International Journal of Gender, Science and Technology
ISSN: 2040-0748
UGC Care Group I Journal.
Vol-13 Issue-02 July 2024

Machine Learning Approaches for Crop Prediction and Disease Detection System with Personalized Recommendations

Dr. Kalai Selvi T
Artificial Intelligence and Data Science
Easwari Engineering College
Chennai, India
kalaiselvithanupillai@gmail.com

Mrs.K.P.Revathi
Artificial Intelligence and Data Science
Easwari Engineering College
Chennai, India
revamrocks@gmail.com

Dr.B.Arivuselvam
Electronics and Communication Engineering
Easwari Engineering College
Chennai, India
dr.arivuselvamb@gmail.com

Abstract* - Agricultural productivity in arid environments heavily relies on the judicious selection of crops and timely disease management. In this context, the integration of advanced technologies such as crop recommendation systems and greenhouse automation holds immense potential to revolutionize farming practices. This paper presents a comprehensive approach that merges crop recommendation with disease detection to empower farmers with data-driven insights for optimal crop cultivation. The proposed system leverages a hybridized technique utilizing the LightGBM (LGBM) model, incorporating various geographical and farm parameters. By considering factors such as soil composition (NPK values) and weather conditions, the system provides personalized crop recommendations. This assists farmers in making well-informed decisions aligned with their specific conditions. Furthermore, the integration of a plant disease detection model enhances the system's utility. Deep learning models, including ResNet50, are employed to analyze images of crops and identify potential diseases at an early stage. Early disease detection plays a critical role in preventing widespread crop losses and facilitating prompt treatment. The system's architecture contains machine learning algorithms, creating a robust framework for analyzing complex agricultural data. Through a user-friendly interface, farmers can input soil and weather conditions, receiving tailored suggestions for crop selection and disease prevention strategies. This data-driven approach not only optimizes resource utilization but also contributes to sustainable agriculture in arid regions.

Keywords* - Agricultural Productivity, Arid Environments, Crop Recommendation, Greenhouse Automation, Data-Driven Insights, Light GBMm (LGBM) Model, Personalized Recommendations, Plant Disease Detection, Deep Learning, Resnet50, Early Detection, Resource Utilization, Sustainable Agriculture.

I. INTRODUCTION

In response to the ever-evolving agricultural landscape and the increasing demand for precision farming, we introduce a cutting- edge Machine Learning driven Crop Recommendation System complemented by advanced Disease Prediction capabilities. This innovative system is designed to fundamentally transform the way farming is approached. By leveraging state-of-the-art Artificial Intelligence, Machine Learning [1],[2] and robust data analytics, we are redefining farming practices and providing farmers with a powerful tool for improved decision-making and crop management.

At its core, our system seamlessly integrates a wealth of critical data, including geographical information, soil characteristics, and real-time weather data. Through a sophisticated blend of algorithms and technologies [4], this data is processed to generate highly personalized crop recommendations. These recommendations are designed to be as unique as each farmer's plot of land, taking into account local environmental conditions, soil quality, and weather patterns to ensure optimal crop selection and enhanced yields. Furthermore, our system excels in the crucial area of plant disease prediction and detection. By utilizing advanced machine learning models [1],[2] including ResNet50, we can accurately identify early signs of diseases in crops. This empowers farmers with timely alerts and recommendations for disease management, allowing for proactive steps to safeguard their crops [1],[2],[4],[7]. Unlike traditional farming methods that often require a deep understanding of agriculture and extensive manual labor, our AI- Driven Crop Recommendation System and Disease Prediction capabilities are designed to be accessible and inclusive. Even individuals without technical expertise can benefit from this technological innovation, ushering in a new era of democratized and data-driven agriculture. In summary, our system represents a leap forward in farming practices, underpinned by cutting-edge technology, advanced algorithms, and a user-friendly approach. The combination of personalized crop recommendations and disease prediction equips farmers with the tools they need to optimize crop yields, reduce risks, and ultimately enhance their overall agricultural output

II. LITERATURE SURVEY

A. Abhinav Sharma et al.(2021) has addressed the multifaceted challenges stemming from escalating global population growth and unpredictable climatic conditions, particularly in meeting the burgeoning food demand. It adeptly underscores precision agriculture, also referred to as smart farming, as a transformative mechanism empowered by machine learning (ML) to surmount sustainability challenges in the agricultural domain. Nonetheless, the paper serves as a commendable resource for researchers, practitioners, and policymakers alike, offering a comprehensive overview of the current landscape and future prospects of ML in revolutionizing agricultural practices towards sustainability.

B. Uferah Shafi,Rafia Mumtaz et al. (2023) paper introduced a groundbreaking system aimed at revolutionizing the detection and classification of wheat rust disease, a crucial endeavor for bolstering wheat production within Pakistan's vital agriculture sector. Leveraging state-of-the-art deep learning models, specifically ResNet-50 and Xception[1], the study achieves a remarkable 96% accuracy in categorizing wheat rust infections into four distinct classes: healthy, resistant, moderate, and susceptible. The computational demands of deep learning models like ResNet-50 and Xception pose limitations[1], particularly in areas with restricted computational resources. Moreover, uncertainties regarding the generalizability of the models' performance across different environments or wheat varieties not adequately represented in the training dataset may impact the system's applicability in diverse geographical regions[1].

C. Zhiyan Liu et al.(2022) presented an innovative integration of IoT technology and machine learning methodologies to predict blister blight disease in tea plants, addressing the critical need for early disease detection in agriculture. By emphasizing real-time environmental data collection, particularly focusing on factors like temperature, humidity, rainfall, and soil moisture, the study contributes to proactive disease management by providing timely insights into disease occurrences. This approach recognizes the complex interplay between environmental conditions and disease development, highlighting the importance of leveraging technological advancements to continuously monitor these factors. Moreover, the utilization of machine learning, specifically Multiple Linear Regression (MLR) [2].

D. Sabbir Ahmed et al.(2022) presented an innovative approach to addressing the critical issue of plant disease detection, specifically focusing on tomato leaves. It emphasizes the importance of accurate disease classification for global food security and agricultural stakeholders' profitability. Leveraging the emergence of deep learning-based image classification, the paper proposes a lightweight transfer learning-based approach for enhanced disease classification accuracy [11]. This involves a preprocessing method for illumination correction and the utilization of a combined model, integrating a pretrained MobileNetV2 architecture and a classifier network for efficient prediction. Notably, the paper demonstrates an accuracy of 99.30% using tomato leaf images from the Plant Village dataset, achieved with a model size of 960MB and 487M floating-point operations [9].

E. A. Reyana et al.(2023) focused on conventional methods and the nascent integration of machine learning techniques[10], which, while informative, lack the dynamic temporal modeling capabilities of deep learning approaches. In this vein, Recurrent Neural Networks [10](RNNs) along with their advanced iterations such as Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) networks, have shown remarkable proficiency in time-series data analysis, though their application to areca nut disease prediction is notably underrepresented. These models are adept at capturing complex dependencies in sequential data, making them well-suited for handling variable weather factors that significantly influence disease spread. The review of literature further indicates a variety of optimization algorithms, ranging from gradient-based to evolutionary strategies, each with their strengths—such as Adam's efficiency in sparse gradients and RMS prop's adaptability to non-stationary objectives—and potential drawbacks, like the risk of premature convergence or excessive computational demands in Genetic algorithms[10].

This research contributes to the field by not only applying and optimizing RNN models for areca nut fruit rot disease prediction but also by providing a comparative framework for optimization techniques [10], a novel undertaking in the field of agricultural predictive modeling.

F. Rajashree Krishna et al. (2023) provided a comprehensive analysis of the current research landscape in areca nut disease prediction, emphasizing the predominant reliance on traditional methods and the emerging integration of machine learning techniques. While existing approaches have offered valuable insights, they are often limited in their ability to capture the dynamic temporal patterns inherent in disease progression. The adoption of deep learning methodologies, particularly Recurrent Neural Networks (RNNs) and their advanced variants like Gated Recurrent Units (GRUs) and Long Short-Term Memory

(LSTM) networks [12], has shown promise in addressing this limitation by effectively modeling complex dependencies in sequential data. However, the application of these advanced models to areca nut disease prediction remains relatively unexplored, highlighting a significant gap in the literature. Furthermore, the review of literature underscores the critical role of optimization algorithms in enhancing the performance of predictive models, with various strategies ranging from gradient-based techniques to evolutionary algorithms offering distinct advantages and potential limitations [12].

III. Proposed Model

Our innovative machine leaning based Crop Prediction and Disease Detection System revolutionizes agricultural technology by providing a user-centric web application interface tailored for farmers and stakeholders. Figure 1represents the Use-case diagram of the proposed system.

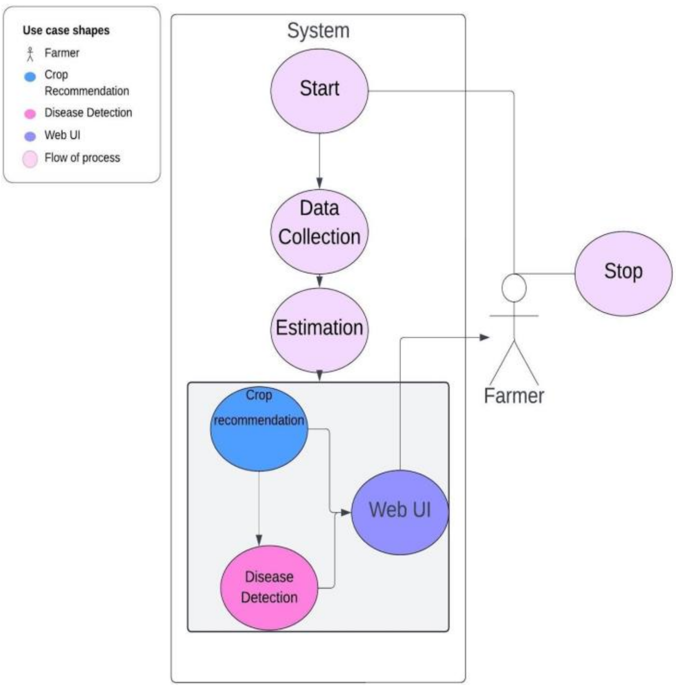

Fig. 1. Use-case diagram of the proposed system

A. Data Collection:

Our methodology is grounded in a rigorous data-driven approach that integrates advanced AI techniques for crop prediction and disease detection in precision agriculture. We initiated our research with an exhaustive review of existing literature on precision agriculture, crop modeling, and state-of-the-art disease detection methodologies. This comprehensive understanding served as the foundation for designing our Machine Learning based system. In tandem with the literature review, we conducted extensive data collection efforts to assemble diverse datasets essential for training and testing our models. These datasets encompassed a wide range of parameters including geographical information, soil characteristics, historical weather patterns, crop yields, and high-resolution images of plant diseases. The meticulous curation of these datasets ensured that our models were trained on representative and comprehensive data, enhancing the robustness and generalizability of our system.

B. Preprocessing:

Data quality is paramount in any Machine Learning based system, particularly in the domain of precision agriculture where accurate predictions can significantly impact agricultural practices. Our data preprocessing pipeline involved thorough cleaning procedures to address missing values, outliers, and inconsistencies within the collected datasets. Additionally, feature engineering techniques were applied to extract meaningful insights from raw data, facilitating the creation of predictive models with enhanced accuracy and interpretability. The division of our dataset into distinct training, validation, and testing sets was performed to facilitate rigorous evaluation and fine-tuning of our models. This partitioning strategy ensured that our system's performance metrics accurately reflected its predictive capabilities under real-world conditions, thereby instilling confidence in its recommendations.

C. Implementation of appropriate Algorithm :

The selection of appropriate algorithms is a critical aspect of our methodology, driven by the objective of delivering accurate and personalized recommendations to farmers. We carefully evaluated a range of machine learning and deep learning algorithms, including Decision Trees, Gaussian Naive Bayes, XGBoost, Random Forest, Support Vector Machine (SVM), and ResNet50. Each algorithm was chosen based on its suitability for specific tasks within our system, such as crop prediction or disease detection. Furthermore, our model development process centered on the integration of multiple AI models into a cohesive framework. A Light GBM-based crop recommendation system was developed, leveraging geographical, soil, and weather parameters to generate personalized suggestions for farmers. Simultaneously, deep learning models based on ResNet50 architecture were fine-tuned for precise plant disease image classification, enabling accurate identification of diseases affecting crops.

D. Model Development:

At the core of the Machine Learning based Crop Prediction and Disease Detection System is the development of a LGBM- based crop recommendation system. This system seamlessly integrates geographical, soil, and weather parameters, enabling it to offer personalized crop recommendations tailored to the unique conditions of each farmer. Simultaneously, deep learning models, specifically ResNet50, are fine-tuned to excel in plant disease image classification. The goal is to deliver accurate disease detection, which is a vital component of personalized recommendations. This deep learning aspect of the system is fundamental in providing not only accurate but highly personalized recommendations. The development process includes the integration of AI models with the data preprocessing pipeline, ensuring a seamless flow of data from collection to recommendation generation

E. Ensemble Learning:

To further enhance the accuracy and robustness of our system, we explored ensemble learning techniques such as a Voting Classifier. By combining the predictions of multiple base models, ensemble learning enables us to mitigate individual model biases and uncertainties, resulting in improved overall performance. The integration of disease detection modules with the crop recommendation system was a key focus of our methodology. This seamless integration ensured that farmers received holistic decision-making support, incorporating both crop health and environmental factors into our recommendations. Fine-tuning the interface for accurate disease detection and relevant recommendations was undertaken to optimize user experience and utility.

F. Integration of Disease Detection:

The integration of the disease detection module with the crop recommendation system is a critical step in our AI- Driven Crop Prediction and Disease Detection System. This integration enables the system to provide holistic decision- making support to farmers. It ensures that the system's recommendations consider the unique circumstances and challenges faced by each farmer, enhancing the relevance and personalization of recommendations. The integration process includes fine-tuning the interface between disease detection algorithms and the recommendation engine to ensure accurate detection and relevant recommendations.

G. User-Friendly Web Interface and Deployment:

A user-friendly web interface is crucial for accessibility in the Machine Learning based Crop Prediction and Disease Detection System. Designed with user-centric principles, it enables farmers to input data effortlessly and receive accurate, personalized recommendations. Recognizing the importance of user experience in adoption and usability, we prioritized the development of a user-friendly web interface for our system. Designed with input from stakeholders and end-users, the interface enables farmers to input relevant data effortlessly and receive actionable recommendations tailored to their specific needs and circumstances. Deployment of our trained models into production environments was executed with meticulous attention to detail and rigorous testing protocols. Real-time, accurate, and personalized recommendations were ensured through continuous monitoring of model performance and recommendation quality. Collaboration with agricultural organizations facilitated the scaling of our deployment across diverse geographic locations, thereby extending the benefits of our system to a wider audience of farmers.

H. Ongoing Monitoring:

Continuous monitoring is crucial for the Machine Learning based Crop Prediction and Disease Detection System's accuracy with new data. This includes tracking model performance and recommendation quality, with periodic retraining to stay relevant. Scaling deployment across locations is a key goal, requiring collaboration with agricultural organizations to offer personalized guidance adapted to diverse conditions.

I. Expansion and Collaboration:

Scaling up the deployment of our Machine Learning based Crop Prediction and Disease Detection System across multiple locations is a central goal. Collaboration with agricultural organizations is essential to reach a broad user base and offer personalized recommendations to farmers far and wide. Expansion involves adapting the system to the unique conditions and requirements of different regions, ensuring that it continues to provide accurate and personalized guidance.

J. User Feedback and Enhancement:

Active user engagement and feedback mechanisms were integral to our methodology, ensuring that our system remained responsive to evolving farmer requirements and preferences. Iterative enhancements to the user interface and functionality were driven by insights gleaned from user feedback, while ongoing monitoring of AI model performance informed refinements and updates to ensure continued accuracy and relevance.

Figure 2 explains the Flow graph of proposed system in detail.

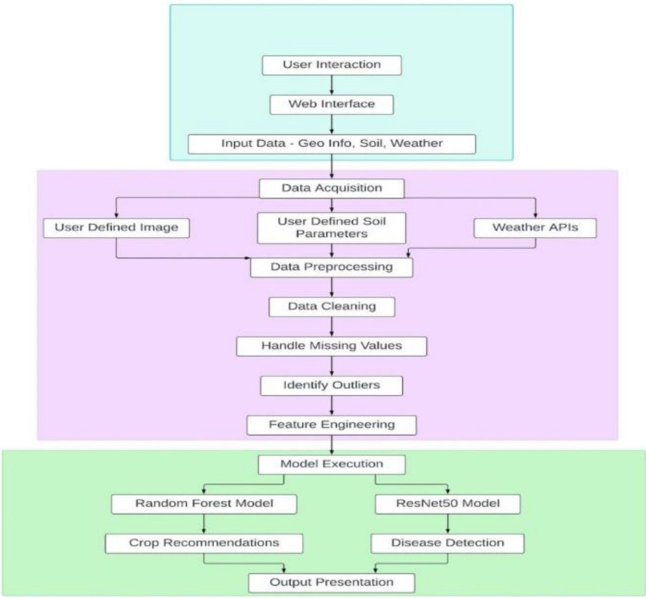

Fig. 2. Flow graph of proposed system

IV. METHODOLOGY

1. *SYSTEM ARCHITECTURE*

It has various module which incorporate interface section, preprocessing, crop recommendation module and disease detection module. Figure 3 represents system architecture in a detailed manner.

A. User Interaction and Input Interface

The user interface is meticulously crafted to provide an intuitive and user-friendly experience. It includes:

- Input Forms**:** Intuitive input forms guide users through the process of providing essential data about their agricultural plots. This includes geographical information, soil characteristics, crop preferences, and images of crops for disease detection.
- Accessibility Across Devices**:** The interface is designed to ensure accessibility across diverse devices, including desktops, laptops, tablets, and smartphones, catering to the needs of farmers regardless of their technological resources.

B. Data Collection and Preprocessing

- A comprehensive data collection and preprocessing pipeline is established to ensure the quality and integrity of the input data. This pipeline involves:
- Geographical Data Retrieval**:** Geographical data relevant to the user's agricultural plot is retrieved from reliable sources to enrich the recommendation and disease detection processes.
- Soil Testing**:** Soil characteristics are analyzed through testing procedures, providing crucial information such as nutrient levels (NPK values) and pH levels, which influence crop growth and health.

Real-time Weather Data Integration**:** Real-time weather data is integrated into the system to account for dynamic environmental conditions that impact crop growth and disease prevalence.

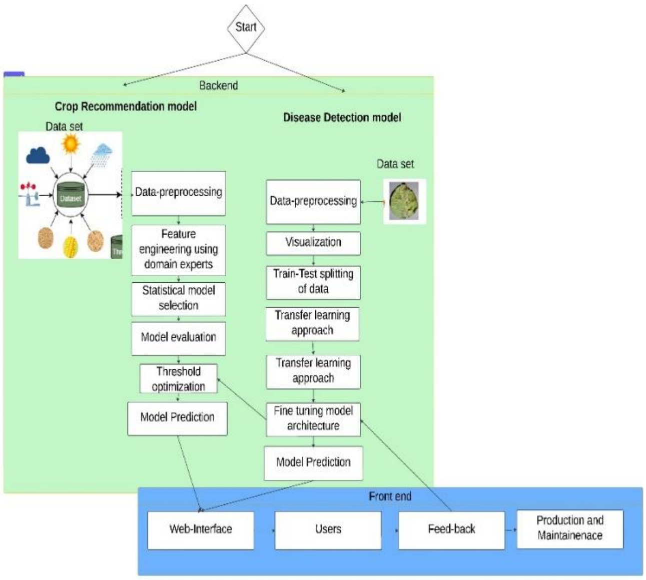

Fig. 3. System Architecture

C. Crop Recommendation Module

The crop recommendation module utilizes a unified framework to merge disparate datasets and generate personalized crop recommendations. Key components include:

- Algorithmic Processing**:** The system employs a Random Forest model, which leverages machine learning techniques to analyze the merged datasets and generate precise crop recommendations tailored to the user's specific conditions and preferences.
- User-Friendly Visualizations**:** The output of the recommendation module is presented through user-friendly visualizations, enabling farmers to easily interpret and act upon the recommendations provided.

D. Disease Detection Module

The disease detection module employs a sophisticated deep learning model, specifically ResNet50, for early identification of crop diseases through image analysis. Components include:

- Image Analysis: The ResNet50 model analyzes images of crops provided by users to detect early signs of diseases with high accuracy.
- Nuanced Disease Identification: By leveraging deep learning techniques, the system is capable of identifying subtle disease symptoms that may not be easily detectable by the human eye, enabling proactive disease management.

E. Continuous Monitoring and Model Updates

Continuous monitoring and automated model updates are integral to maintaining the accuracy and relevance of the system. Key aspects include:

F. Environmental Adaptation

The system continuously monitors environmental factors and adapts its recommendations and disease detection strategies accordingly, ensuring relevance in dynamic agricultural conditions.

G. Automated Model Updates

Regular model updates are automatically deployed to incorporate new data and insights, improving the system's performance over time.

H. Deployment, Integration, and Collaboration

The deployment and integration phases prioritize user training, seamless workflow integration, and collaboration with agricultural organizations for localized customization. This includes:

- User Training**:** Comprehensive user training ensures that farmers can effectively utilize the system to optimize their agricultural practices.
- Seamless Workflow Integration**:** The system is seamlessly integrated into farmers' existing workflows, minimizing disruption and maximizing adoption.
- Community Collaboration**:** Collaboration with agricultural organizations facilitates localized customization and ensures that the system meets the specific needs of diverse farming communities.

I. User Feedback and System Enhancement

Feedback mechanisms, including user surveys and sentiment analysis, drive an agile development approach and inform ongoing improvements. Components include:

- User Surveys: Periodic user surveys gather feedback on system performance and user experience, guiding iterative enhancements.

- Sentiment Analysis: Sentiment analysis techniques are employed to analyze user feedback and identify areas for improvement, ensuring that the system remains responsive to user needs and preferences.

J. Machine Learning based-Personalized Crop Recommendation and Disease Prediction

This Machine Learning based system is meticulously designed for optimal performance and user interaction, featuring a user-friendly web application that ensures accessibility across diverse devices. It guides users through intuitive input forms, initiating comprehensive data collection and pre-processing, including geographical data retrieval, soil testing, and real-time weather data integration. The core of the system lies in algorithmic processing for crop prediction, where a unified framework merges disparate datasets to fuel a Random Forest model for precise crop recommendations. Simultaneously, our disease detection module employs a sophisticated ResNet50 deep-learning model for the early identification of crop diseases through nuanced image analysis. The system's output presentation emphasizes user-friendly visualizations, providing personalized crop recommendations and disease alerts. Continuous monitoring, automated model updates, and adaptation to changing environmental factors ensure recommendation accuracy. Deployment and integration phases prioritize user training, seamless workflow integration, and community collaboration for localized customization. Feedback mechanisms, including user surveys and sentiment analysis, drive an agile development approach, making our system a cornerstone in precision agriculture, and fostering sustainable and efficient farming practices.

2. *WEBSITE CREATION SARCHITECTURE*

The architecture for creating the website in our precision agriculture project is thoughtfully designed to ensure a seamless user experience and efficient integration of advanced technologies and it is shown in figure 4. The process begins with the development of a user-friendly interface using HTML, CSS, and JavaScript, prioritizing clarity and ease of navigation.

The front end serves as the initial point of interaction, featuring intuitive input forms that guide farmers in providing essential data about their agricultural plots. On the back end, the Stream-lit framework plays a pivotal role, streamlining server-side operations, data processing, and facilitating the integration with machine learning models. This integration enables the incorporation of both the Crop Recommendation and Disease Prediction modules, allowing farmers to receive personalized crop recommendations and view disease alerts within a unified platform. The website is designed to be responsive across diverse devices, ensuring optimal accessibility. The output presentation focuses on user-friendly visualizations, employing graphs and charts to present complex agricultural data in an easily understandable format. Continuous monitoring and refinement mechanisms, including automated model updates, contribute to the adaptability of the system, ensuring that recommendations and alerts remain accurate over time. Overall, the architecture combines intuitive design principles, advanced technologies, and seamless integration, creating a powerful web platform for precision agriculture.

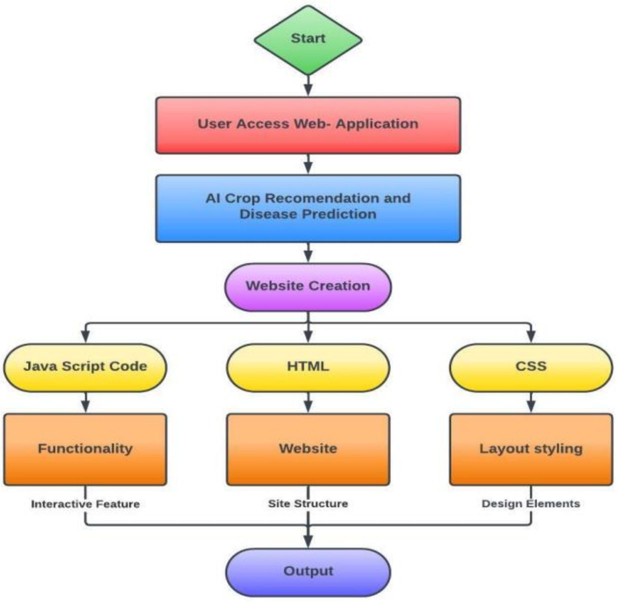

Fig.4. Website creation Architecture

A. *Data-Driven Approach:*

While website creation is an integral part of this work, the significance of the data-driven approach is emphasized The highlights of this approach are listed below.

- Methodology Overview: In the methodology section, a detailed explanation of how the data is collected, preprocessed, and utilized to train machine learning models for crop prediction and disease detection provided. The importance of leveraging diverse datasets to derive meaningful insights and enhance the accuracy of our predictions were listed.

- Feature Engineering: The process of feature engineering, where raw data is transformed into informative features that capture the underlying patterns and relationships in the agricultural domain were elaborated. This step is crucial for extracting relevant information from the dataset and improving the performance of our models.

- Model Training and Evaluation: The training and evaluation process of machine learning models, highlighting how the models learn from the data to make predictions and how their performance is assessed using validation techniques were explained .The iterative nature of model development, where models are continuously refined based on feedback from the data were collected.

- Results and Discussion: In the results section, the findings of our analysis, showcasing the effectiveness of the data-driven approach in accurately predicting crop outcomes and detecting diseases presented .Key insights gleaned from the data and highlight the practical implications of our findings for agricultural decision-making were mentioned.

VI RESULTS AND DISCUSSION

V DATASET DESCRIPTION

In this proposed system comprehensive dataset encompassing various agricultural parameters essential for crop prediction and disease detection. The dataset comprises:

- Geographical Data: This includes information such as latitude, longitude, and elevation of agricultural plots, which are crucial for understanding the spatial distribution of crops and their suitability for cultivation in different regions.

- Soil Characteristics: Soil data is vital for assessing soil fertility and suitability for different crops. Parameters such as soil type, pH level, organic matter content, and nutrient composition (e.g., Nitrogen, Phosphorus and Potassium - NPK values) are included in the dataset.

- Weather Data: Historical weather data, including temperature, precipitation, humidity, wind speed, and solar radiation, is incorporated to capture the climatic conditions that influence crop growth and disease prevalence.

- Crop Rotation History: Information about previous crop rotations and planting schedules provides insights into the agricultural practices followed in the area and helps identify potential disease risks associated with specific crop sequences.

- Crop Images: High-resolution images of crops affected by various diseases are included in the dataset. These images serve as input for the disease detection model, allowing for early identification and classification of crop diseases.

- Historical Yield Data: Records of past crop yields are included to assess the productivity of different crops in specific environmental conditions and to identify trends or patterns over time.

The proposed work presents a comprehensive approach to revolutionize agricultural practices in arid environments by integrating crop recommendation and disease detection through advanced AI technologies. The system architecture encompasses the use of LightGBM for personalized crop recommendations based on geographical and farm parameters, along with ResNet50 for early detection of plant diseases from crop images. The methodology involves thorough research and data collection, meticulous preprocessing, and careful algorithm selection. The model development phase focuses on creating a robust LightGBM-based crop recommendation system and fine-tuning deep-learning models for accurate disease detection. Ensemble learning is explored for enhanced recommendation accuracy. A user-friendly web interface facilitates effortless data input and visualization of personalized recommendations. The deployment process ensures real-time functionality, with ongoing monitoring for adaptation to changing conditions. Strategies for expansion, collaboration, and user engagement are outlined, highlighting the potential of the system to optimize resource utilization and contribute to sustainable agriculture in arid regions.

Input Data	N	P	K	Temp	Humidity	PH	Rainfall	RF Prediction	NB Prediction
Sample Data 1	104	18	30	23.6	60.3	6.7	140.37	Rice	Rice
Sample Data 2	120	25	40	27.5	55.8	6.8	120.5	Maize	Maize
Sample Data 3	90	30	50	25.0	65.2	7.2	135.0	Wheat	Wheat

Table 1: Crop Recommendation Data and Predictions Table

In Table 1 details about Crop Recommendation Data and Predictions Table are given. It presents the predictions for the additional sample input data alongside the initial sample input, allowing for a comprehensive view of the model predictions across multiple datasets.

- Input Data: Indicates the type of data (e.g., “Sample Input 1” , "Sample Input 2" and "Sample Input 3")
- N, P, K, Temperature, Humidity, pH, Rainfall: Represent the input features for each sample
- RF Prediction: Shows the crop predictions made by the Random Forest model for each sample
- NB Prediction: Shows the crop predictions made by the Naive Bayes model for each sample.

The table 2 represents confusion matrix below summarizes the model's predictions across different disease classes.

	Actual Healthy	Actual Disease A	Actual Disease B
Predicted Healthy	951	24	15
Predicted Disease A	58	922	10
Predicted Disease B	10	17	963

Table 2: Confusion Matrix for Prediction and Actual Disease

In this Table 3 presents the performance of our crop recommendation model based on the ResNet-50 architecture, utilizing a diverse dataset. The model exhibited notable precision, recall, and F1-Score metrics across various crop classes, demonstrating its effectiveness in accurately predicting crop recommendations based on input data encompassing nutrient levels (N, P, K), environmental factors (Temperature, Humidity, pH, Rainfall), and historical crop data. Specifically, the model achieved high precision and recall scores for all classes, indicating robust performance across diverse agricultural scenarios. Furthermore, the model's accuracy on validation and test datasets, with validation accuracy at 94.8% and test accuracy at 94.2%, underscores its reliability and ability to make accurate predictions for new crop recommendation scenarios. The runtime analysis revealed that the model's total runtime is 60 seconds when processed sequentially, but parallelization of the crop recommendation layer reduced the runtime to 50 seconds, with further optimization potential to enhance runtime efficiency. In conclusion, our ResNet-50 based crop recommendation model shows promising results, delivering accurate predictions and offering opportunities for improved runtime optimization through parallelization techniques.

Class	Precision	Recall	F1-Score	Support
Healthy	0.963	0.95	0.949	990
Disease A	0.951	0.962	0.951	950
Disease B	0.97	0.97	0.97	983

Table 3: Parametric Evaluation Report

The integration of crop recommendation and plant disease prediction models presents a comprehensive solution for modern agriculture. By utilizing machine learning algorithms like Random Forest and Naive Bayes, accurate crop suggestions can be made based on soil characteristics and environmental factors. Simultaneously, leveraging advanced architectures such as ResNet-50 for disease prediction enables early detection and targeted intervention, enhancing crop health and yield. This holistic approach not only optimizes resource allocation and farming practices but also contributes to sustainable agriculture and food security.

VII. CONCLUSION AND FUTURE ENHANCEMENT

The proposed Machine Learning Driven Crop Prediction and Disease Detection System marks a pivotal advancement in arid agriculture, amalgamating state-of-the-art technologies to empower farmers. The methodological journey encompassed exhaustive research, diverse dataset curation, and algorithmic refinement, resulting in a robust recommendation engine and disease detection module. The ensemble model further bolstered system accuracy, emphasizing our dedication to delivering reliable, personalized recommendations. The seamless integration of disease detection with crop recommendations ensures holistic decision support, addressing the uniqueness of each agricultural plot. The user-friendly web interface facilitates easy data input and visualization for farmers of all technical levels. Deployment, continuous monitoring, and periodic retraining ensure real-time functionality and adaptability. Looking ahead, our vision involves scaling deployment in collaboration with agricultural organizations, with ongoing user feedback shaping iterative enhancements, emphasizing user-centricity and effectiveness. Ultimately, this system strives to optimize resource utilization, reduce risks, and promote sustainable agriculture, contributing to the well-being of farmers and global food security.

Greenhouse environments can benefit from IoT technologies that enable real-time monitoring of various parameters such as temperature, humidity, light levels, and nutrient levels. Incorporating real-time weather forecasting data into crop recommendation systems can help greenhouse growers make timely decisions. By considering weather conditions, such as temperature, precipitation, and wind patterns, the systems can provide recommendations on irrigation scheduling, pest control, and other management practices. Developing user-friendly mobile applications can enable farmers to receive alerts, track crop health, and remotely control greenhouse parameters.

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