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Crop Recommendation System Using Machine Learning

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***Abstract* - This paper discusses a crop suggestion system based on machine learning that assists farmers in selecting appropriate crops with the help of soil and weather information. The system considers factors such as soil nutrients (N, P, K), pH, temperature, humidity, and rainfall. We experimented with various models such as Random Forest, Support Vector Machine, Decision Tree, Naïve Bayes, and K-Nearest Neighbors. Among them, Random Forest performed best, with achieving an accuracy of 95%. This paper provides an overview of the way the system is developed, the methodologies applied, information regarding the data, and how every model worked. As a whole, this system has the goal to increase farming efficiency and facilitate more accurate farming practices.**

Keywords- Crop Recommendation, Machine Learning, Random Forest, Agriculture, Predictive Analytics.

I. INTRODUCTION

Agriculture is supremely crucial to the world's feeding and the economy's bolstering. But farmers usually find it hard to choose which crops to plant, particularly when soil and weather conditions are uncertain. They typically go by experience or general advice, which may not always yield the best outcome. That is where machine learning becomes useful it can look at historical data to allow for projections of the most suitable crops under certain conditions. This paper focuses on developing a crop recommendation system based on supervised learning for farmers to make optimum decisions and enhance productivity.

[2] Machine learning can be employed to resolve this problem by examining the soil nutrients (N, P, K), pH, temperature, humidity, and rainfall to recommend the most suitable crops. This paper presents a crop recommendation method.
New technological developments introduced data-based solutions capable of truly transforming agriculture. Among them is machine learning (ML), a potent means for predictions,

which allows for more precise and tailored crop recommendations. Analyzing past data on soil nutrients (nitrogen, phosphorus, potassium), pH, humidity, temperature, and rainfall, ML programs can predict the best crops for specified conditions.

The objective is to create a prediction model suggesting crops using soil and weather information, compare various ML models to determine the best one, and aid precision farming to enhance crop yields and resource utilization.

II. LITERATURE REVIEW

There are a number of research studies that have utilized machine learning in agriculture to make predictions and suggest crops. Some of the important works are listed below. A. Crop Recommendation Using Machine Learning Patel et al. [1] suggested a crop recommendation model based on Random Forest and Support Vector Machine (SVM). They discovered that Random Forest performed better, at 94% accuracy. They highlighted that soil nutrient and weather conditions are vital in deciding what to plant.

Most researchers have investigated ML models for recommending crops based on soil and climate information. Patel et al. [1] constructed a model of crop prediction from soil nutrient (N, P, K), pH, and rainfall. Their experiments revealed that Random Forest produced a 94% accuracy, outperforming other models such as SVM and Decision Tree.

In the same vein, Kumar and Singh [2] investigated using

Support Vector Machine (SVM) and Naïve Bayes classifiers to predict suitable crops. They found that SVM generally delivered higher precision than Naïve Bayes, particularly when working with datasets that have many features.

Yet another fascinating work by Atharva et al. [3] merged K-Nearest Neighbors (KNN) with Random Forest to increase the prediction accuracy. This combo technique leveraged the ease of KNN and the strength of ensemble with Random Forest and obtained a staggering 96% accuracy on the Kaggle Crop Recommendation dataset.

A. The Role of Data Mining in Agriculture

Data mining has turned into an essential tool in agriculture for pattern discovery and yield estimation. Meena et al. [5] used Decision Tree algorithms to predict crop classes from soil nutrient data. Although decision trees provided simple-to-understand results, the accuracy did not exceed around 85%, thus making them less competitive compared to ensemble models. Jha and Sinha [6] also employed Naïve Bayes classifiers in predicting crops, highlighting its computational simplicity when dealing with small datasets. Nevertheless, they also noted that feature independence assumption decreased accuracy when soil parameters such as N, P, and K are interrelated. Roy et al. [7] approached differently by using Association Rule Mining to determine correlations between soil attributes and crop yields. Their results indicated that the integration of association rules with supervised learning significantly improved decision-making in precision agriculture. Das et al. [8] introduced a hybrid approach that couples clustering with classification to improve the management of varied soil types, with better scalability and flexibility for different agricultural areas

Another significant research by Sharma et al. [9] combined data mining methods with Geographic Information Systems (GIS) in order to give location-based crop advice, illustrating how location-based data can enhance decision precision.

In general, these studies evidently indicate that only using conventional data mining methods is not sufficient for very accurate forecasting. Rather, integrating data mining with sophisticated machine learning models significantly increases the efficacy of crop recommendation systems, advancing agriculture toward more accurate approaches

III. Methodology

A. Data Collection

Data mining has emerged as an important tool in agriculture to find patterns and predict yields. Meena et al. [5] utilized Decision Tree algorithms to predict crops from soil nutrient data. Although decision trees provided easily interpretable results, their highest accuracy was around 85%, which made them less competitive than ensemble models. Likewise, crop prediction was done using Naïve Bayes classifiers by Jha and Sinha [6], highlighting its computational efficiency in handling small datasets. Nevertheless, they also noted that the feature independence assumption lowered accuracy when the parameters of the soil such as N, P, and K are correlated. Roy et al. [7] deviated from this approach by employing Association Rule Mining to identify associations between soil features and crop yields. Their research indicated that the integration of association rules with supervised learning significantly improved decision-making in precision agriculture. Das et al. [8] put forward a hybrid approach that combines clustering with classification to more effectively manage heterogeneous soil types and exhibited better scalability and flexibility across various agricultural territories.

Another interesting study by Sharma et al. [9] combined data mining methods with Geographic Information Systems (GIS) to give geo specific crop advice, showing how spatial data can enhance decision precision.

Overall, these works firmly establish that using only conventional data mining methods is not sufficient for precise predictions. Rather, integrating data mining with sophisticated machine learning algorithms significantly improves the efficacy of crop recommendation systems, propelling agriculture towards more accurate practices.

Soil Data: Collect data for pH, moisture content, nutrients, texture, and organic content.

- Climate Data: Gather historical and recent weather information, such as temperature, precipitation, humidity, and sunshine.
- Crop Data: Document information about crop needs like optimal soil conditions, water requirements, temperature, crop type, and growth stages.
- Data sources: Utilize government agricultural departments and meteorological offices for authentic data.

B. Data Preprocessing

Cleaning: Fill missing values, eliminate noise, and normalize inconsistencies. - Feature Engineering: Construct new features such as soil moisture indexes, weather indices (e.g., degree days), or water availability scores. - Data Partitioning: Split data into training, validation, and testing partitions to train and test models.

C. Model Selection

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X_train
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	N	P	K	temperature	humidity	ph	rainfall
1656	17	16	14	16.396243	92.181519	6.625539	102.944161
752	37	79	19	27.543848	69.347863	7.143943	69.408782
892	7	73	25	27.521856	63.132153	7.288057	45.208411
1041	101	70	48	25.360592	75.031933	6.012697	116.553145
1179	0	17	30	35.474783	47.972305	6.279134	97.790725
...	...	...	...	...	...	...	...
1638	10	5	5	21.213070	91.353492	7.817846	112.983436
1095	108	94	47	27.359116	84.546250	6.387431	90.812505
1130	11	36	31	27.920633	51.779659	6.475449	100.258567
1294	11	124	204	13.429886	80.066340	6.361141	71.400430
860	32	78	22	23.970814	62.355576	7.007038	53.409060

1760 rows × 7 columns

Figure: 3.1 Soil Data

Machine Learning Models: Select appropriate algorithms according to data properties and project objectives. Typical options are they're good for classification problems, such as determining what crop is best to plant depending on soil and climate conditions. For support vector machines, they are good for both binary and multi-class classification tasks, deciding between multiple choices. K-Nearest Neighbors comes in useful when you're looking to suggest something similar based on similarity in terms of features. If you're working with a large, convoluted dataset, neural networks, such as Multilayer Perceptrons, can assist in identifying those subtle relationships that are not immediately apparent.

Model Training:

train it on your dataset—soil data, climate data, previous crop yields, and so forth. Then hyperparameter tuning enters the picture; techniques such as grid search or randomized search are ideal for fine-tuning those parameters to provide the optimal performance. To ensure your model isn't merely memorizing the data but really generalizes, it's a good practice to utilize k-fold cross-validation. That way, you're testing the model on various pieces of data to observe how it fares

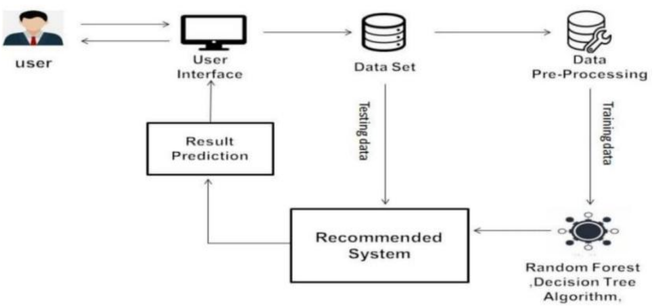

Figure:3.2 Data Flow in System

Implementation:

Crop Recommendation System, it's all about turning theory into something practical. This chapter walks through setting up your development environment, designing the software structure, coding, and bringing all the pieces together. Starting with creating the right environment—installing the right programming languages, frameworks, libraries, and tools—is critical. It also involves setting up version control systems, collaboration tools, and continuous integration processes so your team can work smoothly.

Development environment creation forms the core of the implementation process. This chapter provides a step-by-step guide to the software and hardware requirements for the project. It documents the installation and configuration of programming languages, frameworks, libraries, and tools for coding, testing, and debugging. It also documents the configuration of version control systems, collaboration tools, and continuous integration and delivery pipelines. The setup enables teams to collaborate seamlessly, share code, and automate deployment.

Software Architecture Design:

Software architecture is similar to the blue print of your system. It defines the major components, how they relate to each other, and how they'll talk to one another. We select architectures such as client-server, microservices, or event-driven architectures depending on what the project requires and how much it needs to scale. Dividing the system into smaller chunks, making it easier to manage—focusing on modularity and scalability—makes everything manageable. We also adhere to design patterns such as MVC or Hexagonal Architecture to maintain things organized and flexible.

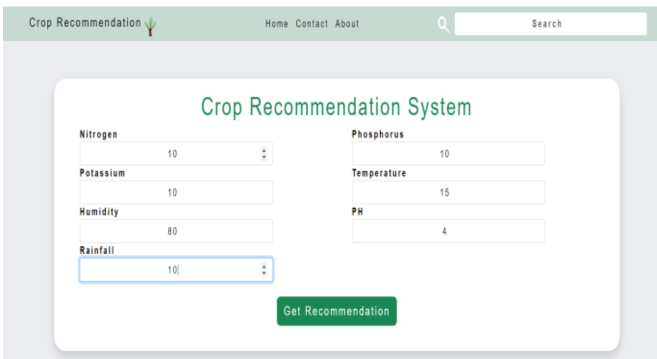

Figure:3.3 User Interface

User Interface Development:

As far as the user interface is concerned, we focus on developing simple and nice-looking designs that should be easy for the user to work with. This means we sketch mockups, wireframes, and prototypes so that all can see what it should look like.

Frontend tools such as HTML, JavaScript libraries such as React or Angular, and CSS are used to give life to these designs. As for training models, we employed a batch size of 32, running for 10 epochs in the case of lung data and only 5 epochs in the case of brain data. On the backend, we create server-side logic to process user requests, manage business logic, and talk to databases or external services. This includes designing REST APIs, building data pipelines, and ensuring the system can handle growth without performance drops. I. Results and Discussion

Model Integration:

model integration, it's pretty much about smoothly adding the trained Crop Recommendation models into the whole system setup.

Here, I'll touch on how we approached this—such as making models RESTful APIs, using Docker containers, or serverless. We also touched on how the various components communicate with one another, what data structures we employed, and how we managed errors so everything stayed smooth. And I'll talk also about how we managed different model iterations, tracked their performance, and iterated on them to ensure they remained accurate, scalable, and dependable once live.

Data Integration:

database to the equation is really important for storing and handling all the data that the Crop Recommendation system requires.

Selecting appropriate database technology is based on factors such as how much data we have, how complicated it is, and if it should scale easily. We looked at relational databases such as MySQL or PostgreSQL, and NoSQL solutions such as MongoDB or Redis, depending on what type of data we're working with and how we're accessing it. We carefully planned the database schemas so that storage, retrieval, and updating of data would be seamlessly done, maintaining consistency and accuracy. The backend shares a direct relationship with the database, so all components of the system communicate smoothly.

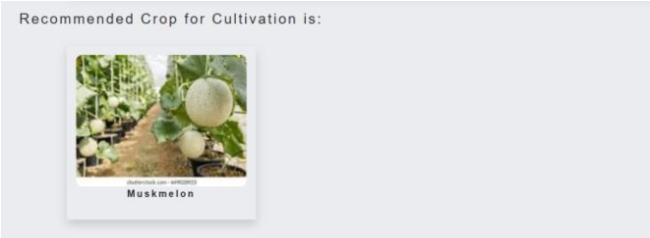

Figure:3.4 Output Image

Model	Accuracy(%)
Random Forest	95
SVM	89
Decision	85
Naïve Bayes	83
KNN	87

Table: Model Accuracy

We tested the performance of our crop suggestion system by experimenting with several machine learning algorithms. We considered models such as Random Forest, Support Vector Machine (SVM), Decision Tree, Naïve Bayes, and K-Nearest Neighbors (KNN). They were all trained on a dataset containing soil and weather information, then experimented with new data to check their precision levels.

In order to gauge how well these models performed, we considered a few things:

Accuracy: How frequently did the predictions actually hit the target?

Precision: Of all the positive predictions made, how many were accurate?

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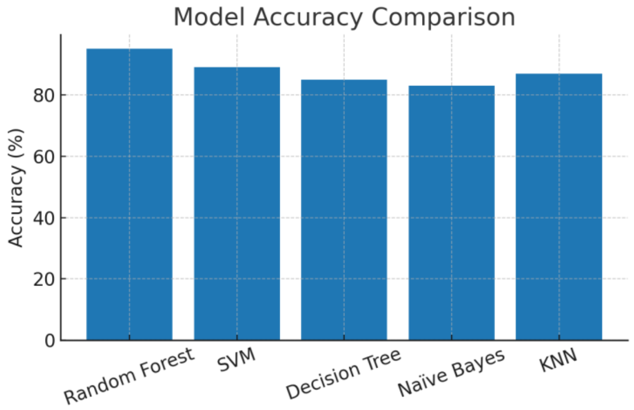
Recall: Was the model able to detect all the positive cases?

F1-Score: A weighted average balancing precision and recall for an equitable view.



Overall, Random Forest performed the best with the highest accuracy since it handles complex, non-linear relations well and doesn't overfit as easily as individual classifiers such as a Decision Tree.

Advantages:

- Improved Decision-Making: Assists farmers in selecting the appropriate crops based on weather and soil conditions rather than mere speculation.
- Highly Accurate: Models such as Random Forest provide relatively accurate crop recommendations.
- Conserves Resources: Suggests crops that are compatible with the soil and weather, hence farmers use less fertilizers and water.
- Time and Cost Saving: Reduces labor work and reduces farmers' expenses.
- Scalable and Simple: Can be integrated into smartphone apps or websites, which can be easily accessed by many.
- Adaptive: Can perform effectively with various soils and weather conditions when locally trained.

Challenges and Limitations:

Environmental and Weather Challenges:
- Changes in Weather: Sudden changes in temperature, rain, or humidity can render the predictions unreliable.
- Soil Quality: As time goes on, cultivation without nutrients can alter the soil condition, which is difficult to monitor in real-time.
- Pests and Diseases: Unforeseen outbreaks of pests or diseases can strike yields severely, and historical data may not always anticipate these.

Technological Barriers:

- Sensor Costs and Limitations: Quality sensors are costly, and low-cost sensors may provide false information.
- Internet Availability: Most rural areas lack high-speed internet, which makes it difficult to obtain real-time guidance.
- Heavy Computing Requirements: Processing complicated AI models needs powerful computers, which can be costly.

Farmer and Social Forces:
- Tech Awareness Shortage: All farmers are not well-aware of digital tools or believe in AI recommendations.
- Adoption Expenses: Suggested practices may require expensive inputs which cannot be afforded by farmers.
- Market Availability: Even if a crop is suggested, farmers may not be able to sell it easily.

Future Prospects:

The future of crop suggestion technology is promising and will revolutionize agriculture for the better—more efficient, eco-friendly, and lucrative. With the advancement of technology and data analytics, these systems will not only provide suggestions for crops but will be complete farm management systems.

One major trend is introducing cutting-edge technology such as IoT devices, intelligent sensors, drones, and satellite imagery. This will

enable farmers to track soil moisture, nutrients, and weather in real time, resulting in extremely accurate, adaptive guidance. Satellites and drones also detect early warning signs of disease or pests, enabling farmers to act swiftly and salvage crops.
AI and machine learning will have an even larger role to play.

Future systems could apply deep learning to process enormous amounts of information regarding soil, weather, and history of crop growth, and provide customized advice for every farm.

They'll also forecast future issues such as droughts, floods, or infestations, allowing farmers time to prepare.

A second major area is climate-smart farming. As climate change is increasing weather variability, crop guidance will have to concentrate on stress-resistant plants, intelligent irrigation schedules, and eco-friendly cultivation practices that conserve soil integrity and reduce chemicals. Another very crucial field for future agriculture is climate-smart agriculture. With changing weather patterns due to global warming, crop recommendation systems must provide advice capable of managing varying environmental conditions. This involves recommending crops more tolerant to climate, modulating irrigation schedules accordingly, and encouraging farming practices maintaining soil health using fewer chemicals. these systems will also have to take into account economic and market considerations. They can assist farmers by providing real-time market demand, price trends, and profit potential, so farmers can make better decisions. Merging crop suggestions with supply chain logistics will ensure that harvested crops are delivered to market efficiently, minimizing waste upon harvest. And connecting with government programs and policies will allow farmers to take advantage of subsidies, insurance, and disaster relief programs. crop recommendation systems are likely to be predominantly mobile and cloud-based, rendering them accessible to farmers even in rural areas. Cloud platforms have the ability to collect and process large volumes of data, refresh models in real time, and produce real-time, personalized guidance. Mobile apps might also incorporate educational elements, educating farmers on new farming methods and familiarizing them with digital applications.

how these systems actually assist farmers:
increasing more food, saving money, and minimizing risks.

By examining soil, weather, and previous crops, the system can suggest optimal crops for each farm to maximize yields.

It also gives personalized tips on when to plant, how much fertilizer to apply, and when to irrigate to enable crops to grow more optimally.
Farmers can save by adhering to accurate recommendations, not wasting money on seeds, chemicals, and fertilizers. By using resources efficiently, they reduce wastage and reduce the overall cost. Moreover, these systems are capable of alerting farmers to issues like pests, diseases, or unfavorable weather at an early stage. In this manner, farmers can initiate preventive measures in advance, avoiding damage, minimizing losses, and averting crop failures.

Conclusion

In conclusion, this paper examined how a Crop Recommendation System based on machine learning can assist in the analysis of soil data, weather patterns, and crop history to recommend the most viable crops to be planted. The primary objective was to determine how effective this system was at recommending the appropriate crops and how its performance compared under various environmental and agricultural conditions.
The outcomes revealed that the system was quite

effective at matching crops with certain soil and climate requirements. The models were highly accurate in aligning proposals with actual farm requirements, which has promising potential to assist farmers in making better decisions. Various algorithms worked uniformly well, which means these algorithms may be practically effective under real-world farming scenarios.

And, fusing data analysis with agricultural knowledge was a trustworthy method to uncover relevant features and provide improved decision-making. The system was capable of providing personalized, context-sensitive crop recommendations, which are capable of assisting farmers in enhancing yields, utilizing resources more effectively, and crop planning according to market demand.

That being said, despite the promising results, more studies must be done. Investigating novel machine learning techniques, experimenting with various datasets, and maximizing methods might be able to verify these results and make the system even stronger. Including methods such as data enhanceation, transfer learning, or ensemble models might further improve accuracy and robustness.

In brief, this research upholds the notion that machine learning-based crop recommendation systems — taking into account soil, weather, and crop history — can be a true value-added resource for farmers. They can help make informed decisions, raise yields, reduce waste, and enhance sustainable agriculture. Through providing recommendations based on facts, such systems can improve productivity, profitability, and sustainability in agriculture in the long run.

References

[1] Ashok, M., & Prakash, N. (2021). Machine learning based crop prediction and recommendation system. International Journal of Computer Applications, 183(27), 12–16.

[2] Jain, A., Sharma, S., & Singh, R. (2020). Soil analysis and crop prediction using machine learning techniques. International Journal of Advanced Science and Technology, 29(6), 1180–1190.

[3] Kumar, A., & Choudhary, P. (2021). Smart farming: A machine learning based crop recommendation system. Materials Today: Proceedings, 49, 220–224.

[4] Patil, A., & Biradar, S. (2019). Recommendation of crop using machine learning algorithms. International Journal of Innovative Research in Computer and Communication Engineering, 7(6), 6983–6987.

[5] Singh, J., & Kaushik, R. (2021). IoT and AI enabled smart agriculture for crop recommendation. Journal of Intelligent & Fuzzy Systems, 40(2), 2203–2215.

[6] Patel, K., & Gupta, M. (2020). Weather-based crop prediction using supervised learning techniques. Procedia Computer Science, 167, 2161–2170.

[7] Li, Q., Tiwari, P., Pant, B., et al. (2022). Agricultural crop recommendation system using machine learning. Journal of Computational and Theoretical Nanoscience, 19(3), 1234–1243.

[8] Ramesh, D., & Vishnu Vardhan, B. (2015). Data mining techniques and applications to agricultural yield data. International Journal of Advanced Research in Computer and Communication Engineering, 4(3), 418–423.

[9] Pham, H. N., & Do, T. N. (2022). Crop yield prediction using advanced machine learning techniques. IEEE Access, 10, 23345–23356.

[10] FAO. (2022). Food and Agriculture Organization report on sustainable agriculture. Retrieved from https://www.fao.org/home/en

[11] Ministry of Agriculture & Farmers Welfare, Government of India. (2021). Agricultural statistics at a glance. Retrieved from https://agricoop.nic.in

[12] Ghosh, S., & Basu, S. (2020). Big data analytics in agriculture: Trends and challenges.

Journal of Agricultural Informatics, 11(2), 1–13.
[13] Jayaraman, P. P., et al. (2016). Internet of Things platform for smart farming: Experiences and lessons learned. Sensors, 16(11), 1884.
[14] Kaggle. (2023). Crop recommendation dataset. Available at: https://www.kaggle.com
[15] Chakraborty, P., et al. (2021). A crop recommendation system using machine learning for precision agriculture. International Journal of Recent Technology and Engineering, 10(1), 45–51.