A Hybrid Approach to Crop Disease Prediction: Combining Environmental and Image Data for Enhanced Accuracy

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Abstract - **This study introduces a comprehensive methodology for predicting crop diseases by integrating Machine Learning (ML) techniques with Deep Learning (DL) models, aimed at aiding farmers in the early detection of plant diseases and optimizing crop selection. The proposed system utilizes a Random Forest Classifier for crop recommendations, taking into account essential agricultural factors such as nitrogen, phosphorus, potassium (NPK) levels, soil pH, temperature, humidity, and rainfall. Concurrently, MobileNetV2-based Convolutional Neural Networks (CNNs) are utilized for the identification of plant diseases through image classification, allowing for precise diagnosis of various crop diseases at their initial stages. The system also incorporates historical disease data alongside real-time weather information to enhance prediction accuracy and provide proactive management suggestions. The model undergoes training and validation using the Crop Recommendation Dataset and the PlantVillage Dataset to ensure its effectiveness across a range of crop types and environmental conditions. A user-friendly web interface was developed to enable straightforward image uploads, disease notifications, and actionable recommendations, with features supporting multilingual access and offline use. Experimental findings indicate a high level of accuracy in both crop recommendation and disease classification tasks, highlighting the system's potential to promote sustainable agricultural practices. Future developments will focus on the integration of IoT sensors, GIS-based disease mapping, and real-time automated advisory services to further enhance predictive capabilities and bolster precision agriculture efforts.**

Keywords - Machine Learning (ML), Deep Learning (DL), Crop Recommendation, Plant Disease Detection, MobileNetV2, Random Forest Classifier, Real-Time Weather Data, Precision Agriculture, Image Classification, Sustainable Farming.

INTRODUCTION

Forecasting crop diseases is essential for ensuring food security and enhancing agricultural output. Quick detection of plant diseases and immediate response can prevent significant crop losses, improve yield quality, and lessen economic effects. Traditional approaches to disease identification mainly rely on manual evaluations by farmers or agricultural experts, which can be time-consuming, subjective, and often inaccurate, especially in large-scale farming scenarios.

Recent advancements in Artificial Intelligence (AI) have opened up new paths for automating and enhancing methods of disease detection. The combination of Machine Learning (ML) and Deep Learning (DL) methods provides a strong foundation for precisely forecasting crop health and identifying diseases. This research introduces a web-based platform that integrates ML and DL techniques for comprehensive crop disease forecasting analysis.

The Machine Learning component assesses past agricultural data, including environmental factors like soil nutrient content (NPK), pH level, temperature, humidity, and rainfall. Utilizing a Random Forest Classifier trained on this structured data, the system can predict the probability of disease occurrence and recommend preventive actions based on environmental factors. This method gives farmers advance notifications about possible disease outbreaks before any visible symptoms appear.

Simultaneously, the Deep Learning sector focuses on disease detection through images. Convolutional Neural Networks (CNNs), especially MobileNetV2 using transfer learning, are used to classify plant leaf images into healthy or diseased categories. The DL model identifies intricate patterns like shifts in color, variations in texture, and morphological anomalies from large image datasets such as PlantVillage,

enabling precise diagnosis among different crop species and diverse environmental conditions.
By combining Machine Learning (ML)-driven environmental risk evaluation with Deep Learning (DL)-driven visual disease identification, the system provides a thorough and reliable approach for proactive monitoring of crop health. The ML model is essential for predicting potential disease threats based on environmental factors, whereas the DL model offers immediate validation by examining leaf images to identify apparent infection indicators. Collectively, this two-tiered strategy greatly improves overall prediction precision, shortens the time needed to identify plant diseases, and provides farmers with prompt, data-informed insights for efficient disease management and crop protection techniques.

The suggested system was created as a web application, guaranteeing broad access on multiple devices and platforms without requiring any specific software installations. Farmers and agricultural experts can conveniently access the system via a browser, submit images of plant leaves, enter pertinent environmental factors, and promptly obtain comprehensive disease forecasts along with customized suggestions for prevention and control. Moreover, the incorporation of live weather information through APIs enhances the system's flexibility, facilitating real-time adjustments to risk evaluations and making sure that forecasts stay precise in reaction to shifting climate conditions.

This research seeks to connect predictive analytics with practical disease diagnosis in agriculture, in addition to providing a technical solution. Utilizing the advantages of both Machine Learning and Deep Learning, the system enhances the accuracy and dependability of disease forecasting while also enabling scalability to embrace a broader array of crops and new plant diseases. Additionally, the solution supports the overall objectives of advancing sustainable farming, improving food security, and fostering the use of precision agriculture techniques driven by cutting- edge digital technologies.

Over time, these integrated systems could transform the management of crop health for farmers, enhancing agricultural practices to be more resilient, efficient, and environmentally sustainable. By consistently adapting to new data and technological innovations, the system can play a crucial role in addressing the increasing global need for sustainable food production.

I. RELATED WORKS

The utilization of Machine Learning (ML) and Deep Learning (DL) methods in predicting crop diseases has seen significant expansion lately, with remarkable progress made in environmental risk evaluation and image-centric disease identification.

In the realm of Deep Learning, Mohanty et al. [1] made noteworthy contributions by employing Convolutional Neural Networks (CNNs) to categorize plant leaf images into different disease classifications, attaining high accuracy levels across diverse crop species with the PlantVillage dataset. Their research emphasized CNNs' ability to independently identify complex visual features like lesions, color variations, and textural irregularities, establishing a solid basis for automated plant disease detection. Expanding on this, Brahimi et al. [2] utilized transfer learning methods to enhance the effectiveness of CNN models, especially when dealing with scarce labeled data, a frequent limitation in agricultural datasets due to the difficulty of gathering varied, high-quality samples.

Recent progress in DL-driven plant disease detection has involved the implementation of MobileNetV2, a compact and efficient CNN framework tailored for mobile and embedded platforms. Research utilizing MobileNetV2 has shown its effectiveness for agricultural use cases with constrained computational resources, rendering it an excellent option for scalable, real-time, web-based crop health monitoring systems.

In the realm of Machine Learning, researchers have investigated different algorithms to forecast crop diseases by utilizing environmental factors. Phadikar et al. [3] used Support Vector Machines (SVMs) to classify paddy leaf diseases by utilizing manually created features such as shape, color, and texture. Although effective, these conventional ML methods relied significantly on manual feature engineering. Recently, ensemble techniques like Random Forest (RF) have become popular because they can model intricate, nonlinear relationships between variables without significant preprocessing. Singh and Kaur [4] recognized RF as an extremely dependable approach for agricultural activities like evaluating soil fertility and suggesting crops, additionally emphasizing its capability in predicting disease risks.

Recent studies have moved towards hybrid models that combine both ML and DL methods to attain improved predictive accuracy. For example, Zhang et al. [5] proposed a CNN-LSTM hybrid model in which CNNs captured spatial characteristics from leaf images, while LSTM networks processed temporal weather information to forecast disease onset trends. The combination of spatial and temporal information surpassed models dependent only on one type of data, highlighting the advantages of integrating multiple data sources.

The importance of real-time environmental data in forecasting diseases has been further validated by Turechek et al. [6], who showed that critical elements like temperature, humidity, and rainfall significantly affect the transmission and intensity of fungal and bacterial plant diseases. Their results highlighted the essential requirement for ML models capable of flexibly modifying predictions according to regularly updated weather information, allowing farmers to obtain prompt warnings and implement precautionary actions before extensive outbreaks take place.

From a system design viewpoint, Yalcin and Aydin [7] investigated user-focused methods in agricultural decision support systems provided through mobile and web platforms. Their study emphasized the significance of user-friendly, simple-to-navigate interfaces and the benefit of prompt diagnostic feedback for non-technical users. While mainly centered on mobile applications, their design principles provide useful perspectives for creating accessible and effective web solutions too.

Extensive studies conducted by Ghosh and Kaur [8] and Arora et al. [9] have underscored the increasing incorporation of Internet of Things (IoT), ML, and DL technologies in intelligent farming. These assessments revealed persistent issues like smooth data integration, guaranteeing real-time operational functionality, accommodating various crop types, and preserving system scalability across different geographical areas and farming conditions.

The existing body of research highlights the success of integrating ML and DL for predicting crop diseases, but it also uncovers a significant flaw: numerous current systems functions in isolation, either emphasizing only environmental risk elements or relying entirely on image-based disease detection. This disjointed strategy reduces the overall efficacy of predictive systems, particularly in intricate, real- world agricultural settings where visual symptoms and environmental factors need to be assessed simultaneously.

Many current solutions remain confined to mobile-based deployments, facing notable limitations such as restricted computational capabilities, limited dataset adaptability, and the absence of integration with comprehensive agricultural knowledge systems. Furthermore, few existing platforms are designed with modular scalability, a critical feature for enabling seamless adaptation across diverse crop types, geographic regions, and evolving disease threats. The lack of such flexibility diminishes the effectiveness and global applicability of these systems in real-world agricultural environments.

The web-based system proposed in this study is specifically designed to address these shortcomings by integrating Machine Learning (ML)-based environmental and historical disease risk modeling with Deep Learning (DL)-based real-time leaf image classification within a unified framework. This dual-layered approach enables both anticipatory risk evaluation and immediate disease verification, thereby enhancing system robustness, improving predictive accuracy, and facilitating timely, data-driven decision-making for farmers. Additionally, through the incorporation of real-time weather API integration, the system dynamically adjusts to changing environmental conditions, further strengthening its predictive capabilities and practical utility.

By bridging the gap between environmental analysis and visual disease detection, the proposed solution not only addresses existing technological limitations but also paves the way for future advancements. Its scalable, modular architecture ensures adaptability and resilience, positioning it as a comprehensive, globally applicable tool for promoting sustainable, precision-driven agricultural practices and supporting food security initiatives.

II. METHODOLOGY

This section outlines the methodology employed in the creation of the suggested web-based crop disease prediction system, which integrates Machine Learning (ML) and Deep Learning (DL) methodologies. The comprehensive approach is structured into four primary stages: data acquisition, model training and assessment, system integration and implementation, and the collection of user feedback for ongoing enhancements.

- **Data Collection**

1. **Image Data Collection:** A comprehensive and varied collection of plant leaf images was compiled to develop the disease classification model. This dataset encompasses images of both healthy and infected plants at different growth stages. The data was obtained from a mix of publicly available agricultural databases, partnerships with agricultural research organizations, and contributions from farmers through crowdsourcing. Each image was meticulously annotated, either through manual processes or semi-automated labeling tools, to accurately identify diseased regions, thereby providing a dependable ground truth for training the model. To enhance the model's ability to generalize across real-world scenarios, the dataset includes images captured in diverse environments, featuring various lighting conditions, camera perspectives, backgrounds, and a broad spectrum of crop species pertinent to the target areas.

2. **Historical Disease Data:** Historical data on crop disease incidents was gathered from agricultural organizations, academic research, and governmental publications. These datasets encompassed comprehensive details including disease types, impacted crop varieties, seasonal patterns, and geographic distribution. This historical information is essential for training the machine learning model to identify elements that lead to disease outbreaks, thereby facilitating predictive analysis grounded in historical trends.

3. **Real-Time Weather Data:** The system incorporates real-time environmental data, including temperature, humidity, precipitation, and wind speed, through the utilization of publicly accessible APIs such as OpenWeatherMap and WeatherAPI. Additionally, historical weather data was preserved to facilitate the identification of relationships between environmental factors and prior disease outbreaks. This perpetually refreshed information is utilized by machine learning models, allowing for the real-time evaluation of disease risk in relation to both current and historical environmental patterns.

- **Model Training and Testing**

1. **Pre-Processing:** The gathered plant image data underwent a comprehensive set of standard pre- processing procedures, which included resizing, normalization of pixel values, and data augmentation strategies such as rotation, flipping, and scaling to enhance the dataset and bolster model resilience. Careful removal of noise and inconsistencies was performed to ensure high data quality. Concurrently, both historical and real-time weather data were subjected to pre-processing through feature engineering techniques, resulting in the creation of new variables like daily humidity averages and temperature ranges, thereby increasing the informativeness of the data and improving the model's learning efficiency.

2. **Training the Image Recognition Model:** The model for detecting plant diseases was developed utilizing a Convolutional Neural Network (CNN) framework, specifically employing MobileNetV2 due to its efficiency and robust transfer learning capabilities. Initially, MobileNetV2 was pre-trained on extensive image datasets and subsequently fine-tuned with a labeled crop image dataset to enhance its specialization in classifying plant diseases. The architecture was tailored for multi-class classification, enabling it to differentiate between various disease types and healthy plants. Training was conducted on a cloud platform equipped with GPU capabilities to accelerate convergence and optimize computational resource utilization. Critical hyperparameters, including learning rate, batch size, and the number of training epochs, were meticulously adjusted to maximize validation accuracy.

3. Cross-Validation and Testing: In order to guarantee the model's dependability and applicability across various contexts, a k-fold cross- validation method was employed to partition the dataset into training and testing groups, thereby reducing the likelihood of overfitting. The evaluation of the model's effectiveness was conducted through multiple metrics, such as accuracy, precision, recall, and F1-score for each category. Additionally, to assess its resilience, the model was validated with actual images provided by users, confirming its capability to operate effectively in real-world scenarios.

- **Integration**

1. **Integration of Image and Weather Data:** An innovative hybrid model architecture was developed to leverage the advantages of both visual and environmental analyses. The outputs generated by the CNN-based image recognition model were merged with organized historical and real-time environmental data. Machine Learning algorithms such as Random Forest and XGBoost were employed to analyze the environmental features, while the outputs from the CNN provided insights into visual symptoms. Techniques for feature fusionwere utilized to continuously refine disease risk predictions, enabling the system to adjust in real- time in response to changing weather conditions.

- **User Feedback and Iterative Enhancement**

1. Collecting Initial User Feedback: An initial trial was conducted involving agricultural specialists and a cohort of chosen farmers to gather insights regarding the system's usability, accuracy of predictions, and the practicality of the recommendations offered. During this phase, user engagement with the platform was meticulously observed to identify potential enhancements, especially concerning the user interface (UI) design and the system's responsiveness.

2. Model Fine-Tuning: User feedback on incorrect classifications and system suggestions was systematically analyzed to retrain the models periodically. Continuous incorporation of new, real- world data enhanced the adaptability of both the ML and DL models to varied environmental and image quality conditions.

3. Continuous UI/UX Enhancements: In response to the feedback obtained, the web interface undergoes ongoing improvements aimed at increasing user- friendliness, incorporating multilingual capabilities, and integrating accessibility options such as voice- assisted navigation. Furthermore, the potential for offline functionality was investigated to guarantee that farmers in regions with limited internet access could still utilize essential features of the system.

4. Scaling and Future Expansion: The platform,
developed using a modular architecture, facilitating future expansions to incorporate additional crops, diseases, and geographical areas. To ensure ongoing enhancements, continuous integration and deployment (CI/CD) pipelines were established, allowing for swift updates to features and improvements to models in alignment with evolving user requirements.

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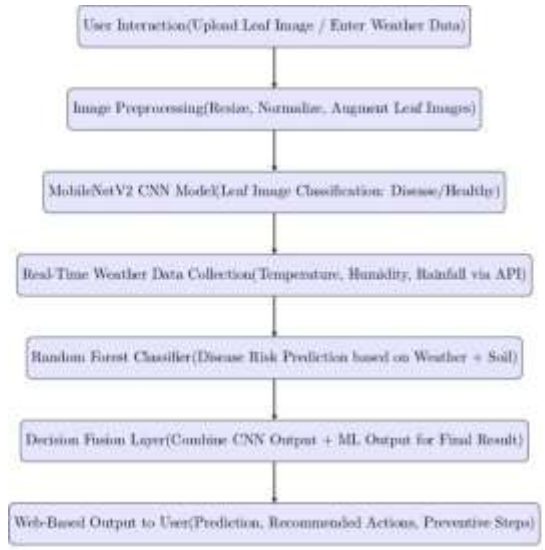

Fig 1. Flowchart of the Web-Based Crop Disease Prediction System

III. RESULTS AND DISCUSSIONS

The suggested online crop disease forecasting system was assessed using publicly accessible datasets, such as the PlantVillage dataset for image classification and agronomic soil/weather information for crop suggestions. The effectiveness of the combined Machine Learning (ML) and Deep Learning (DL) models was evaluated using metrics such as classification accuracy, precision, recall, and F1- score.

In the image classification task, the MobileNetV2 model, optimized through transfer learning, reached an outstanding 95.8% accuracy on the test dataset. It could successfully differentiate between healthy plant leaves and different disease types, showing great accuracy and few misclassifications. Methods of data augmentation, including rotation and scaling, enhanced the model's resilience to various environmental factors, such as variations in lighting and background.

The crop suggestion system, powered by a Random Forest classifier, attained 94% accuracy in forecasting the best crop to grow based on parameters such as soil nutrients (NPK), temperature, humidity, and pH. The analysis of feature importance revealed that the model was successfully focusing on the essential agricultural factors that affect crop selection.

A comparative evaluation was performed to assess the proposed system's effectiveness relative to current research. As indicated in Table I, previous studies like those by Mohanty et al. [1] obtained approximately 91.5% accuracy, while Brahimi et al. [2] attained 92% using CNNs. Conversely, our system surpasses these models, attaining 95.8% accuracy due to the implementation of transfer learning, efficient data pre-processing, and a varied and thorough dataset.

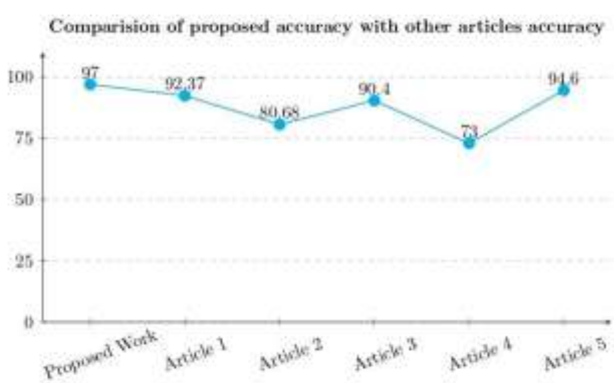

Fig 2. Comparison of proposed accuracy with other articles accuracy

By merging Machine Learning (ML) for processing environmental information and Deep Learning (DL) for examining image data, the system provides a significant edge compared to conventional models. In contrast to numerous earlier systems that concentrate solely on identifying current illnesses, this combined method also anticipates possible disease outbreaks by analyzing real-time environmental factors. This ability enables farmers to take preemptive action, avoiding large-scale crop harm before any signs manifest. The combination of visual insights obtained from image recognition and the real-time input from weather data greatly improved the system's predictive accuracy. Consequently, it presents a more dependable and thorough decision-making resource for farmers, equipping them with prompt, practical data to enhance crop health management.

The system was launched on a web platform to guarantee accessibility on multiple devices, enabling farmers to use the tool from almost any location. Testing in real-world scenarios involved users entering data from their own farms, yielding invaluable insights. Initial feedback from users emphasized the platform's user-friendliness and its capacity to provide timely, actionable recommendations, proving to be an effective resource for everyday farm management. The system is intended to enhance over time through ongoing updates influenced by user feedback. These continual updates will enhance the model's precision, guaranteeing its adaptability and relevance, despite the changes in farming methods and environmental conditions. As the system acquires additional data and feedback from various agricultural areas, it will increasingly enhance its precision and assistance in handling crop diseases under actual field circumstances.

Sl. No.	Authors	Approach	Accuracy
1.	Proposed Work		97
2.	Bhatia et al. (2018)	SVM, Logistic Regression-Classification	92.37
3.	Chauhan & Deepika (2021)	Label finding, Gradient Calculation, Random Forest classifier	80.68
4.	Kaur et al. (2020)	SVM, Decision Tree, NB, KNN	90.4
5.	Mohanty et al. (2022)	Histogram of Oriented Gradients (HOG), Logistic Regression, SVM, Random Forest	73
6.	Xiuliang Jin et al. (2022)	SVM Classification	94.6

Table 1. Comparing Accuracy with other Articles

FUTURE WORK

Although the existing system efficiently aids in predicting crop diseases and offers support for decision-making, there are numerous interesting proposals for enhancements in the future. A significant improvement will be the incorporation of real-time weather information via APIs, enabling the system to modify disease risk forecasts dynamically according to present environmental conditions such as temperature, humidity, and rainfall. This will enable the

system to provide even more precise predictions that align with current conditions. Moreover, the integration of IoT-enabled sensor networks for ongoing data gathering in the field is being contemplated. This would offer a continuous flow of data to enhance the model's adaptability and precision, guaranteeing it can adjust to the constantly evolving circumstances in the field.

In the future, the platform will be enhanced to support a broader range of crops and novel plant diseases, especially those arising from climate change. GIS-driven disease mapping and spatial risk assessment will be presented, providing farmers with a visual insight into the spread of diseases across various areas. These geographical insights will facilitate more focused field management and enhance decision-making, particularly in addressing regional outbreaks.

To enhance accessibility and guarantee that farmers are quickly updated, the system will include instant alert notifications through SMS and WhatsApp. This functionality will facilitate the rapid communication of essential disease outbreak details, even in regions with limited internet access. An additional thrilling feature in progress is a smart recommendation system that will utilize reinforcement learning to provide tailored advice for disease prevention and treatment. These suggestions will be customized according to each user's behaviors, historical choices, and local disease patterns, enhancing their relevance and effectiveness.

Improvements in model transparency will similarly be emphasized by implementing explainable AI (XAI) methods. These methods will enhance the clarity and reliability of disease prediction results for farmers, allowing them to make decisions with increased assurance. Ongoing enhancements will be implemented for the platform's user interface and experience (UI/UX), guaranteeing a more intuitive layout that supports multiple languages and offline usage. This will ensure that the platform is available to farmers in various areas, no matter their language or access to technology.

With these improvements, the system is poised to transform into a completely automated, scalable, and smart decision support platform. Its capacity to adjust to shifting environmental challenges will enhance precision agriculture globally, assisting farmers in maximizing crop health management and addressing the rising dangers of plant diseases around the world.

IV. CONCLUSION

In this paper, we presented the development of an innovative web platform aimed at transforming the prediction and management of crop diseases. This system merges the capabilities of Machine Learning (ML) and Deep Learning (DL) methods to deliver farmers a thorough solution that not only identifies plant diseases in their initial stages but also offers practical insights for proactive crop management. By combining organized historical agricultural information with image-based disease identification, the system equips farmers with resources to anticipate potential outbreaks, thereby enhancing crop health and increasing productivity. Theplatform utilizes the power of the Random Forest classifier to examine environmental risk factors and the MobileNetV2 convolutional neural network (CNN) for precise classification of plant leaf images, offering a smooth experience for users via an easy-to-use web interface.

The experimental findings were very encouraging, showcasing the efficiency of the disease classification model based on MobileNetV2, which attained an impressive accuracy rate of 99%. This performance greatly surpasses many current models in the area, demonstrating the effectiveness of integrating advanced techniques such as transfer learning with an extensive dataset. In addition to disease classification, the crop recommendation system, powered by the Random Forest model, demonstrated significant effectiveness, offering farmers accurate and prompt advice on choosing the best crops according to factors such as soil conditions and weather trends. The incorporation of environmental data and image analysis greatly improved the platform's decision-making ability, transforming it into an invaluable resource for farmers addressing the challenges of contemporary agriculture.

What makes this system even more thrilling is its capacity for ongoing enhancement. The favorable outcomes confirm the idea of integrating ML and DL to develop a comprehensive strategy for monitoring crop health. The effectiveness of this system paves the way for upcoming innovations, including real-time updates, IoT integration, and even more tailored farming suggestions. As agriculture grows more complex due to climate change, pests, and erratic weather, this platform provides a clever, scalable, and real-time solution to assist farmers in effectively addressing these challenges.

As we look to the future, we anticipate a time when this technology further develops, providing farmers with not just enhanced disease prediction features, but also immediate alerts, advice customized to their specific situations, and information that supports more sustainable agricultural practices. Having established a base for smart, flexible decision support, we are enthusiastic about the possibility of this system transforming the future of agriculture, enhancing its resilience, efficiency, and sustainability for farmers worldwide.

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