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Agroscan: Ai-Driven Corn Plant Disease Detection

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Abstract: Early Identification of crop infections is a critical component of sustainable agriculture, as it is essential to maximize crop yields and minimize losses. Corn plants are susceptible to various infections that can have a substantial impact on crop production, including Northern Corn Leaf Blight, Common Rust, and Gray Leaf Spot. This research introduces a computational framework that incorporates artificial intelligence (AI) and employs deep learning techniques to identify diseases in maize plants while assessing their severity. The system will use high-resolution images that will be used to train a convolutional neural network (CNN) for robustly diagnosing disease. The system design incorporates a MongoDB database that will allow for efficient storage, retrieval, and management of disease-related data. The system will be able to provide growers with flexibility through real-time tracking and instant feedback to help growers make informed decisions to help control and prevent plant disease. The models are implemented utilizing TensorFlow and PyTorch, and are designed to be scalable and accurate. A well-organized interface will allow farmers and agronomists ease of access to the prediction process. The system design shows how automated disease detection can be combined with real-time information for smart farming. Future improvements will depend on improving the detection accuracy and later applying these models to more crops. This study reinforces sustainable agricultural practices and integrates AI-based precision farming systems.

Index Terms - Maize crop disease identification, AI-driven plant health monitoring, CNN-based disease classification, advanced deep learning in agriculture, intelligent farming systems, automated crop disease recognition, real-time agricultural diagnostics.

I. Introduction

Agricultural practices serve a crucial function in achieving global food security, but plant diseases seriously threaten crop productivity and yield. Corn is a major staple agricultural crop grown around the world and is highly susceptible to many diseases of the corn leaf, which reduce yield and productivity, and if left untreated, could result in millions of dollars of economic losses. Timely identification and assessment of disease severity are crucial for effective intervention and achieving the best possible agricultural results. While the traditional methods of disease identification can be accurate, they are time-consuming and require expertise, making them impractical for large farming operations. However, with advancements in artificial intelligence (AI) and deep learning, automated identification and accurate classification of plant disease is possible, which minimizes dependence on the time-consuming manual inspection. In this study, we introduce AgroScan, an AI-based system developed for real-time identification and classification of corn leaf diseases based on severity into mild, moderate, and severe. We employ the DenseNet201 deep neural network model to assess the severity of diseases. Different classification levels are applied based on various criteria, and we use a MongoDB database for storing data, ensuring efficient storage and retrieval of data, and enabling rapid access to disease predictions along with treatment options. The model was developed using high-resolution images of corn leaves affected by various diseases to improve classification accuracy. AgroScan enables farmers to make decisions based on data, which would reduce crop losses through the treatment of diseased corn plants and reduce pesticide use through decision-making. The AgroScan system will foster smart farming and efficient intervention based on moisture levels from the soil, predictive disease markers, and more.

A. Objectives
1. Implement an Efficient Disease Detection System
2. Facilitate Real-Time Disease Monitoring
3. Enhance Data Management and Accessibility
4. Promote Sustainable Farming
5. Ensure Scalability and User-Friendly Interface

B. Applications

1. Early Disease Detection
➢The system enables early identification of corn plant diseases, helping farmers take preventive measures and reduce crop loses
2. Smart Farming and Real-Time Monitoring
➢Integrating deep learning models enables real-time tracking of plant health, reducing dependency on manual inspections and optimizing resource usage.
3. Mobile-Based Farmer Assistance
➢A mobile-friendly platform assists farmers by identifying in-plant diseases, providing treatment suggestions, and enhancing agricultural decision-making.
4. Large-Scale Agricultural Surveillance
➢Government agencies and agribusinesses can employ this system for extensive crop monitoring, ensuring proactive disease.

II. LITERATURE REVIEW

Recent strides in deep learning (DL) have significantly advanced plant disease detection and classification automation, contributing to the emergence of intelligent systems in agriculture. Research findings consistently highlight the superior effectiveness of DL approaches—particularly Convolutional Neural Networks (CNNs)—in processing plant images for disease identification, often surpassing the accuracy of traditional machine learning algorithms.
For example, Mohammed Madhurya and Jubilson introduced the YR2S framework, a sophisticated deep learning model that employs high-resolution imagery of plant foliage to categorize diseases according to severity levels. Their methodology achieved notably higher classification performance compared to conventional approaches, offering a solid foundation for AI-enabled plant disease management systems [1]. Similarly, Mohanty et al. demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in accurately identifying plant diseases, reinforcing the potential of DL-based models in automated crop health evaluation using comprehensive image datasets [6], [9].
The effectiveness of deep learning models is heavily dependent on the quality and variability of the datasets used during training. To this end, Moupojou developed the FieldPlant dataset, comprising high-resolution images collected under authentic agricultural conditions. This dataset effectively addresses real-world challenges such as inconsistent lighting and background noise, thereby improving model reliability in field scenarios [2]. Similarly, Hughes and Salathé assembled a publicly available image dataset designed to support mobile-based diagnostic platforms, enhancing the accessibility of AI-driven solutions for the farming sector [4].
Kamilaris and Prenafeta-Boldú conducted an extensive survey analyzing the deployment of deep learning techniques across multiple agricultural applications, including crop surveillance, plant disease identification, and yield prediction. Their study underscored key benefits such as enhanced accuracy, reduced dependency on manual labor, and greater sustainability in agricultural practices. The review also

pointed out critical limitations, including substantial computational demands, the necessity for large annotated datasets, and the complexity involved in interpreting deep learning model outputs. Importantly, the authors recognized the value of transfer learning in addressing data scarcity while sustaining high model performance [5].
Ngugi provided a detailed examination of deep learning methodologies, particularly Convolutional Neural Networks (CNNs), for detecting plant diseases. The study explored technical challenges, including the scalability of DL frameworks, increasing computational requirements, and the necessity of continuously augmenting datasets to maintain model accuracy and adaptability in evolving agricultural contexts [3].
Significant strides have been made toward enabling real-time plant disease diagnosis. Zhang introduced a smartphone-based application powered by cloud-integrated CNNs, capable of providing rapid disease identification in the field. Designed to operate effectively under varying environmental conditions, the system illustrates the practical potential of mobile deep learning solutions for on-site agricultural diagnostics [7]. In a related advancement, Singh and Jain proposed a comprehensive framework that merges CNN architectures with IoT-enabled environmental sensing. By monitoring factors such as temperature, humidity, and soil moisture, their system enhances diagnostic precision and supports timely intervention through mobile-based farmer notifications [8].
The integration of deep learning (DL) with Internet of Things (IoT) technologies for plant health surveillance has garnered considerable interest in recent research. Militante highlighted the advantages of deploying DL-IoT frameworks for continuous, real-time plant condition monitoring, which supports more informed and timely agricultural decision-making. Contributions from both Militante and Singh and Jain demonstrate the effectiveness of these integrated systems in minimizing manual labor while significantly improving the efficiency and responsiveness of smart agricultural practices [13], [8].
Recent studies have investigated the role of image preprocessing techniques in enhancing the accuracy of plant disease classification models. Hirani emphasized that effective preprocessing helps mitigate challenges posed by fluctuating environmental conditions, thereby boosting the reliability of CNN-based models [12]. Tulshan and Raul established that deep learning methods significantly outperform traditional machine learning algorithms in accurately detecting diseases during their early stages [14]. Furthermore, Panchal highlighted the critical role of sophisticated image enhancement and feature extraction strategies in improving the precision of disease identification in crops [16].

Numerous researchers, including Ahmad [10], Li [11], and Wani [15], have performed comprehensive evaluations and comparative studies of various deep learning architectures applied to plant disease diagnosis. Their investigations consistently identified Convolutional Neural Networks (CNNs) as the most effective models for image-based detection tasks in agriculture. However, they also emphasized persistent challenges such as high computational demands, limited access to annotated datasets, and difficulties in interpreting model decisions.
In summary, the surveyed research underscores the promising capabilities of deep learning, particularly Convolutional Neural Networks (CNNs), in advancing precision agriculture through automated and real-time detection of plant diseases. The effectiveness of these approaches is significantly enhanced by the use of diverse, high-resolution datasets and the integration of Internet of Things (IoT) technologies. However, ongoing challenges such as scalability, environmental inconsistencies, and intensive computational demands remain critical barriers. Addressing these limitations will require continued interdisciplinary efforts and technological advancements to enable the widespread adoption of deep learning in smart agricultural systems.

III. IMPORTANCE OF PROBLEM

The early identification of diseases in corn plants plays a vital role in minimizing crop losses and safeguarding food supply. Manual inspection methods are inefficient and prone to errors, leading to delayed intervention and reduced agricultural productivity. Implementing an AI-driven detection system enhances accuracy, supports real-time monitoring, and enables farmers to take timely corrective actions, promoting sustainable farming practices.

A. Problem Statement

Corn plants are vulnerable to numerous leaf diseases that can greatly affect crop production if not identified promptly. Conventional methods of disease detection depend on manual inspections, which can be slow, labor-intensive, and prone to errors. This study aims to develop an AI-driven system utilizing deep learning techniques for accurate and real-time classification of corn plant diseases, assisting farmers in making timely decisions to minimize crop losses.

B. Implemented System Summary

Our proposed agricultural diagnostic tool, AgroScan, utilizes AI-powered deep learning techniques to accurately identify and categorize diseases in corn plants. The system integrates the following key components:

• Computer Vision for Disease Detection: An Advanced Densenet201 deep learning model is utilized for analyzing high-resolution corn leaf images to classify diseases into predefined severity levels (mild, moderate, and severe).

• Integrated Treatment Recommendations: Provides both organic and inorganic solutions for effective disease management based on AI predictions.

• Database for Efficient Data Management: Utilizes MongoDB for real-time data storage, retrieval, and analysis, ensuring efficient handling of large datasets.

•User-Friendly Interface for Accessibility: A web-based and mobile application interface enables farmers and agricultural experts to interact seamlessly with the system for disease detection and treatment suggestions.

• Scalable and High-Performance Backend: The system is optimized for rapid processing and continuous monitoring, ensuring low delay and exceptional scalability for widespread agricultural use.

This implementation significantly enhances precision farming and sustainable agriculture by offering early disease detection, real-time monitoring, and AI-powered decision-making, thereby minimizing crop losses and improving overall yield productivity.

C. Related work

Numerous AI-based systems for detecting plant diseases have been created, utilizing deep learning techniques for effective classification. Existing solutions, such as Plant Village and Deep-Leaf, primarily focus on image-based disease identification but often lack real-time adaptability and explainability. Conventional models rely on static datasets, limiting their effectiveness in handling newly emerging plant diseases. Recent advancements in AI, such as transformers and vision-based deep learning, have shown promise in improving classification accuracy and generalizability. However, these methods often suffer from scalability challenges, high computational costs, and the inability to provide actionable insights for farmers. Our system addresses these limitations by integrating real-time database updates, adaptive deep learning models, and a user-centric interface for enhanced accessibility and decision-making in precision agriculture.

IV. METHODOLOGY

A. Data Collection and Preprocessing

This study employs a dataset composed of high-definition, real-time photographs of corn leaf samples, including both healthy and disease-affected instances. Each image is carefully annotated to facilitate supervised learning processes such as disease classification and severity estimation. The image capture was performed under varying environmental and illumination conditions to better simulate field settings and enhance the model's adaptability. To strengthen the model's generalization capabilities and reduce the risk of overfitting, various data augmentation strategies were applied. These included geometric operations like image rotation and flipping (both horizontal and vertical), alongside photometric enhancements such as brightness adjustment and contrast modification. These augmentations introduce variability reflective of real-world agricultural environments. Furthermore, a chronological dataset of disease events was maintained, providing valuable historical context for trend analysis and validating predictive accuracy over time. This temporal component supports a more comprehensive understanding of disease development and reinforces the reliability of the deep learning model in practical farming scenarios.

B. System Architecture

The system architecture follows a client-server structure where the front-end application interacts with a cloud-server-based deep-learning derived city classification model. The architecture contains three main modules:
1. Image Acquisition: The users upload the images of the leaves from a web or mobile application.
2. Preprocessing & Feature Extraction: The OpenCV and PIL libraries are used to reduce noise and enhance features.
3. Deep learning model: The classification is performed by DenseNet201, which is a convolutional neural network (CNN), pre-trained on ImageNet and fine-tuned with the dataset we collected.

C. Model Development and Enhancement

The model was developed using TensorFlow and PyTorch frameworks, employing categorical cross-entropy as the loss function. To optimize the model's performance, the Adam optimizer was used, enabling faster convergence. Hyperparameter tuning was performed to further enhance efficiency. The dataset was partitioned into 80% for training, 10% for validation, and 10% for testing to mitigate the risk of overfitting. Training took place on a high-performance GPU system.

D. Database Integration

To store and retrieve data effectively, MongoDB was selected as the database management system. It provides quick querying and storage of image metadata, classification results, and user interaction logs. The database offers the functionality of scaling up and seamless integration with the front-end system.

E. Flowchart

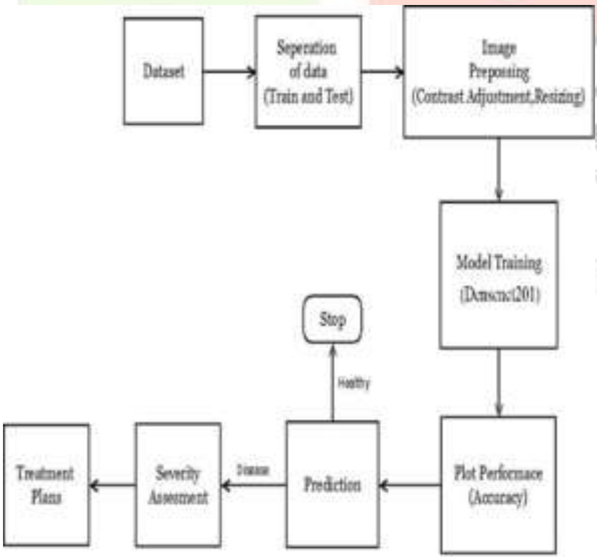

Fig 1. Schematic representation of the system workflow.

Fig 1. Depicts the operational process of the suggested medical image classification system using DenseNet201.The process begins with preparing the dataset, which includes data splitting and image preprocessing. Afterward, the model is trained, and its performance is evaluated based on accuracy. Once training is completed, the system predicts the disease conditions and assesses their severity. Lastly, the severity assessment is used to determine the appropriate treatment strategy.

F. Working

The suggested system captures detailed images of corn plant leaves and analyzes them through a deep learning model. A convolutional neural network (CNN) classifies diseases into different severity levels based on predefined categories. The processed data is stored in a MongoDB database for efficient retrieval and analysis. A real-time monitoring interface provides farmers with accurate disease predictions and treatment recommendations. This approach enhances precision farming by enabling timely interventions and reducing crop losses.

V. RESULTS

• The project employs a deep learning method for detecting corn plant diseases, using a Convolutional Neural Network (CNN) model trained on a dataset of labeled real-time images of corn leaves.
• The training process involves image preprocessing (resizing, normalization, and augmentation) to improve generalization. The dataset is divided into training, validation, and testing subsets to ensure the model performs optimally. The CNN architecture is implemented using TensorFlow/Keras, incorporating convolutional, pooling, and fully connected layers to extract relevant features and classify the diseases.
• The model is compiled with an appropriate loss function and optimizer, and training is performed over multiple epochs with batch processing.
• The performance is evaluated using metrics such as accuracy, precision, recall, and loss curves. The trained model is saved and deployed in the backend, which is integrated with Streamlit for the frontend, allowing users to upload leaf images and receive real-time disease classification results.
• Enhancements like UI improvements, animations, interactivity, real-time detection via webcam, and detailed disease insights with recommendations can be added to improve the user experience.

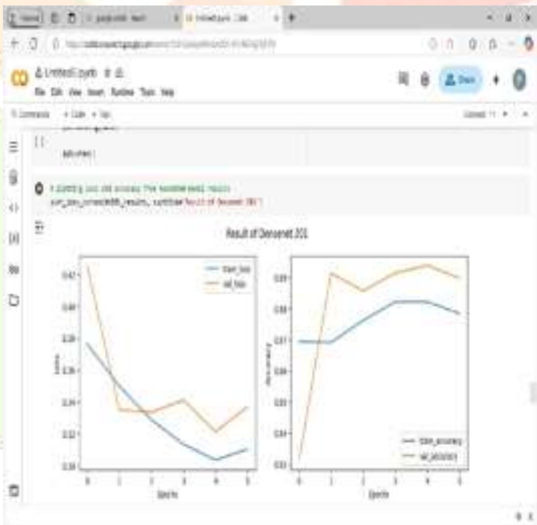

Fig 2. Result of DenseNet 201

Figure 2 shows the training and validation loss (left) and accuracy (right) curves for a DenseNet-201 model over five epochs. The results indicate a decreasing loss trend and improving accuracy, demonstrating effective model training.

Fig 3: Severity of a leaf

Figure 3 shows the model successfully classifies a maize leaf as infected with Cercospora leaf spot, displaying a mild severity of 23.11%, demonstrating the model's capability in precise disease identification. The visual representation reinforces the effectiveness of deep learning in early-stage disease detection for improved crop management.

Summary of Key Findings

The AgroScan framework demonstrated strong effectiveness in automating the detection and classification of corn leaf diseases. Utilizing the DenseNet201 convolutional neural network, the model was trained on a collection of high-resolution, well-annotated images. It exhibited solid generalization ability, as evidenced by progressive improvements in accuracy and a consistent reduction in loss throughout training iterations.

The integration of MongoDB enhanced the system's ability to handle large volumes of data efficiently, enabling swift storage, retrieval, and user interaction tracking. The model accurately distinguished between different disease types and assigned them to distinct severity categories, namely: mild, moderate, and severe.

Deployment via both mobile and web-based interfaces, combined with built-in treatment recommendation features, verified the practicality of the system in real-world agricultural scenarios. In comparison to manual inspection methods, AgroScan significantly decreased the time required for diagnosis while boosting consistency and precision in disease identification.

Overall, the findings confirm that AgroScan provides a scalable and flexible AI-driven solution capable of supporting informed agricultural decision-making. The system encourages early intervention, minimizes unnecessary chemical usage, and contributes to improved crop productivity—offering strong potential for widespread implementation in precision farming applications.

VI. DISCUSSION

The proposed AgroScan framework presents an effective solution for automating the diagnosis of corn plant diseases by integrating deep learning and real-time monitoring. The implementation of DenseNet201, a deep convolutional neural network, has yielded high accuracy in identifying disease categories and estimating their severity. This is evidenced by the observed reduction in training loss and improvement in accuracy over successive epochs, indicating the model's robustness across various disease types and environmental conditions (refer to Fig. 2).

In addition to the core model, using MongoDB significantly enhances the system's data handling capabilities. It ensures efficient storage, rapid retrieval, and seamless access to classification results, enabling smooth backend operations. The database's dynamic nature supports adaptability to changing field conditions and offers scalability for large-scale deployments. Unlike static models, AgroScan processes real-time imagery, which allows for more context-aware and reliable predictions.

Compared to existing systems such as YR2S [1], FieldPlant [2], and other CNN-based approaches [6], [7], AgroScan introduces meaningful improvements. Notably, it includes an intuitive user interface and supports web and mobile platforms, improving accessibility for end users. Furthermore, the integration of disease-specific treatment recommendations—both organic and inorganic—adds practical value, making it more applicable for real-world agricultural operations.

Nevertheless, certain limitations remain. The system's accuracy is sensitive to variations in image quality, such as poor lighting, occlusions, or complex backgrounds, which may degrade prediction outcomes. Furthermore, the DenseNet201 model, while effective, demands considerable computational resources, which can pose challenges for deployment on low-power edge devices in remote or rural settings.
Another area of concern is generalization. The current model is tailored specifically to corn leaf diseases, limiting its applicability to other crops. To extend its utility, future work should focus on expanding the dataset to include a broader range of plant species and disease categories. Additionally, integrating multi-modal data sources—such as soil moisture levels, temperature, and humidity—could enhance predictive accuracy through sensor fusion.
Despite these constraints, AgroScan makes a substantial contribution to precision agriculture. It merges advanced CNN-based classification with real-time diagnostics, cloud-based data management, and accessible user interfaces to provide a holistic disease monitoring solution. Future enhancements will focus on model optimization for edge computing, expansion to other crops, and integration with drone imagery or IoT-based sensing systems for broader agricultural monitoring.
Ultimately, AgroScan addresses a critical gap between research and practical implementation in AI-driven crop disease detection. It supports sustainable farming practices by enabling timely interventions, minimizing pesticide overuse, and enhancing crop yield through informed decision-making.

VII. CONCLUSION

This work proposes a deep learning-based algorithm for identifying and classifying corn crop diseases. The deep learning model processes high-resolution images within a structured database, ensuring efficient data storage and management. This system facilitates real-time monitoring, empowering farmers to take timely actions that mitigate crop losses. It supports the adoption of sustainable agricultural practices, enhancing pest control strategies. Designed to be user-friendly and scalable, the model can be extended to larger agricultural areas, paving the way for precision farming. Future developments will focus on enhancing real-time processing capabilities and exploring applications for additional crops. Technology-based work from this research promotes advances in agriculture and food security.

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