Agroadvisor: Empowering Farmers with Data-Driven Crop, Fertilizer Recommendation, And Leaf Disease Detection

1.Rani Ishwarashetti (P.G Research Scholars)
School of Science and Computer Studies
2. Syeeda Mujeebunnisa,

Assistant Professor, CMR University, Bangalore

Abstract

Agriculture is a cornerstone of the global economy, playing a crucial role in GDP and employment. As the global population continues to rise, enhancing agricultural productivity is essential to ensure food security. Crop yield is influenced by a range of factors including temperature, rainfall, soil conditions, and fertilizer application, leading to fluctuations in production. Over the years, soil fertility has been declining due to environmental factors, making it increasingly challenging to maintain high crop yields. This research introduces a web application that assists farmers in making informed decisions regarding crop selection, fertilizer application, and leaf disease management. By harnessing advanced data analysis and machine learning techniques, the platform provides personalized recommendations based on soil quality, climate, and geographical data. Machine learning algorithms are used for crop and fertilizer suggestions, while deep learning models like CNN ResNet-50 are employed for leaf disease detection. The system aims to enhance yield and sustainability, thereby improving agricultural productivity and ensuring global food security. By optimizing resource use and reducing crop losses due to diseases, this solution addresses the challenges posed by declining soil fertility and promotes sustainable farming practices.

IndexTerms - *Crop Selection, Fertilizer Optimization, Leaf Disease Management, Machine Learning, Data Analysis, Precision Agriculture, Soil Fertility Decline, Convolutional Neural Networks (CNNs), Random Forest, ResNet-50 Model, Environmental Impact on Agriculture.*

I. INTRODUCTION

India's agricultural sector plays a crucial role in the country's economy, contributing significantly to GDP and providing employment for a large portion of the population. However, this sector faces major challenges, particularly due to unpredictable climatic and environmental conditions. These include irregular rainfall, rising temperatures, prolonged droughts, and unexpected storms, all of which disrupt traditional farming practices. These challenges often lead to significant losses for farmers who rely on conventional methods without utilizing modern data analysis. While other industries have rapidly adopted new technologies, the uptake of advanced techniques in Indian agriculture has been slower. This presents a key opportunity: by integrating modern technology into farming, India can improve crop yields and boost economic growth.

A pressing issue in Indian agriculture is the ongoing decline in soil fertility, worsened by environmental factors over time. Intensive farming, excessive chemical fertilizer use, soil erosion, and loss of organic matter have all contributed to poor soil health. As soil fertility decreases, crop yields drop, creating a cycle of reduced productivity that threatens food security and farmers' livelihoods. This study seeks to tackle this issue by developing a solution that uses machine learning and data analysis to optimize fertilizer use and improve soil health. By analyzing historical and real-time environmental data, the system offers precise recommendations to help restore and maintain soil fertility, ensuring sustainable crop production year after year.

The growing unpredictability of climate conditions, such as changes in monsoon patterns and extreme temperature shifts, highlights the need for innovative agricultural solutions that can adapt to these changes. Machine learning algorithms can be particularly useful here, as they allow for predictions of crop yields based on past data and factors like temperature, rainfall, and soil moisture. These predictions enable farmers to anticipate potential issues and make informed decisions before planting, which can reduce risks and improve productivity. Additionally, incorporating machine learning into agricultural practices can make farming operations more efficient, lower labor costs, and increase overall effectiveness, making farming a more viable and profitable industry that contributes more strongly to the economy.

Effective fertilizer management is essential for maintaining soil fertility and ensuring healthy crop growth. Traditional methods of applying fertilizers often result in either overuse or underuse, both of which can harm soil health and crop productivity. Excessive fertilizer use over time can lead to nutrient imbalances in the soil, while insufficient application can cause poor crop growth and lower yields. This study proposes using machine learning algorithms to analyze soil characteristics—such as levels of nitrogen, phosphorus, potassium, pH, humidity, and moisture content—to provide precise fertilizer recommendations tailored to the specific needs of each crop and soil type. By optimizing fertilizer use, this approach not only enhances crop yields but also supports the long-term sustainability of agricultural practices.

The solution presented in this research focuses on creating a web-based application that integrates advanced data analysis techniques and machine learning algorithms. This application will give farmers personalized recommendations for crop selection, fertilizer use, and leaf disease management, based on both real-time and historical data insights. By offering accurate predictions and practical advice, this system aims to increase agricultural productivity, promote sustainability, and improve economic outcomes for farmers. Additionally, the platform is designed to be user-friendly and includes multilingual support, making it accessible to a wide range of users. The goal is to encourage widespread adoption of these advanced agricultural techniques, ultimately maximizing their positive impact on the farming community and contributing to the country's food security.

II. RELATED WORK

Integrating advanced technologies such as remote sensing, machine learning, and deep learning with traditional farming techniques enhances agricultural productivity and sustainability. These modern technologies help in recommending optimal crops and fertilizers while also detecting crop weeds, pests, and diseases. By leveraging precise, data-driven insights into crop health and soil conditions, farmers can make more informed decisions that improve yield predictions and resource management. Remote sensing provides valuable environmental data, while machine learning and deep learning algorithms offer comprehensive analyses, leading to better resource allocation and farming practices. This holistic approach enables farmers to optimize their operations, ultimately resulting in higher productivity and more sustainable agricultural practices [1].

Enhancing plant leaf disease detection and classification through automated image processing systems is essential for modern agriculture. These systems utilize computer vision techniques to efficiently identify diseases, significantly reducing the dependence on manual inspections, which are often time-consuming and expensive. Advanced algorithms used in these image processing systems achieve high accuracy in disease classification, allowing for timely and effective management solutions that can mitigate crop losses. By automating the detection process, these technologies provide consistent and reliable results, crucial for maintaining crop health and maximizing yields. This advancement in technology supports better crop management and early intervention strategies, essential for sustaining agricultural productivity [2].

Managing plant disease severity detection and fertilizer recommendations using machine learning techniques such as K-nearest neighbors (KNN) and support vector machines (SVM), alongside deep learning models like convolutional neural networks (CNN) and artificial neural networks (ANN), is critical for maintaining optimal crop health. These sophisticated techniques offer real-time disease assessment and tailored fertilizer suggestions, improving agricultural productivity. Machine learning models can analyze a variety of data inputs to provide precise detection and management strategies for plant diseases. This capability is crucial for sustaining crop yields and minimizing the adverse effects of diseases on agricultural output. By incorporating these advanced methods, farmers can enhance their decision-making processes and improve overall crop health [3].

Monitoring and assessing plant leaf changes through image processing for effective plant disease detection is a key advancement in modern farming. The transition from traditional visual inspections to sophisticated algorithms has greatly improved the accuracy and timeliness of diagnosing plant diseases. These advanced image processing techniques enable rapid identification of potential disease outbreaks, allowing farmers to respond more swiftly. This capability supports better crop management and yield optimization, helping to protect plant health and enhance productivity. The use of these technologies ensures that farmers can address disease issues promptly and effectively, contributing to more robust agricultural practices [4].

Analyzing crop recommendation systems based on soil properties optimizes agricultural practices by offering crop suggestions tailored to specific soil conditions. By evaluating factors such as nutrient levels and soil texture, these systems help maximize yield potential and minimize environmental impact. The integration of detailed soil data into crop recommendation models ensures that recommendations are well-suited to the growing environment, enhancing the likelihood of successful crop production. This approach leads to better decision-making and resource utilization, promoting more effective and sustainable farming practices. Tailoring crop recommendations to soil characteristics supports improved agricultural outcomes and reduces the risk of crop failure [5].

Exploring the use of machine learning classifiers, including linear regression and random forests, for precise crop and fertilizer recommendations involves incorporating environmental factors and soil characteristics into decisionmaking processes. These models adapt to local conditions, ensuring optimal crop selection and fertilizer application. By integrating machine learning techniques, farmers receive accurate and reliable recommendations, enhancing productivity and resource efficiency. This approach allows for more precise agricultural practices and supports sustainable farming by optimizing resource use based on detailed environmental and soil data [6].

Applying the Light GBM algorithm for weather-based crop recommendations involves analyzing soil nutrient levels to help farmers make optimal crop selection decisions. This technique integrates data science with agricultural practices to improve yield outcomes and resilience to climatic variations. By leveraging detailed weather and soil data, farmers receive actionable insights that aid in selecting crops best suited to current conditions. This approach enhances decision-making, leading to improved crop yields and better adaptation to changing weather patterns [7].

Utilizing machine learning algorithms such as AdaBoost to predict crop yields and recommend fertilizers based on parameters including state, district, area, seasons, rainfall, temperature, and soil characteristics improves the accuracy of yield predictions. AdaBoost's robust predictions and optimized fertilizer recommendations support higher productivity and efficient resource use. By considering a wide range of variables, this method ensures comprehensive and tailored recommendations, enhancing agricultural outcomes. This approach helps farmers achieve better yields and more effective fertilizer management, contributing to overall agricultural efficiency [8].

Investigating the use of machine learning methods such as XGBoost and Random Forest for accurate crop yield prediction and fertilizer recommendation provides a thorough analysis of the effectiveness of these techniques. Comparing XGBoost and Random Forest highlights their strengths in handling diverse datasets and optimizing cropspecific fertilizer recommendations. This research supports the development of precise models that enhance agricultural productivity by providing reliable yield predictions and effective fertilizer suggestions [9].

Reviewing various plant disease detection methods using image processing covers the evolution from traditional visual inspections to advanced algorithms. These automated methods, including deep learning and machine learning techniques, have significantly improved the accuracy and timeliness of plant disease detection. By employing these advanced techniques, farmers can achieve faster and more accurate diagnoses, leading to better crop management and reduced losses from diseases. This evolution supports improved agricultural practices and enhances crop health management [10].

Exploring plant disease identification and detection using machine learning algorithms involves applying various techniques to classify diseased and healthy leaves. Algorithms such as random forests enhance the accuracy of disease detection and classification, providing reliable and timely identification of plant diseases. This capability enables better management and treatment strategies, ensuring healthy crops and maintaining high productivity. The use of these advanced algorithms supports effective disease control and contributes to improved crop health [11].

Addressing crop and fertilizer recommendations to improve crop yield using deep learning involves utilizing models to provide optimized suggestions for crops and fertilizers. These advanced algorithms deliver precise and actionable insights that enhance crop yields. By integrating deep learning techniques, the system ensures that recommendations are based on comprehensive data analysis, leading to more effective agricultural practices. This approach supports higher productivity and better resource management [12].

Presenting a proficient approach to crop recommendation using the Gradient Boosting Machine technique involves employing gradient boosting algorithms to suggest suitable crops. This method optimizes crop selection based on various environmental and soil parameters, improving decision-making for farmers. By ensuring better agricultural outcomes, this approach supports sustainable farming practices and enhances productivity. The use of gradient boosting techniques helps achieve more accurate crop recommendations [13].

Investigating multisensor data fusion and machine learning for agriculture text classification emphasizes the integration of multiple data sources to improve crop yield and support effective agricultural management. This comprehensive approach provides valuable insights that aid in efficient resource management. By leveraging multisensor data and advanced machine learning techniques, farmers can achieve better yield outcomes and optimize their use of resources, leading to more productive and sustainable farming practices [14].

Proposing a system for weather-based crop prediction in India using big data analytics involves predicting crop suitability based on weather conditions. Integrating big data techniques enhances agricultural outcomes by providing actionable insights for farmers. This system improves decision-making in agriculture, leading to better crop management and increased productivity. By analyzing weather data, farmers can make more informed choices about crop selection, enhancing overall agricultural performance [15].

Analyzing formal concepts for verifying pests and diseases of crops using machine learning methods involves exploring techniques for systematic pest and disease management. This approach improves the accuracy and efficiency of diagnosing and managing crop pests and diseases. Machine learning applications enable more reliable pest and disease control, supporting healthier crops and higher yields. By using advanced techniques, farmers can better manage pest and disease issues [16].

Focusing on predicting crop fertilizer consumption involves utilizing machine learning techniques to estimate fertilizer needs based on various factors. This approach supports efficient fertilizer usage, enhancing crop productivity by ensuring optimal application. Accurate predictions of fertilizer requirements help maintain soil health and achieve better crop outcomes. By optimizing fertilizer use, farmers can improve overall agricultural efficiency [17].

Employing a machine learning-based approach for crop yield prediction and fertilizer recommendation highlights the application of algorithms to optimize resource use and enhance agricultural productivity. This integrated approach supports better decision-making in farming, ensuring higher yields and efficient fertilizer use. Leveraging machine learning helps achieve more precise agricultural management, contributing to improved productivity and resource efficiency [18].

Introducing a crop and fertilizer recommender system with leaf disease prediction combines crop and fertilizer recommendations with disease prediction capabilities for comprehensive agricultural management. This multifaceted approach assists farmers in managing crops more effectively and sustainably by offering integrated solutions for crop selection, fertilizer use, and disease management. By providing a holistic tool, this system enhances agricultural productivity and sustainability [19].

Presenting a system for identifying fertilizers based on NPK levels using machine learning algorithms involves applying advanced techniques to determine the most suitable fertilizers. This approach improves crop yield and optimizes fertilizer usage by providing precise nutrient management recommendations. By matching fertilizers to soil nutrient levels, farmers can achieve better crop health and productivity, supporting more effective and efficient agricultural practices [20].

III . TRANSFORMATIVE IMPACT OF MACHINE LEARNING ON MODERN FARMING

The evolution of machine learning (ML) in agriculture marks a transformative shift from traditional management practices to advanced, data-driven approaches. Machine learning technologies, particularly artificial neural networks (ANN) and convolutional neural networks (CNN), have significantly enhanced agricultural practices by providing sophisticated knowledge-based systems. These advancements have revolutionized data processing and application in agriculture, delivering more accurate and reliable solutions compared to conventional methods. The adoption of ML represents a major leap towards more efficient and precise farming practices.

Machine learning improves various aspects of agriculture, including weed identification, disease detection, and yield forecasting. By analyzing crop needs, soil characteristics, and climate conditions, ML algorithms enhance decisionmaking and boost productivity and sustainability. Additionally, these technologies optimize spraying and fertilization processes, reducing waste and minimizing environmental impacts. With predictive insights, farmers can better plan planting and harvesting schedules, improving overall efficiency and resource management. Real-time data and actionable recommendations provided by ML empower farmers to adapt and respond effectively to evolving environmental conditions, fostering more resilient agricultural practices..

IV . PROPOSED SYSTEM METHODOLGY

The outlined approach aims to boost agricultural productivity through targeted crop recommendations, optimized fertilizer usage, and early disease detection. Leveraging specialized datasets, this system offers personalized recommendations based on comprehensive soil characteristics, environmental conditions, and image-based disease analysis. By integrating data from diverse sources, such as soil nutrient levels, weather patterns, and local geographic factors, the methodology provides nuanced insights into crop management. This advanced integration of technology addresses key agricultural challenges by promoting efficient farming practices and enhancing resource use. The system's ability to tailor recommendations to specific conditions helps farmers achieve higher yields and better sustainability, making it a vital tool for modern agriculture.

In the first component of the system, crop recommendations are enriched by incorporating detailed soil nutrient data, including Nitrogen (N), Phosphorus (P), Potassium (K), rainfall, pH value, and location-specific information such as state and city. This component also integrates real-time weather data via a weather API to account for current climatic conditions, ensuring that recommendations reflect the most recent environmental factors. We trained the model using six machine learning algorithms: Decision Tree, Random Forest, Naive Bayes, Logistic Regression, XGBoost, and Support Vector Machine (SVM). XGBoost, demonstrating the highest accuracy in predictive performance, was selected for crop prediction. Additionally, the system provides detailed information about the recommended crops, including their caloric and nutrient content and recent production data for the specified area. This comprehensive analysis ensures that recommendations are both precise and contextually relevant, supporting informed decisionmaking for farmers.

The second component focuses on optimizing fertilizer application. The system requests details about the crop to be grown and collects soil nutrient information, including Nitrogen, Phosphorus, and Potassium levels. By employing big data techniques and machine learning algorithms, it cross-references this data with the crop's specific nutrient requirements to recommend the most suitable fertilizers. Furthermore, the system provides tailored advice on land preparation techniques to enhance soil conditions and support optimal crop growth. This approach not only improves nutrient management but also ensures that fertilizer applications are efficient and effective, reducing waste and environmental impact. The detailed recommendations are designed to maximize crop yield and sustainability, aligning with best practices in precision agriculture.

The third component addresses crop leaf disease detection using the ResNet Convolutional Neural Network (CNN). Farmers can upload images of affected crop leaves, which the system analyzes to identify the disease and provide real-time treatment recommendations. This module employs advanced deep learning techniques to achieve high accuracy in disease detection, surpassing traditional manual methods. In addition to disease identification, the system provides insights into potential causes and suggests effective intervention strategies. By offering timely and accurate diagnoses, the system helps farmers take prompt action to mitigate disease spread and reduce crop losses. This integration of deep learning into plant health monitoring represents a significant advancement, providing a robust tool for maintaining crop health and enhancing overall agricultural productivity.

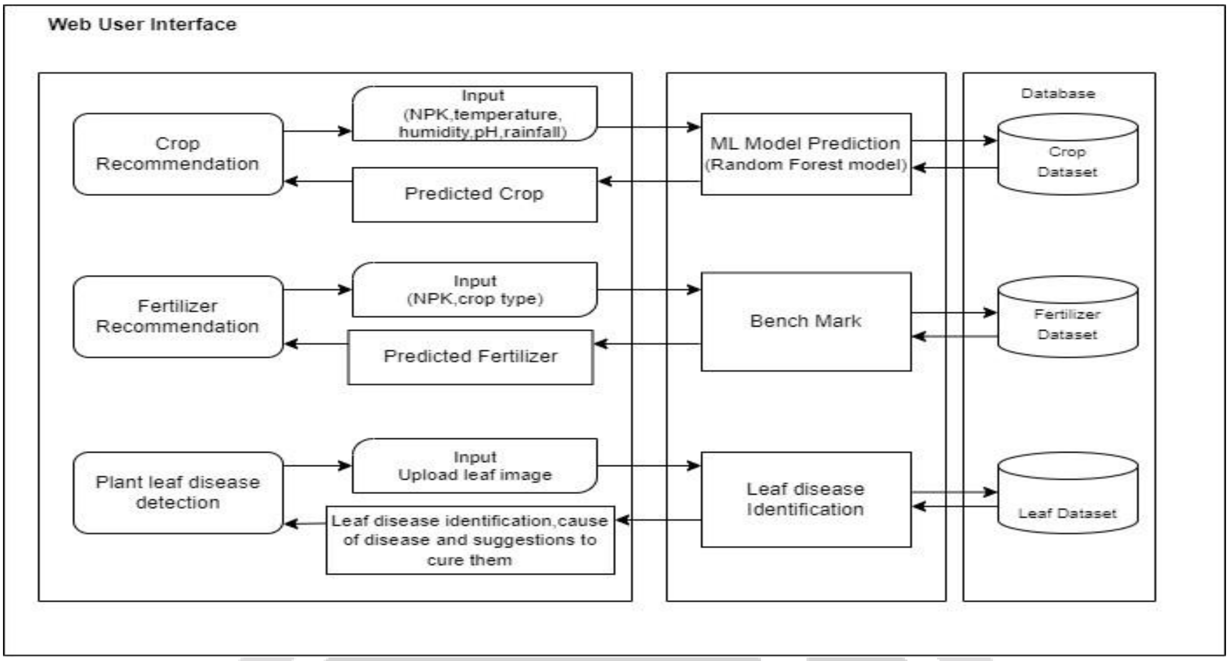

Figure 1 : Architectural diagram of proposed model

The diagram in Figure 1 illustrates a comprehensive web-based agricultural advisory system designed to streamline and enhance farming practices through advanced technology. This system features several interconnected modules, each serving a specific function. Initially, data preprocessing and preparation involve collecting and organizing usersubmitted information, such as soil characteristics, climatic conditions, and crop preferences. This data is then fed into machine learning models for training, where algorithms learn from historical data to improve their predictive capabilities. The system utilizes these trained models to generate tailored recommendations, including optimal crop selection based on soil and environmental factors, as well as personalized fertilizer suggestions to enhance soil fertility. Additionally, the system incorporates a plant leaf disease detection module, which analyzes images of crop leaves to identify potential diseases and provide actionable treatment advice. All results and recommendations are benchmarked against a comprehensive database to ensure their accuracy and relevance, thereby offering users reliable and actionable insights for better decision-making in their agricultural practices.

V . IMPLEMENTATION

This research employs a holistic approach to enhancing agricultural practices by integrating advanced technologies. It combines machine learning models for precise crop and fertilizer recommendations with deep learning techniques for accurate plant disease detection. The research is facilitated through a user-friendly web application interface, which simplifies data input and provides real-time recommendations and diagnoses. This approach ensures that farmers can easily access the necessary insights. The effectiveness of these solutions relies on diverse datasets, which are critical for training and validating the models. These datasets, encompassing detailed information on soil properties, climatic conditions, and plant health, form the foundation for the system's predictive and diagnostic capabilities.

A) DATASET DESCRIPTION

The datasets utilized in this study encompass three primary domains: crop recommendation, fertilizer recommendation, and plant disease detection. For crop recommendation, the dataset includes a range of environmental and soil parameters, such as temperature, rainfall, soil pH, and nutrient levels, along with corresponding crop labels to facilitate accurate predictions. The fertilizer recommendation dataset contains detailed information on the nutrient requirements for various crops, helping to tailor fertilizer applications based on specific crop needs and soil conditions. Meanwhile, the plant disease detection dataset comprises a collection of images depicting both healthy and diseased plants across multiple crop types. This dataset enables the deep learning models to distinguish between different plant health conditions with high precision. The figures below provide a detailed view of the structure and composition of these datasets, illustrating how each dataset contributes to the overall effectiveness and accuracy of the system's recommendations and diagnoses.

Sl no	N	P	K	Temperature	Humidity	Ph	Rainfall	Label
1	90	42	43	20.87974371	82.00274423	6.502985292	202.9355362	rice
2	71	54	16	22.61359953	63.69070564	5.749914421	87.75953857	maize
3	40	72	77	17.02498456	16.98861173	7.485996067	88.55123143	chickpea
4	28	80	17	19.62207826	18.67170854	5.809419584	144.1567454	kidneybeans
5	24	42	23	28.22471276	82.35916228	6.428054409	44.01206619	mungbean
6	52	71	16	27.74274761	68.53997144	7.075886472	71.78615328	blackgram
7	40	27	45	21.6602498	94.79397419	5.885638185	112.4349689	pomegranate

Table 1 : Structure of the Crop and Fertilizer Recommendation Datasets

The above table 1 presents the structure of the datasets utilized for both crop and fertilizer recommendations. The crop recommendation dataset includes features such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall, along with the target variable "label," which indicates the recommended crop. This dataset consists of 2,200 instances, providing a robust foundation for accurate crop predictions. Additionally, the fertilizer recommendation dataset comprises attributes such as crop name, nitrogen (N), phosphorus (P), potassium (K), and pH levels. This dataset is crucial for recommending appropriate fertilizers based on the specific nutrient needs of various crops. The table consolidates the structure and content of these datasets, facilitating an understanding of the data used for generating precise recommendations and supporting effective agricultural decision-making.

CropName	Diseases
Apple	Apple scab, Black rot, Cedar apple rust, Healthy
Blueberry	Healthy
Cherry (including sour)	Healthy, Powdery mildew
Corn (maize)	Cercospora leaf spot, Gray leaf spot, Common rust, Healthy, Northern Leaf Blight
Grape	Black rot, Esca (Black Measles), Healthy, Leaf blight (Isariopsis Leaf Spot)
Orange	Huanglongbing (Citrus greening)

Peach	Bacterial spot, Healthy
Pepper, bell	Bacterial spot, Healthy
Potato	Early blight, Healthy, Late blight
Raspberry	Healthy
Soybean	Healthy
Squash	Powdery mildew
Strawberry	Healthy, Leaf scorch
Tomato	Bacterial spot, Early blight, Healthy, Late blight, Leaf Mold, Septoria leaf spot, Spide mites Two-spotted spider mite, Target Spot, Tomato mosaic virus, Tomato Yellow Leaf Curl Virus

Table 2 : Structure of the Plant Disease Dataset

The above table 2 outlines the structure of the plant disease dataset, which provides comprehensive information on various crops and their associated diseases. This dataset includes a range of crops such as apple, blueberry, cherry, and tomato, among others, each with specific diseases or conditions that they may exhibit. For instance, apple crops may suffer from diseases like apple scab or black rot, while tomatoes can be affected by conditions such as bacterial spot or early blight. The dataset categorizes each crop based on the diseases they may encounter, offering valuable insights for plant health monitoring and disease management. By consolidating this information, the dataset supports effective plant disease diagnosis and helps in developing targeted interventions for disease prevention and control.

B) DATA PREPROCESSING AND PREPARATION

For the crop dataset, data preprocessing begins with data cleaning to manage missing values and outliers. Exploratory Data Analysis (EDA) is then conducted to comprehend the data distribution and the relationships between features.

Feature engineering follows, creating new features or transforming existing ones to enhance the dataset's predictive power. Categorical variables are encoded using one-hot encoding to facilitate model training. The fertilizer dataset also undergoes thorough preprocessing, where column names are standardized for consistency, and crop names are uniformed through string replacements. Data is filtered based on unique crop names, and captions are standardized for case uniformity. The plant disease dataset requires data cleaning to address any irregularities in the images, resizing to a uniform size, and data augmentation techniques to increase the diversity of the training set.

Once the data preprocessing is complete, the datasets are prepared for model training by splitting them into training, testing, and validation sets in a 70%-20%-10% ratio. This ensures that the model has a robust dataset to learn from, validate its performance, and test its accuracy. The training set, comprising 70% of the data, is used to train the machine learning models. The testing set, making up 20% of the data, is used to evaluate the model's performance during the training phase. The validation set, constituting 10% of the data, is used to fine-tune and validate the model to prevent overfitting. This split ensures that the models developed for crop recommendation, fertilizer optimization, and plant leaf disease detection are well-trained, accurately validated, and thoroughly tested before deployment.

C) MODEL TRAINING

For crop recommendation, the dataset is split into training ,testing and validation sets using the train_test_split method. Six machine learning models—Decision Tree, Naive Bayes, SVM, Logistic Regression, and Random Forest—are trained and evaluated on the testing set. Metrics such as accuracy, precision, recall, and F1-score are calculated for each model, and crossvalidation scores ensure robustness. Trained models are stored using the pickle module. For fertilizer recommendation, a function is implemented to standardize data and calculate differences between user input levels and dataset levels. Recommendations are generated based on the largest differences identified. For disease detection, the dataset is split into training, validation, and testing sets. A deep learning model using architectures like ResNet is trained and evaluated on the validation dataset using performance metrics such as F1 score, recall, accuracy, and precision. Hyperparameters are fine-tuned to optimize model performance and evaluated on the validation dataset using performance metrics such as F1 score, recall, accuracy, and precision. Hyperparameters are fine-tuned to optimize model performance.

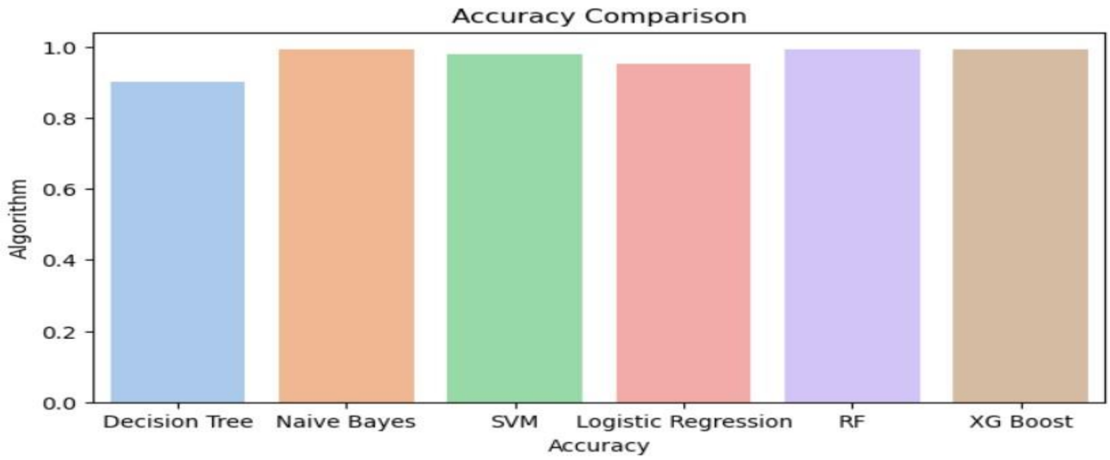

Figure 2: Evaluation of Model Accuracy

Finally, the accuracy of all trained models is compared to determine the best-performing model for each recommendation as shown in the figure above. After comparing the accuracies, both Random Forest and XGBoost were found to have the highest accuracy of 99.09%. Between these two, Random Forest was selected for the crop and fertilizer recommendation system in this project.

For the plant disease detection system within the AgroAdvisor project, a deep learning approach is utilized, leveraging the ResNet Convolutional Neural Network (CNN) model. The training of this model involves carefully configuring several hyperparameters to ensure optimal performance. These hyperparameters include the number of epochs, the learning rate, gradient clipping, and weight decay, all of which play a critical role in refining the model's learning process. The Adam optimizer is employed to enhance the training efficiency by adapting the learning rate based on the gradient information. The training and validation datasets are processed in iterative cycles to fine-tune the model's parameters. Throughout this process, the accuracy of the model is meticulously monitored at each epoch to evaluate its performance and make necessary adjustments.

The training process is meticulously documented, reflecting the setup of hyperparameters and the corresponding training outcomes. Key metrics such as training and validation loss, as well as validation accuracy, are tracked to gauge the model's effectiveness. The ResNet model demonstrated exceptional performance, achieving a validation accuracy of 99.2%. This high level of accuracy highlights the model’s capability to accurately detect and classify plant diseases, underscoring its robustness and effectiveness in real-world applications. This level of performance indicates that the ResNet model is well-suited for practical deployment in plant disease detection systems.

D) CROP/FERTILIZER RECOMMENDATION

The Random Forest model, with a high accuracy of 99.09%, significantly enhances both crop selection and fertilizer recommendations through sophisticated machine learning techniques.

For crop recommendations, the model analyzes a range of factors including nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall. During training, the model constructs multiple decision trees, each trained on various subsets of these input features. Each tree evaluates how these factors interact to determine the suitability of different crops. By aggregating the results from these numerous trees, the model generates a consensus on which crop is best suited for the specific set of conditions. This ensemble approach leverages the diverse decision trees to improve accuracy and reliability, ensuring that the crop recommendations are highly tailored to the given soil and environmental conditions.

In the case of fertilizer recommendations, the Random Forest model focuses on nitrogen (N), phosphorus (P), potassium (K), and the crop type. The model compares the provided nutrient levels with optimal values for each crop type, as derived from a comprehensive dataset. By identifying discrepancies between the current nutrient levels and the ideal ranges, the model uses its ensemble of decision trees to determine the most effective fertilizers and soil amendments. The aggregated results provide precise recommendations for adjusting nutrient levels, ensuring that the soil conditions are appropriately managed to support the selected crop's growth. The model's high accuracy ensures that these recommendations are actionable and tailored to meet the specific needs of the crop and soil conditions.

Random Forest Implementation Process for Crop and Fertilizer Recommendations

1. Preprocess the dataset by handling missing values, encoding categorical variables, and normalizing features.
2. Split the dataset into training and testing sets.
3. Initialize the Random Forest model with specified hyperparameters like n_estimators, max_depth, min_samples_split, and max_features.
4. For each tree in the Random Forest, create a bootstrap sample by randomly selecting data points from the training set with replacement.
5. At each node in the tree, randomly select a subset of features and calculate the best split based on Gini impurity or entropy.
6. Split the node into child nodes and continue this process until the stopping criteria, such as max_depth or min_samples_split, are met.
7. Assign a final class label to each leaf node based on the majority class of samples in that node.
8. For each input sample in the test set, pass the sample through all trees in the forest, recording the predicted class label from each tree.
9. Perform majority voting on the predictions from all trees to determine the final recommendation.
10. Evaluate the model's performance on the test set by calculating accuracy, precision, recall, and F1-score, and provide the final recommendation along with performance metrics.

E) LEAF DISEASE DETECTION

In the disease detection process, the trained ResNet model, achieving an accuracy of 99.2%, plays a crucial role in identifying plant diseases from images. The model is trained on a diverse dataset of leaf images, including both healthy and diseased samples. During training, the ResNet architecture employs residual blocks to learn and refine features from these images, enabling it to recognize complex patterns and subtle differences between various plant diseases.

When new plant images are input into the model, it processes these images through its deep convolutional layers, extracting and analyzing features to determine the presence of specific diseases. The model's high accuracy of 99.2% reflects its effectiveness in accurately classifying diseases based on the learned features. This precise disease detection capability provides valuable insights for crop management, allowing users to make informed decisions regarding treatment and care based on the model's predictions.

ResNet-50 Steps for Leaf Disease Detection

1. Preprocess the dataset by resizing all images to 224x224 pixels and normalizing pixel values to a range of [0, 1].
2. Apply data augmentation techniques like rotation, flipping, and zoom to increase the diversity of the training samples.
3. Split the dataset into training, validation, and testing sets.
4. Load the ResNet-50 model, initializing it with pre-trained weights if transfer learning is employed.
5. Modify the output layer to match the number of disease classes, and compile the model with the selected optimizer and loss function.
6. Train the model by shuffling the training data and processing batches through the network, updating weights using the optimizer after each batch.
7. After each epoch, validate the model using the validation set and record training and validation metrics.
8. Test the model on the test set, evaluating its performance with accuracy, precision, recall, and F1-score.
9. Save the trained model, and during inference, preprocess new images before passing them through the model to obtain and output the predicted disease label or "healthy" classification.

VI. TESTING

Testing is a crucial step in verifying the functionality and accuracy of the implemented models and systems. For the crop and fertilizer recommendation components, extensive validation was carried out using a diverse range of data samples to ensure the reliability of the models' predictions and recommendations. The Random Forest model's performance for crop recommendations was assessed through various metrics, including accuracy, precision, recall, and F1-score, utilizing a separate testing dataset. Similarly, the fertilizer recommendation component was evaluated with different nutrient input scenarios to confirm its ability to accurately calculate differences and provide appropriate fertilizer suggestions.

In the plant disease detection module, rigorous testing was performed with a broad set of plant images to evaluate the ResNet model's accuracy in diagnosing different plant diseases. The model was tested on new, unseen images to ensure its robustness and ability to generalize across various disease conditions. Additionally, the functionality of the disease detection system was reviewed to ensure effective image processing and accurate disease identification. Continuous refinement was made based on testing feedback to enhance both the performance and user experience of the system.

VII. RESULTS

The research involved a thorough evaluation of various machine learning algorithms to assess their performance based on classification metrics such as accuracy, precision, and recall. This comparative analysis was crucial in selecting the most effective algorithms for both crop and fertilizer recommendations. A user-focused platform was developed to allow input of soil data and crop information. This system evaluates soil nutrient levels, identifies imbalances, and provides tailored recommendations to improve soil conditions. By suggesting crops that are optimally matched to the soil and environmental parameters, the system enhances crop yields and promotes sustainable agricultural practices.

The crop recommendation component addresses a key agricultural challenge by recommending crops that are ideally suited to specific soil and environmental conditions. This approach not only leads to better crop yields but also supports more sustainable farming methods. Similarly, the fertilizer recommendation feature plays a critical role in managing soil fertility by providing customized advice based on nutrient analysis, ensuring that soil nutrient levels are balanced for optimal crop growth. Overall, the study underscores the value of applying machine learning and data analytics to deliver actionable insights that enhance farming efficiency and contribute to long-term agricultural sustainability.

VIII . CONCLUSION

This research utilizes advanced machine learning and deep learning algorithms to provide highly accurate recommendations for crop selection, fertilizer application, and disease management. By meticulously analyzing data on soil characteristics, environmental conditions, and plant health images, the study offers tailored insights that significantly boost agricultural productivity and promote sustainability. The integration of these cutting-edge technologies ensures that farmers receive precise and actionable guidance, enabling informed decision-making that enhances crop yields and optimizes resource utilization.

Looking forward, the study aims to expand the dataset by incorporating additional agricultural parameters, which will further refine prediction accuracy. The development of more sophisticated models for disease detection is also planned, enhancing the system's capability in diagnosing and managing plant diseases with greater precision. Furthermore, the integration of IoT technology will enable real-time monitoring of crop health and environmental factors, providing farmers with immediate insights and actionable data. These future advancements are designed to overcome current limitations in agricultural technology, driving more efficient and sustainable farming practices. By continuing to innovate and refine these tools, this research aspires to contribute to a more resilient and productive agricultural sector, addressing the growing global demands for food security and sustainable resource management.

IX . REFERENCES

[1] S. Mahalakshmi, A. Jose Anand and T. Sampath, *"Recommendation of Crops and Fertilizer, Detection of Crop Weed, Pest and Diseases using Machine Learning,"* 2023 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI), Chennai, India, 2023, pp. 1-6, doi: 10.1109/ICDSAAI59313.2023.10452616.

[2] S. Amritraj, N. Hans and C. P. Diana Cyril, *"An Automated and Fine- Tuned Image Detection and Classification System for Plant Leaf Diseases,"* 2023 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI), Chennai, India, 2023, pp. 1-5, doi: 10.1109/RAEEUCCI57140.2023.10134461.

[3] B. Sudhir, D. C. Teja, K. Sai, P. Sridhar and T. Daniya, *"Plant Disease Severity Detection and Fertilizer Recommendation using Deep Learning Techniques,"* 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 2023, pp. 215-221, doi: 10.1109/ICAAIC56838.2023.10140467.

[4] D. Tandekar and S. Dongre, *"A Review on Various Plant Disease Detection Using Image Processing,"* 2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN), Salem, India, 2023, pp. 552-558, doi: 10.1109/ICPCSN58827.2023.00096.

[5] A. Agarwal, S. Ahmad and A. Pandey, *"Crop Recommendation Based on Soil Properties: A Comprehensive Analysis,"* 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1-6, doi: 10.1109/ICCCNT56998.2023.10307999.

[6] S. Iniyan, M. S. Raja, R. Srinivasan, C. Santhanakrishnan and A. Srinivasan, *"Crop and Fertilizer Recommendation System Applying Machine Learning Classifiers,"* 2023 International Conference on Emerging Research in Computational Science (ICERCS), Coimbatore, India, 2023, pp. 1-6, doi: 10.1109/ICERCS57948.2023.10433972.

[7] R. Jaichandran, T. M. Krishna, S. H. Arigela, R. Raman, N. Dharani and A. Kumar, *"Light GBM Algorithm based Crop Recommendation by Weather Detection and Acquired Soil Nutrients,"* 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), Chennai, India, 2022, pp. 1-5, doi: 10.1109/ICPECTS56089.2022.10047765.

[8] J. R, H. D and P. B, *"A Machine Learning-based Approach for Crop Yield Prediction and Fertilizer Recommendation,"* 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2022, pp. 13301334, doi: 10.1109/ICOEI53556.2022.9777230.

[9] P. B. G, T. D. K and T. K. N, *"ML based methods XGBoost and Random Forest for Crop and Fertilizer Prediction,"* 2022 14th International Conference on Computational Intelligence and Communication Networks (CICN), Al-Khobar, Saudi Arabia, 2022, pp. 492-497, doi: 10.1109/CICN56167.2022.10008234.

[10] D. Tandekar and S. Dongre, *"A Review on Various Plant Disease Detection Using Image Processing,"* 2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN), Salem, India, 2023, pp. 552-558, doi: 10.1109/ICPCSN58827.2023.00096.

[11] Kumud, D. Gupta, S. Kumar, M. Johri and A. Ashish, *"Plant Disease Identification and Detection Using Machine Learning Algorithms,"* 2023 12th International Conference on System Modeling & Advancement in Research Trends (SMART), Moradabad, India, 2023, pp. 106-111, doi: 10.1109/SMART59791.2023.10428282.

[12] R. Thendral and M. Vinothini, "Crop And Fertilizer Recommendation to Improve Crop Yield using Deep Learning," 2023 Second International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2023, pp. 1123-1130, doi: 10.1109/ICEARS56392.2023.10085054.

[13] K. J. Kumar, N. P. K. Reddy, A. Vasu and S. Sandosh, "A Proficient Approach in Crop Recommendation System using Gradient Boosting Machine Technique," 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), Bengaluru, India, 2023, pp. 928-935, doi: 10.1109/ICIMIA60377.2023.10425893.

[14] A. Reyana, S. Kautish, P. M. S. Karthik, I. A. Al-Baltah, M. B. Jasser and A. W. Mohamed, "Accelerating Crop Yield: Multisensor Data Fusion and Machine Learning for Agriculture Text Classification," in IEEE Access, vol. 11, pp. 20795-20805, 2023, doi: 10.1109/ACCESS.2023.3249205.

[15] R. Gupta et al., "WB-CPI: Weather Based Crop Prediction in India Using Big Data Analytics," in IEEE Access, vol. 9, pp. 137869-137885, 2021, doi: 10.1109/ACCESS.2021.3117247.

[16] J. Tussupov et al., "Analysis of Formal Concepts for Verification of Pests and Diseases of Crops Using Machine Learning Methods," in IEEE Access, vol. 12, pp. 19902-19910, 2024, doi: 10.1109/ACCESS.2024.3361046.

[17] K. Hampannavar, V. Bhajantri and S. G. Totad, "Prediction of Crop Fertilizer Consumption," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, pp. 1-5, doi: 10.1109/ICCUBEA.2018.8697827.

[18] J. R, H. D and P. B, "A Machine Learning-based Approach for Crop Yield Prediction and Fertilizer Recommendation," 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2022, pp. 1330-1334, doi: 10.1109/ICOEI53556.2022.9777230.

[19] K. Devi Priya, A. S. Samyogitha, A. V. Krishna Reddy and B. Divya Sri, "ENSEMBLED CROPIFY – Crop & Fertilizer Recommender System with Leaf Disease Prediction," 2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA), Uttarakhand, India, 2023, pp. 600-604, doi: 10.1109/ICIDCA56705.2023.10100117.

[20] M. Vimaladevi, T. R, D. K, K. G and A. S, "FertiForecast: Identification of Fertilizer Based on NPK Levels using Machine Learning Algorithms," 2024 International Conference on Computing and Data Science (ICCDS), Chennai, India, 2024, pp. 1-6, doi: 10.1109/ICCDS60734.2024.10560386.