

Smart Harvest: Machine Learning Powered Agri-System For Sustainable Farming

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Abstract

Agriculture stands as the lifeblood of humanity, feeding nations, driving economies, and fostering livelihoods worldwide. Amidst escalating challenges, this innovative Agri-system focuses on optimizing crop management while ensuring environmental sustainability. Smart Harvest, an innovative Agri-system, integrates machine learning (ML), deep learning and data-driven intelligence to revolutionize farming methodologies in alignment with the Sustainable Development Goal 2: Zero Hunger. It accurately predicts crops by leveraging historical data, weather patterns, and soil analyses, empowering farmers with insights for resource allocation and strategic planning. ML algorithms, it generates crop fertilizers aiding farmers in selecting sustainable crops suitable for their specific environment. Using image recognition and ML techniques, it identifies and predicts potential plant diseases, enabling proactive interventions to preserve crop yield. It prioritizes community engagement by fostering collaboration among farmers through an intuitive interface. Smart Harvest redefines farming practices, empowers farmers, ensures global food security, and champions sustainable agricultural methodologies, highlighting agriculture's critical role in shaping a prosperous and nourished world. In this paper aim to reduce the complexity of the supply chain and improve the quality of food and crops wastages.

Keywords: Machine Learning, Smart Harvesting, Random Forest, Crop Fertilizers.

Introduction

The agriculture sector plays a pivotal role in sustaining global food security and economic stability. With advancements in technology, the agricultural landscape is witnessing a transformative shift towards smart and data-driven practices. The Smart Harvest App emerges as a beacon of innovation, empowering farmers and agriculture enthusiasts with cutting-edge tools and insights to optimize productivity and mitigate risks. This comprehensive platform integrates various features and functionalities to cater to the diverse needs of modern agriculture.

1.1 Crop Prediction

One of the core features of the Smart Harvest App is its ability to predict the most suitable crops based on environmental parameters. Leveraging a sophisticated Random Forest model, the app analyses factors such as nitrogen, phosphorus, potassium levels, temperature, humidity, pH, and rainfall. By providing personalized crop recommendations, the app enables farmers to make informed decisions about crop selection, leading to improved yields and resource utilization.

1.2 Plant Disease Detection

Early detection and management of plant diseases are critical for preserving crop health and optimizing yields. The Smart Harvest App integrates a pre-trained deep learning model capable of accurately identifying and classifying plant diseases. By uploading images of diseased plant leaves, users can receive prompt diagnoses and recommended treatment strategies, thereby minimizing crop losses and promoting sustainable farming practices.

1.3 Fertilizer Prediction

System Optimal nutrient management is essential for ensuring healthy plant growth and maximizing yields. The app's Fertilizer Prediction System utilizes machine learning algorithms to recommend suitable fertilizers based on soil type, crop selection, and nutrient levels.

1.4 Agri News

Updates Staying informed about the latest agricultural trends, policies, and market developments is crucial for decision-making. The Smart Harvest App features an integrated news feed that delivers real time updates on agriculture-related news, innovations, and best practices. Users can access relevant articles, reports, and insights to stay abreast of industry trends and make strategic decisions.

1.5 Interactive Agri

Chatbot The app's interactive chatbot serves as a virtual agricultural assistant, offering personalized advice, recommendations, and solutions to users' queries. Whether it's optimizing crop management practices,

accessing government schemes, or seeking expert guidance, the chatbot provides valuable support and fosters knowledge-sharing within the agricultural community. The Smart Harvest App represents a paradigm shift in agricultural technology, empowering farmers with data-driven solutions, predictive analytics, and real-time information.

Related Works

One method of unsupervised categorization that is used is clustering [4]. Numerous clustering methods have been created for various applications. Partitioning clustering, Hierarchical clustering, Density-based methods, Grid-based methods, and Model-based clustering methods are the several types of clustering techniques. Algorithms for partitioning clusters, such as K-means, K-medoids, PAM, CLARA, and CLARANS, divide items into K clusters and then repeatedly reallocate those objects to enhance the quality of the clustering outcomes.

In order to maintain the content of data points in the legislative of low level clusters, the hierarchical clustering algorithms distribute material among three created clusters. Density-based clustering algorithms operate on the premise that there are at least a minimum number of clusters in the vicinity of a given unit of distance for every point in a cluster [7]. Density-based clustering, which is employed in machine learning techniques, finds the neighborhood of a given unit distance that has at least a minimum number of points for each cluster. In the subject of agriculture, academics worldwide have created and assessed a variety of forecasting approaches.

A number of research by Ramesh and Vishnu Vardhan analyze the agricultural statistics from 2015 to 2023. The K means clustering algorithm is used to group rain fall data into 4 groups. The process of modeling the linear connection between a dependent variable and one or more independent variables is called multiple linear regressions, or MLR for short. Rainfall is a necessary variable, and self-governing factors include the year, the planting area, and yield. The goal of this effort is to identify appropriate data models with high prediction capabilities that are both highly accurate and very simplified [9].

Existing System

The existing agricultural system predominantly relies on traditional manual farming practices, where farmers make decisions based on their experience, observational data, and advice from local agricultural services. Data collection methods are largely manual, with minimal use of technology for soil sampling, crop monitoring, and pest detection. Crop prediction and management are based on historical patterns rather than advanced predictive models, while disease and pest control strategies often involve visual inspection and traditional remedies.

Fertilizer application is guided by general guidelines rather than precise soil nutrient analysis. Information sharing occurs through local extension services and traditional knowledge networks, with limited digital platforms for real-time information access. Challenges include limited data-driven insights, inefficient resource use, and vulnerability to climate and market fluctuations.

Proposed Work

The proposed Smart Harvest system represents a paradigm shift in agriculture, leveraging cutting edge technologies to revolutionize farming practices. At its core, the system integrates IoT (Internet of Things) devices such as weather stations, soil sensors, and drones to gather real-time data on environmental conditions, soil health, and crop status. This data is then processed using advanced machine learning algorithms to provide actionable insights and recommendations to farmers. For crop management, the system includes a crop prediction model trained on historical data and environmental variables, enabling accurate predictions of crop types and growth patterns. Disease detection is enhanced through a deep learning model that analyzes plant images to identify and classify diseases early, allowing for targeted interventions. Additionally, the system offers personalized fertilizer recommendations based on soil nutrient analysis, crop requirements, and environmental factors, optimizing nutrient use efficiency and crop yields.

The Smart Harvest system also features a user-friendly interface developed using web technologies and the Streamlit framework, enabling farmers to access information, receive alerts, and interact with the system seamlessly. Cloud integration ensures scalability, data storage, and accessibility from anywhere, while regular updates and maintenance guarantee system reliability and performance. Overall, the proposed system empowers farmers with data-driven decision-making, precision agriculture techniques, and sustainable farming practices, ushering in a new era of smart agriculture.

4.1 Random Forest Classifier Used for Crop and Fertilizer Prediction

A potent machine learning approach for both classification and regression applications is the Random Forest Classifier. In the context of your Smart Harvest project, Random Forest Classifier is utilized for crop prediction and fertilizer recommendation. Here's a detailed explanation of how Random Forest Classifier works and its role in your project:

1. Random Forest Classifier Overview: Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. It is called "random" because it creates each tree in the forest using a random subset of features and samples from the training dataset. This randomness helps to reduce over fitting and improve generalization.

2. Training Process: The Random Forest Classifier creates a forest of decision trees during the training phase. Each decision tree is constructed using a subset of the training data and a random selection of features. This randomness ensures that each tree is different and captures unique patterns in the data.

3. Decision Making: When making predictions, each tree in the Random Forest independently predicts the target variable (crop type or fertilizer recommendation) based on the input features. For classification tasks like crop prediction, the majority voting mechanism is used, where the final prediction is determined by the most frequent prediction across all trees. In regression tasks like fertilizer recommendation, the average prediction from all trees is considered.

4. Feature Importance: One of the key advantages of Random Forest is its ability to assess the importance of features in the prediction process. The algorithm calculates feature importance based on how much each feature contributes to reducing impurity (e.g., Gini impurity for classification) across all decision trees. This information is valuable for understanding which features have the most significant impact on crop prediction and fertilizer recommendation.

5. Handling Missing Values and Outliers: Random Forest is robust to missing values and outliers in the data. It can handle missing values by imputing them based on other features in the dataset. Additionally, because Random Forest uses multiple trees and feature subsets, outliers have less influence on the overall model compared to single decision tree models.

6. Scalability and Performance: Random Forest is highly scalable and can handle large datasets with numerous features efficiently. The parallel nature of training decision trees makes Random Forest suitable for both small-scale and big data applications. Moreover, it generally performs well without extensive hyper parameter tuning, making it a popular choice for various machine learning tasks.

Random Forest Classifier is trained on agricultural data such as soil properties, weather conditions, nutrient levels, and historical yield data. For crop prediction, it predicts the most likely crop type based on input environmental factors. For fertilizer recommendation, it suggests suitable fertilizers based on soil type, crop type, and nutrient requirements. The randomness and ensemble nature of Random Forest contribute to accurate and robust predictions, enhancing the Smart Harvest App's functionality and usability for farmers.

4.2 Objectives Of Smart Harvest App

The primary objective of the Smart Harvest App is to revolutionize the agriculture sector by leveraging advanced technologies and data-driven solutions to address key challenges faced by farmers and promote

sustainable farming practices. The app is designed with the following objectives in mind:

1. Optimizing Crop Management: The app aims to optimize crop management practices by providing accurate predictions for crop types based on environmental factors such as soil composition, temperature, humidity, and rainfall. This helps farmers make informed decisions regarding crop selection, planting schedules, and resource allocation.

2. Enhancing Disease Detection: One of the key objectives of the Smart Harvest App is to enhance disease detection in plants. By utilizing deep learning algorithms and image recognition technology, the app can identify plant diseases early on, allowing farmers to take timely preventive measures and minimize crop losses.

3. Improving Fertilizer Recommendations: The app's Fertilizer Prediction System is designed to improve fertilizer recommendations by analyzing soil nutrient levels, crop types, and environmental conditions. This ensures optimal use of fertilizers, reduces nutrient wastage, and promotes sustainable agricultural practices.

4. Promoting Sustainable Agriculture: Sustainable agriculture is a critical focus of the Smart Harvest App. It aims to promote practices that conserve natural resources, minimize environmental impact, and enhance long-term agricultural productivity. By encouraging sustainable farming methods, the app contributes to the overall resilience of the agriculture sector.

5. Empowering Farmers with Technology: Another objective of the app is to empower farmers with technology-driven tools and insights. By providing access to real-time data, predictive analytics, and actionable recommendations, the app enables farmers to make informed decisions, increase efficiency, and improve their livelihoods.

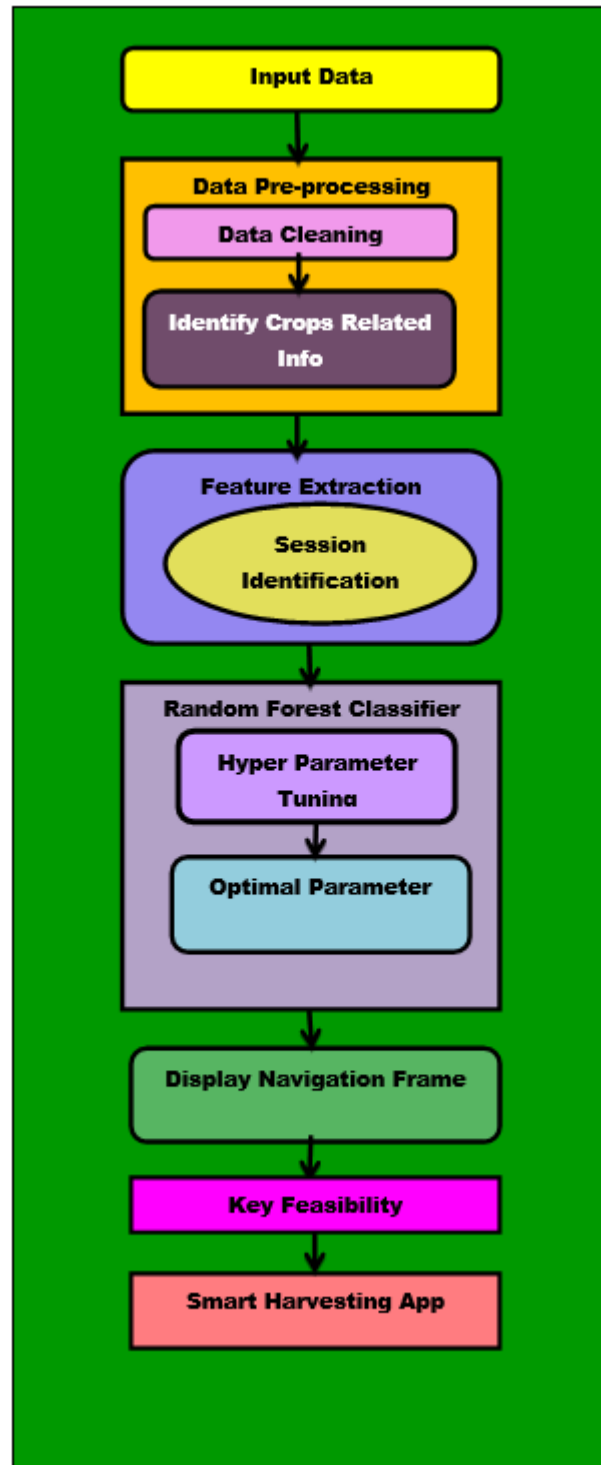


Fig. 1.1. Smart Harvest: Machine Learning Powered Agri-System for Sustainable Farming

6. System Requirements

OS	Windows 11
Processor	AMD Ryzen 5 5500U with Radeon Grap
RAM	8.00GB
Hard Disk	500GB
IDE	Anaconda Navigator and Google Colab
Coding Language	Python

4.3 Data Cleaning

Data quality is the most important aspect of excellent information management. Problems with data quality management can emerge anyplace in information systems. Companies have been perplexed as to whether they should cleanse their data first before proceeding with data analytics, or whether they should proceed with data analytics to determine whether their data is unclear. These issues are resolved by data cleansing. It is the process of determining erroneous, incomplete, or inappropriate data and subsequently improving its quality by addressing identified mistakes and omissions. Overall, data cleaning minimizes mistakes and increases data quality. Correcting data inaccuracies and removing incorrect entries can be a time-consuming and laborious procedure, but it cannot be avoided.

The bi-level feature extraction-based text mining for defect diagnosis addresses the aforementioned issues by automatically assessing. Our fundamental approach is to extract defect characteristics at the syntactic and semantic levels, which are then fused to obtain the desired outcomes. Given that the extracted features at each level place a distinct focus on a specific component of feature spaces and have limitations, the suggested feature fusion of two levels may improve the precision of fault detection for all fault classes, particularly minority ones.

4.3.1 Fertilizer Prediction App

Planning for the harvesting, processing, and related inventory control issues is crucial for agricultural economics. Crops that are especially prone to deterioration require integrated planning before harvesting and processing in order to minimize food waste and maximize food quality. There is a dearth of empirical testing and a limited reflection of reality in these models. A lot of attention has been focused on agricultural supply chain management in an effort to meet the world's expanding food demand. Its significance is anticipated to rise in tandem with the anticipated sharp growth in food demand.

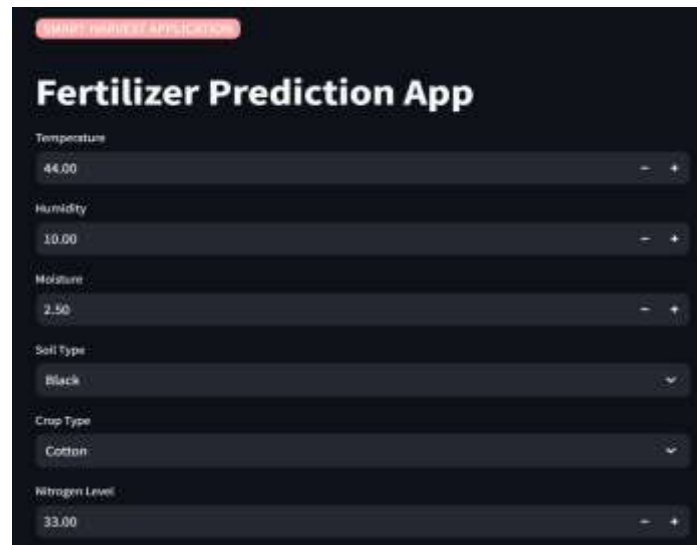


Fig. 1.2 Fertilizer Prediction App

The food processing industry is infect the largest manufacturing sector in many developed and developing countries harvesting, storage and processing may be done by different entities. In developing countries the lack of storage conditions is a major source of lost production.

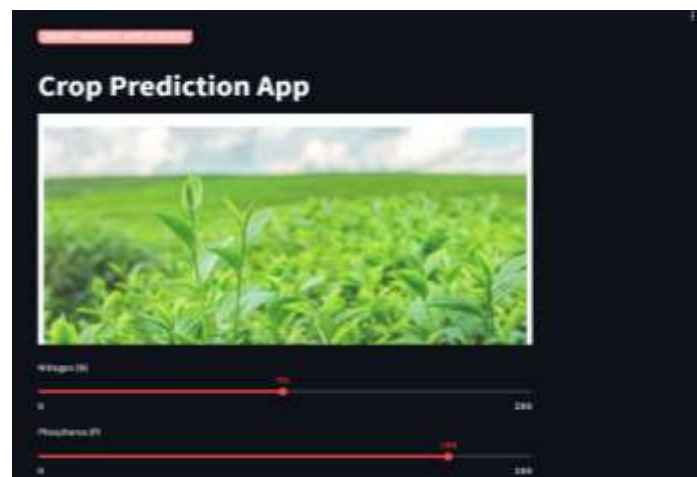


Fig. 1.3 Crop Prediction Application

Integrated planning is crucial to reducing food waste and maximizing food quality since crops are more vulnerable to degradation after harvesting and before to processing. When handling goods with a high rate of quality degradation, it's important to have enough processing and storage space. Harvesting, storing, and processing should be handled by separate organizations.

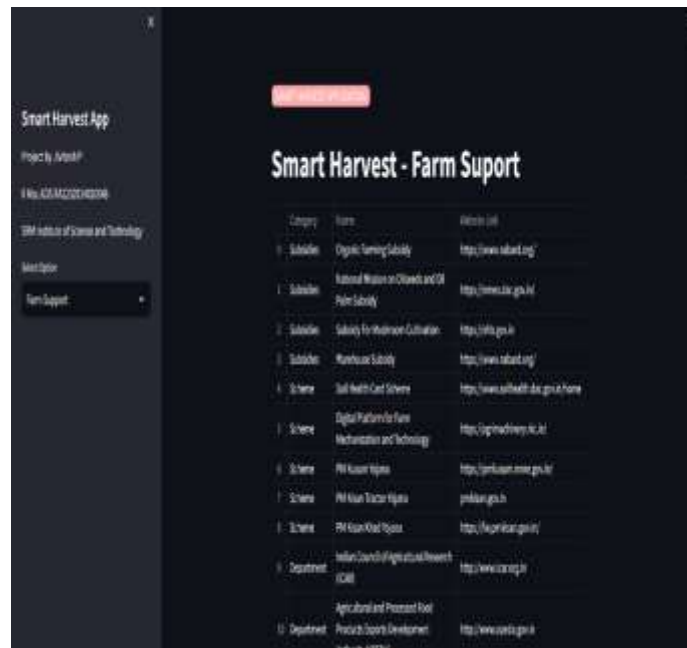


Fig. 1.4 Smart Harvest and Farm Support

The Smart Harvest system also features a user-friendly interface developed using web technologies and the Stream lit framework, enabling farmers to access information, receive alerts, and interact with the system seamlessly. Cloud integration ensures scalability, data storage, and accessibility from anywhere, while regular updates and maintenance guarantee system reliability and performance. Overall, the proposed system empowers farmers with data-driven decision-making, precision agriculture techniques, and sustainable farming practices, ushering in a new era of smart agriculture.

4.4 Feasibility Study

As the name implies, a feasibility study is used to determine the viability of an idea, such as ensuring this project is legally and technically feasible as well as economically justifiable. This indicates whether this project is worth the investment some cases, a project may not be doable. There can be many reasons for this, including requiring too many resources, which not only prevents those resources from performing other tasks but also may cost more than an organization would earn back by taking on a project that isn't profitable.

The objective of the feasibility study is not only to solve the problem but also to acquire a sense of its scope. During the study, the problem definition is crystallized and aspects of the problem to be included in the system are determined. Consequently, benefits are estimated with greater accuracy at this stage. The key considerations are:

- Economic feasibility
- Technical feasibility
- Operational feasibility.

4.4.1 Economic Feasibility

Economic feasibility studies not only the cost of hardware, and software is included but also the benefits in the form of reduced costs are considered here. This project, will certainly be beneficial since there will be a reduction in manual work due to the recommendation system and an increase in the productivity. It need not require any additional hardware resources as well as it will save saving lot of time.

4.4.2 Technical Feasibility

Technical feasibility evaluates the hardware requirements, software technology, and available personnel etc., This project is very much technically feasible. This project is very much concerned with specifying equipment and the project will successfully satisfy almost all the user's requirements. The technical need for this system may vary considerably but might include: the facility to produce results instantly after entering the data in the tab. It is used to predict the disease where the patient is having diabetics, heart disease and Parkinson's disease. Ability to manage the data easily. Therefore, the basic input/output of all data is identified. Thus, the project will be technically feasible and easily scalable.

4.4.3 Operational Feasibility

Proposed system is beneficial only if it can be turned into information systems that will meet the organizational requirements. This system supports producing good results and reduces manual work and aids in decision-making on the project.

4.4.4 Agricultural Chat bot Application

Chat bot is a latest technology to duplicate human conversation. Artificial Intelligence (AI) technologies and natural language processing techniques are integrated into the chatbot. Chat bot can be trained to converse with human in any domain.

Particularly for the senior population, the Agri Chatbot is a very user-friendly and simple-to-use tool [15]. In addition, the elderly are excited to interact with this virtual agent since they find it comforting while they are alone. Agri Chatbot is one form of information system that is used to match an information source to a predefined or desired acknowledgement [16]. The Agri chatbot application is an adoption of a computer program that is artificially intelligent (AI). It imitates the communication behaviours of humans, including spoken or text, using intelligent techniques such as video processing, Natural Language Processing (NLP) or image processing [19].

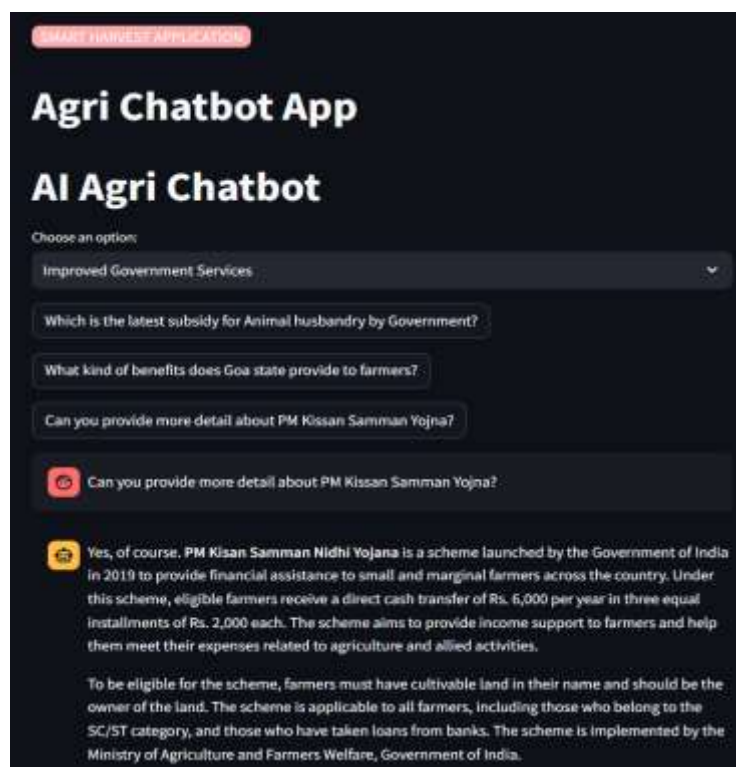


Fig. 1.5 Agricultural Chat bot Application



Fig. 1.6 Chatbot Agriculture in Machine Learning

As a result, chatbot apps are created to manage large user bases economically since they aid in eliminating the erroneous judgments and irrationalities brought on by human behavior.

4.4.5 Classification of Plant Diseases

The science of predicting and identifying the onset of serious plant illnesses is known as "plant health care." Early detection of any symptoms

can help lower the plant mortality rate. One way to reduce plant fatality rates is to identify these diseases early. This study uses machine learning (ML), a kind of artificial intelligence technology, to construct early prediction models for plant disease detection. ML allows researchers to improve and grow without being explicitly trained.

Crop diseases pose a significant threat to food security, but because the necessary foundation is missing in many places of the world, it is difficult to quickly identify them. Impressive achievements have been observed in the field of leaf-based image categorization with the emergence of accurate approaches. distinguishing between healthy and unhealthy leaves using the generated data sets.



Fig. 1.7 Classification of Plant Diseases

A variety of plant diseases can lower the number and quality of agricultural goods produced.

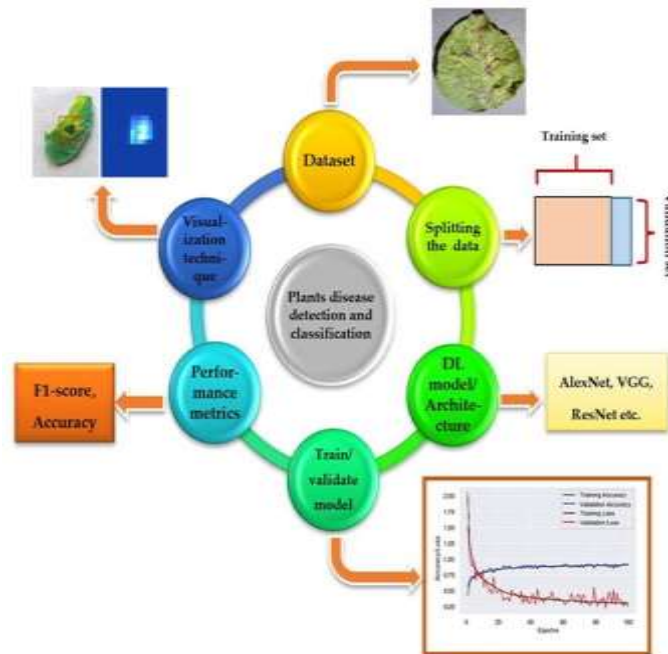


Fig. 1.8 Plant Disease Classification

Compared to the manual method, the machine learning methodology makes it easier to identify certain disorders. Therefore, the impacted leaf photos may be identified using a machine learning technique. Various image processing techniques will be used to the images that are acquired by the camera.

Results and Discussions

The ability of an IR system to return pertinent documents, as well as the accuracy and precision of these retrieved documents, is commonly measured.

$$\text{Precision} = \frac{|\text{relevant documents} \cap \text{retrieved documents}|}{|\text{retrieved documents}|} \quad \text{---- (1)}$$

The second measure is Recall. It is the proportion of documents that are related to the query and have been found.

$$\text{Recall} = \frac{|\text{relevant documents} \cap \text{retrieved documents}|}{|\text{relevant document}|} \quad \text{----- (2)}$$

These binary measures benefit to compute additional information retrieval metrics which is F-measure

$$F - \text{measure} = \frac{2 * \text{precision} * \text{recall}}{\text{Precision} + \text{recall}} \quad \text{----- (3)}$$

Accuracy is used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition is

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{-----}(4)$$

In this approach, the values are computed using a predefined formula and the correctness of the system is calculated using cross validation. The system's performance in the first five experiments. The required files may be easily found by using keyword searching.

Table. 4.1 Advanced Level K-NN Classification Method

Methods	Precision (%)	Recall (%)	F-Measure (%)	Accuracy (%)
SVM	89.24	87.45	88.23	89.54
PDM	90.12	90.34	87.59	91.67
Advanced Level K-NN	90.23	90.16	92.67	95.12

Table 4.1 lists the current approaches as the suggested Advanced Level K-NN approach, together with the support vector machine and pattern recognition methods, has a higher accuracy rate. The suggested approach yields great accuracy and an enhanced F-Measure value when compared to the previously mentioned methods.

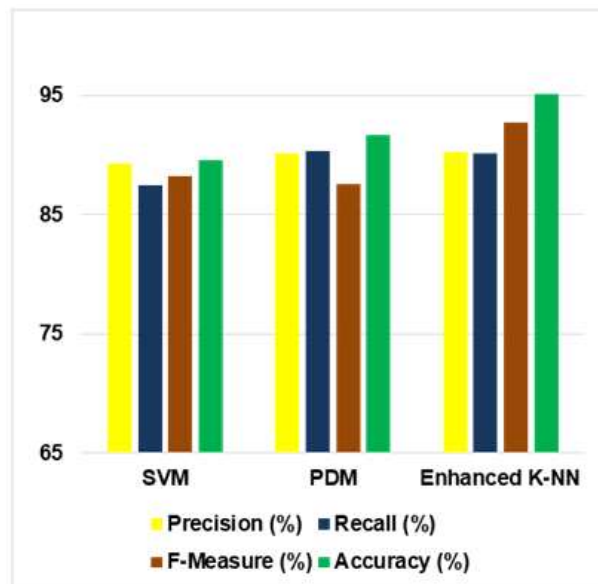


Fig. 4.1 Advanced Level K-NN Classification Method

The comparison chart between the K-NN classification technique and other approaches is explained in Fig. 4.1. The Advanced Level K-NN yields

an accuracy of 95.12% and an F-measure value of 92.67. When compared to current approaches, the suggested method yields findings with a high degree of accuracy.

Conclusion

The Smart Harvest App offers a comprehensive solution to solve major difficulties encountered by farmers and promotes sustainable farming techniques, marking a significant advancement in the agriculture industry. The app accomplishes its goals of maximizing crop management, improving disease detection, improving fertilizer recommendations, promoting sustainability, and equipping farmers with technology-driven tools by utilizing cutting-edge technologies like machine learning, deep learning, and data analytics. The application's capacity to offer precise forecasts for crop kinds according to environmental conditions, prompt identification of plant ailments, and enhanced suggestions for fertilizer greatly enhances agricultural output, guarantees food security, and preserves natural resources. Additionally, the app is essential in providing farmers with the information, understanding, and tools they need to make wise decisions, increase productivity, and improve their standard of living. All things considered, the Smart Harvest App supports sustainable agriculture, improves food security, and promotes the welfare of agricultural communities, all of which are in line with the Sustainable Development Goal 2 (SDG 2) of "Zero Hunger". It establishes the groundwork for a more robust, effective, and sustainable agricultural ecosystem and is evidence of the ability of technology to bring about good change in the agriculture industry.

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