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Article

Analyzing Soil to Recommend Crop and Plant Health Monitoring

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Abstract: The backbone of India's economy and jobs is agriculture, which is strongly dependent on it. Poor crop selection is a major cause of agricultural sector losses, which are made worse by farmers' ignorance of the nutrients, minerals, and moisture content of the soil. Using cutting-edge technology like machine learning and deep learning, it may be possible to address this problem by creating a model that recommends the optimal crop determined by weather and soil data.Farmers have historically been in charge of choosing crops, managing their development, and, using their knowledge, deciding when to harvest them. Farmers have always depended on their hands-on experience to manage their crops. Rapid environmental change, however, brings with it new difficulties. With deeper accuracy in crop result forecasting than standard prediction techniques, deep learning approaches are gradually taking the place of the former. In order to maximize the performance of these models and assist farmers in improving agricultural productivity and adapting to changing environmental conditions, effective feature selection approaches are essential. Rapid environmental change, however, presents difficulties for the agricultural community of today. Therefore, deep learning approaches are gradually taking the place of conventional prediction methods in the more accurate calculation of agricultural productivity. Techniques for selecting features effectively are crucial.

Keywords: agricultural technology; crop management; sustainable agriculture; yield optimization; crop monitoring; agricultural automation; deep learning techniques; plant health monitoring

1. Introduction

Forecasting crop outcomes in agriculture is a multifaceted process, with numerous models proposed and examined for this specific objective. Addressing the issue necessitates the utilization of varied datasets, because biotic and abiotic variables affect crop development. Biologic variables are those that have an influence on the environment either directly or indirectly through living things including plants, animals, bacteria, parasites, predators, and pests. In addition, this group comprises factors linked to human actions, such as protection of plants, fertilisers, irrigation, contamination of water, soil, air, and so on. The Figure 1 describes the Crop Recommendation for the farmers based on soil data.

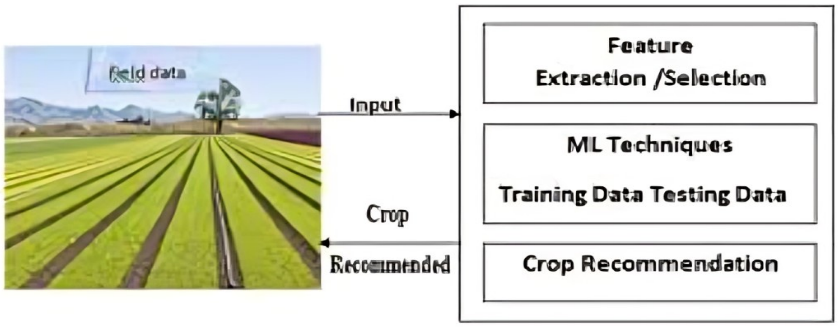

Figure 1. Crop Recommendation by Soil data.

These factors can cause internal defects, morphological abnormalities, and changes in the chemical makeup of the farmed plants, in addition to causing a variety of other changes in crop output. Both biotic and abiotic variables influence the development and quality of plants as well as the structure of the surrounding environment. The classification of abiotic factors includes components that are physical, chemical, and extra. Recognised physical elements include mechanical effects like noise and vibration, different kinds of radiation including electromagnetic, ultraviolet, and infrared, and weather conditions like humidity, temperature, air pressure, light, and sun. This classification also includes elements like soil composition, topography, soil composition, atmospheric conditions, and water chemistry, particularly salinity. Chemical factors include major pollutants found in the environment, such as sulphur dioxide and its derivatives, nitrogen oxides and their derivatives, polycyclic aromatic hydrocarbons (PAHs), lead and its compounds, fluorine and its compounds, cadmium and its compounds, and nitrogen and carbon fertilisers and pesticides.The Figure 2 describes the Plant Health Monitoring system for the farmer to monitor the agricultural crop.

Figure 2. Plant Health Monitoring.

A farmer's decision to grow a particular crop is often influenced by his gut feeling and other factors such as immediate profits, ignorance of market demand, over confidence in the ability of the soil to support the crop, etc. A very wrong decision made by a farmer can have a huge impact on his family's financial situation. In a nation such as India, where agriculture constitutes roughly 20.4% of the GDP, an incorrect decision of this magnitude will not only significantly impact the farmer's family but also have extensive consequences on the well-being of the community and the broader regional economy.

The field of agriculture research is expanding. Specifically, crop prediction is very important in agriculture and mostly depends on soil and environmental factors including temperature, humidity, and rainfall. In the past, farmers could choose the crop to grow, track its progress, and select when it was ready for harvest. If applied properly, modern technologies such as machine learning and deep learning have the potential to revolutionize these industries. In order to give farmers the most support possible in the area of crop recommendation, this article will demonstrate how to use such technology effectively. Crop recommendation, or recommending the best crops to plant in a given location based on soil and meteorological conditions, is a significant component of precision agriculture. Using soil imagery and meteorological data, we present a novel approach to crop recommendation. It has become challenging for the farming community to do so, nevertheless, due to the quick fluctuations in environmental circumstances. As such, the role of prediction has been largely replaced in recent years by machine learning approaches, several of which have been applied in this work to estimate crop production. Effective feature selection techniques must be used to pre-process the raw data into a readily computed format in order to guarantee that a particular machine learning (ML) model operates at a high degree of precision.

In order to decrease redundancies and improve the accuracy of the machine learning model, only elements of the dataset that are highly relevant in predicting the model's final output should be used. Additionally, the ML model's time and space complexity will rise with the addition of features that don't significantly improve it, which will have an impact on the output accuracy of the model. According to the findings, an ensemble approach outperforms the current classification method in terms of prediction accuracy. This project has significant ramifications for sustainable agricultural practices and will add to the expanding corpus of research in precision agriculture.

The optimization of machine learning models within the realm of sustainable agriculture is a multifaceted endeavour crucial for advancing precision farming practices. Central to this optimization is the meticulous selection of features from datasets, prioritizing those most relevant to accurately predict the model's output while mitigating redundancies. By doing so, the model's efficiency is enhanced, as unnecessary complexities that could impede performance are avoided. Additionally, the adoption of ensemble approaches, which amalgamate the strengths of multiple models, proves instrumental in achieving superior prediction accuracy compared to individual methods. Such advancements hold significant promise for sustainable agriculture, offering insights that can revolutionize decision-making processes and resource allocation in farming. This confluence of machine learning and agricultural practices not only augments crop yields but also fosters environmentally conscious approaches, thereby contributing to the overarching goal of sustainable food production.

1.1. Origin of the Proposal

The proposal for a crop recommendation system using deep learning likely arose from a desire to leverage advanced technology to address challenges in agriculture. A data-driven approach to crop selection is needed that can take into account various environmental and market factors to provide farmers with personalized crop planting recommendations. The primary objective of this paper is to create a crop recommendation system utilizing deep learning methods, aiming to offer farmers personalized and precise crop advice based on factors such as soil type and quality. To add additional features such as monitoring plant health

1.2. Definition of the Problem

A significant problem for a nation where around half of the people works as farmers is when farmers fail to use conventional, non-scientific methods to determine which crop is best for their soil. Working on generating nation case studies is impeded by the availability and accessibility of accurate and current information for potential researchers**.**

1.3. Objectives

1.3.1. Create a Robust Deep Learning Model That Combines Various Techniques for Effective Crop Recommendation

Creating a robust deep learning model for crop recommendation involves comprehensive data collection, pre-processing, and feature engineering. A multi-modal input architecture handles diverse data types, while techniques like RNNs capture temporal dependencies. Attention mechanisms and embedding layers enhance focus on critical features. Ensemble methods and hybrid models combine strengths for improved performance. Regularization and optimization ensure model stability, and evaluation metrics validate results. Interpretability techniques provide insights into decision-making. This integrated approach results in an effective crop recommendation system, capable of utilizing diverse agricultural data for informed decision-making.

1.3.2. Propose Crop Options to Farmers Based on an Analysis of Soil Characteristics and Quality

This is a crucial step towards maximizing agricultural productivity. By leveraging advanced technologies and data-driven insights, we can assess key factors such as soil pH levels, nutrient content, and texture. This information serves as the foundation for recommending crops that are best suited to the specific conditions of the land. For instance, acidic soils may be ideal for crops like blueberries or potatoes, while alkaline soils could favour crops such as asparagus or beans. Additionally, the soil's drainage capacity and moisture retention capabilities play a pivotal role in determining suitable crop options. By tailoring recommendations to the unique soil profile, we aim to empower farmers with actionable insights that not only optimize yield potential but also contribute to sustainable and profitable agricultural practices.

1.3.3. Monitoring Health of Plants Using Deep Learning Models

Monitoring the health of plants through the application of deep learning models represents a significant advancement in precision agriculture. By employing advanced computer vision techniques, these models analyse visual data from images of plants, leaves, or even entire fields. They can detect subtle signs of stress, nutrient deficiencies, pest infestations, and diseases, often imperceptible to the human eye. Through extensive training on diverse datasets, these models become adept at distinguishing between healthy and compromised vegetation, enabling timely intervention. This technology holds the potential to revolutionize farming practices, allowing for targeted treatments and resource allocation, reducing the need for broad-spectrum interventions. These models facilitate more sustainable and ecologically friendly farming methods in addition to increasing agricultural output by offering real-time, data-driven insights into plant health.

1.3.4. Optimize the Architecture and Hyperparameters of the Model for Improved Accuracy

Optimizing the architecture and hyperparameters of the model is a critical endeavour to enhance its accuracy and efficacy in recommending crops. This process involves a systematic exploration of various neural network architectures, fine-tuning layers, units, and activation functions to find the optimal configuration. Additionally, hyperparameters such as learning rates, batch sizes, and regularization techniques are meticulously adjusted through rigorous experimentation. This iterative refinement is guided by performance metrics, ensuring that the model achieves the highest level of precision in its recommendations. Additionally, methods like as cross-validation are utilised to evaluate the resilience of the model across different datasets and circumstances. Through this strategic tuning process, we aim to create a crop recommendation system with a heightened level of accuracy and reliability, ultimately empowering farmers with more precise and actionable insights for their agricultural endeavours.

2. Literature Review

In reference, based on the titles and authors of the papers, it's clear that they all focus on different aspects of improving agriculture through technology and data analysis. Let us discuss about each of the papers that have been done under the survey.

[1] The combined study by Routhu Sathish, Thulluru Prem Chand, and T. Daniya provides an extensive analysis of smart farming, emphasizing environmental and soil aspects while utilizing deep learning methods. The main goal is to investigate existing methods for automated agricultural processes, emphasizing K Means, SVM, and Random Forest approaches. The authors emphasize the importance of addressing real-time challenges commonly faced by farmers and propose the use of advanced techniques as a means to achieve this goal. The paper not only provides insights into current practices but also looks ahead, identifying the future scope of their work. The authors envision a trajectory where the application of advanced techniques becomes instrumental in resolving real-time issues encountered in agriculture. By positioning their research in this forward-looking context, the paper aims to contribute to the ongoing evolution of agricultural practices. This study is poised to benefit researchers, practitioners, and stakeholders seeking a deeper understanding of smart farming methodologies.

[2] The paper authored by S.P. Raja and Barbara Sawicka explores crop forecast with agricultural environmental characteristics, utilizing a dataset containing non-public information on environmental and soil factors. The work addresses dataset imbalance by utilizing ensemble approaches and advanced models like SMOTE and ROSE, in addition to a variety of feature selection techniques and classification algorithms including Support Vector Machine, K Nearest Neighbors, Naïve Bayes, and Random Forest. The results demonstrate that the ensemble technique yields superior prediction accuracy, effectively mitigating the dataset's inherent imbalance. Notably, the paper suggests the implementation of an algorithm to predict one environmental factor using two others, offering an additional layer of complexity to the predictive model. By encompassing a range of environmental factors as inputs, the research contributes to a comprehensive understanding of crop prediction. The utilization of advanced techniques and the exploration of ensemble methods signal a nuanced approach

to improving prediction accuracy in agricultural settings. Researchers and practitioners in agriculture can find valuable insights in this study for refining crop prediction models.

[3] By using machine learning to analyse soil, Pabasara M.G.P. and Dimantha M.A.C. collaborate to select crops. Using IoT sensors, the authors collect soil metrics including pH, temperature, humidity, and wetness, which are then analyzed using a graphical user interface (GUI).This graphical interface then generates crop recommendations based on the collected parameters, intending to empower farmers with decision-making tools for improved agricultural practices. The proposed system underscores the critical role of accurate and complete data from IoT sensors in ensuring the precision of crop recommendations. The study acknowledges the potential downside: inaccurate or incomplete sensor data may lead to inappropriate agricultural suggestions. Additionally, a notable concern arises from the absence of data security measures, posing a risk to the confidentiality and integrity of the collected information. While the system aims to enhance agricultural decision-making, the need for robust data quality and security measures is paramount to realize its full potential and safeguard against potential risks.

[4] Jyothi, B. Veera; Mangaiahgari, Vaishnavi; Kandi, Meghana; Vangoor, Sidhartha Reddy; Ramalakshmi, Eliganti "AgriCrop-Crop Recommendation Through Soil Analysis and Plant Monitoring" provide a special technique for crop recommendation based on soil and meteorological information. Agriculture, especially, depends significantly on soil and environmental elements for predicting crop outcomes. Historically, farmers held authority over choosing crops, overseeing their growth, and determining the optimal harvest timing. Today, the agricultural community finds it challenging to carry on due to the fast changes in the environment. As a result, deep learning approaches have increasingly replaced traditional prediction methods. This work has employed a number of these methods to calculate agricultural production. Employing effective feature selection techniques is essential to guarantee that a deep learning model operates with a high degree of precision.

[5] Saranya K, Deena Dhayalan S, and Prasanth R present an innovative Agriculture-based Recommendation System leveraging Image Processing. The system begins by accessing the user's location and extracting weather details using latitude and longitude from the Open Weather API. Employing algorithms such as Decision Tree, SVM Classification, ANN models, and Random Forest, two distinct models are created—one for users who have tested their soil and another for those who haven't. The models consider weather and soil parameters to recommend the top 3 crops. In Disease Prediction, a neural network anticipates plant diseases based on an image database. Users can upload images of infected plant parts, and if a disease is predicted, the system suggests suitable fertilizers. The authors propose developing a device capable of identifying soil parameters, enabling direct crop recommendations to farmers via the Internet. The system's versatility is enhanced by continually expanding the dataset with various crops. This holistic approach combines weather, soil, and disease prediction, offering farmers a comprehensive tool for informed decision-making and crop management.

[6] In their article, K Gnana Sandhya and Sandeep Vemuria introduce a cutting-edge Ensemble Learning-based crop recommendation system that harnesses the power of various machine learning algorithms including KNN, Random Forest, Gaussian Naïve Bayes, Logistic Regression, and SVM. By leveraging soil and environmental parameters, this system delivers highly accurate crop suggestions, marking a significant advancement in agricultural decision-making. The authors underscore the system's superiority over existing methods, emphasizing its ability to provide tailored recommendations tailored to specific farming conditions. Looking ahead, their future research agenda is poised to introduce a ranking system that evaluates crop suitability based on farm-specific soil characteristics, thereby enhancing the precision and personalization of agricultural recommendations. This forward-thinking approach not only reflects a commitment to technological innovation but also underscores the authors' dedication to improving the efficiency and sustainability of agricultural practices through data-driven solutions.

[7] In order to help the agriculture sector, Ashwani Kumar Kushwaha offers a "Improved Machine Learning-based Crop Recommendation System" that aims to improve crop yield estimates. The article evaluates the models' temporal and geographical extrapolation capabilities using machine learning techniques, namely Random Forest and Decision Trees. The creation of computer software to assess several machine learning techniques for forecasting agricultural productivity is emphasized by the author. The goal of the article is to improve the recommendation system by adding more characteristics based on economic considerations such crop demand, supply, and farm retail pricing. This method emphasizes a comprehensive viewpoint, acknowledging the interdependence of agricultural systems and indicating a dedication to improving and enhancing crop recommendation systems' capacities.

[8] In the study, a Convolutional Neural Network (CNN) emerges as a powerful tool for the classification of plant leaf diseases, encompassing a wide range of 15 distinct classes. Among these, the CNN effectively distinguishes three classes representing healthy leaves, while the remaining twelve

classes encompass various disease groups affecting plants, including those caused by bacteria and fungus. Notably, the CNN exhibits exceptional performance both in training and testing phases, boasting a remarkable testing accuracy of 98.029% and a training accuracy of 98.29% across the entirety of the dataset. This high level of accuracy underscores the efficacy of the suggested technique in detecting and categorizing plant leaf diseases, affirming its potential as a reliable and precise tool for agricultural diagnostics. By leveraging advanced machine learning algorithms, such as CNNs, researchers and practitioners can significantly enhance the efficiency and effectiveness of disease detection processes in agriculture, ultimately contributing to the preservation of crop health and productivity.

[9] Image processing methods for plant leaf disease detection are presented in Rahul Kundu, Usha Chauhan, and S.P.S. Chauhan's work. By masking green pixels and applying the color co-occurrence approach, the study's vision-based detection system is put to work. Notably, while evaluating illness diagnosis accuracy, the researchers stress the need of taking illumination and resolution into account as input picture quality elements. In order to increase accuracy and dependability in disease detection systems, image processing techniques have been prioritized, demonstrating a dedication to tackling issues associated with disease identification in plant leaves.

[10] A paper on precision agriculture, a contemporary farming method that makes use of study data on soil properties and crop output, is presented by S. Pudumalar, E. Ramanujam, and R. Harine Rajashree. The authors provide a recommendation system that combines the Random Tree, CHAID, K-Nearest Neighbor, and Naive Bayes algorithms into an ensemble model with a majority voting method. By helping farmers make well-informed crop selection decisions based on site-specific data, this approach hopes to decrease the possibility that they will pick inappropriate crops and eventually boost production. The potential advantages of using ensemble approaches for crop recommendations in the context of precision agriculture are highlighted by the emphasis on accuracy and data-driven decision-making.

[11] A precision agriculture-based "Smart Crop Recommendation System" that makes use of data analytics and machine learning models is presented by Preeti Kathiria, Usha Patel, and Shriya Madhwani. For crop prediction, the system uses machine learning models (ML) such as Random Forest, SVM, KNN, LGBM, and Decision Trees. The method makes recommendations for ideal crops for certain land resources based on factors including pH, temperature, humidity, nitrogen, potassium, phosphorus, and rainfall. In order to support farmers, the government, and other agriculture sector players, the paper highlights how the system may offer insightful information that will help them make well-informed decisions. By emphasizing the value of utilizing technology and data analytics to optimize crop suggestions, this integrated approach is consistent with the concepts of precision agriculture.

[12] In their Systematic Literature Review (SLR), Ayalew Kassahun and Cagatay Catal concentrated on the use of machine learning algorithms in research on agricultural production prediction. The research indicates that Convolutional Neural Networks (CNN) are extensively utilized in this field, along with Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN). Artificial Neural Networks (ANN) are still the most often used technique for predicting agricultural productivity, even with the emergence of deep learning. The study demonstrates the widespread use of deep learning methods, especially DNN, which expands upon the ideas of conventional ANN and demonstrates its efficacy in a variety of fields, including picture classification and face recognition. The current state of machine learning techniques used to forecast agricultural productivity is thoroughly reviewed in this study..

[13] An expert system based on computational intelligence is proposed by Lavika Goel and Shray Mathur. It makes predictions using characteristics related to soil found in Landsat 8 pictures. In order to develop a hybridized approach, the study uses two nature-inspired algorithms: biogeography-based optimization and plate tectonics-based optimization. The authors also present PBO and the Adam optimization algorithm together to create a hybrid PBO/Adam method. The final objective is to advise farmers on the best crop to plant depending on various farm and regional factors. The hybrid algorithm that was created is utilized to optimize the weights of a soft-max classifier in the suggested system. This technique demonstrates a holistic strategy that combines computational intelligence with nature-inspired optimization to enhance crop recommendations.

[14] A unique crop recommendation system is presented by Pradeepa Bandara and Thilini Weerasooriya, which incorporates a feedback mechanism in addition to predicting the optimal crop variety. With the use of machine learning methods like Naïve Bayes and Support Vector Machine, the crop recommendation model in the suggested system is trained using data from Arduino sensors to determine which crop has the best chance of succeeding in cultivation. The system's overall accuracy is higher than 92%, and when additional data is added to it over time, its accuracy gets better. The authors

highlight the system's flexibility and dependability for well-informed agricultural decision-making, estimating that farmers may expect accuracy to exceed 95% with continued use.

[15] In order to help farmers choose crops depending on soil nutrients and climate, Madhuri Shripathi Rao and Arushi Singh's article aims to identify the best model for crop prediction. The study uses Gini and Entropy criteria to analyze three widely used algorithms: Random Forest Classifier, Decision Tree, and K-Nearest Neighbor (KNN). Based on both the Gini and Entropy Criterion, the Random Forest Classifier has the maximum accuracy of 99.32%, which makes it the best model for predicting crops. K-Nearest Neighbor, on the other hand, has the lowest accuracy (97.04%), with Decision Tree Classifier falling somewhere in the middle. Interestingly, with an accuracy of 98.86%, the Decision Tree Gini criteria performs better than the Decision Tree Entropy criteria. The findings provide insightful information on how to choose the best model for precise crop forecast while making agricultural decisions.

[16] A study on a crop categorization system based on Deep Reinforcement Learning (DRL) and designed for precision agriculture is presented by Mohamed Bouni and Badr Hssina. With the goal of improving crop output in the recommendation system and removing less-than-ideal possibilities, the DRL technique seeks to solve problems faced by farmers. The accuracy of the suggested DRL-based system for site-specific crop recommendations is evaluated by contrasting it with well-known machine learning algorithms like Random Tree, Naive Bayes, and K-Nearest Neighbor. The results show that using these algorithms increases accuracy, allowing for efficient crop categorization for precision agriculture and offering accurate recommendations to reduce farmers' problems. The study emphasizes how precision agricultural practices may be advanced via the use of DRL and conventional machine learning.

[17] A user-friendly yield forecast system with GPS-enabled position identification is presented by Shilpa Mangesh Pande and Prem Kumar Ramesh for farmers, improving connection. The system uses a few chosen machine learning methods to forecast agricultural yield, including K-Nearest Neighbor (KNN), Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Multivariate Linear Regression (MLR). With an accuracy rate of 95%, the Random Forest algorithm exhibits the most favorable results among them all. The suggested approach offers suggestions for the best time to apply fertilizer, going above and beyond yield prediction to provide farmers a complete tool to help them make decisions and increase agricultural output.

[18] A technique that suggests appropriate crops for sites with varying soil nutrients is introduced by K. Suriya Krishnaan and L. Charan Kumar. With an astounding accuracy of 98%, the suggested approach uses the Random Forest classifier to select crops. In addition, a PyTorch neural network is used to predict diseases, with a high accuracy of 99.2%. By addressing both crop recommendation and disease prediction, this integrated strategy demonstrates how machine learning techniques may be used to optimize agricultural practices for increased yield.

[19] Manuj Joshi and Swapnil Desai make significant strides in the realm of precision agriculture with a keen focus on supporting Indian farmers. Their innovative algorithm serves as a valuable tool for recommending suitable crops by meticulously considering various factors such as the optimal time for planting, geographical location, and soil characteristics. By integrating these variables, the algorithm provides tailored recommendations that align with the principles of precision agriculture, ensuring optimal crop selection for each farming scenario. Notably, the technology goes beyond mere suggestions by offering yield projections for the recommended crops, thereby making it possible for farmers to choose crops with knowledge and anticipate potential harvest outcomes. This approach not only facilitates educated crop selections but also contributes to the overarching goal of improving total agricultural productivity. By equipping farmers with insightful information and leveraging data-driven insights, Joshi and Desai's contributions enable farmers in India and elsewhere to increase yields, make the most use of resources, and eventually promote sustainable farming methods.

[20] Aditya Motwani and Param Patil introduce a sophisticated crop recommendation system that integrates both a Random Forest Model and a Convolutional Neural Network (CNN), showcasing the synergy between neural networks and traditional machine learning algorithms. By analyzing a range of variables such as geography, soil type, yield, and selling price, this innovative method accurately forecasts the most suitable crops for cultivation. Notably, the CNN architecture achieves an impressive accuracy of 95.21% in crop prediction, highlighting its efficacy in leveraging complex data patterns to deliver precise recommendations. Additionally, the inclusion of the Random Forest Algorithm enriches the recommendation system, even with an accuracy rate of 75%, emphasizing its complementary role in enhancing the overall accuracy and reliability of crop recommendations. This multi-method approach underscores the versatility and effectiveness of combining neural networks with conventional machine learning techniques to provide farmers with informed and dependable guidance for crop selection. By leveraging the strengths of both approaches, this system empowers agricultural

practitioners to make optimized decisions, ultimately contributing to improved productivity and sustainability in farming practices.

[21] Parameswari, N. Rajathi, and K. J. Harshanaa have created a model that offers guidance and crop-related information to farmers in order to assist them. The Indian Chamber of Food and Agriculture provides data via Kaggle, which is used in the study's trials to build machine learning algorithms including PART, Decision Table, and JRip. With a maximum precision of 98.33% and effective model development, the PART technique performs well according to assessment measures such as F-Measure, recall, accuracy, and precision. The study highlights how farmers may benefit from machine learning techniques by receiving precise and timely crop recommendations.

[22] A crop recommendation system, taking into account peasant location, soil composition, and meteorological features, is presented by Sakshi, Sanjana Drall, Sukriti Singh, and Monika Choudhary. It is based on a multi-label classification model. With an F1 score of 78.67%, recall of 80.92%, and accuracy of 82.74%, the suggested model outperforms the competition using the RF approach. With an intuitive UI for a better user experience, this ideal model offers farmers a prioritized list of recommended crops. The study demonstrates how well a multi-label classification strategy works to provide accurate crop recommendations that are customized for certain farming situations.

[23] The agricultural domain benefits from the model developed by Parameswari, N. Rajathi, and K. J. Harshanaa, who provide advice and crop-related information to farmers. The study makes use of machine learning techniques including JRip, PART, and Decision Table. Data from the Indian Chamber of Food and Agriculture was obtained through Kaggle for the trials. The PART method performs exceptionally well, as evidenced by evaluation criteria like as accuracy, precision, recall, and F-measure. It achieves the greatest precision of 98.33% and demonstrates efficiency in model creation. The study emphasises how machine learning approaches may help farmers receive fast and accurate crop suggestions.

[24] In order to boost productivity, Nidhi H. Kulkarni, G. N. Srinivasan, B. M. Sagar, and N. K. Cauvery offer a crop recommendation system using a machine learning ensembling technique. The goal of the ensemble model is to very accurately select the best crop based on particular soil features by combining basic learners such as Random Forest, Naive Bayes, and Linear SVM. The dataset contains samples of surface temperature and rainfall as well as characteristics unique to soil. The ensemble model achieves an impressive average classification accuracy of 99.91%, highlighting the effectiveness of combining diverse machine learning models for accurate crop recommendations tailored to soil characteristics.

[25] Vaishnavi Jayaraman and Saravanan Parthasarathy have introduced an innovative agricultural application designed to revolutionize farming practices by integrating cutting-edge technology and data-driven insights. The core objective of the application is to assess soil nutrient levels, a critical factor in determining optimal crop selection, and to provide farmers with tailored recommendations for sustainable and high-yielding agriculture. The application employs associative features, leveraging ambient variables to gather a comprehensive understanding of the environmental conditions influencing agricultural land. By considering a wide range of factors such as temperature, humidity, and sunlight, the system captures a holistic view of the farm's ecosystem. This holistic approach ensures that the recommendations provided by the application are not solely based on isolated soil nutrient levels but are also influenced by the prevailing ambient conditions, contributing to a more nuanced and accurate crop selection process.

[26] In their pursuit of advancing precision agriculture, Jeevaganesh R, Harish D, and Priya B have ingeniously harnessed the power of machine learning methods to enhance crop production projections and optimize fertilizer recommendations. The core of their work lies in the application of advanced algorithms, specifically the AdaBoost algorithm for yield prediction and the Random Forest (RF) algorithm for fertilizer suggestion. This team uses the robust ensemble learning approach known as AdaBoost, which combines several weak learners to produce a powerful predictive model, to estimate crop yields. Leveraging variables such as state, district, area, seasons, rainfall, temperature, and more, this algorithm is adept at capturing complex relationships and patterns within the data. By integrating diverse factors, AdaBoost provides a comprehensive framework for accurate yield predictions, enabling farmers to anticipate production outcomes with a high degree of precision.

[27] In a study presented by K Anguraj, B Thiyaneswaran, G Megashree, JGP Shri, S Navya, and J Jayanthi, it is explored how machine learning algorithms, IoT technology, and data analysis may be integrated to help move from traditional farming to precision agriculture. For prompt and precise crop recommendations based on soil factors, the ensemble model combines Random Forest, Naive Bayes, and Linear SVM. The study highlights how using machine learning in agriculture may have significant advantages, especially when it comes to crop recommendations based on soil analysis. Higher crop

yields and economic growth in agriculture are facilitated by this integration, IoT, and data analysis, which together enable a shift towards precision farming.

[28] In a groundbreaking approach to agricultural decision support, A Chougule, VK Jha, and D Mukhopadhyay have proposed an ontology-based recommendation system that seamlessly integrates data mining techniques, specifically leveraging the power of the random forest and k-means clustering algorithms. The central objective of their work is to harness the properties of soil efficiently, providing farmers with precise recommendations regarding suitable crops and optimal fertilizer quantities. The utilization of an ontology-based framework underscores the structured representation of agricultural knowledge, allowing for a systematic and standardized understanding of soil properties. By incorporating data mining techniques, the recommendation system enhances its predictive capabilities, offering a more nuanced and accurate approach to suggesting crops and fertilizer amounts tailored to specific soil conditions.

[29] Vaishnavi Jayaraman and Saravanan Parthasarathy have developed an innovative agricultural application that revolutionizes farming practices by integrating advanced techniques to assess soil nutrient levels and predict production rates. By harnessing associative qualities that consider both soil characteristics and environmental factors, the application employs regression techniques to forecast production rates accurately. Additionally, classification algorithms are leveraged to recommend suitable crops based on specific land conditions, empowering farmers to make informed decisions about crop selection. By taking into account soil nutrient content and environmental conditions, the program enables farmers to optimize agricultural operations, ensuring more effective and knowledgeable farming practices. This holistic approach not only enhances crop productivity but also contributes to sustainable agriculture by promoting resource-efficient farming methods and minimizing environmental impact. Overall, the application represents a significant advancement in agricultural technology, offering practical solutions to address the challenges faced by farmers and improve overall agricultural sustainability.

[30] K P K Devan, B Swetha, P Uma Sruthi, and S Varshini have introduced an innovative agricultural system designed to forecast crop yields and provide tailored fertilizer recommendations by seamlessly integrating machine learning algorithms. This unique approach stands out by placing a strong emphasis on critical elements, notably weather patterns and soil properties, to enhance the accuracy of predictions and recommendations. The foundation of their methodology lies in combining two powerful machine learning algorithms: Random Forest and Logistic Regression. This strategic amalgamation capitalizes on the strengths of each algorithm to create a robust and effective system for estimating crop yields. The Random Forest algorithm, known for its ensemble learning capabilities, excels at handling complex datasets and capturing intricate relationships between various factors influencing crop growth. By aggregating the predictions from multiple decision trees, Random Forest enhances the accuracy and reliability of the yield forecasting component. Complementing this, the inclusion of the Logistic Regression algorithm brings a probabilistic perspective to the model. Logistic Regression is adept at modeling the probability of an event occurring, making it particularly valuable in scenarios where understanding the likelihood of crop yield outcomes is essential. By considering factors such as weather conditions and soil properties, Logistic Regression contributes to a more nuanced prediction model, providing insights into the probability of successful crop yields under different circumstances.

3. Methodology

The methodology for the proposed system involves several key steps:

3.1. Data Collection and Preparation

Begin by gathering a diverse and comprehensive dataset that includes relevant agricultural information such as soil characteristics, climate conditions, historical crop yields, and market trends. Ensure the data is sourced from reliable agricultural databases, local institutions, and reputable sources. Clean and pre-process the dataset to remove any inconsistencies, outliers, or missing values. This may involve tasks like data imputation, normalization, and standardization to ensure uniformity and reliability in the dataset. Categorize and organize the data into distinct features such as soil type, climate variables, historical performance metrics, and market trends.

Data collection and preparation are critical steps in any data-driven project, including those related to crop recommendation systems or plant health monitoring. This step consists of defining objectives and scope, identifying data sources, data collection, data quality assurance, data cleaning, data integration, data transformation, feature engineering, data splitting, data visualization and exploration, data privacy and security.

3.2. Feature Selection

Identifying and selecting relevant features that are critical for making accurate crop recommendations. This may include soil pH levels, nutrient content, climate variables, and historical performance of crops. Engineer additional features if needed, considering factors like crop rotation history and pest incidence. Feature selection and engineering are crucial steps in building effective machine learning models. They involve choosing the most relevant variables (features) and transforming them to improve model performance. Feature Selection consists of Univariate Selection, recursively removing less important features based on model weights until the desired number of features is reached, using various models, lasso regression can be used to select a subset of the most important features, performing PCA and measuring the dependency between two variables and can be used for feature selection.

3.3. Model Architecture

To create a versatile deep learning architecture capable of processing diverse data types, a multi-modal approach is adopted, integrating convolutional layers for image data, recurrent layers for handling temporal dependencies, and attention mechanisms for focusing on critical features. The architecture begins with input layers tailored to accommodate various data formats, including numerical, categorical, and image data. For numerical and categorical inputs, dense layers are employed to capture complex relationships and patterns within the data. Simultaneously, convolutional layers are incorporated for processing image data, extracting hierarchical features through filters to capture spatial information. To address temporal dependencies, recurrent layers such as Long Short-Term Memory (LSTM) cells are integrated, allowing the model to comprehend sequential patterns and time-dependent relationships present in the data.

3.4. Model Development

This step involves both the crop recommendation and plant health monitoring systems.

Crop Recommendation System**:** The process of advising farmers on the most suitable crops to cultivate based on various factors such as climate conditions, soil type, market trends and historical crop performance. It uses various deep learning networks such as CNNs and predict the best crop to be grown in that particular soil.

Plant Monitoring System**:** To develop a deep learning model, possibly employing convolutional neural networks (CNNs) to analyse visual data and assess plant health indicators and specifiers.

3.5. Integration of Crop Recommendation and Plant Health Monitoring

The fusion of a Crop Recommendation System with a Plant Health Monitoring System establishes an influential framework for precision agriculture, representing a paradigm shift in farming practices. This integrated system harnesses cutting-edge technologies to furnish farmers with a comprehensive solution that goes beyond traditional crop recommendations. By synergizing historical data with real-time health assessments, the Crop Recommendation System not only suggests optimal crops based on factors like soil conditions and climate but also dynamically adapts its recommendations in response to the continuously monitored health status of the plants.

This integration enables a two-fold advantage: precision in crop selection and proactive health management. The Crop Recommendation System ensures that farmers receive tailored advice, optimizing their yield potential. Simultaneously, the Plant Health Monitoring System, employing sensors and imaging devices, provides instant insights into the well-being of crops, enabling early detection of issues such as diseases, nutrient deficiencies, or pests. The result is a holistic approach to farming, where decisions are informed by a real-time understanding of both environmental conditions and plant health. In essence, this integrated system not only maximizes productivity but also fosters sustainable agricultural practices by mitigating risks and enhancing resource efficiency.

3.6. Evaluation and Validation

In evaluating the performance of the integrated Crop Recommendation System and Plant Health Monitoring System, a comprehensive set of metrics provides insights into their efficacy in supporting precision agriculture. For the Crop Recommendation System, standard classification metrics such as accuracy, precision, and recall are paramount. Accuracy gauges the overall correctness of the crop recommendations, measuring the ratio of correctly predicted crops to the total recommendations. Precision assesses the system’s ability to accurately identify recommended crops, while recall evaluates its capacity to capture all relevant recommendations among the actual optimal crops.

3.7. Optimization and Refinement

Based on evaluation results, optimize, and refine the system to improve accuracy and reduce false predictions. Deploy the combined system in real-world agricultural settings. Gather feedback from farmers and continuously iterate on the models and system based on empirical results and user input.

This methodology combines computer vision techniques, deep learning models, and a fine imposition mechanism. The project's methodology aims to establish a unified system designed to offer farmers suggestions on optimizing crop selection and concurrently keeping a close watch on the health of their plants. The overarching goal is to foster more effective, sustainable, and financially viable agricultural practices. Figure 3 depicts the flowchart of how the algorithm and the model works.

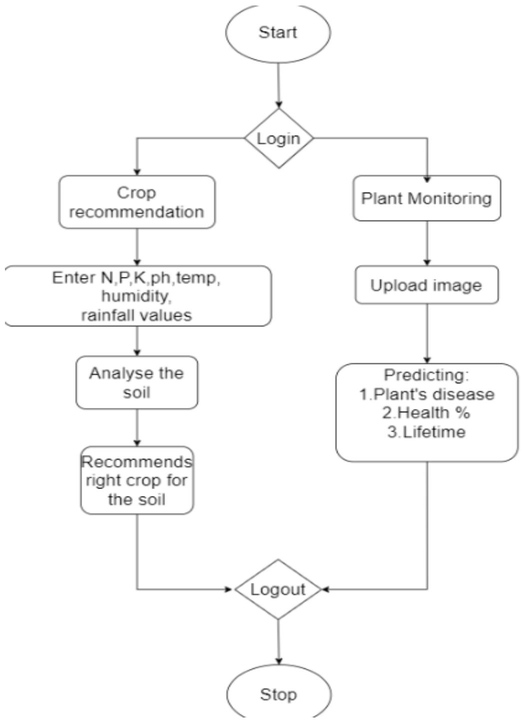

Figure 3. System Design of Crop Recommendation and Plant Monitoring Integrated System.

The flow starts by logging into the system. Once the user enters the system , there are 2 options. One is to check for the crop that can be grown in a particular area by entering all the parameters. And then Plant's image can be uploaded to check the health of the plant.

4. Datasets

4.1. Crop Recommendation Dataset

The rainfall, temperature, and fertiliser data sets that are already available for India were supplemented to create this dataset.The Figure 4 depicts the Sample records of the dataset.

1	N	P	K	temperatu	humidity	ph	rainfall	label
2	90	42	43	20.87974	82.00274	6.502985	202.9355	rice
3	85	58	41	21.77046	80.31964	7.038096	226.6555	rice
4	60	55	44	23.00446	82.32076	7.840207	263.9642	rice
5	74	35	40	26.4911	80.15836	6.980401	242.864	rice
6	78	42	42	20.13017	81.60487	7.628473	262.7173	rice
7	69	37	42	23.05805	83.37012	7.073454	251.055	rice
8	69	55	38	22.70884	82.63941	5.700806	271.3249	rice
9	94	53	40	20.27774	82.89409	5.718627	241.9742	rice
10	89	54	38	24.51588	83.53522	6.685346	230.4462	rice
11	68	58	38	23.22397	83.03323	6.336254	221.2092	rice
12	91	53	40	26.52724	81.41754	5.386168	264.6149	rice
13	90	46	42	23.97898	81.45062	7.502834	250.0832	rice
14	78	58	44	26.8008	80.88685	5.108682	284.4365	rice
15	93	56	36	24.01498	82.05687	6.984354	185.2773	rice

Figure 4. Sample records of the dataset.

4.2. Leaves: India's Most Famous Basil Plant Leaves Quality Dataset

In India, the Basil/Tulsi plant holds cultural and spiritual significance, leading to its cultivation. This plant is harvested for its essential oil and pharmaceutical applications. Figure 5 describes the features of the dataset.

Sr.No	Basil Plant Leave Region wise	Quality Category	Size of Image	Number of Images
1	Amravti	Healthy/Diseased	256x256	31
2	Bad	Diseased	256x256	481
3	Nagpur	Healthy/Diseased	256x256	473
4	Pune	Healthy/Diseased	256x256	146
Total number of images in Dataset				**1131**

Figure 5. Features of the dataset.

Dataset Description:

a. A dataset accessible to the research community for open use.
b. Images of basil plants were taken in both indoor and outdoor settings.
c. Pictures were gathered in various orientations, diverse lighting situations, and against different backgrounds.
d. Used High resolution mobile cameras to capture to images.
e. The dataset includes two kinds of basil plants, each labelled with quality indicators specifying their health condition (Healthy/Diseased).
f. Dataset comprises 1,200 high-quality images, showcasing leaves from two distinct classes of basil.

5. Implementation

Plant health monitoring as well as the Crop Recommendation System are implemented as part of AgriCrop programmes. Currently, there is a developed crop recommendation system. Let's talk about how the Crop Recommendation was implemented, as it includes varied actions.

Data exploration is an indispensable phase in tackling machine learning challenges, acting as the compass that guides model development and decision-making processes. At the outset, understanding the structure of our dataset becomes paramount, and Pandas, a powerful data manipulation library in Python, aids in this endeavour through the use of the shape attribute. Upon applying df.shape to our dataset, the returned result, such as (2200, 8), furnishes crucial information. In this instance, it indicates that the dataset contains 2,200 items or records, distributed across 8 columns or features. This knowledge serves as a foundational pillar, enabling researchers and practitioners to grasp the scale and dimensionality of the data under consideration.

In the context of a classification challenge, identifying the number of classes within the target label becomes a pivotal task. This step is essential for devising an effective machine learning model that can accurately categorize new instances. To achieve this, one must delve into the distribution of documents across each class in the dataset. The methodology involves scrutinizing the target label to discern the prevalence of each unique class. This information is vital for comprehending the data's inherent class imbalance or balance, which, in turn, influences the choice of evaluation metrics and model performance assessment.

Correlation matrices are a widely used tool for investigating the relationships among the variables in our data. To completely understand the features in our data, we may make use of the correlation matrix that Pandas offers for a data frame. According to Pearson, the default association. Here, the values range from –1 to +1.

The Figure 6 represents the Correlation Matrix of Dataset Features.

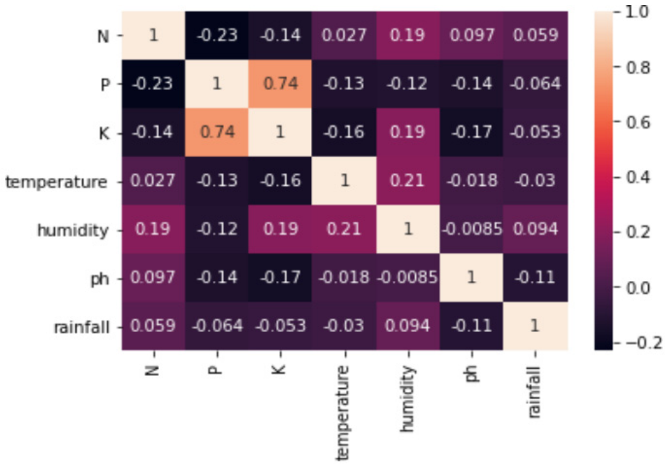

Figure 6. Correlation Matrix Of Dataset Features.

Splitting the data into training and testing datasets is necessary to tackle the classification problem.

The data used in the testing set is used to assess the performance of our model using different metrics, whereas the training data set is the set of data that will be used to train our models. Our method is the Importing the sklearn module's classification_report, we can also get the necessary implementation for the split process. We'll need this in the future while assessing our model.

In constructing a Decision Tree for classification problems, one often opts for the efficiency and convenience offered by the scikit-learn library. In this context, a Decision Tree is instantiated using the DecisionTreeClassifier class, and several crucial arguments determine its behaviour:

Criterion: The criterion parameter defines the method for assessing the quality of a split in the decision tree. The two main options are 'gini' for Gini impurity and 'entropy' for information gain. In this instance, the choice leans towards 'entropy' for the model.

max_depth: The max_depth parameter regulates the depth of the decision tree, influencing its complexity and potential overfitting. It is crucial to select a suitable number for the intended decision tree depth depending on the particulars of the current situation. random_state: The repeatability of the outcomes is enhanced by the random_state option. It regulates how randomly features are chosen at each decision tree split. Setting a specific value for random_state ensures consistent outcomes across different runs of the model. By configuring these parameters, one can tailor the Decision Tree to the characteristics of the dataset and the objectives of the classification task. This methodology facilitates the rapid and efficient creation of Decision Trees for predictive modelling.

The model has given an accuracy of 90%.

When it comes to handling categorization difficulties, the KNN is a good substitute for tree-based methods. We can quickly and efficiently construct the K Nearest Neighbours model with Sklearn. We construct an object belonging to the KNeighborsClassifier class.

While implementing using K Nearest Neighbours, the following are the arguments: n_neighbors: This illustrates what k is worth. That's how many neighbours there are. metric It is set as "minkowski" by default, which stands for Minkowski distance. KNeighborsClassifier(5) = knn After creating a KNeighborsClassifier object, we need to fit the model using our training set of data. We provide the training dataset's features and labels in the manner described below. x_train, y_train in knn.fit.

The accuracy of the model's output was 97.5%. As it stands, the model outperformed the decision tree classifier by a wide margin. To determine if there is a better solution, we can investigate how different algorithms function with the data. Let's do k-fold cross validation to check how our model works before looking into additional possibilities.

Shown as a CART model, the Random Forest is a framework for classification and regression trees. This is an example of an ensemble approach application in which several classifiers are combined. Decision Trees are the classifiers we are merging in this case. As a result, several decision trees are combined to create a random forest. We can accomplish this quickly and efficiently with Sklearn. We generate a Random Forest instance belonging to the RandomForestClassifier class. Many of the reasons we have seen in the implementation of Decision Trees are also apparent here, since we are using Decision Trees.

The following are the arguments: criterion: This is the method for assessing a split's quality. We have the option to select "entropy" for information gain or "gini" for Gini impurity. maximum depth This is a reference to each decision tree's depth. We select an appropriate number for every forest's decision tree.

The term "random_state" describes how randomly the features are permuted at each split. The number of decision trees we would like in our model is indicated by the term "n_estimators". RF is same to RandomForestClassifier(max_depth = 10, random_state = 0, n_estimators = 20).We need to fit the model using our training set of data now that we have an instance of the model constructed. We provide the training dataset's features and labels in the manner described below. RF.fit (trains, x, y)

The evaluation of the model reveals a notable accuracy rate of 98.8%**,** surpassing both the KNN and Decision Tree models by a substantial margin. From the available data, it can be inferred that this particular model demonstrates superior performance. However, prior to preservation, a prudent approach involves conducting k-fold cross-validation to thoroughly assess the model's efficacy. The close alignment of precision across the 10 folds in the cross-validation process indicates consistent and commendable performance by the model. This convergence in precision values lends further support to the assertion that the model is operating effectively across diverse subsets of the data.

The primary function of the Crop Recommendation System is to suggest the best crop to the farmer. As more and more sectors move towards digitalization, it's critical that the agricultural industry do the same by utilising a variety of technologies to address issues that farmers confront. The next part of the project involves implementation of a Plant Health Monitoring System. The implementation of a Plant Health Monitoring System represents a crucial step forward in the modernization and digital transformation of the agricultural industry. As various sectors embrace digitalization, it becomes imperative for agriculture, a sector fundamental to human sustenance, to leverage technology to enhance productivity, efficiency, and sustainability. The introduction of a Plant Health Monitoring System complements the Crop Recommendation System, forming an integrated approach that addresses the multifaceted challenges faced by farmers.

6. Conclusions and Discussion

The integration of machine learning into crop recommendation offers a promising opportunity to improve agriculture. If machine learning algorithms are used, the system's recommendations might lack transparency, making it challenging for farmers to understand why a particular crop is recommended. Machine learning and Deep learning powered crop recommendation systems have the potential to significantly improve agricultural practices, benefiting both farmers and the global food supply chain. As research and development in this field evolve, finding a harmony between technological innovation and the traditional farming wisdom defined by human touch is essential. By doing so, we can usher in a new era of precision agriculture that optimizes productivity, minimizes environmental impact, and contributes to a more sustainable future.

Furthermore, the plant monitoring system proved to be an indispensable component, providing real-time data on the health and growth status of crops. The combination of sensor technologies and image processing algorithms enabled the early detection of pests, diseases, and nutrient deficiencies. This timely information empowers farmers to take proactive measures, thereby minimizing yield losses and optimizing resource allocation. The system's potential to scale and adapt to diverse crop types and geographical regions makes it well-suited for broad adoption. Moreover, the inclusion of a feedback loop mechanism facilitates ongoing learning and enhancement of the recommendation engine. This ensures its continuous alignment with evolving agricultural practices and emerging technologies.

In conclusion, the integration of a crop recommendation system with a plant monitoring system represents a ground breaking leap towards fostering sustainable and efficient agricultural practices. This innovative approach harnesses the power of advanced technologies, particularly deep learning, and real-time monitoring, to bring about transformative changes in the realm of farming. The implications of such a system extend far beyond mere convenience, offering solutions that have the potential to revolutionize traditional agricultural methodologies and address pressing challenges faced by the global agricultural community. The synergy between a crop recommendation system and a plant monitoring system is particularly noteworthy. The crop recommendation system, fueled by sophisticated algorithms and machine learning models, provides farmers with tailored insights into optimal crop choices based on various factors such as soil conditions, climate, and historical data. This not only streamlines decision-making processes but also enhances resource efficiency by ensuring that farmers invest in crops with the highest probability of success. The integration with a plant monitoring system adds another layer of dynamism to this agricultural paradigm. Real-time monitoring of plant health, growth patterns, and environmental conditions enables farmers to proactively address issues such as pests, diseases, or nutrient deficiencies.

By providing actionable insights, the plant monitoring system contributes to early detection and timely intervention, ultimately minimizing crop losses and maximizing yields. The overarching impact of such a system on global food security is profound. By optimizing crop choices and ensuring the health and productivity of cultivated plants, this technology has the potential to significantly increase overall agricultural output. This is especially crucial as the world faces challenges such as a growing population, climate change, and the need for sustainable farming practices. Looking towards the future, the potential for further research and development in this field is immense. Continued advancements in technology, data analytics, and machine learning can refine and expand the capabilities of these systems. Fine-tuning algorithms, incorporating more comprehensive datasets, and enhancing the interoperability of these technologies with other agricultural tools can lead to even greater precision and efficiency in farming practices. In essence, the marriage of deep learning-driven crop recommendations and real-time plant monitoring is not just a technological innovation; it is a pathway towards a more sustainable, productive, and resilient agriculture. As we embrace these advancements and continue to invest in the evolution of agricultural technologies, we pave the way for a future where technology plays a pivotal role in shaping the landscape of global food production and security.

The integration of deep learning and plant monitoring in a crop recommendation system holds the promise to transform agriculture. It can empower farmers with intelligent, data-driven insights, fostering more sustainable and productive farming practices. However, it's important to ensure that such systems are accessible, user-friendly, and adapted to the specific needs of different farming communities. Additionally, addressing data privacy and security concerns will be crucial for widespread adoption. The next stage of development involves combining the crop recommendation system with an additional subsystem, the yield predictor. This integration aims to furnish farmers with an estimated production figure if they choose to cultivate the recommended crop.

Author Contributions

B.V.J. contributed in identification and developing the concept of the research problem. E.R. contributed towards Methodology for the proposed system. M.V., M.K. and S.R.V. contributed towards implementation, results analysis and data validation. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

India's Most Famous Basil Plant Leaves Quality Dataset—A dataset accessible to the research community for open use.

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