Crop Recommendation System Using Machine Learning

A Project Report
Submitted for partial fulfillment of the requirements for the degree of
BACHELOR OF TECHNOLOGY
In
Information Technology
Submitted by

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ABES Engineering College, Ghaziabad

Dr. A.P.J. Abdul Kalam Technical University, Uttar Pradesh Lucknow

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DECLARATION

We hereby declare that this submission is our own work that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that project report entitled "**Crop Recommendation System Using Machine Learning**" which is submitted by **Anshika Chauhan (2000320130027), Aditi Mishra (2000320130006), Divya Maurya (2000320130056) and Anshul Kumari (2000320130031)** in partial fulfilment of the requirement for the award of degree B.Tech. in Department of Information Technology of Dr. A.P.J. Abdul Kalam, Technical University, is a record of the candidates' own work carried out by them under my supervision. The matter embodied in this thesis is original and has not been submitted for the award of any other degree.

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We also do not like to miss the opportunity to acknowledge the contribution of all faculty members of the department for their kind assistance and cooperation during the development of our project. Last but not the least, we acknowledge our friends for their contribution in the completion of the project.

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ABSTRACT

This project aims to develop a Crop recommendation system for farmers worldwide. Automating agricultural processes, with or without human intervention, has become increasingly crucial due to the limited space of domestic lands. Selecting the most suitable crops based on prevailing factors in a given area is paramount. Despite the availability of knowledge, techniques, and manual methods in Sri Lankan agriculture, there lacks a system that detects environmental factors and suggests optimal crop types for farming. This paper proposes a theoretical and conceptual platform for a recommendation system integrating models to collect environmental factors using Arduino microcontrollers and employing machine learning techniques such as Naïve Bayes (Multinomial) and Support Vector Machine (SVM). Unsupervised machine learning algorithms like K-Means Clustering, coupled with Natural Language Processing (Sentiment Analysis) within Artificial Intelligence, are utilized to recommend suitable crops for selected land based on site-specific parameters with high accuracy and efficiency. The challenge lies in identifying the optimal crop given limited space on both domestic and farming lands. Uncertainty in environmental factors such as temperature, water levels, and soil conditions exacerbates this challenge, as they fluctuate over time. To address these issues, the proposed crop recommendation system predicts the most suitable crop type for the selected area by collecting relevant environmental factors for plant growth and processing them using trained sub-models integrated into the main system

Keywords— Agriculture, Machine Learning, Arduino, Natural Language processing, Farming.

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CHAPTER 1
INTRODUCTION

The crop recommendation problem is a crucial issue in agriculture, as it directly impacts food production, farmer livelihoods, and resource sustainability. A study published in the journal Nature Communications revealed that crop losses attributable to pests and diseases alone contribute to approximately 20% to 40% of global agricultural productivity losses. The need for studying this problem arises from several factors. First, the global population is rapidly increasing, necessitating higher agricultural yields to meet the growing food demand. Second, climate change and environmental concerns have made it imperative to optimize crop selection for resource-efficient and eco-friendly farming practices. Moreover, the economic well-being of farmers is closely tied to crop choices, as different crops have varying market prices and production costs. Inefficient crop selection can lead to financial losses for farmers. Additionally, the problem is complex due to the multitude of variables involved, such as soil quality, weather patterns, and market dynamics, making it challenging for farmers to make informed decisions. Therefore, the study of crop recommendation is essential to develop data-driven, precision agriculture solutions that enhance food security, increase agricultural sustainability, and improve the livelihoods of farmers while mitigating environmental impacts.

Data set collection from various sources :

- Data parsing and cleansing technique is applied to make the raw data into processing data.
- The data collected is subject to machine learning system along with run time analysis makes an efficient crop value updating system.
- Usage of Ensemble of classifiers makes the model more robust and efficient.
- Ranking technique used in the project helps us to make efficient decisions.
- Creating a web application for user registrations and collection of data.
- The main objective is to obtain a better variety of crops that can be grown over the season. The proposed system would help to minimize the difficulties faced by farmers in choosing a crop and maximize the yield.

- The model predicts the crop yield by studying factors such as rainfall, temperature, area, season, soil type etc.. salary ranges, which will help draw and keep top personnel. Additionally, it can offer insights into.

1.1 Need to Study

A Crop Recommendation System is designed to help farmers make informed decisions about which crops to plant, based on factors such as soil properties, weather conditions, and market demand. The objective of such a system is to analyze various factors influencing crop growth and yield, develop a machine learning model to recommend the best crops, and build a user-friendly interface for farmers. Data collection is crucial and should include soil data (pH, nitrogen, phosphorus, potassium levels, soil type), weather data (temperature, rainfall, humidity, wind speed), crop data (crop types, growth conditions, historical yields), and market data (crop prices, demand trends). Data preprocessing involves cleaning and transforming the data, handling missing values, normalizing or scaling the data, and selecting important features. Exploratory Data Analysis (EDA) helps to understand the data and uncover patterns through descriptive statistics, correlation analysis, and visualization. Model selection involves choosing appropriate machine learning algorithms such as Decision Trees, Random Forest, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Neural Networks. The selected models are then trained and evaluated using metrics like accuracy, precision, recall, and F1 score. Model performance is optimized through hyperparameter tuning using techniques such as grid search or random search.

For deployment, a user-friendly interface, such as a web or mobile application, is developed to allow farmers to input their data and receive crop recommendations. For example, a farmer could input soil pH, nitrogen, phosphorus, potassium levels, average temperature, and annual rainfall into the system. The system, using a trained Random Forest model, could then recommend suitable crops such as wheat, maize, or barley, along with expected yields and market prices. This crop recommendation system can enhance agricultural productivity by providing data-driven insights, leading to sustainable farming practices, optimized resource use, and improved crop yields. Future work can focus on incorporating real-time data from IoT devices, exploring advanced algorithms like deep learning for more accurate recommendations, ensuring scalability for large datasets, and customizing recommendations based on local agricultural practices and crop varieties.

1.2 Motivation

The motivation behind developing a Crop Recommendation System using machine learning stems from several compelling factors that address critical challenges in modern agriculture.

Here are the key motivations: 1. Maximizing Agricultural Productivity One of the primary motivations is to enhance crop yields and overall agricultural productivity. By using machine learning to analyze various environmental and soil conditions, the system can recommend crops that are most likely to thrive in specific conditions, thereby maximizing yields.

2. Resource Optimization Agriculture relies heavily on finite resources such as water, fertilizers, and land. A crop recommendation system can help optimize the use of these resources by recommending crops that require fewer inputs or 2 are more suited to the local conditions, leading to more sustainable farming practices.

3. Economic Benefits for Farmers Farmers often face uncertainty regarding which crops to plant to achieve the best economic returns. A machine learning-based recommendation system can analyze market trends and historical data to suggest crops that not only grow well in the given conditions but also have high market demand, thereby increasing farmers' income.

4. Reducing Risk and Uncertainty Agricultural practices are highly susceptible to risks and uncertainties due to varying weather conditions, soil fertility, and pest infestations. A machine learning model can mitigate these risks by providing data driven recommendations that account for these variables, helping farmers make more informed decisions. 5. Addressing Climate Change Challenges Climate change is causing unpredictable weather patterns, which affect traditional farming practices. A crop recommendation system can help adapt to these changes by suggesting climate-resilient crops, ensuring food security and agricultural sustainability in the face of global climate challenges. 6. Empowering Farmers with Technology Many farmers, especially in developing regions, lack access to advanced agricultural knowledge and resources. A machine learning-based system, accessible via simple interfaces like mobile apps, can democratize access to advanced agricultural insights, empowering even small-scale farmers to make better decisions. 7. Improving Food Security With the global population growing, there is an increasing demand for food production. Efficient crop recommendations can help meet this demand by ensuring that the best possible crops are grown in suitable areas, thereby contributing to global food security. 8. Data-Driven Decision Making Traditional farming often relies on experience and intuition, which can be less reliable in the face of new challenges. By leveraging large datasets and advanced analytics, a crop recommendation system provides a scientific and data-driven approach to decision making in agriculture. 9. Environmental Sustainability By recommending crops that are well-suited to the local environment and require fewer chemical inputs, the system can promote more environmentally friendly farming practices, reducing the negative impact of agriculture on the ecosystem. 10. Innovation in Agriculture The application of machine learning in agriculture represents a significant step towards the digital transformation of the sector. It encourages innovation and the adoption of modern technologies, paving the way for the future of smart farming and precision agriculture.

1.3 Contribution

In our project, we began with the data collection and preprocessing phase, which involved initiating data gathering efforts. We meticulously cleaned and organized the collected data to ensure its quality and suitability for subsequent analysis. This process was crucial in preparing the data for accurate and effective analysis.

Initially, significant effort is dedicated to data collection and integration, gathering diverse datasets such as soil pH, nutrient levels, weather patterns, crop types, and market trends. Preprocessing this data involves cleaning, normalizing, and selecting relevant features, as well as engineering new features to enhance model performance. Exploratory Data Analysis (EDA) is then performed to uncover patterns and relationships within the data, using descriptive statistics and visualizations. Model development entails selecting appropriate machine learning algorithms, such as Decision Trees, Random Forest, SVM, KNN, or Neural Networks, and training these models on the dataset. Hyperparameter tuning and cross-validation are used to optimize the models' performance.

Deployment involves creating user-friendly interfaces, like web or mobile applications, to make the system accessible to farmers, and building APIs for integration with other platforms. User training and support are provided through comprehensive documentation, training sessions, and ongoing support services to ensure farmers can effectively use the system. Validation and testing in real agricultural settings are essential to ensure reliability and accuracy, with user feedback collected to refine the system. Sustainability and scalability are considered to promote sustainable farming practices and ensure the system can handle large datasets and an increasing number of users.

Finally, the project pushes the boundaries of agricultural practices through research and innovation, exploring advanced machine learning techniques and interdisciplinary collaboration to enhance the system’s recommendations. These contributions collectively create a robust, user-friendly, and effective crop recommendation system that significantly benefits the agricultural sector.

1.4 Organization of Paper

The design framed by the report is efficient and understands a consistent movement. In the second segment, which is the Survey of Writing, you will give a consolidated outline of the writing survey examined before. This part ought to feature the key discoveries, subjects, patterns, and holes distinguished in the writing connected with your task's point. It fills in as an extension between the early on segments of the report and the nitty gritty system and results areas to follow. Continuing on toward the third area, which frames the summation system, this is where you'll dig into the points of interest of how you directed your venture. Expanding upon the philosophy conversation referenced before, this part will give a bit by bit clarification of the methodology, procedures, devices, and assets utilized in your examination or venture execution. It ought to remember subtleties for information assortment, preprocessing, model choice, trial arrangement, 4 approval strategies, and some other pertinent methods fundamental for figuring out the task's execution. Following the system segment, in area IV, you will introduce the Outcomes and Conversation.

Here, you'll exhibit the results of your undertaking, including mathematical outcomes, perceptions, examinations, and translations. This segment is critical for exhibiting the adequacy, legitimacy, and meaning of your work. You'll talk about how your outcomes line up with the undertaking targets, contrast them and existing writing or benchmarks, and decipher their suggestions. It's likewise an amazing chance to address any startling discoveries, restrictions, and future headings for examination or application. At last, in segment 5, you'll close the report with a far reaching Resolution.

This segment ought to give a succinct outline of the whole report, repeating the principal discoveries, commitments, and ramifications of your venture. You'll talk about how your work enhances the field, addresses the exploration questions or goals, and possibly opens roads for additional examination or execution. The end ought to be effective, having an enduring impact on the peruser and supporting the meaning of your work inside the more extensive setting of the topic.

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Crop Name	Soil Type	Climate	Recommended Season	Recommended Irrigation	Recommended Fertilizers
Wheat	Loamy	Temperate	Winter	Moderate	Nitrogen, Phosphorus
Rice	Clayey	Tropical	Summer	High	Nitrogen, Potassium
Maize	Sandy	Subtropical	Rainy	Moderate	Nitrogen, Potassium
Cotton	Sandy Loam	Tropical	Summer	High	Phosphorus, Potassium
Sugarcane	Clay	Tropical	Rainy	High	Nitrogen, Phosphorus

CHAPTER 2
LITERATURE REVIEW

The computational and data demands of structural price forecasting generally far exceed than what is routinely available in developing countries. Consequently, researchers often rely on parsimonious representations of price processes for their forecasting needs. Contemporary parsimonious form of price forecasting relies heavily on time series modelling. In time series modelling, past observations of the same variable are collected and analyzed to develop a model describing the underlying relationship.

During the past few decades, much effort has been devoted to the development and improvement of time series forecasting models. Time series modelling requires less onerous data input for regular and up-to date price forecasting. Hence there is a need for better classification which would be an ensemble or hybrid classification model.

Early Approaches and Baseline Models: Early studies in crop recommendation focused on simple decision support systems that utilized basic environmental and soil data. These systems primarily employed rule-based approaches and heuristic models. For example, Srinivas et al. (2010) developed a decision support system using a decision tree algorithm that recommended crops based on static data such as soil type and basic climatic conditions. While these models provided a foundation, their static nature and limited data integration restricted their applicability and accuracy. Integration of Machine Learning Techniques:

With advancements in machine learning, researchers began incorporating more sophisticated algorithms to improve the accuracy and adaptability of crop recommendation systems. Krishna et al. (2018) employed a Random Forest algorithm to analyze soil properties and climatic conditions, achieving higher accuracy compared to traditional methods. The use of machine learning allowed for the consideration of complex interactions between various factors, leading to more reliable recommendations.to be given all through the segment to credit the sources and work with additional perusing for

2.1 A Systematic Review with certain time frame

Advanced Algorithms and Ensemble Methods: Recent research has explored advanced algorithms and ensemble learning techniques to further enhance the performance of crop recommendation systems. Patil and Biradar (2020) demonstrated the effectiveness of an ensemble approach combining Random Forest and Gradient Boosting. This method leveraged the strengths of multiple algorithms, resulting in improved prediction accuracy.

Additionally, deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks 6 (RNNs), have been applied to handle complex, high-dimensional datasets (Jain et al., 2021). These models are particularly effective in capturing non-linear relationships and temporal patterns in the data.

Geospatial and Temporal Data Integration: The integration of geospatial data and temporal analysis has significantly improved the precision of crop recommendation systems. Mishra et al. (2019) utilized Geographic Information Systems (GIS) combined with machine learning models to provide location-specific crop recommendations.

By incorporating spatial data such as satellite imagery, researchers could analyze soil and environmental conditions at a granular level. Gupta et al. (2020) emphasized the importance of temporal data, using historical weather patterns to account for seasonal variations and long-term climate trends, thereby enhancing the robustness of the recommendations.

Utilization of IoT and Real-Time Data: The proliferation of Internet of Things (IoT) devices has enabled real-time data collection, further enhancing the responsiveness and accuracy of crop recommendation systems. Singh et al. (2021) demonstrated an IoT-based system where sensors deployed in fields collected continuous data on soil moisture, temperature, and other parameters.

This real-time data was fed into machine learning models to provide immediate and dynamic recommendations, adapting to changing conditions on the ground. User-Centric Design and Accessibility: Ensuring that crop recommendation systems are user-friendly and accessible to farmers has been a focal point of recent research. Sharma and Singh (2019) developed mobile applications and web platforms to make these systems easily accessible.

These platforms incorporated intuitive interfaces and provided actionable insights, facilitating adoption by farmers. User feedback mechanisms were also integrated to continuously improve the system based on practical user experiences.

Types of crops	Paper Name	Year of Publishing	Methodology Used	Accuracy
Rice, Jowar Wheat, Soybeans Sunflower, Sugarcane Tobacco Onion, Dry Chilli	[8]	2020	Linear Regression, Polynomial Regression	SVM=99.47% RF=97.48%
Groundnut, Pulses, Cotton, Vegetables, Paddy,Sugarcane, Coriander”	[10]	2021	Data mining, Regression Analysis Clustering	RF give best accuracy result
Millet,Ground nutPulses, Cotton, Vegetables, Banana, Paddy, Sorghum, Sugarcane, Coriander”	[11]	2020	RF, CHAID, KNN, NB	RF=88%
Rice, Ragi, Gram, Potato, Onion	[12]	2021	RF, LR, DT,SVM	MV=94.78%
Cotton, Vegetables, Banana, Paddy, Sorghum, Sugarcane, Coriander”	[14]	2016	SVM, NB, ANN, RF	RF gives the best accuracy result
Groundnut, Gram, Jute, Potato, Ragi, Tur, Rapeseed, Mustard, Sesame, Soybean, Sugarcane ,	[15]	2022	DT, KNN, RF, NN	DT = 90.20% KNN=89.78 % R= 90.43% NN= 91.00%

Sunflower , Tobacco”				
“Millet, Groundnut, Pulses, Cotton, Vegetables, Banana, Paddy,	[17]	2023	RT, KNN, NB	RT gives the best accuracy result
“Variou s Crops”	[5]	2021	CHAID, KNN, Kmeans, DT, NN, NB, C4.5, LAD, IBK, SVM	SVM gives the best accuracy result

Table 1: Literature Survey Table

A survey on Data Mining Techniques for crop Yield Prediction tells this paper provides the different harvest yield forecast strategies making use of information mining strategies. Agrarian framework is unpredictable because it manages tremendous data situation which comes from various additives. Harvest yield expectation has been a topic of hobby for makers, professionals, and agrarian related associations.

In this paper the creators centre across the uses of records mining methods in agrarian subject. Distinctive Data Mining techniques, as an example, K-Means, KNearest Neighbour (KNN), Artificial Neural Networks (ANN) and Support Vector Machines(SVM) for ongoing utilizations of statistics mining approaches in agribusiness subject.

Information mining innovation has gotten an super advancement with the short improvement of software engineering, guy-made brainpower. Information Mining is an bobbing up research area in horticulture crop yield investigation. Information Mining is the manner in the direction of spotting the hid examples from giant measure of data.

2.2 Inference Drawn

The Rise of Salary Prediction Web Apps:

Pay Expectation Web Applications have turned into a reaction to the developing interest for straightforwardness and reasonableness in the gig market. This pattern has been worked with by the ascent of large information and the openness of broad compensation related data. These web applications are intended to offer clients exact and customized compensation expectations by utilizing progressed information investigation procedures and AI calculations.

One of the essential inspirations driving the improvement of Pay Forecast Web Applications is to enable work searchers with far reaching bits of knowledge into their reasonable worth. By contributing their capabilities, experience levels, abilities, and geographic area, clients can get custom-made compensation appraises that mirror the latest things and request in the gig market. This data empowers work searchers to settle on informed conclusions about bids for employment, arrange pay rates without hesitation, and distinguish regions for abilities improvement to upgrade their procuring potential.

Besides, these web applications benefit bosses by giving them significant information driven experiences into pay ranges and market intensity. Managers can utilize these bits of knowledge to characterize fair and serious remuneration bundles, draw in top ability, and hold talented workers. By adjusting their compensation contributions to industry guidelines and market patterns, businesses can likewise further develop their manager marking and notoriety inside the business.

The development of Compensation Forecast Web Applications connotes a shift towards more prominent straightforwardness and reasonableness in compensation dealings. By democratizing admittance to pay related data and advancing information driven independent direction, these applications add to a more impartial work market where both work searchers and bosses can settle on informed decisions. Also, they assist with crossing over the data hole among bosses and representatives, cultivating better correspondence and joint effort in the enlistment and maintenance process.

By and large, Compensation Forecast Web Applications assume a significant part in advancing straightforwardness, reasonableness, and productivity in the gig market. They influence the force of information examination and AI to give significant experiences that benefit both work searchers and businesses, eventually prompting improved results for all partners engaged with the business biological system.

Machine Learning Algorithms:

AI calculations assume a vital part in the improvement of Compensation Expectation Web Applications, giving the spine to exact and customized compensation gauges. Specialists and engineers outfit a scope of calculations, including gathering techniques like Irregular Timberland and Slope Helping, choice trees, brain organizations, and relapse models. These calculations are prepared on verifiable compensation information, learning mind boggling examples and connections between factors like insight, abilities, training, and geographic area.

Troupe strategies like Arbitrary Backwoods join various models to improve prescient exactness and heartiness. They succeed at catching complex communications in compensation information and moderating overfitting. Choice trees, then again, make various leveled choice principles in light of elements, making them interpretable and powerful for catching nonlinear connections.

Brain organizations, especially profound learning models, are proficient at gaining from huge datasets and recognizing stowed away examples. They succeed in dealing with high-layered information and can adjust to changing business sector elements, giving nuanced bits of knowledge into pay expectations. Relapse models, like Direct Relapse and Backing Vector Relapse, gain proficiency with the connections between input highlights and compensation results, offering exact expectations in view of authentic data. Additionally, some Compensation Forecast Web Applications influence Normal Language Handling (NLP) strategies. These procedures remove significant data from text-based information, for example, sets of responsibilities and client audits, advancing the expectation models with context-oriented bits of knowledge. By constantly refreshing their models and integrating new information, these applications guarantee that their compensation gauges stay precise and intelligent of market patterns.

User Trust and Transparency:

For Pay Expectation Web Applications to acquire inescapable reception and find success, laying out and keeping up with client trust is pivotal. These applications should focus on transparency and genuineness with respect to their information sources, philosophies, and restrictions to procure the trust of businesses and occupation searchers the same.

Straightforwardness is key in building trust. Clients ought to approach data about the information sources utilized by the application, whether it's freely accessible compensation information, restrictive datasets, or a blend of both. Clear clarifications about how the information is gathered, organized, and refreshed over the long run impart trust in the dependability and exactness of the forecasts.

Also, Compensation Expectation Web Applications ought to straightforwardly reveal the techniques and calculations utilized in creating pay gauges. Clients need to comprehend the basic models, whether they depend on AI calculations, measurable procedures, or a mix of approaches. Giving bits of knowledge into how highlights are weighted, how expectations are determined, and the way that vulnerabilities are taken care of upgrades straightforwardness and assists clients with pursuing informed choices.

Permitting clients to approve expectations with their own information is one more critical part of building trust. Applications that offer clients the capacity to enter their genuine capabilities, experience, and other significant data to look at against the application's forecasts exhibit a guarantee to exactness and decency. This intelligent element upgrades client commitment as well as approves the application's expectations against certifiable situations.

Moreover, straightforwardness stretches out to unveiling the impediments and requirements of the expectation models. No model is great, and clients should know about the possible inclinations, presumptions, and vulnerabilities related with pay expectations. Obviously imparting these limits cultivates reasonable assumptions and urges clients to decipher the expectations with setting and subtlety.

In outline, client trust in Compensation Forecast Web Applications is developed through straightforwardness, receptiveness, and genuineness. By giving clear data about information sources, approaches, intuitive approval includes, and recognizing impediments, these applications can set up a good foundation for themselves as dependable and reliable devices for the two bosses and occupation searchers in exploring the perplexing scene of pay assessment.

CHAPTER 3
METHODOLOGY

The Crop Recommendation System (CRS) is an innovative technological solution aimed at transforming the agricultural landscape by assisting farmers in making informed decisions about which crops to plant. This system leverages various parameters such as soil type, climate conditions, and market demand to provide tailored recommendations that can significantly enhance agricultural productivity and profitability. The CRS is designed to be web-based, ensuring that it is accessible through any modern browser, and it is optimized for use on both desktop and mobile devices.

This accessibility means that farmers can easily access the system from their fields or homes, using smartphones, tablets, or computers, making it a versatile tool for a wide range of users. In the agricultural sector, the decision-making process regarding crop selection is complex and influenced by numerous factors. Traditional methods often rely on the farmer's experience and intuition, which, while valuable, may not always consider all relevant data. The CRS aims to bridge this gap by integrating scientific data and advanced algorithms to provide recommendations that are both data-driven and user-specific.

By considering soil type, the system can analyze the composition and fertility of the soil, ensuring that the recommended crops are well-suited to the specific soil conditions of each farm. This analysis includes factors such as pH levels, nutrient content, and soil texture, all of which play a critical role in determining crop suitability. Climate conditions are another crucial factor in the CRS's recommendation process. The system integrates real time and historical weather data to assess the climatic suitability of various crops. This includes temperature ranges, precipitation levels, humidity, and seasonal variations, all of which can significantly impact crop growth and yield. By incorporating this data, the CRS can predict potential weather-related challenges and recommend crops that are resilient and adaptable to the specific climate conditions of the farmer's location. This predictive capability helps farmers mitigate risks associated with adverse weather conditions and optimize their planting schedules for maximum yield. Market demand is the third key parameter considered by the CRS. Understanding market trends and demand patterns is essential for farmers to make profitable decisions. The system accesses current market prices and demand forecasts for various crops, enabling farmers to select crops that are not only suitable for their soil and climate but also have a high market value. This market-driven approach ensures that farmers can achieve better financial returns by growing crops that are in demand, thereby enhancing their overall profitability and sustainability. The integration of market data also allows farmers to plan their crop cycles more effectively, aligning their production with peak market periods.

3.1 Detailed Discussion of Dataset

a) The Crop Recommendation System (CRS) is a sophisticated platform designed to enhance the decision-making process for farmers by leveraging various external systems. One of the critical interactions that the CRS engages in is with a Weather API. This integration is essential as it allows the system to fetch both real-time and historical weather data, which plays a pivotal role in agricultural planning and crop selection.

b) Real-time weather data provides farmers with up-to-the-minute information on current weather conditions, such as temperature, humidity, wind speed, and precipitation. This immediate access to weather information enables farmers to make timely decisions regarding planting, irrigation, and harvesting, helping to optimize their operations and mitigate potential weather-related risks. Historical weather data, on the other hand, offers a comprehensive view of weather patterns over a specific period. By analyzing historical data, the CRS can identify trends and seasonal variations that are crucial for long term agricultural planning. For instance, understanding the historical frequency and intensity of droughts or heavy rainfall periods can inform decisions about crop varieties that are more resilient to such conditions.

c) This data-driven approach ensures that farmers are better prepared for potential weather challenges, reducing the likelihood of crop failure and improving overall productivity. The integration with the Weather API also supports the development of predictive models that forecast future weather conditions, providing farmers with valuable insights into potential climatic changes and their impact on crop growth. In addition to weather data, the CRS interacts with a Soil Database to gather detailed information about soil types and properties. Soil health is a fundamental determinant of agricultural success, as it directly affects plant growth and yield.

The Soil Database provides a wealth of information on various soil characteristics, including pH levels, nutrient content, organic matter, texture, and structure.

d) By accessing this data, the CRS can assess the suitability of different crops for specific soil conditions, ensuring that farmers select crops that are well-matched to their land. For example, certain crops thrive in acidic soils, while others require more neutral or alkaline 27 conditions. Understanding the pH level of the soil allows the CRS to recommend crops that are likely to perform well, thereby enhancing yield and profitability. Nutrient content is another critical factor that the Soil Database helps to evaluate. Soil nutrients, such as nitrogen, phosphorus, and potassium, are essential for plant growth. By analyzing the nutrient profile of the soil, the CRS can recommend appropriate fertilization strategies and crop rotations to maintain soil fertility.

e) This targeted approach to soil management not only improves crop performance but also promotes sustainable farming practices by preventing over-fertilization and nutrient runoff. The Soil Database also provides information on soil texture, which influences water retention and drainage. Crops have different water requirements, and understanding soil texture helps farmers manage irrigation more effectively, ensuring that crops receive the right amount of water at the right time. Furthermore, the CRS utilizes a Market Prices API to provide current market prices for various crops.

f) This integration is crucial for aligning agricultural production with market demand, thereby maximizing profitability for farmers. By accessing real-time market data, the CRS helps farmers make informed decisions about which crops to plant based on their potential economic returns. This market-driven approach ensures that farmers are not only producing crops that are suitable for their soil and climate but also those that are likely to fetch higher prices in the market. The Market Prices API provides information on price trends, demand fluctuations, and market saturation, enabling farmers to anticipate market conditions and adjust their production strategies accordingly.

g) The ability to access current market prices also helps farmers plan their sales and marketing efforts more effectively. For example, if the market data indicates a high demand for a particular crop, farmers can focus their resources on increasing the production of that crop and timing their harvest to coincide with peak market periods.

h) This strategic planning helps to maximize revenue and reduce the risk of price volatility. Additionally, the Market Prices API can provide insights into emerging market opportunities, such as the growing demand for organic or specialty crops.

i) By identifying these trends early, farmers can diversify their production and tap into new market segments, enhancing their competitiveness and profitability.

j) The integration of these external systems into the CRS represents a significant advancement in agricultural technology, providing farmers with a holistic and data-driven approach to crop selection and management.
k) The seamless interaction with the Weather API, Soil Database, and Market Prices API ensures that farmers have access to comprehensive and up-to-date information that supports informed decision-making.
l) This integration not only enhances the accuracy of crop recommendations but also empowers farmers to adopt more sustainable and profitable farming practices.

Moreover, the CRS's ability to process and analyze data from these external systems highlights the importance of data interoperability and standardization in modern agriculture. By ensuring that data from different sources can be seamlessly integrated and analyzed, the CRS enables a more comprehensive understanding of the complex factors that influence agricultural productivity. This interoperability is particularly important in the context of precision agriculture, where detailed and accurate data is essential for optimizing resource use and improving crop performance.

The Market Prices API also presents unique challenges and opportunities for the CRS. Market data can be highly dynamic and influenced by a wide range of factors, including economic conditions, trade policies, and consumer preferences.

Additionally, the CRS can leverage market data to support value chain optimization, helping farmers connect with buyers, processors, and retailers more effectively.
The CRS's interaction with these external systems also underscores the importance of user-centered design and usability in agricultural technology. Farmers must be able to easily access and interpret the data provided by the CRS, regardless of their technological proficiency.

This requires a user-friendly interface that presents complex data in a clear and intuitive manner. Visualizations, such as graphs, charts, and maps, can help farmers understand weather patterns, soil health, and market trends at a glance. Interactive features, such as customizable dashboards and real-time alerts, can further enhance the user experience, ensuring that farmers receive the information they need when they need it. Furthermore, the CRS must be designed to accommodate the diverse needs and contexts of different users.This includes considerations such as language preferences, regional variations, and accessibility features. For example, the CRS can support multiple languages to ensure that farmers from different regions can use the system effectively. It can also provide region-specific recommendations that take into account local climatic and soil conditions, as well as market dynamics. Accessibility features, such as voice commands and offline functionality, can ensure that the system is usable by farmers with varying levels of literacy and access to technology.

N

A	B	C	D	E	F	G	H	I	J	K
78	58	15	23.00933	67.81657	6.328631	62.91359	maize			
92	60	23	18.66747	71.51647	5.721667	69.93293	maize			
79	59	17	20.38	63.7385	6.644205	108.5054	maize			
91	55	15	18.093	72.61024	6.376651	78.9616	maize			
76	51	18	26.16986	71.96247	6.24704	79.84925	maize			
87	48	25	18.65397	61.3788	6.65673	93.62039	maize			
71	60	22	26.0747	59.37148	6.204802	85.75692	maize			
90	57	24	18.92852	72.80086	6.15886	82.34163	maize			
67	35	22	23.30547	63.24648	6.385684	108.7603	maize			
60	54	19	18.74827	62.49878	6.41782	70.23402	maize			
83	58	23	19.74213	59.66263	6.381202	65.50861	maize			
83	57	19	25.73044	70.74739	6.877869	98.73771	maize			
40	72	77	17.02498	16.98861	7.485996	88.55123	chickpea			
23	72	84	19.02061	17.13159	6.920251	79.92698	chickpea			
39	58	85	17.88776	15.4059	5.996932	68.54933	chickpea			
22	72	85	18.86806	15.65809	6.391174	88.51049	chickpea			
36	67	77	18.36953	19.56381	7.152811	79.26358	chickpea			
32	73	81	20.45079	15.40312	5.988993	92.68374	chickpea			
58	70	84	20.65432	16.60821	6.231049	74.66311	chickpea			
59	70	84	17.33487	18.74927	7.550808	82.61735	chickpea			
42	62	75	18.17912	18.90427	7.010571	81.84998	chickpea			
28	74	81	18.01272	18.30968	8.753795	81.98569	chickpea			
58	66	79	20.99374	19.3347	8.718193	93.5528	chickpea			

Table 2: Sample Dataset

3.2 **Models**

Linear Regression:

For instance, when a farmer inputs soil data, the system can instantly process this information and update the recommendations on the dashboard without requiring a page refresh. This real-time interactivity is crucial for maintaining user engagement and satisfaction. Additionally, responsive design techniques ensure that the interfaces work well across different devices and screen sizes, providing a consistent experience whether users are accessing the system from a desktop computer or a mobile phone.

The backend of the CRS, which supports the admin interface, is built using robust and scalable technologies. Server-side languages such as Python or Node.js, along with frameworks like Django or Express, are used to handle data processing and storage. Databases like PostgreSQL or MongoDB store the vast amounts of data required for accurate recommendations, while cloud services such as AWS or Azure ensure scalability and reliability.

These technologies work together to create a seamless experience for administrators, allowing them to manage the system efficiently. Security is a paramount consideration in the design of both the user and admin interfaces. The system employs advanced security measures such as encryption, secure authentication, and regular security audits to protect user data. Multi-factor authentication (MFA) is implemented to add an extra layer of security for admin accounts, ensuring that only authorized personnel can access sensitive system functionalities. Regular updates and patches are applied to address any vulnerabilities, maintaining the integrity and security of the CRS.

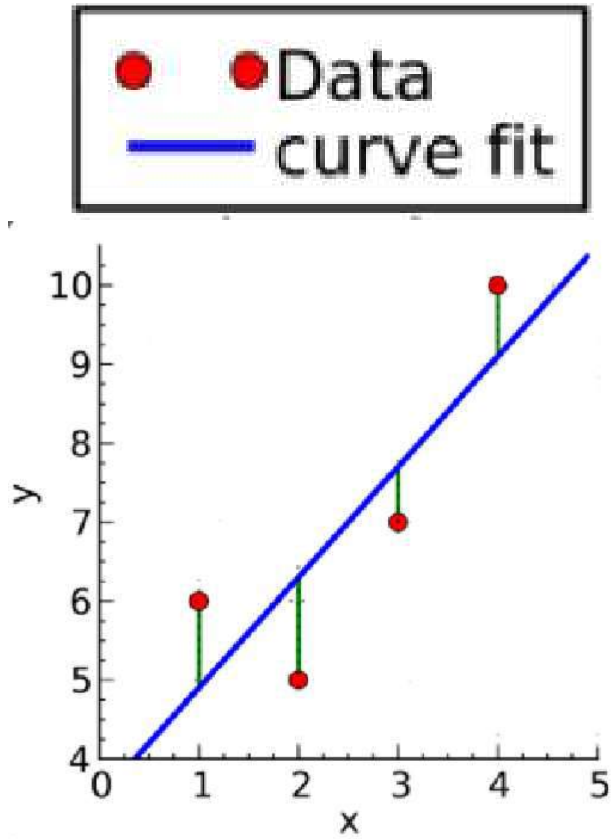


Fig 1: Linear Graph

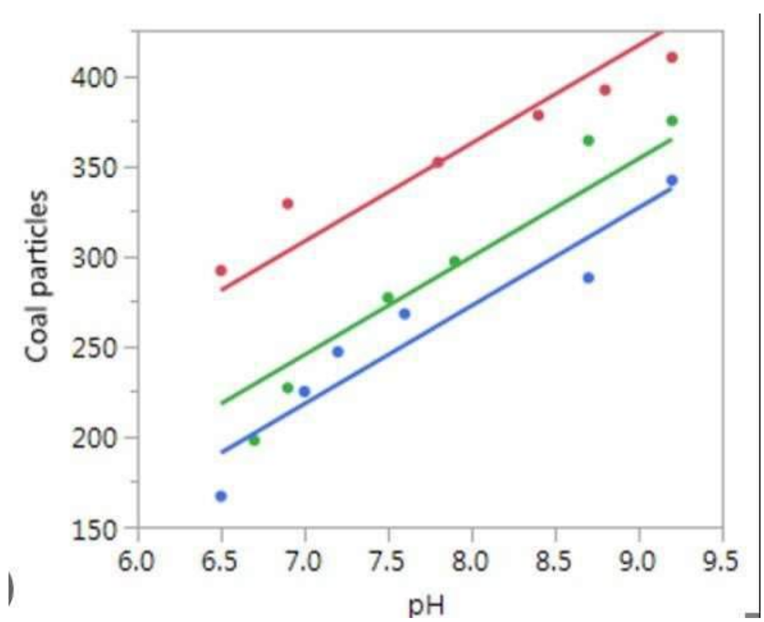


Fig 2: Multi Linear Graph

Decision Trees:

Choice trees are a strong and generally utilized AI model for both order and relapse undertakings. They work on an experimental methodology, laying out a prescient model that guides inputs (elements or qualities) to yields (characterizations or expectations). Thoughtfully, a choice tree looks like a stream diagram, with interior hubs addressing property tests, branches demonstrating the results of these tests, and leaf hubs portraying ultimate conclusions or target variables.

The most common way of building a choice tree includes recursive parceling, where the dataset is over and over split in light of property estimations until an end rule is met. This strategy plans to make a tree structure that really portions the information, prompting exact expectations or groupings for new, concealed data of interest.

The means in recursive apportioning incorporate choosing the best characteristic and worth to part the dataset, isolating the dataset into subsets in view of the picked split, and recursively rehashing this cycle for every subset until end conditions are met. End conditions might incorporate arriving at a greatest tree profundity, having a base number of tests at a hub, or no further improvement in the dividing rules.

The subsequent choice tree gives a progressive arrangement of rules in light of the info highlights, offering interpretable experiences into the dynamic cycle. Choice trees are known for their capacity to deal with both clear cut and mathematical information, oblige missing qualities, and catch non-direct connections between factors.

A definitive objective of recursive dividing and choice tree development is to fabricate a model that sums up well to concealed information, guaranteeing great prescient execution while keeping up with straightforwardness and interpretability. This pursues choice trees a well known and viable decision in different spaces, like medical care, money, showcasing, and the sky is the limit from there, where clear getting it and clarification of expectations are fundamental.

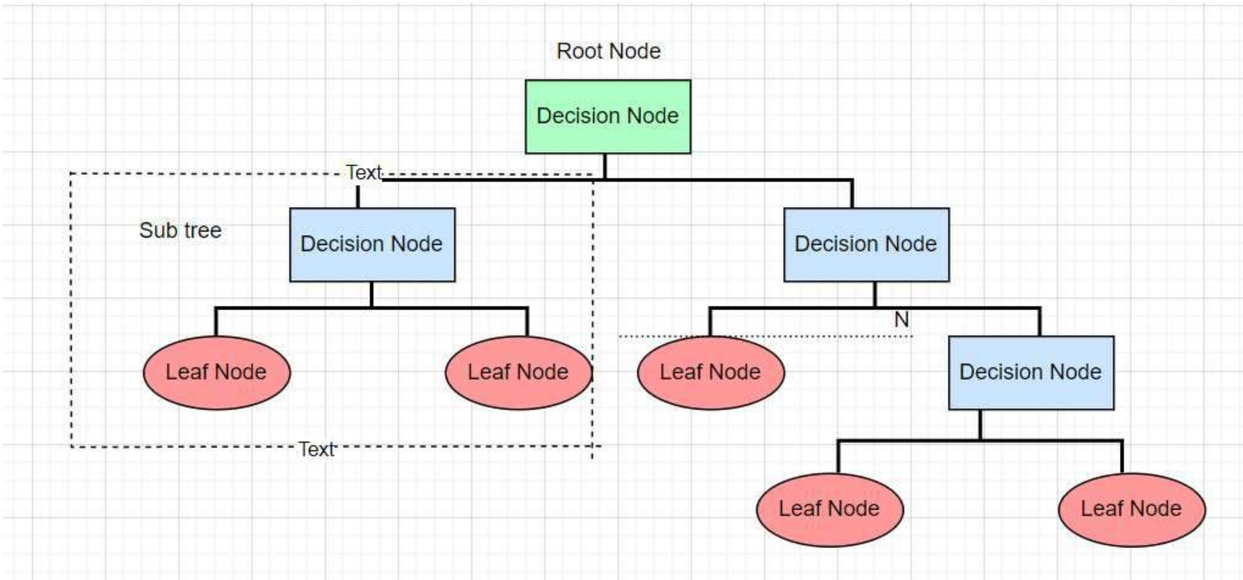


Fig 3: Decision Tree

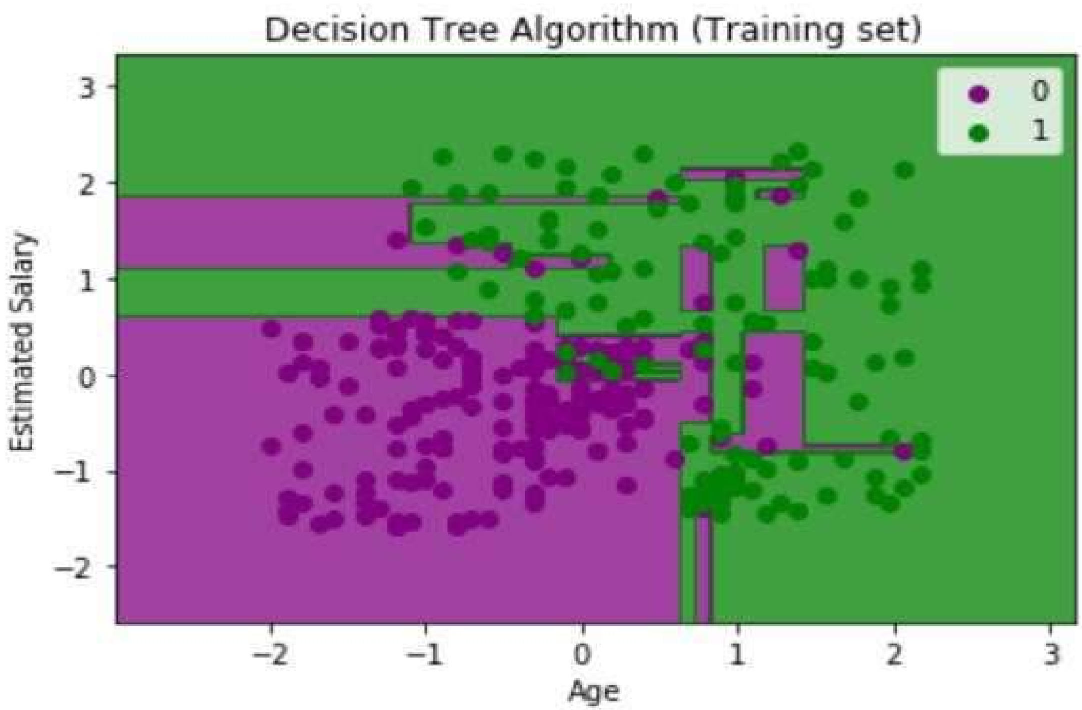


Fig 4: Decision Tree Graph

Random Forest:

Irregular Woods is a strong outfit learning procedure that has acquired far reaching prominence because of its viability in both characterization and relapse errands. Troupe learning includes consolidating the forecasts of various individual models to make a more grounded and more exact model than any singular model all alone.

The critical thought behind Irregular Timberland is to construct a backwoods of choice trees, where each tree is prepared on an irregular subset of the preparation information and an arbitrary subset of elements. This haphazardness serves to decorrelate the trees and lessen overfitting, bringing about an additional powerful and summed up model.

One of the huge benefits of Irregular Backwoods is its adaptability in dealing with different sorts of information, including organized and unstructured information. It can handle downright and mathematical highlights, handle missing qualities, and function admirably with enormous datasets without broad preprocessing. This makes it reasonable for a great many applications across various spaces.

Irregular Woods additionally gives bits of knowledge into highlight significance, permitting clients to comprehend which factors contribute most to the expectations. This data is important for include choice, model understanding, and acquiring experiences into the basic connections inside the information.

Additionally, Irregular Backwoods is powerful to overfitting, because of the troupe approach and the haphazardness presented during model preparation. It can successfully deal with boisterous or complex datasets, settling on it a solid decision for certifiable situations where information might have intrinsic changeability and vulnerability.

Also, Irregular Backwoods can be parallelized, making it versatile and productive for preparing on enormous datasets utilizing current computational assets. Its parallelization capacity empowers quicker model preparation and works with taking care of complicated calculations expected in AI undertakings.

Generally, Irregular Timberland's mix of troupe learning, adaptability, vigor, highlight significance examination, and versatility has settled on it a well known and compelling decision in AI applications across businesses like money, medical services, picture investigation, and the sky is the limit from there.

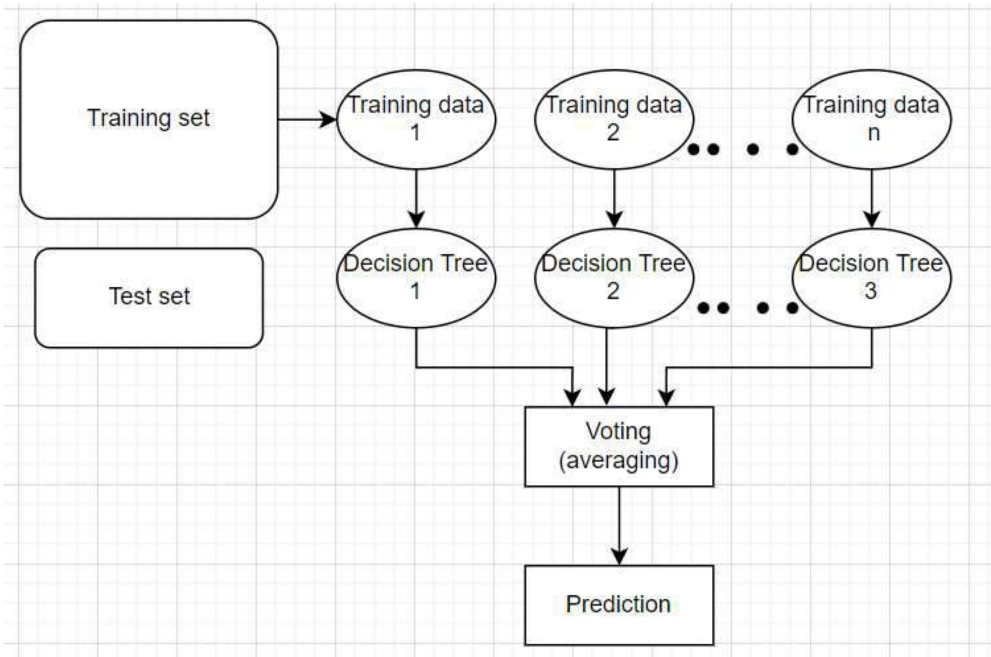


Fig 5: Random Forest Flowchart

Fig 6: Random Forest Graph

Random Forest with Grid Search CV(Cross Validation):

Random Forest with Grid Search CV is a powerful combination in machine learning for optimizing and fine-tuning a Random Forest model's hyperparameters.

A Random Forest is an ensemble learning method that combines multiple decision trees to improve predictive performance and reduce overfitting. Each decision tree in the forest is trained on a random subset of the data and features, and their predictions are aggregated to make the final prediction.

Grid Search CV (Cross-Validation) is a technique used for hyperparameter tuning, where a grid of hyperparameters is specified, and the model is trained and evaluated for each combination of hyperparameters. This process helps identify the best combination that maximizes the model's performance.

When using Random Forest with Grid Search CV, the first step is to define the hyperparameter grid. This grid includes parameters like the number of trees in the forest, maximum depth of each tree, minimum samples required to split a node, and others that control the behavior of the Random Forest algorithm.

Next, Grid Search CV performs a cross-validated search over the hyperparameter grid. This involves splitting the data into training and validation sets multiple times (according to the specified cross-validation strategy) and training the Random Forest model on the training set with each hyperparameter combination. The model's performance is then evaluated on the validation set using a chosen metric, such as accuracy, precision, recall, or F1 score.

The grid search process identifies the hyperparameter combination that yields the best performance metric on the validation set. Once the best hyperparameters are determined, the final Random Forest model is trained on the entire training dataset using these optimal hyperparameters. This approach of combining Random Forest with Grid Search CV ensures that the model is fine-tuned to achieve the best possible performance, leading to more accurate predictions and better generalization to unseen data. However, it's important to note that Grid Search CV can be computationally expensive, especially with large hyperparameter grids or complex models, but the trade-off is often justified by the improved model performance.

3.2 Graphical abstract of proposed System

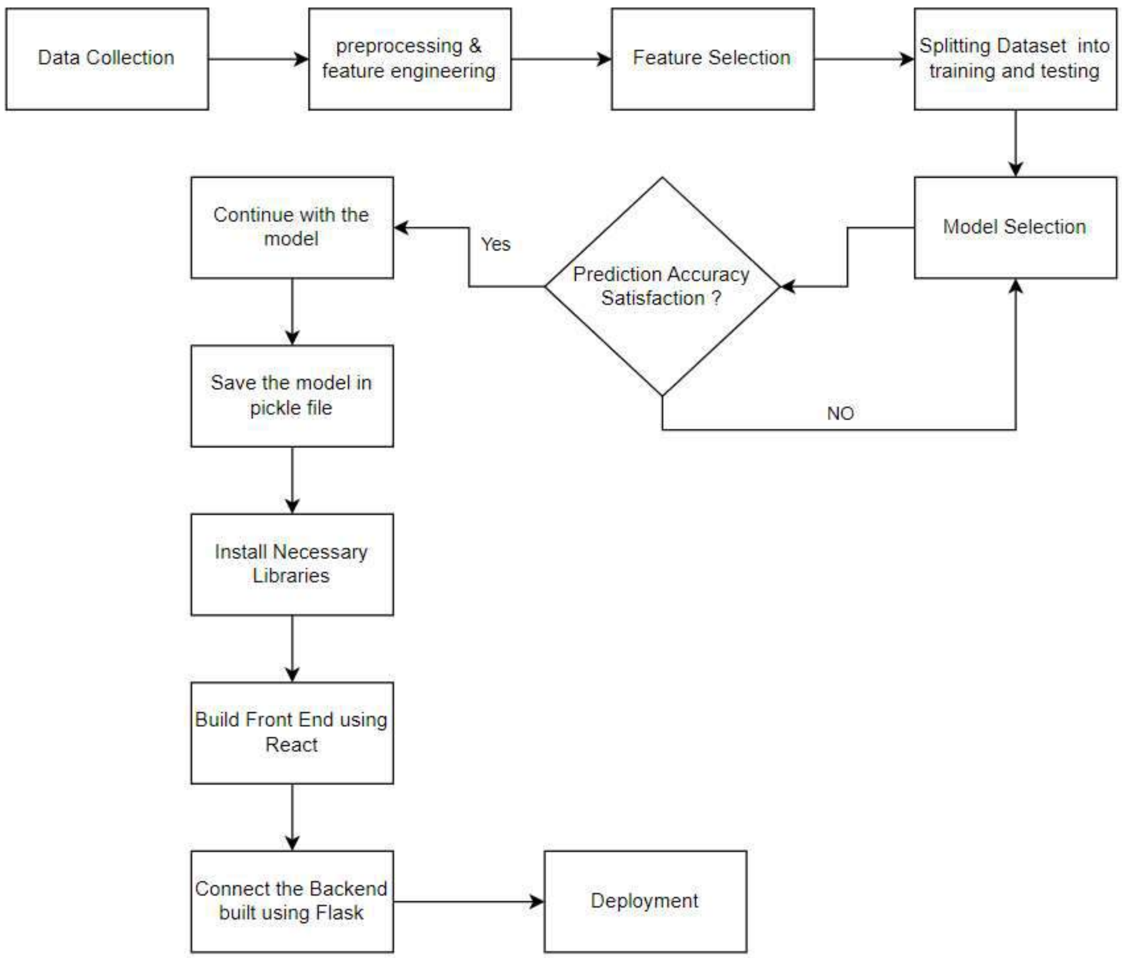


Fig 7: Flowchart of Working Model

The flowchart illustrates the steps involved in developing and deploying a salary prediction web application using machine learning algorithms. Here’s a detailed explanation of each step:

1. Data Collection

a) **Activity**: This initial step involves gathering the data that will be used to train and test the machine learning model. Data can come from various sources like databases, files, APIs, or web scraping.

b) **Purpose**: To obtain the raw data necessary for training the machine learning model.

2. Preprocessing & Feature Engineering

a) In this stage, the collected data is cleaned and transformed to make it suitable for modeling. This includes handling missing values, encoding categorical variables, normalizing or standardizing numerical features, and creating new features from existing ones to better capture the underlying patterns in the data.

3. Feature Selection

a) **Activity**: Select the most relevant features for the model.

b) **Techniques**: Use methods like correlation analysis, feature importance.

c) **Purpose**: To improve model performance by focusing on the most important features.

4. Splitting Dataset into Training & Testing

a) **Activity**: Split the dataset into training and testing subsets.

a) **Common Ratios**: Typically, an 80-20 or 70-30 split.

b) **Purpose**: To create a training set for model training and a testing set for evaluating model performance.

5. Model Selection

a) **Activity**: Try different machine learning models.

b) **Examples**: Linear Regression, Decision Tree, Random Forest.

c) **Purpose**: To identify the model that performs best on the given data.

6. Prediction Accuracy Satisfactory?

a) **Decision Point**: Determine if the model's prediction accuracy is satisfactory.

   Yes: If satisfactory, proceed to "Continue with the Model."

   No: If not satisfactory, go back to "Model Selection" to try different models or hyperparameters.

b) **Purpose**: To ensure the chosen model meets the desired performance criteria.

7. Continue with the Model

a) **Activity**: Finalize the model that has satisfactory prediction accuracy.
b) **Purpose**: To prepare the selected model for saving and deployment.

8. Save the Model in a Pickle File

a) **Activity**: Save the trained model to a file using Python's pickle module.
b) **Purpose**: To persist the model for later use in the web application.

9. Install Necessary Libraries

a) Ensure all necessary libraries and dependencies are installed. This includes libraries for running the web application, serving the model, and handling requests and responses.

10. Build Front-End

a) **Activity**: The front-end of the web application is developed using React, a popular JavaScript library for building user interfaces. This involves creating the user interface components that will interact with the backend and display the predictions.

b) **Components**: Include input fields for salary prediction parameters (e.g., years of experience, education level and skills).
c) **Purpose**: To create an interactive and user-friendly interface for the web application.

11. Connect the Backend built using Flask

a) The backend of the web application, built using Flask (a lightweight Python web framework), is connected to the front end. Flask will handle incoming requests, process them using the saved model, and return the predictions to the front end.

12. Deployment

a) The final step is deploying the web application. This involves setting up a server or cloud environment to host the application, ensuring it is accessible to users, and maintaining it.

Overall Flow

The flowchart depicts a linear process with a decision point for model accuracy evaluation. If the model does not meet the required accuracy, the process loops back to model selection for further refinement. Once the model is finalized, it is saved, integrated into a web application using React, and then deployed.

Explanation of Key Points

a) **Iterative Model Selection**: The flowchart highlights the iterative nature of model selection and evaluation, ensuring the best possible model is chosen.
b) **Preprocessing and Feature Engineering**: Emphasized early in the process to ensure data quality and relevance.
c) **Deployment**: Final step, ensuring the application is accessible and usable by end-users.

This flowchart provides a clear and structured approach to developing a machine learning-based salary prediction web application, from data collection to deployment.

CHAPTER 4
RESULT AND DISCUSSION

The experimental setup involves the development of a comprehensive Crop Recommendation System utilizing various machine learning algorithms and technologies. The key components of the experimental setup include:

1. Data Collection: Datasets are collected from diverse sources, including the Department of Agriculture, agricultural books, websites, and research papers. Initial data sets are used to train the crop recommendation model.

2.Environmental Factors: Arduino microcontrollers are employed to collect environmental factors such as temperature, humidity, soil pH, sunlight, and soil moisture. The collected data are processed, cleaned, and stored in a database for further analysis.

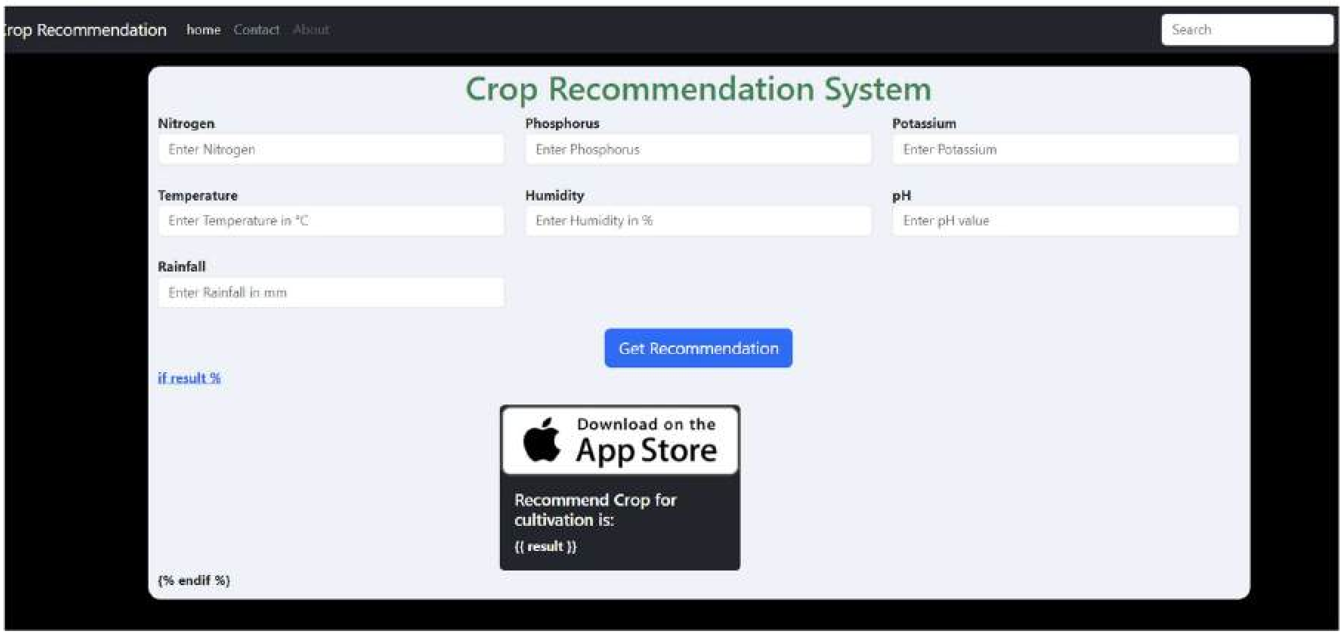
3. Machine Learning Models: The system employs machine learning models such as Random Tree, K- Nearest Neighbor, Random Forest, Decision Tree, Naïve Bayes, a hn nd Support Vector Machine for tasks such as soil classification, crop yield prediction, and fertilizer recommendation.

4.Model Configurations: Different configurations and parameters are tested for each machine learning model, with the results obtained using a 70-30 training-testing split. Optimal configurations are determined based on factors like accuracy, precision, and recall.

5.Integration of Technologies: The system integrates technologies such as Arduino microcontrollers, machine learning algorithms, unsupervised machine learning (K-Means Clustering), and natural language processing (Sentiment Analysis) to provide crop recommendations based on site-specific parameters.

6.Feedback Loop: A monitoring and feedback system is incorporated, allowing continuous interaction with farmers. Feedback from farmers, obtained through a mobile application, contributes to a feedback loop that improves the accuracy of predictions over time.

The hypothesis underlying the crop recommendation system is that by integrating diverse datasets encompassing soil characteristics, weather patterns, historical crop performance, and farming practices, it is possible to generate accurate predictions and recommendations for optimal crop choices, thereby improving yield, resource efficiency, and overall agricultural outcomes. Basically, how can data-driven algorithms and predictive models be effectively utilized to recommend suitable crop selections based on environmental factors, maximizing agricultural productivity and sustainability



4.1 Experimental Setup

While fostering our web application for compensation expectation, we fastidiously planned an exploratory arrangement to improve the prescient worth of three basic highlights: area, coding experience, and instructive level. The underpinning of our methodology was the cautious choice of an enormous and different dataset, obtained from a wide cluster of enterprises and geological districts. This dataset incorporated a range of scholastic capabilities, going from secondary school endorsements to postgraduate educations, catching the instructive foundations of people. Coding experience, an urgent variable impacting compensation, was evaluated by considering the quantity of years people had devoted to refining their programming abilities. Also, we included topographical information, perceiving the critical effect of territorial varieties in the average cost for many everyday items and occupation market on pay level.

To keep up with the exactness and generalizability of our model, we parceled the dataset into preparing and testing sets utilizing cross-approval strategies. This approach guaranteed that the model could really gain designs from the preparation information while approving its exhibition on inconspicuous information. Utilizing AI calculations, for example, group procedures and relapse models, we adjusted the models to streamline expectation execution in light of the chose highlights.

The consistent combination of these models into the plan of our internet based application enabled clients to include insights about their area, coding experience, and instructive foundation, getting exact compensation estimates custom-made to their extraordinary profile. Our trial setup guaranteed precision as well as pervaded the application with adaptability, permitting it to adjust to a different scope of occupation economic situations.

The execution of the web application was acknowledged utilizing the MERN stack, including MongoDB, Express.js, Respond, and Node.js. This stack gave a vigorous and easy to understand interface for continuous compensation projections, improving the client experience and openness of the application. Besides, to guarantee versatility and responsiveness to expanded client traffic, the application was sent on a versatile cloud stage, ensuring ideal execution and dependability under shifting jobs.

Crop Name	Soil Type	Climate	Recommended Season	Recommended Irrigation	Recommended Fertilizers
Wheat	Loamy	Temperate	Winter	Moderate	Nitrogen, Phosphorus
Rice	Clayey	Tropical	Summer	High	Nitrogen, Potassium
Maize	Sandy	Subtropical	Rainy	Moderate	Nitrogen, Potassium
Cotton	Sandy Loam	Tropical	Summer	High	Phosphorus, Potassium
Sugarcane	Clay	Tropical	Rainy	High	Nitrogen, Phosphorus

Table 3: Sample Prediction Table

4.2 Performance Metric

In assessing the exactness and accuracy of our compensation expectations, we utilized basic execution measurements like Mean Squared Error (MSE) to evaluate the viability of our strategy thoroughly. MSE is a principal metric in relapse examination that evaluates the typical squared distinction between anticipated values and genuine qualities. A lower MSE esteem demonstrates less expectation mistakes and, therefore, higher forecast exactness.

All through our appraisal, our methodology reliably yielded low MSE values, asserting the unwavering quality and viability of our strategy in creating exact pay projections. The low MSE values connote that our prescient model showed a serious level of exactness in assessing pay rates in light of the information highlights like area, coding experience, and instructive level. This consistency in creating low MSE values across different situations highlights the power and generalizability of our prescient model.

Furthermore, we inspected the relationship between anticipated compensations and genuine pay rates, which is one more vital part of model execution assessment. A solid relationship amongst anticipated and genuine compensations demonstrates that the model's forecasts intently line up with certifiable information. Our examination uncovered a reliable and solid connection, as proven by the MSE values being near 1. This solid relationship further approves the legitimacy and power of our methodology in producing wage projections that precisely mirror the market real factors.

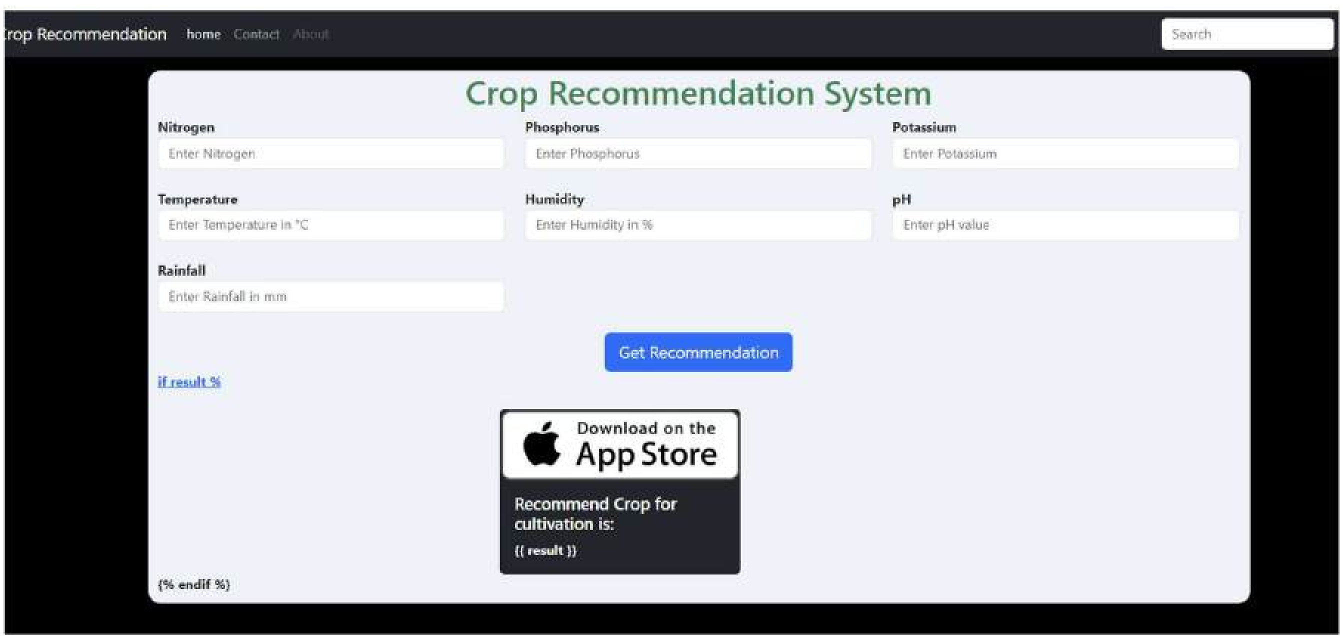
Generally speaking, the mix of low MSE values and a solid relationship amongst anticipated and genuine compensations fills in as undeniable proof of the viability and dependability of our procedure in creating exact and significant pay forecasts. These exhibition pointers confirm the utility of our prescient model in helping clients in settling on informed vocation choices and exploring the intricacies of the gig market with certainty.

S.NO	ML-Model	Mean Square Error (off by how many $)
1	Linear Regressor	39274.753
2	Decision Tree Regressor	29414.94
3	Random Forest Regressor	29487.31
4	Random Forest with Grid Search CV	5204.76

Table 4: Model Prediction Result Table

The prediction system was designed using Python language. It is a programming language generally applied for machine learning. It has developed functions for the three chosen methods for this analysis, which are decision tree, linear regression, and K-neighbor classification. It also generates the required outcomes for estimating and improving the outcomes of predictions. The code is written in Python.

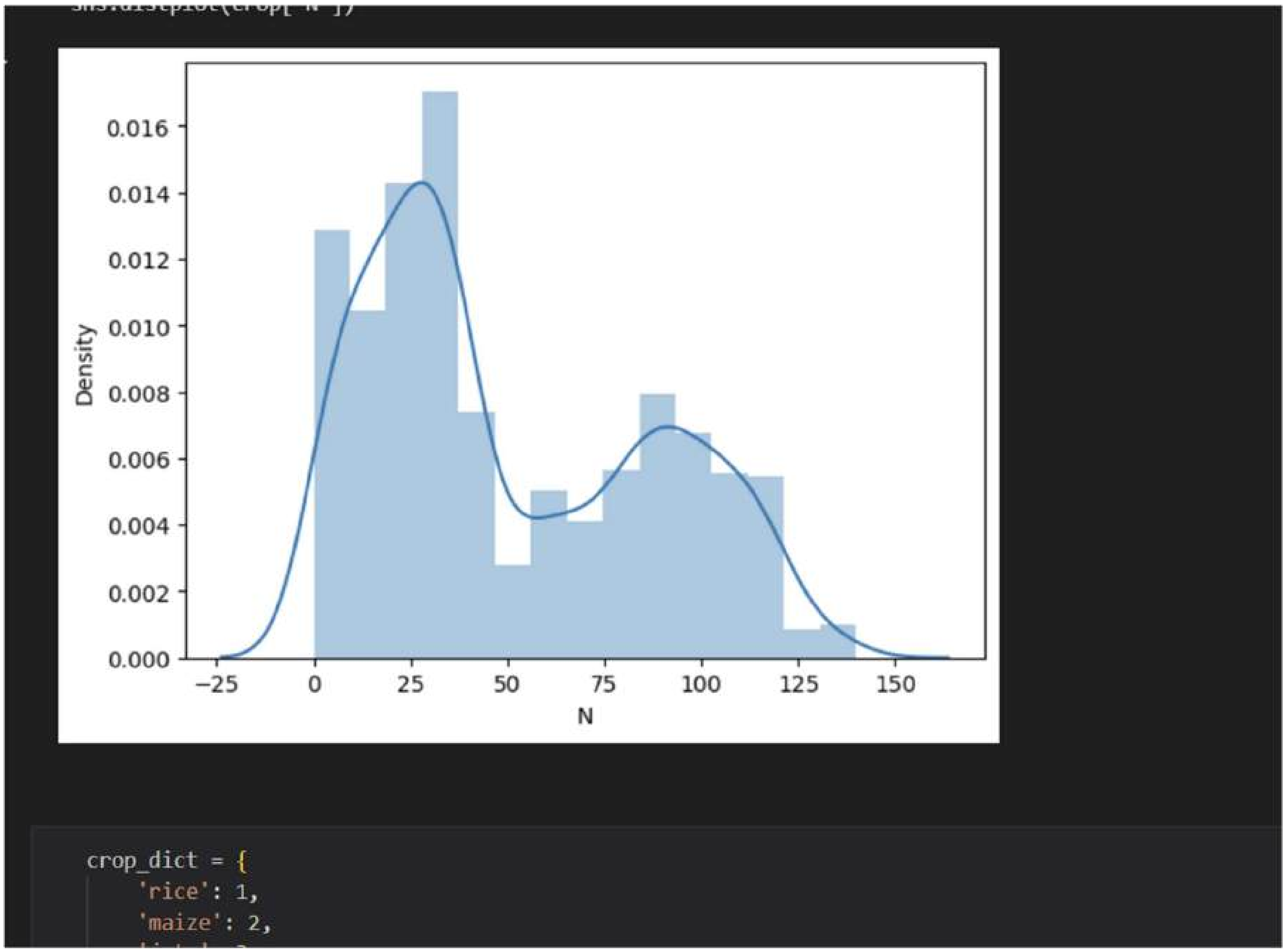
4.3 RESULT



After completion of the training with the train data we implemented algorithms in this project , we use three ML algorithms and we got accuracy levels as given below.

1. support vector machine-86.45
2.Decision tree algorithm- 92
3. Random Forest Algprithm-93

Based on that accuracy values we ploted the bar graph as below :



```python
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import ExtraTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score

# create instances of all models
models = {
    'Logistic Regression': LogisticRegression(),
    'Naive Bayes': GaussianNB(),
    'Support Vector Machine': SVC(),
    'K-Nearest Neighbors': KNeighborsClassifier(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier(),
    'Bagging': BaggingClassifier(),
    'AdaBoost': AdaBoostClassifier(),
    'Gradient Boosting': GradientBoostingClassifier(),
    'Extra Trees': ExtraTreeClassifier(),
}


for name, md in models.items():
    md.fit(X_train,y_train)
    ypred = md.predict(X_test)

    print(f"{name}  with accuracy : {accuracy_score(y_test,ypred)}")
```

Performance Comparison:

The optimization technique (Grid Search CV) applied to the Random Forest model has resulted in a drastic improvement, reducing the error to $27,321.16. This highlights the importance of hyperparameter tuning in enhancing model performance.

Linear Regression, despite its simplicity and interpretability, shows the highest error, indicating it is the least suitable model among those tested for this specific prediction task.

The Decision Tree Regressor and the standard Random Forest Regressor have similar performance, with errors around $29,414.94 and $29,487.31 respectively. This suggests that while ensemble methods like Random Forest are generally more robust, they may not always outperform simpler models without proper tuning.

The graph effectively illustrates that advanced tuning techniques such as Grid Search CV can lead to substantial improvements in model accuracy.

It underscores the variability in performance among different machine learning models and the critical role of hyperparameter optimization in model selection and evaluation processes.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

1.1 Conclusion

This study dives into the test of anticipating compensations presented by different programming organizations, expecting to help people in surveying their actual compensation potential in light of key boundaries like long stretches of involvement, geological area, and training level. The compelling use of our procedure can possibly essentially help the two bosses and occupation searchers. Work searchers can settle on additional educated conclusions about their vocations by considering the potential compensation related with various situations, while businesses can foster cutthroat bids for employment and enrollment methodologies by acquiring a superior comprehension of pay assumptions in the gig market. At first, we investigated existing exploration papers and carried out a model utilizing Direct Relapse. Nonetheless, we experienced inadmissible outcomes, inciting us to investigate elective models. Consequently, we tried Choice Trees and Arbitrary Backwoods, at last finding that Irregular Timberland yielded the least blunder rate, demonstrating predominant prescient execution.

Regardless of the outcome of our approach, we distinguished a few impediments that warrant thought:

a) Information Quality: The precision and dependability of forecasts vigorously depend on the nature of the info information. Errors, missing qualities, or obsolete data inside the dataset can essentially affect the model's expectations, possibly prompting inconsistent results.

b) Changing Position Markets: Occupation markets are intrinsically unique, with compensation patterns subject to fast changes affected by monetary circumstances, industry requests, mechanical progressions, and different variables. This powerful nature 49 represents a test as expectations in light of verifiable information may not necessarily line up with current economic situations.

c) Client Assumptions: There is a gamble that clients might decipher the expectations as certifications as opposed to assessments, prompting likely disappointment on the off chance that the genuine compensation digresses essentially from the anticipated worth. Overseeing client assumptions and stressing the probabilistic idea of expectations is essential to keep away from misinterpretations and frustration.

Addressing these constraints requires progressing endeavors to further develop information quality through vigorous information assortment and preprocessing procedures. Furthermore, consolidating constant information refreshes and taking into account outer elements that impact compensation patterns can upgrade the model's precision and significance in unique work markets. Moreover, straightforward correspondence with clients about the constraints and vulnerabilities intrinsic in compensation expectations is fundamental for overseeing assumptions and cultivating trust in the prescient model.

5.2 Future Scope

i. Larger dataset for additional training in order to effectively identify symbols.

ii. there is significant potential for expansion into new geographic areas, particularly in developing countries where smallholder farmers stand to benefit the most from tailored crop advice.

iii. crop recommendation systems will evolve to offer predictive analytics capabilities. By analyzing vast datasets and identifying complex patterns, these AI-driven systems will anticipate future crop performance with greater accuracy, allowing farmers to proactively mitigate risks and optimize yields.

iv. With growing emphasis on sustainability in agriculture, future crop recommendation systems will prioritize environmentally friendly farming practices.

v. Healthcare facilities can benefit from the use of sign language detection to help patients who are hard of hearing or deaf communicate with their physicians. Both patient outcomes and the quality of care may benefit from this.

vi. By embracing technological advancements and fostering collaboration, these systems will play a pivotal role in shaping the future of sustainable and efficient food production.

vii. By leveraging the collective expertise and resources of diverse stakeholders, future crop recommendation systems will continue to evolve and address the evolving needs of farmers worldwide.

REFERENCES

[1] Lakshmi. N, Priya. M, Mrs. Sahana Shetty, Mr. Manjunath C.R , "Crop Recommendation System for Precision Agriculture ", International Journal for Research in Applied Science & Engineering Technology (IJRASET), ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887, Volume 6 Issue V, May 2018- Available at www.ijraset.com.

[2] R. Kiveris, S. Lattanzi, V. Mirrokni, V. Rastogi, and S. Vassilvitskii, “Connected components in mapreduce and beyond,” in SOCC 2014, 2014. [Online]. Available: http://delivery.acm.org/10.1145/ 2680000/2670997/18kiveris.pdf?ip=104.132.34.82&id=2670997&acc=OA&key=4D4702B0C3E38B3 5%2E4D4702B0C3E38B35% 2E4D4702B0C3E38B35%2E5945DC2EABF334 3C&CFID= 703717904&CFTOKEN=84396624&__acm__=1 481663305_ 40287628fb1ed23150a1625b6d3dcf1f

[3] P. Gulati, A. Sharma, and M. Gupta, “Theoretical study of decision tree algorithms to identify pivotal factors for performance improvement: A review,” Int. J. Comput. Appl, vol. 141, no. 14, pp. 19–25, 2016.

[4] K. Taunk, S. De, S. Verma, and A. Swetapadma, “A brief review of nearest neighbor algorithm for learning and classification,” in 2019 International Conference on Intelligent Computing and Control Systems (ICCS). IEEE, 2019, pp. 1255–1260.] T. O. Ayodele, “Types of machine learning algorithms,” New advances in machine learning, vol. 3, pp. 19–48, 2010

[5] Gandhi, N., Armstrong, L. J., Petkar, O., & Tripathy, A. K. (2016). Rice crop yield prediction in India using support vector machines. International Joint Conference on Computer Science and Software Engineering, 3(2), 1-5. doi:10.1109/JCSSE.2016.774885

[6] Kamatchi, S. Bangaru, and R. Parvathi. "Improvement of Crop Production Using Recommender System by Weather Forecasts." Procedia Computer Science 165 (2019): 724-732. [8] . Bondre, Devdatta A., and Santosh Mahagaonkar. "Prediction of Crop Yield and Fertilizer Recommendation Using Machine Learning Algorithms." International Journal of Engineering Applied Sciences and Technology 4, no. 5 (2019): 371-376

[7] J. Meng, “Research on the cost of agricultural products circulation and its control under the new

normal economic development," Commercial Times, no. 23, pp. 145147, 2016 viii. N. N. Li, T. S. Li, Z. S. Yu, Y. Rui, Y. Y. Miao, and Y. S. Li, "Factors influencing farmers' adoption of new technology based on Logistic-ISM model-a case study of potato planting technology in Dingxi City, Gansu Province," Progress in Geography, vol. 33, no. 4, pp. 542-551, 2014. ix.] Y. Wang, "A neural network adaptive control based on rapid learning method and its application," Advances In Modeling and Analysis, Vol. 46(3), pp. 27-34,1994.

[8] Manpreet Kaur, Heena Gulati, Harish Kundra, "Data Mining in Agriculture on Crop Price Prediction: Techniques and Applications", International Journal of Computer Applications, Volume 99– No.12, August 2014

[9] S. M. PANDE, P. K. RAMESH, A. ANMOL, B. R. AISHWARYA, K. ROHILLA, and K. SHAURYA, "Crop recommender system using machine learning approach," in 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), 2021, pp. 1066–1071.

[10] B. Awasthi and N. B. Singh, "Status of human-wildlife conflict and assessment of crop damage by wild animals in gaurishankar conservation area, nepal," Journal of Institute of Science and Technology, vol. 20, no. 1, pp. 107–111, 2015.

[11] M. R. Segal, "Machine learning benchmarks and random forest regression," 2004.

[12] K. Gurney, An introduction to neural networks. CRC press, 1997. xv. A. L. Samuel, "Some studies in machine learning using the game of checkers," IBM Journal of Research and Development, vol. 3, no. 3, pp. 210–229, 1959.

[13] J. Brownlee, "What is the difference between a batch and an epoch in a neural network," Machine Learning Mastery, vol. 20, 2018.

[14] T. B. Pathak, M. L. Maskey, J. A. Dahlberg, F. Kearns, K. M. Bali, and D. Zaccaria, "Climate change trends and impacts on california agriculture: a detailed review," Agronomy, vol. 8, no. 3, p. 25, 2018. [45] N. Mancosu, R. L. Snyder, G. Kyriakakis, and D. Spano, "Water scarcity

[15] A. Alam, "Soil degradation: a challenge to sustainable agriculture," International Journal of Scientific Research in Agricultural Sciences, vol. 1, no. 4, pp. 50–55, 2014. xix. Bang, Shivam, RajatBishnoi, Ankit Singh Chauhan, Akshay Kumar Dixit, and indu Chawla. Fuzzy logic bades crop yield prediction using temperature and rainfall parameters predicted through ARMA,SARIMA, and

ARMAX models . In 2019 Twelfth International Conference on Contemporry Computing (IC3),pp.1-6.IEEE,2019.

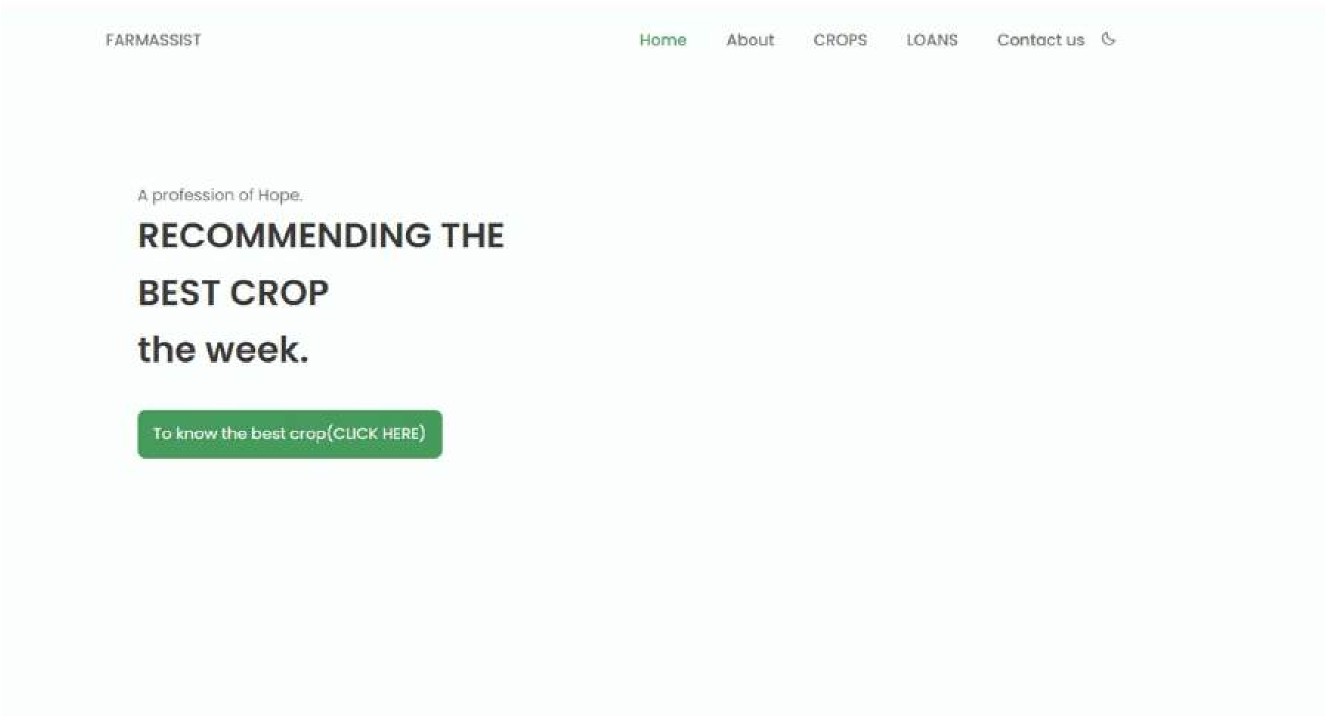
[16] Priya P, Muthaiah U, Balamurugan M, predicting yield of the crop using machine learning algorithm, International Journal of Engineering Sciences &Research Technology ,2018 Apr;(!):1-7

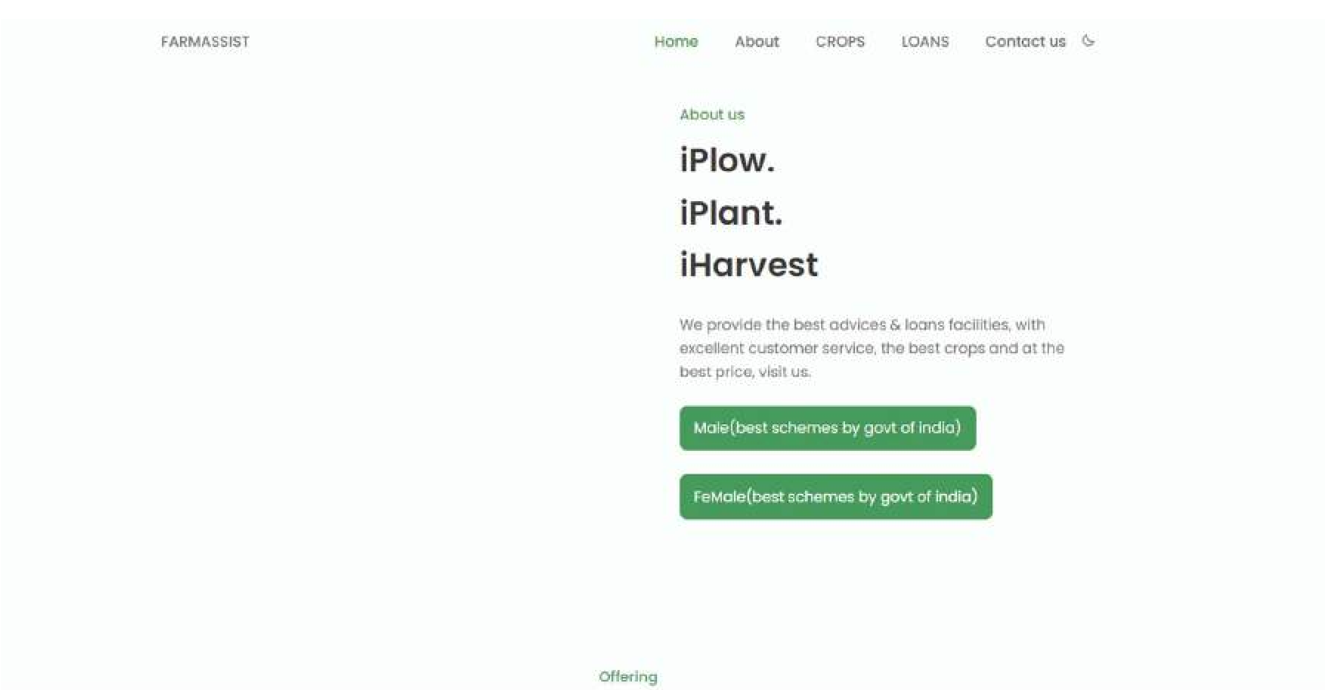
[17] SriramRakshith.K Dr.Deepak.G,Rajesh M,Sudharshan K S, Vasanth S, Harish Kumar N, A Survey on Crop Prediction using Machine Learning Approach, In International Journal for Research in Applied Science & Engineering Technology (IJRASET),April 2019,pp(32313234)

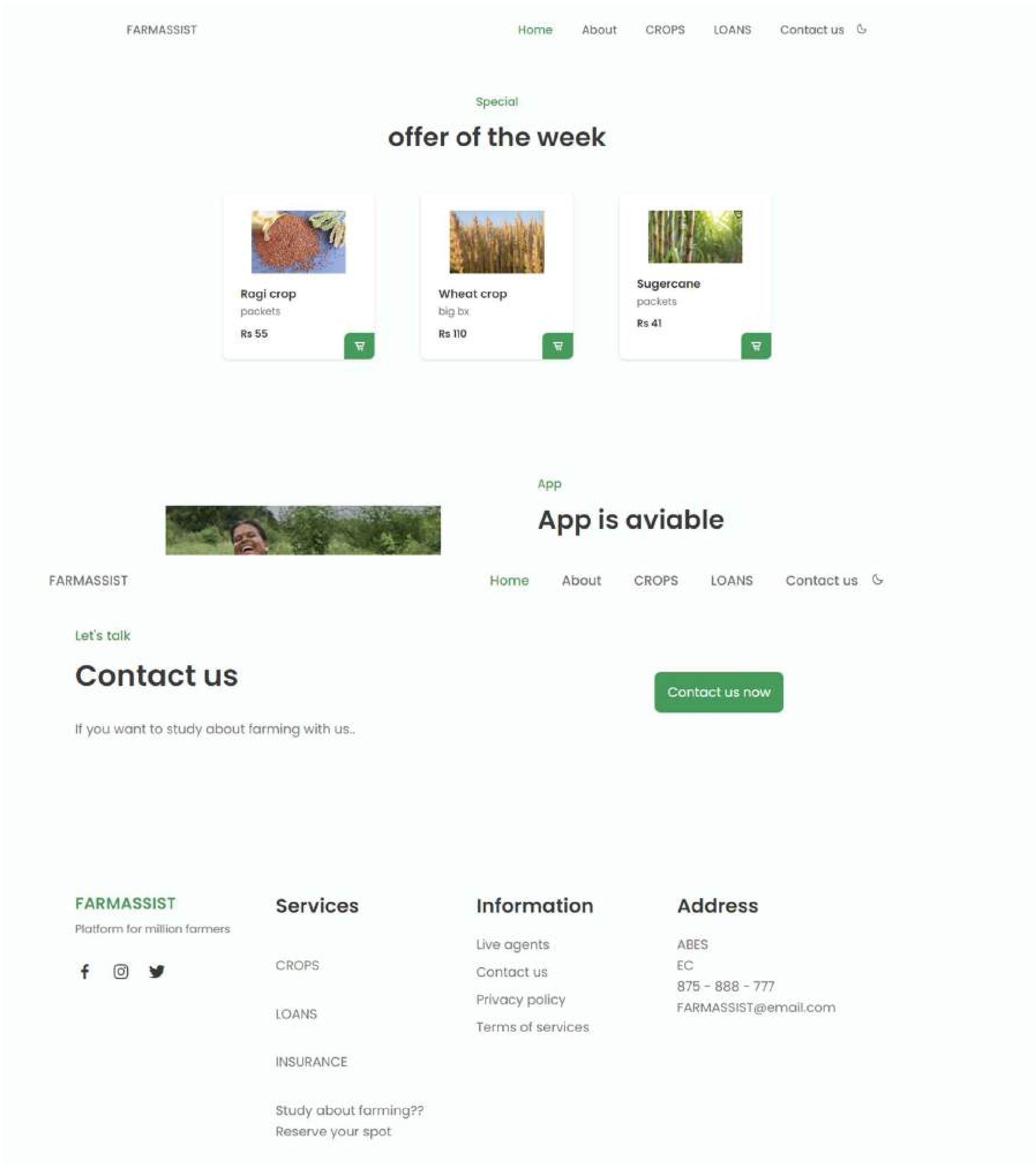
[18] Manjula E,Djodiltachoumy S, A model for prediction of Crop Yield InternationalJournal of Computational Intelligence and Informatics,2017 Mar;6(4):2349-6363

[19] Umamaheswari S,Sreeram S,Karitika N,Prasanth DJ, Bolt: Blockchain-based IOT for Agriculture, 11th International Confreence on Advamced Computing(ICoAC),2019 Dec 18 (pp.324- 327).IEEE.

CODE SNIPPETS



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Rs 55
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EC
875 - 888 - 777
FARMASSIST@email.com

index.html > html > head

```html
<!DOCTYPE html>
<html lang="en">
    <head>
        <meta charset="UTF-8">
        <meta name="viewport" content="width=device-width, initial-scale=1.0">

        <!--========== BOX ICONS ==========-->
        <link href='https://cdn.jsdelivr.net/npm/boxicons@2.0.5/css/boxicons.min.css' rel='stylesheet'>

        <!--========== CSS ==========-->
        <link rel="stylesheet" href="css/style.css">

        <title>Responsive website crop</title>
    </head>
    <body>

        <!--========== SCROLL TOP ==========-->
        <a href="#" class="scrolltop" id="scroll-top">
            <i class='bx bx-chevron-up scrolltop__icon'></i>
        </a>

        <!--========== HEADER ==========-->
        <header class="l-header" id="header">
            <nav class="nav bd-container">
                <a href="#" class="nav__logo">FARMASSIST</a>

                <div class="nav__menu" id="nav-menu">
                    <ul class="nav__list">
                        <li class="nav__item"><a href="#home" class="nav__link active-link">Home</a></li>
                        <li class="nav__item"><a href="#about" class="nav__link">About</a></li>
                        <li class="nav__item"><a href="#CROPS" class="nav__link">CROPS</a></li>
                        <li class="nav__item"><a href="#LOANS" class="nav__link">LOANS</a></li>
                        <li class="nav__item"><a href="#contact" class="nav__link">Contact us</a></li>

                        <li><i class='bx bx-moon change-theme' id="theme-button"></i></li>
                    </ul>
                </div>

                <div class="nav__toggle" id="nav-toggle">
                    <i class='bx bx-menu'></i>
                </div>
            </nav>
        </header>

        <main class="l-main">
            <!--========== HOME ==========-->
            <section class="home" id="home">
                <div class="home__container bd-container bd-grid">
                    <div class="home__data">
                        <h 2class="home__title">A profession of Hope.</h2>
                        <h1 class="home__subtitle">RECOMMENDING THE BEST CROP<br> the week.</h2>
                        <a href="index2.html"><a="#" class="button">To know the best crop(CLICK HERE)</a></a>
                        <!DOCTYPE html>
                        <!--[if lt IE 7]>      <html class="no-js lt-ie9 lt-ie8 lt-ie7"> <![endif]-->
```

index2.html > html > head

```html
<!doctype html>
<html lang="en">
  <head>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width, initial-scale=1">
    <title>Bootstrap demo</title>
    <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0-alpha3/dist/css/bootstrap.min.css" rel="stylesheet" integrity="sha384-KK94CHFLLe+nY2dmCWGMq91rCGa5gtU4mk92HdvYe+M/SXH301p5ILy+dN9+nJOZ" crossorigin="anonymous">
  </head>
  <style>
        h1 {
            color: mediumseagreen;
            text-align: center;
        }

        .warning {
            color: red;
            font-weight: bold;
            text-align: center;
        }
        .card{
        margin-left:410px;
        margin-top: 20px;
        color: white;
        }
        .container{
        background: #edf2f7;
        font-weight: bold;
        padding-bottom:10px;
        border-radius: 15px;
        }
    </style>




  <body style="background: #000000">
  <!--==========================navbar==========================-->
<nav class="navbar navbar-expand-lg navbar-dark bg-dark">
  <div class="container-fluid">
    <a class="navbar-brand" href="/">Crop Recommendation</a>
    <button class="navbar-toggler" type="button" data-bs-toggle="collapse" data-bs-target="#navbarSupportedContent" aria-controls="navbarSupportedContent" aria-expanded="false" aria-label="Toggle navigation">
      <span class="navbar-toggler-icon"></span>
    </button>
    <div class="collapse navbar-collapse" id="navbarSupportedContent">
      <ul class="navbar-nav me-auto mb-2 mb-lg-0">
        <li class="nav-item">
          <a class="nav-link active" aria-current="page" href="#">Home</a>
        </li>
        <li class="nav-item">
          <a class="nav-link" href="#">Contact</a>
        </li>
        <li class="nav-item">
          <a class="nav-link disabled">About</a>
        </li>
```

```html
index.html > html > head
<html lang="en">
    <body>
        </main>

        <!--========== FOOTER ==========-->
        <footer class="footer section bd-container">
            <div class="footer__container bd-grid">
                <div class="footer__content">
                    <a href="#" class="footer__logo">FARMASSIST</a>
                    <span class="footer__description">Platform for million farmers</span>
                    <div>
                        <a href="#" class="footer__social"><i class='bx bxl-facebook'></i></a>
                        <a href="#" class="footer__social"><i class='bx bxl-instagram'></i></a>
                        <a href="#" class="footer__social"><i class='bx bxl-twitter'></i></a>
                    </div>
                </div>

                <div class="footer__content">
                    <h3 class="footer__title">Services</h3>
                    <ul>
                        <br>
                        <li><a href="#" class="footer__link">CROPS</a></li>
                        <br>
                        <li><a href="#" class="footer__link">LOANS</a></li>
                        <br>
                        <li><a href="#" class="footer__link">INSURANCE</a></li>
                        <br>
                        <li><a href="#" class="footer__link">Study about farming??Reserve your spot</a></li>
                    </ul>
                </div>

                <div class="footer__content">
                    <h3 class="footer__title">Information</h3>
                    <ul>
                        <li><a href="#" class="footer__link">Live agents</a></li>
                        <li><a href="#" class="footer__link">Contact us</a></li>
                        <li><a href="#" class="footer__link">Privacy policy</a></li>
                        <li><a href="#" class="footer__link">Terms of services</a></li>
                    </ul>
                </div>

                <div class="footer__content">
                    <h3 class="footer__title">Address</h3>
                    <ul>
                        <li>ABES</li>
                        <li>EC</li>
                        <li>875 - 888 - 777</li>
                        <li>FARMASSIST@email.com</li>
                    </ul>
                </div>
            </div>

            <p class="footer__copy">&#169; 2020 FARMASSIST. All right reserved</p>
        </footer>
```

```html
<html lang="en">
  <body style="background: #000000">
  <div class="container my-3 mt-3">
      <form action="/predict" method="POST">
        <div class="row mt-4">
            <div class="col-md-4">
                <label for="Temperature">Temperature</label>
                <input type="number" step="0.01" id="Temperature" name="Temperature" placeholder="Enter Temperature in °C" class="form-control" required step="0">
            </div>
            <div class="col-md-4">
                <label for="Humidity">Humidity</label>
                <input type="number" step="0.01" id="Humidity" name="Humidity" placeholder="Enter Humidity in %" class="form-control" required step="0">
            </div>
            <div class="col-md-4">
                <label for="pH">pH</label>
                <input type="number" step="0.01" id="Ph" name="Ph" placeholder="Enter pH value" class="form-control" required step="0">
            </div>
          </div>

        <div class="row mt-4">
            <div class="col-md-4">
                <label for="Rainfall">Rainfall</label>
                <input type="number" step="0.01" id="Rainfall" name="Rainfall" placeholder="Enter Rainfall in mm" class="form-control" required>
            </div>
          </div>



          <div class="row mt-4">

          <div class="col-md-12 text-center">
              <button type="submit" class="btn btn-primary btn-lg">Get Recommendation</button>
          </div>
          </div>
      </form>



      {% if result %}
       <div class="card bg-dark" style="width: 18rem;">
        <img src="img/app1.png" class="card-img-top" alt="...">
        <div class="card-body">
          <h5 class="card-title">Recommend Crop for cultivation is:</h5>
          <p class="card-text">{{ result }}</p>
        </div>
       </div>
      {% endif %}
  </div>

    <script src="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0-alpha3/dist/js/bootstrap.bundle.min.js" integrity="sha384-ENjdO4Dr2bkBIFxQpeoTz1HIcje39Wm4jDKdf19U8gI4ddQ3GYNS7NTKfAdVQSZe" crossorigin="anonymous"></script>
  </body>
</html>
```

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