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AGROVISION: INTELLIGENT DETECTION OF LEAF DISEASES USING CNN MODEL

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ABSTRACT:
Agriculture is a crucial sector for global sustenance, yet it suffers significant losses due to plant diseases. Early detection and diagnosis of leaf diseases play a vital role in preventing crop damage and ensuring better yield. This project, "AgroVision: Intelligent Detection of Leaf Diseases Using CNN Model," aims to develop an intelligent and reliable system that uses Convolutional Neural Networks (CNNs) to detect plant leaf diseases accurately. The methodology involves collecting a comprehensive dataset of potato leaf images, preprocessing the data using TensorFlow. A CNN model is constructed and trained to identify disease patterns with high precision. The trained model is exported and integrated into a user friendly React.js that allows farmers to upload or capture leaf images for real-time analysis and disease detection. The system is designed to provide early diagnosis, enabling farmers to take prompt action to mitigate the spread of diseases, thereby reducing economic losses. The expected outcomes of the project include accurate model predictions, a seamless user interface, faster response times, and easy deployment for practical use in the agricultural domain. This solution not only assists in minimizing crop loss but also empowers farmers with advanced technology to improve crop management and productivity.
Keywords: Convolutional Neural Network (CNN), Image Classification, Deep Learning, Artificial intelligence (AI), Disease Detection, Crop Management, Precision Farming, Real-Time Analysis, React.js, FastAPI, TensorFlow, Data Preprocessing, Image Segmentation, Material UI, User-Friendly Interface, Model Training and Validation, Dataset Augmentation, Economic Loss Mitigation, Sustainable Agriculture, Scalability, Accuracy and Precision, Farm Productivity, Disease Pattern Recognition, Lightweight AI Models, Real-Time Monitoring

INTRODUCTION:
Agriculture plays a fundamental role in ensuring food security and supporting economies worldwide. However, plant diseases significantly impact crop yield, leading to considerable economic losses for farmers. Identifying these diseases at an early stage is crucial to minimizing damage and improving productivity. Traditional methods of disease detection rely on manual observation, which is time-consuming, labor-intensive, and often inaccurate due to human limitations. With advancements in Artificial Intelligence (AI) and Computer Vision, automated systems can now be developed to identify plant diseases effectively. This project, titled "AgroVision: Intelligent Detection of Leaf Diseases Using CNN Model," leverages Convolutional Neural Networks (CNNs) to create a robust, intelligent detection system. By processing leaf images, the system accurately identifies diseases, enabling timely intervention and minimizing crop damage. The project also focuses on developing a user-friendly web application using React JS, where farmers can upload or capture images of plant leaves for real-time

analysis. This system not only ensures precision but also empowers farmers with technological solutions to enhance crop management and yield.

LITERATURE:

Recent approaches in plant disease detection have used deep learning to particularly perform remarkable work with the help of Convolutional Neural Networks, i.e., CNNs. In 2023, Yashasavi Khaparde et al. introduced "Plant Check," a CNN-based model for early potato leaf disease, at an accuracy of 91.41%, emphasizing early detection, challenges in datasets, and IoT for real-time monitoring. In the same year, Cemal Ishan Sojoglu et al. also created another CNN model for potato plant leaf disease and achieved a whopping 98.28% accuracy while concentrating on lighting robustness and scalability in smart farming solutions. In 2022, Maha Altalak et al. presented a hybrid approach which combined CNN, SVM, and CBAM that achieved an accuracy of 97.20% by differentiating similar diseases while optimizing architecture. Earlier, in 2020, Liu and Wang had integrated CNNs with image segmentation for plant disease detection, and it achieved a high accuracy of 96.30% with minimal false positives and modular scalability. Ma et al. developed a segmentation-based CNN framework for the apple leaf diseases, focusing on early detection and dataset augmentation.

RESEACH GAPS:

Agrovision addresses critical gaps in existing plant disease detection systems with a specialized, user-centric, and efficient solution tailored for potato leaf diseases. In contrast to generalized models detecting diseases across various crops, Agrovision is specialized in potato farming, which means optimizing datasets, model architecture, and preprocessing techniques to maximize accuracy and relevance. It has a strong error-handling mechanism that verifies the input image category before making a classification, ensuring reliability and garnering the trust of the user. Agrovision also places prime importance on usability: its clean, intuitive interface designed using React.js. Leverage the power of modern frameworks such as FastAPI, which ensures real-time processing is fast and efficient with minimal latency for practical applications in agriculture. The system trains its CNN model on high-quality, disease-specific features using a curated dataset of potato leaf images and advanced preprocessing techniques, including data augmentation and noise removal, which significantly improve prediction accuracy. Designed with practicality and scalability in mind, Agrovision works efficiently on standard computing devices to cater to small-scale farmers in resource-constrained environments. In addition, it has potential for future enhancements such as disease management recommendations and IoT integrations, making it a robust and scalable solution for modern agriculture.

METHODOLOGY AND IMPLEMENTATION:

The methodology and implementation of Agrovision are designed to provide a robust and user-friendly system for potato leaf disease detection. The dataset was sourced from Kaggle, comprising labeled images of healthy leaves and those affected by diseases like early blight and late blight. Images were resized to 256x256 pixels, normalized to a [0, 1] range, and split into training, validation, and testing subsets (80-10-10 split). Ambiguous or irrelevant images were rejected to preserve quality. A custom CNN using TensorFlow was built, with dropout layers to prevent overfitting, sparse categorical crossentropy as the loss function, and Adam optimizer for stable convergence. The model was trained through several epochs to an accuracy and generalization that were satisfactory and then saved for deployment. The backend is implemented with FastAPI, where the pre-trained CNN model loads and processes the incoming images. It preprocesses these images to match the model's input format and gives predictions through a POST API endpoint, returning results in JSON format. Error-handling logic was added to detect non-potato leaf images, ensuring reliable outputs. The frontend, built with React.js and styled using Material UI, offers a user-friendly interface with features like image upload, live capture, and real-time results display. Axios was used to transfer data very smoothly to the backend.

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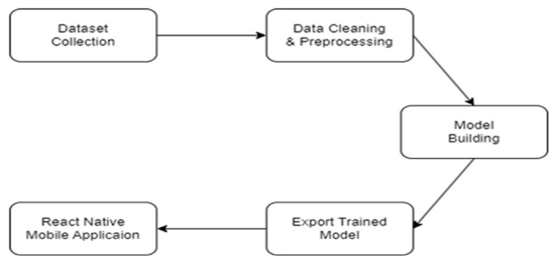
Integration was meant to configure API endpoints so the frontend and backend could converse seamlessly. The user uploads the image. The backend processes the image and classifies it as Healthy, Early Blight, or Late Blight (or returns an error if the input is invalid). Results are shown dynamically on the frontend, with confidence scores that improve reliability. End-to-end testing validated the functionality of the system toward accuracy, error handling, and ease of use.



OBJECTIVES:

Develop an Accurate Detection System: Design and implement a Convolutional Neural Network (CNN)-based automated detection tool that accurately identifies plant leaf diseases. The system will focus on achieving high precision, ensuring reliable and consistent results to assist farmers in making informed decisions.

Enable Early Diagnosis: Build a system capable of detecting plant diseases at an early stage. Early diagnosis will empower farmers to take preventive actions promptly, reducing the spread of diseases and safeguarding crops.

Economic Loss Minimization: Reduce financial losses in agriculture by enabling timely disease detection and intervention. By preventing severe damage to crops, the system will help farmers optimize yields and minimize the economic impact of crop diseases.

Increase Awareness and Knowledge: Develop a user-friendly tool that educates farmers and users on plant disease symptoms, their causes, and treatment options. This will empower farmers with better crop management practices, enhancing their knowledge and contributing to healthier agricultural practices.

Enhance Real-Time Monitoring: Integrate real-time monitoring features using mobile-friendly platforms. This will allow farmers to identify diseases as soon as symptoms appear and monitor the health of their crops remotely.

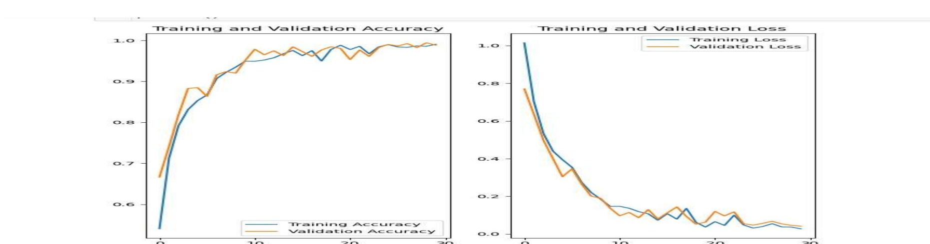
RESULTS AND DISCUSSIONS:

Accuracy And Precision

Model Performance

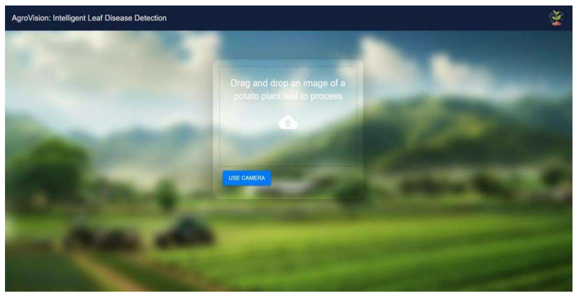
The CNN model was evaluated using a dataset of diseased and healthy leaf images. The performance metrics used to assess the model include accuracy, precision.

- Accuracy: The model achieved an accuracy of 98.8%, indicating its reliability in correctly classifying leaf diseases.
- Precision: The precision of the model across various disease categories ranged from 90% to 98%, ensuring accurate predictions with minimal false positives.



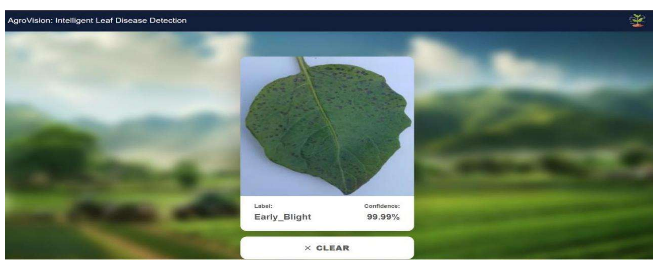
HOME PAGE:

The front page of the Agrovision website is designed for simplicity and usability. At the top, a clean navbar prominently displays the Agrovision logo and navigation links for easy access to other sections. Below, a drag-and-drop box allows users to effortlessly upload leaf images for disease detection. Alternatively, a capture button is provided for users who prefer to take real-time photos of the leaf directly from their device. The layout is visually appealing and intuitive, ensuring users can quickly interact with the system. The design reflects Agrovision's commitment to a seamless user experience, catering to the needs of farmers and agricultural enthusiasts.



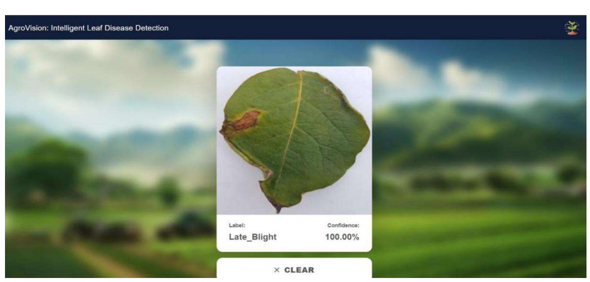
EARLY BLIGHT DETECTION:

After the image is uploaded or captured, the output page displays the detection result prominently. The page shows "Early Blight" in bold text, making it immediately noticeable. Alongside this, the confidence score, such as 99.99%, is displayed to highlight the accuracy of the prediction. The layout is clean and focused, ensuring users can quickly understand the result without distractions. This straightforward presentation aligns with Agrovision's goal of providing clear and actionable feedback to farmers efficiently.



LATE BLIGHT DETECTION:

After the image is uploaded or captured, the output page prominently displays the detection result as "Late Blight" in bold, ensuring immediate visibility. The confidence score of 100% is highlighted alongside, indicating absolute certainty in the prediction. The page is designed to focus solely on delivering this critical information, ensuring it is clear and actionable. This precise and unambiguous feedback helps users quickly understand the situation and take necessary actions to manage the disease effectively.



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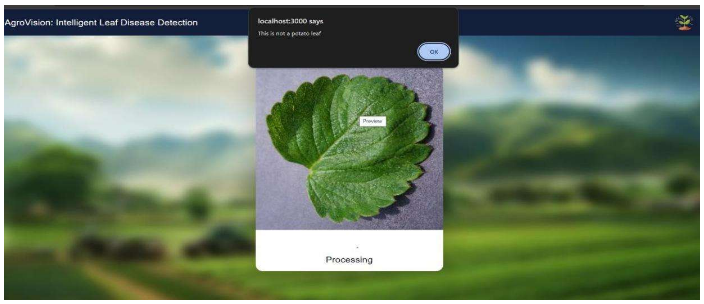
NOT A POTATO LEAF:

When the image uploaded is not a potato leaf, a dialog box appears with the message, "This is not a potato leaf" indicating the app's recognition of the incorrect input. This screenshot highlights the app's input validation, a crucial feature for preventing errors and ensuring accurate results. The message reinforces that the app is specifically designed for potato leaf analysis. It provides helpful feedback to the user, informing them of the issue. And also by identifying non-potato leaves, the app avoids providing incorrect disease diagnoses.



DISCUSSION:

Successes:

- Improved Accuracy and Speed: Compared to traditional methods, AgroVision significantly boosts both the accuracy (percentage of correct diagnoses) and speed of detecting plant diseases.
- High Precision and Recall: The model delivers trustworthy predictions, meaning it correctly identifies positive cases (diseases) and avoids false positives (healthy leaves mistaken for diseased). Additionally, it has high recall, indicating it catches most actual diseases and minimizes false negatives (diseased leaves missed).
- Fast Response Time: The system processes images in seconds, making it practical for real-time use in the field, allowing farmers to take immediate action based on the diagnosis.
- User-Friendly Interface: Testing the app's usability and efficiency, suggesting a well- designed and easy-to-use interface.

Challenges:

- Ambiguous Images: Low-quality images, blurry photos, or partially obscured leaves can sometimes reduce the accuracy of the diagnosis.
- Rare Diseases: The dataset used to train the model might not have included enough examples of less common diseases. This limited coverage can impact the system's ability to detect those specific diseases accurately.

CONCLUSION:

The Agrovision project is the biggest leap for technology in fighting critical agricultural problems, especially in potato farming. Using a CNN-based system, Agrovision is able to offer an accurate and automated solution for detecting potato leaf diseases such as early blight and late blight, while correctly distinguishing healthy leaves. This precision allows for proper diagnosis at the right time and enables farmers to take the appropriate measures to avoid crop damage and minimize economic loss. Its intuitive design, with drag-and-drop functionality and real-time image analysis, makes it easy to use for people with minimal technical knowledge. The use of modern frameworks such as FastAPI for backend processing, React.js for the frontend, and Material UI for a polished user interface highlights the technical sophistication of the project. Agrovision not only increases agricultural productivity but also contributes to sustainable practices by minimizing pesticide misuse and optimizing treatment strategies. The end aims to create the possibility of achieving precision farming on a large scale, and there's a potential great impact on world food security with this action. This will open up new ground for using artificial intelligence solutions to make agriculture much more efficient and profitable and beneficial for the environment. In Agrovision's future development, it can certainly change traditional approaches to farming forever, greatly impacting the farming industry.

Future work for Agrovision is to expand its scope to detect diseases in other crops such as tomatoes, wheat, and rice. It will be addressing broader agricultural needs. IoT integration will enhance precision by incorporating environmental data such as temperature and humidity. A multilingual interface is planned to improve accessibility for diverse user bases, along with a lightweight mobile application for on-the-go usage. Advanced AI techniques like attention mechanisms and transfer learning will further refine accuracy and robustness. Extensive real-world testing will ensure reliability under varying conditions, and advisory features like treatment recommendations and market insights will provide a holistic solution. Scalability will be prioritized for large-scale deployment across cooperatives and government agencies, thus positioning Agrovision as a transformative tool for modern agriculture.

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