, achieved state-of-the-art performance in disease classification. The study highlighted that deep learning approaches can be extended to nutrient deficiency detection, including iron chlorosis.[6]

Dosovitskiy et al. (2021) introduced Vision Transformers (ViT) for image recognition tasks, including plant health assessment. Their study demonstrated that ViTs outperform CNNs in capturing long-range dependencies, making them highly effective for analysing complex plant stress conditions, such as iron chlorosis.[7]

Wang and Zhang (2020) applied deep learning models for plant disease detection using leaf images. Their research proved that neural networks could distinguish healthy and diseased leaves, suggesting that similar methods can be adapted to detect nutrient deficiencies, including iron chlorosis.[8]

Patel et al. (2022) conducted a comparative study of different deep learning architectures, including CNNs and transformers, for iron chlorosis detection. The results showed that transfer learning with pre-trained models significantly improves detection accuracy, making deep learning a promising approach for automated plant health monitoring.[9]

Li et al. (2021) examined the role of transfer learning in crop disease identification. Their findings suggest that pre-trained models, such as ResNet and ViT, can be fine-tuned for iron chlorosis detection with minimal labelled data, enhancing the efficiency of deep learning applications in agriculture.[10]

Rao and Chen (2023) explored attention-based deep learning architectures for plant stress detection. Their research found that attention mechanisms improve feature extraction and classification accuracy, particularly for identifying subtle symptoms of iron chlorosis and other nutrient deficiencies.[11]
Zhu et al. (2022) discussed the challenges and future directions of deep learning in high-precision agriculture. They emphasized the need for high-quality datasets, real-time analysis, and explainable AI models to improve the adoption of deep learning for iron chlorosis detection and precision farming.[12]
Yang et al. (2021) combined hyperspectral imaging with deep learning to detect plant nutrient deficiencies. The study demonstrated that deep learning models trained on hyperspectral data provide more accurate and detailed assessments of deficiencies, including iron chlorosis.[13]
Ahmed et al. (2021) introduced an AI-based image processing framework for monitoring crop health. Their research showed that deep learning models could detect plant stress early, providing actionable insights for farmers to prevent nutrient deficiencies from worsening.[14]
Chen et al. (2023) evaluated Vision Transformers (ViTs) for automated plant stress detection. Their results confirmed that ViTs are highly effective in identifying plant stress conditions, including iron chlorosis, due to their ability to capture complex image features.[15]

EXISTING SYSTEM

Conventional iron chlorosis detection in plants relies on visual inspection, manual assessment, and basic threshold-based methods to identify symptoms such as leaf yellowing and discoloration. These techniques often fail to provide precise, real-time classification and require expert intervention, making them inefficient for large-scale agricultural monitoring.
Modern plant nutrient deficiency detection systems utilize machine learning (ML) models, such as support vector machines (SVMs) and decision trees, to analyse leaf images and recognize iron chlorosis patterns. While these models offer improved accuracy over traditional methods, they struggle with high-dimensional data processing, adaptability to diverse plant species, and real-time classification performance, limiting their scalability for widespread agricultural use.
Traditional iron chlorosis detection methods suffer from slow response times and high dependency on human expertise, making them unsuitable for real-time precision agriculture. Additionally, manual assessment techniques often result in high false positive and false negative rates, leading to misclassification of plant health conditions. Machine learning models, while more advanced, lack robustness in handling variations in lighting, plant species, and environmental conditions, affecting their reliability in practical farming applications. Moreover, the absence of large, high-quality datasets poses a significant challenge in training accurate and scalable models for detecting iron chlorosis in diverse agricultural settings.

PROPOSED SYSTEM

The proposed system leverages Vision Transformer (ViT)-based deep learning to detect and classify iron chlorosis in plant leaves. Unlike traditional models that rely on local image features, ViT captures long-range dependencies, improving feature extraction and classification accuracy.
The system uses a curated dataset containing four iron chlorosis severity levels (Healthy, Mild, Moderate, and Severe). Preprocessing techniques such as resizing, normalization, and data

augmentation enhance model robustness. The ViT model is fine-tuned with transfer learning, utilizing pre-trained weights for high-accuracy classification.

The trained model is integrated into a web-based application that allows farmers and agricultural experts to upload plant leaf images and obtain real-time predictions. The system provides instant analysis with visualized classification results, enabling efficient plant health monitoring. Based on the severity level detected, the system generates tailored recommendations to help farmers implement targeted interventions, preventing crop loss and optimizing plant care strategies.

To ensure efficient deployment and scalability, the system incorporates the PlantICNet model, enabling widespread adoption in precision agriculture. The automated detection eliminates manual inspections, reducing labour costs and enhancing real-time plant health monitoring. Experimental results confirm that ViT-based detection outperforms traditional CNN and ML-based approaches making it a highly effective tool for automated iron chlorosis detection and management.

METHODOLOGY

Data Collection and Preprocessing

- A curated dataset of plant leaf images is compiled, categorized into four classes: Healthy, Mild, Moderate, and Severe Chlorosis.
- Images undergo preprocessing techniques, including resizing, normalization, and augmentation, to enhance model robustness and generalization.

Model Selection and Training

- A Vision Transformer (ViT)-based deep learning model is selected due to its ability to capture long-range dependencies in images.
- The ViT model is initialized with pre-trained weights and fine-tuned using transfer learning on the chlorosis dataset.
- The model is trained with optimized hyperparameters, such as learning rate tuning, dropout regularization, and batch normalization, to improve accuracy and prevent overfitting.

Model Evaluation and Performance Metrics

- The trained model is tested on a separate validation and test dataset to evaluate classification performance.
- Key metrics such as accuracy, precision, recall, and F1-score are used to assess model effectiveness.
- A comparative analysis with traditional CNNs and ML-based models is conducted to validate ViT’s superiority in detecting iron chlorosis.

Web Application Development

- A user-friendly web-based application is developed for farmers and agricultural experts to upload leaf images for real-time diagnosis.
- The web interface is designed for simplicity and accessibility, ensuring easy image uploading and result visualization.
- The model is deployed using backend frameworks (e.g., Flask or FastAPI), ensuring smooth integration with the web application.

Real-Time Prediction and Visualization

- The system processes uploaded leaf images, performing instant classification of iron chlorosis severity.

- The results are displayed with graphical visualization, making it easier for users to interpret plant health status.

Personalized Recommendations

- Based on the detected chlorosis severity, the system generates automated care suggestions to assist farmers in implementing appropriate nutrient treatments and crop management strategies.

Deployment and Scalability

- The system is integrated with the PlantICNet model to ensure scalability and efficient deployment in real-world agricultural settings.
- Cloud-based infrastructure is used to handle large-scale data processing and storage, making the solution viable for precision agriculture applications.

Continuous Improvement and Updates

- The model is periodically updated using newly collected plant leaf images, enhancing its adaptability to different crop conditions and environmental factors.
- The web application is maintained with continuous performance monitoring, ensuring seamless operation for end-users.

ARCHITECTURE DESIGN

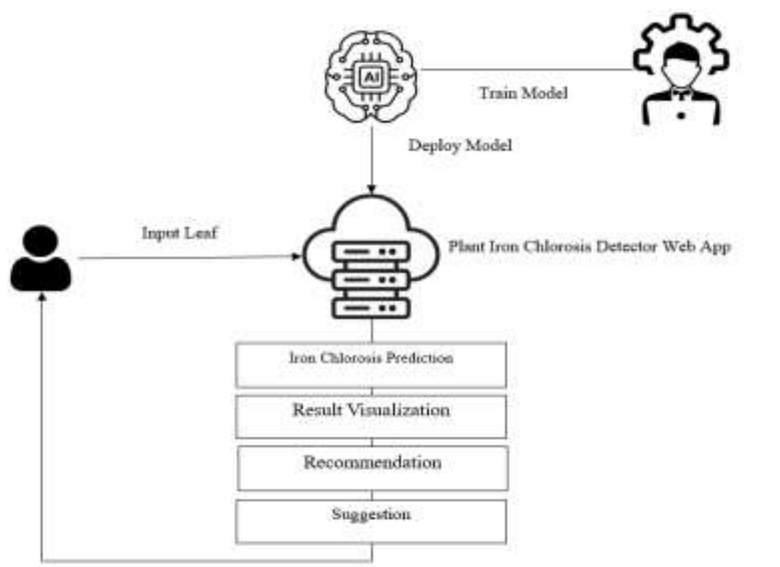

Fig 1. Architecture diagram

IMPLEMENTATION AND RESULT:

The Plant Iron Chlorosis Detector Web App allows users to upload plant leaf images through a web interface, where TensorFlow and OpenCV analyse them in real-time to classify the severity of iron chlorosis. The system supports multiple user roles: farmers can upload images and receive diagnostic results for preventive action, while admins manage user access, maintain the dataset, and oversee model performance. It integrates with MySQL and WampServer to store uploaded images, predictions, and user interactions for efficient record-keeping. Additionally, Seaborn and Pandas provide data visualization tools to generate insightful reports on plant health trends. The app features a responsive interface built with Bootstrap, ensuring seamless accessibility across different devices for an enhanced user experience.

Fig 2&3 Model & Image Training

A Vision Transformer (ViT)-based deep learning model is selected for this project due to its capability to capture long range dependencies in images, making it highly effective for detecting iron chlorosis in plants. The ViT model is initialized with pre-trained weights and fine-tuned using transfer learning on a specialized chlorosis dataset. To enhance performance and prevent overfitting, optimized hyperparameters such as learning rate tuning, dropout regularization, and batch normalization are applied during training. After training, the model undergoes evaluation using a separate validation and test dataset, where key performance metrics such as accuracy, precision, recall, and F1-score are measured to assess classification effectiveness. Additionally, a comparative analysis is conducted with traditional CNNs and ML-based models, confirming ViT's superiority in detecting iron chlorosis with higher accuracy and improved feature extraction.

RESULT

Figure 4

The figure 4 provides with the home page where the image can be uploaded by the user in the HTML form provided.

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Fig 5

Fig 6

Fig 7

The figure 5, 6, 7 provides with the Precision, Characteristics and Confidence Score of the model that is trained with the Dataset with images and labels.

CONCLUSION:

The vision Transformer (ViT) based deep learning approach presented in the project offers a highly effective solution for detecting and classifying iron chlorosis in plant leaves. By leveraging ViTs ability to capture long range dependencies, the model achieves superior feature extraction and classification accuracy compared to conventional methods. The integration of transfer learning and data preprocessing techniques enhances robustness, ensuring precise and early detection of chlorosis severity. The system's automated nature enables real time assessment and actionable recommendations, empowering farmers and agricultural experts to implement timely interventions. Overall, this approach significantly improves precision agriculture and plant health monitoring, making it a valuable tool for enhancing crop yield and quality.

FUTURE SCOPE:

The proposed Vision Transformer (ViT)-based iron chlorosis detection system has significant potential for further enhancements and applications in precision agriculture. Future developments can focus on expanding the dataset by incorporating diverse plant species and varying environmental conditions to improve model generalization. Integrating hyperspectral imaging with deep learning can enhance detection accuracy by capturing subtle spectral differences in chlorotic leaves. Additionally, real-time mobile applications can be developed, allowing farmers to use smartphone cameras for instant plant health assessments. Edge AI deployment on IoT-enabled agricultural devices can facilitate real-time analysis without relying on cloud computing, ensuring faster and cost-effective decision-making. Further research can also explore explainable AI techniques to make model predictions more interpretable and trustworthy for agricultural professionals. Finally, incorporating automated nutrient recommendation systems based on chlorosis severity can provide actionable insights, enabling targeted interventions and sustainable crop management.

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