

Data-Driven Framework for Crop Categorization using Random Forest-Based Approach for Precision Farming Optimization

Adefemi Joshua Ayoola¹, Joe Essien², Martin Ogharandukun³, Felix Uloko⁴

^(1,2,4) Department of Computer Science, Veritas University, Abuja

⁽³⁾ Department of Pure and Applied Physics, Veritas University, Abuja

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ABSTRACT: *Making incorrect choices when selecting crops can result in substantial financial losses for farmers, primarily because of a limited understanding of the unique needs of each crop. Each farm possesses unique characteristics, influencing the effectiveness of modern agricultural solutions. Challenges persist in optimizing farming methods to maximize yield. This study aims to mitigate these issues by developing a data-driven crop classification and cultivation advisory system, leveraging machine learning algorithms and agricultural data. By analysing variables such as soil nutrient levels, temperature, humidity, pH, and rainfall, the system offers tailored recommendations for crop selection and cultivation practices. This approach optimizes resource utilization, enhances crop productivity, and promotes sustainable agriculture. The study emphasizes the importance of pre-processing data, such as handling missing values and normalizing features, to ensure reliable model training. Various machine learning models, including Random Forests, Bagging Classifier, and AdaBoost Classifier, were employed, demonstrating high accuracy rates in crop classification tasks. The integration of real-time weather data, market prices, and profitability analysis further refines decision-making, while a mobile application facilitates convenient access for farmers. By incorporating user feedback and continuous data collection, the system's performance can be continuously improved, offering precise and economically viable agricultural advice.*

KEYWORDS: random forest, machine learning, crop classification, cultivation advisory, precision farming.

INTRODUCTION

Erroneous crop selection is a prevalent issue among farmers, often resulting in significant crop losses. This problem arises due to a lack of understanding of the specific requirements of different crops in

terms of minerals, soil moisture, and other soil needs [1]. Consequently, farmers may unknowingly choose crops that are ill-suited to their land holdings, leading to mental and financial distress. Each farm possesses unique characteristics such as landscapes, soil compositions, available technology, and potential yields, all of which influence the effectiveness of modern agricultural solutions [2]. Furthermore, while irrigation has been identified as a key factor in improving agricultural production and increasing farmers' income, challenges persist in optimizing farming methods to match expenditure and maximize yield [3].

Crop production is intricately linked to various factors including yields, macroeconomic uncertainties, and consumption trends, all of which significantly influence the prices of agricultural commodities [3]. Traditionally, plants are cultivated using soil as the growing medium, which provides essential nutrients, water, anchorage, and air for plant growth. However, soil-based agriculture presents limitations such as unsuitable soil conditions, erosion leading to degradation, presence of pathogens and nematodes, poor drainage, and soil compaction, necessitating the adoption of soil-less techniques like hydroponics, where plants grow in nutrient-rich water solutions [2].

According to Wang [3], crop yield prediction plays a crucial role in the agriculture industry, aiding farmers in anticipating crop yields for better decision-making regarding planting and harvesting schedules. Predictive analytics emerges as a valuable tool in improving agricultural practices, offering insights into optimal crop management strategies [1]. Agriculture holds a central position in the Nigerian economy, serving as the primary source of livelihood for a majority of the population. However, due to prevalent losses in agriculture, many farmers are shifting away from farming towards other daily wage jobs. To mitigate these losses, it's imperative for farmers to employ precise methods for crop selection, planting, and harvesting [3]. By utilizing advanced predictive analytics techniques, farmers can make informed decisions that optimize crop yields, thereby safeguarding their livelihoods and promoting sustainable agricultural practices in Nigeria.

To address these issues, this study aims to provide recommendations for appropriate crops to be grown on specific plots of land during particular seasons, with the goal of enhancing farmers' harvests. The study's primary objectives are to improve farming practices in Nigeria by offering accurate and efficient data analysis, thereby generating quick results. Additionally, the work seeks to optimize resource utilization by recommending crops that align with the unique soil and climate conditions of the region. By focusing on tailored crop recommendations based on detailed land assessments, this study aims to mitigate the challenges faced by farmers and promote sustainable agricultural practices that contribute to increased productivity and economic stability in the farming community.

REVIEW OF LITERATURE

Crop yield prediction is a crucial aspect of national food security assessment and policymaking, essential for regulating agricultural cultivation systems and operational management [1]. Climate change poses direct and indirect challenges to crop production, influencing yields and requiring strategic interventions from agricultural departments to enhance productivity. The complexity of crop production is influenced by a myriad of factors including climatic, geographical, biological, political,

and economic variables, necessitating the application of appropriate mathematical or statistical methodologies to quantify associated risks and inform decision-making processes [4]. Statistical and crop models can serve as primary tools for analyzing the effects of climate change on crop yields, with a focus on biological mechanisms to improve productivity. Factors such as crop variety, seed type, and environmental parameters significantly impact crop yield outcomes, underscoring the importance of accurate yield estimation. Remote sensing applications play a crucial role in crop identification and yield prediction, aiding in agricultural management [4].

Various crop classification and cultivation advisory systems have been developed, utilizing computer vision, machine learning, and cloud computing technologies [5]. For instance, 'AgroMobile' integrates weather monitoring and crop analysis functionalities, providing real-time information on weather conditions and crop-specific requirements to farmers [6]. Additionally, systems like the 'Crop Recommendation System' [6] incorporate environmental factors to predict soil pH levels and recommend suitable crops, thereby optimizing resource utilization and reducing setup costs for farmers [5]. Innovative applications such as disease detection and soil analysis tools further enhance agricultural management. For instance, an Android application developed in Bangladesh employs image processing techniques to detect crop diseases, assess soil humidity, and determine fertilizer requirements based on leaf images [6].

The existing research gap in personalized advisory recommendations underscores the necessity for the development of a system capable of delivering tailored guidance to individual farmers, considering their unique soil type, crop history, and geographical location [1]. While current systems offer general recommendations based on environmental factors, the integration of personalized recommendations could significantly enhance the pertinence and efficacy of advisory services for farmers. For instance, Rodriguez [6] introduced the AgroMobile system, which furnishes real-time weather updates and crop suggestions based on environmental variables. However, the system lacks the capacity to incorporate specific soil types, crop histories, or geographical locations of individual farmers. Similarly, Kim [7] devised a crop recommendation system that considers environmental inputs but falls short of providing personalized recommendations tailored to soil type, crop history, or geographical location. Furthermore, Nguyen [8] proposed an Android application for disease detection in crops and fertilizer input estimation based on leaf images and soil types. However, the system does not offer personalized recommendations based on crop history or geographical location.

Hence, there exists a pressing need to develop a system that furnishes personalized advisory recommendations to individual farmers based on their distinct soil type, crop history, and geographical location [6]. Such customization could substantially enhance the pertinence and efficacy of recommendations, consequently fostering improvements in crop yields and farmer incomes [5]. Machine learning algorithms could be employed to generate personalized recommendations, leveraging historical data on crop yields, soil types, weather patterns, and real-time information on crop growth and environmental conditions [9]. Additionally, geographical information systems (GIS) could be integrated to provide location-specific recommendations, considering factors like soil type, topography, and climate [2]. By furnishing personalized guidance, the system could empower farmers to make well-

informed decisions regarding crop selection, planting schedules, irrigation practices, and fertilizer applications, ultimately leading to heightened productivity and profitability in agriculture [2].

METHODOLOGY

Machine learning is utilized in various computing tasks where designing explicit algorithms is challenging, including email filtering, network intrusion detection, and computer vision [10]. It intersects with computational statistics and mathematical optimization, leveraging methods for prediction and optimization [11]. Often confused with data mining, machine learning is distinct in its focus on prediction and supervised learning [4]. It plays a crucial role in data analytics, enabling the creation of complex models for predictive analytics [10]. By learning from historical data, machine learning facilitates reliable decision-making and reveals hidden insights.

This work implements a systematic machine learning process to exhaustively analyze and evaluate the effectiveness of various models for crop classification and recommendation in agriculture. It uses cutting-edge methodologies and techniques to highlight the strengths and weaknesses of machine learning-based systems for recommending suitable crops [12]. In machine learning, two primary types of training methods are commonly utilized to develop models: supervised learning and unsupervised learning [10]. Supervised learning involves training a model to learn a function that maps input data to output values based on labeled training examples. The algorithm analyzes these labeled examples to derive a function capable of accurately predicting output values for new, unseen instances [13]. The aim is for the model to generalize effectively from the training data, ensuring accurate predictions for previously unseen data points [11]. For this project, supervised learning was employed to develop models capable of making accurate predictions.

On the other hand, unsupervised learning focuses on inferring the structure of unlabeled data, where examples lack predefined categories or classifications [10]. Without labeled examples, the learning algorithm must deduce the underlying structure of the data based on inherent similarities or distances. Unlike supervised learning, there is no straightforward method to assess the accuracy of the structure produced by unsupervised learning algorithms [10]. Within supervised learning, two key methods are commonly employed: classification and regression [11]. Classification involves assigning new observations to predefined categories based on a training set of labeled data, while regression calculates the conditional expectation of the dependent variable given the independent variables [4]. Regression analysis is extensively used for forecasting, prediction, and investigating relationships between variables, although caution must be exercised to avoid inferring causality from correlation alone.

Random Forest Machine Learning Technique adopted in this work is a supervised machine learning technique utilized for both Classification and Regression tasks [4]. It employs ensemble learning, combining multiple decision trees to enhance model performance. By averaging predictions from numerous trees, Random Forest improves predictive accuracy [4]. Unlike single decision trees, which may overfit data, Random Forest aggregates predictions through majority voting, providing a robust and reliable method for generating final outputs [11]. The work adheres to Random Forest disciplined methodology, exploring data collection, preprocessing, model selection, training, evaluation, and

interpretation to offer insightful information about the field of agricultural recommendations. This research helps improve the efficiency and reliability of crop selection.

Dataset

The dataset used in this work is obtained from Kaggle [14]. The resource provides a vast repository of open datasets spanning various domains, offering data scientists the opportunity to explore, analyze, and collaborate on these datasets. The Kaggle dataset comprises soil specific attributes in addition, similar online sources of general crop data were also used (Figure 1). The crops considered in our model include rice, maize, chickpea, kidney beans, pigeon peas, moth beans, black gram, lentil, pomegranate, banana, mango, grapes, watermelon, muskmelon, apple, orange, papaya, coconut, cotton, jute, coffee gives an analysis of the dataset.

	A	B	C	D	E	F	G	H
1	N	P	K	temperature	humidity	ph	rainfall	label
2	90	42	43	20.8797437	82.0027442	6.502985292	202.935536	rice
3	85	58	41	21.7704617	80.3196441	7.03809636	226.655537	rice
4	60	55	44	23.0044592	82.3207629	7.84020714	263.964248	rice
5	74	35	40	26.4910964	80.1583626	6.98040091	242.864034	rice
6	78	42	42	20.1301748	81.6048729	7.62847289	262.717341	rice
7	69	37	42	23.0580487	83.3701177	7.0734535	251.055	rice
8	69	55	38	22.708838	82.6394139	5.70080568	271.32486	rice
9	94	53	40	20.2777436	82.8940862	5.718627177	241.974195	rice
10	89	54	38	24.5158807	83.53521629	6.68534642	230.446236	rice
11	68	58	38	23.2239739	83.0332269	6.33625353	221.209196	rice
12	91	53	40	26.5272351	81.4175385	5.38616779	264.61487	rice
13	90	46	42	23.9789822	81.450616	7.50283396	250.083234	rice
14	78	58	44	26.800796	80.8868482	5.10868179	284.436457	rice
15	93	56	36	24.0149762	82.0568718	6.98435366	185.277339	rice
16	94	50	37	25.6658521	80.6638505	6.94801983	209.586971	rice
17	60	48	39	24.2820942	80.3002559	7.042299068	231.086335	rice
18	85	38	41	21.5871178	82.7883708	6.249050656	276.6552458	rice
19	91	35	39	23.7939196	80.4181796	6.97085975	206.261186	rice

Figure 1. Crop Recommendation Dataset

The attributes considered where Nitrogen(N), Potassium(K), Phosphorus(P), Temperature, Humidity, Ph and Rainfall. Soil parameters such as nitrogen, phosphorus, and potassium play pivotal roles in crop growth, influencing root development, leaf growth, and overall plant functions. Temperature, light levels, humidity, and water availability also significantly impact plant growth and crop yields [13]. pH levels affect soil nutrient availability and microbial activity, while rainfall and irrigation patterns determine germination time and harvest readiness [6]. Considering these factors is crucial for recommending suitable crops, as they directly affect a crop's ability to extract nutrients and water from the soil, ultimately influencing its growth and yield potential.

RESULTS AND FINDINGS

The dataset is structured for crop recommendation, aiding agricultural decision-making by representing specific agricultural fields or regions through distinct samples [9]. Each entry records various soil and environmental parameters essential for crop cultivation, such as nitrogen (N), phosphorus (P), and potassium (K) levels, crucial nutrients for plant development [1]. Environmental factors like temperature, humidity, pH level, and rainfall are also included, significantly influencing crop growth

and yield. A key feature is the 'label' column, denoting the recommended crop type for specific conditions, serving as the target variable for predictive modeling to guide crop recommendations based on these input features.

Understanding the distribution of variables is crucial for assessing farmland characteristics comprehensively. Distributions reveal the frequency and variability of factors relevant to crop cultivation, offering insights into the diversity of agricultural conditions within the dataset [13]. For instance, Figure 2 visualizing the nitrogen (N) levels in the dataset illustrates the spread and frequency of different nitrogen levels. The x-axis represents the range of nitrogen values, while the y-axis shows the count of each value. The varying heights of the bars indicate the frequency of each nitrogen level, providing a clear depiction of its distribution across the dataset.

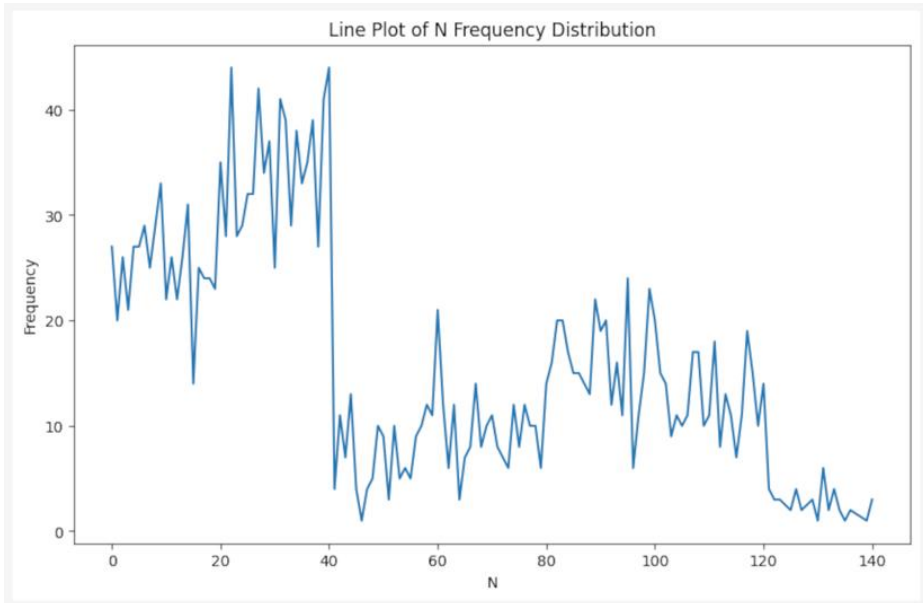


Figure 2. Frequency Distribution Chart

The frequency distribution for crop categorization using a Random Forest-based approach involves a thorough analysis of crop categories' distribution within a dataset to discern the prevalence and variability of various crops [13]. Figure 2 illustrates data collected on agricultural specifics and historical crop yields sourced from the Kaggle dataset [14]. Following dataset categorization into subsets representing distinct crop categories, the frequency of each category is computed [8]. Subsequently, a Random Forest algorithm is applied to the dataset to construct a predictive model capable of categorizing crops based on input variables [4], [15]. This algorithm functions by generating multiple decision trees and amalgamating their predictions to achieve accurate classifications [13]. Examination of the frequency distribution depicted in Figure 2 reveals a noticeable upsurge in leverage up to a dataset range of 40, succeeded by a sharp decline resonating with the range of 80. Leveraging the predictive capacity of Random Forest enables farmers and agricultural stakeholders to gain insights into prevalent crops grown in diverse regions, facilitating informed decisions regarding crop selection,

cultivation practices, and resource allocation to enhance agricultural productivity and sustainability. Moreover, it provides a framework for identifying trends and patterns in crop production over time, thereby aiding strategic planning and policy formulation in the agricultural domain [7].

Relationships Between Variables:

To understand the interactions between different variables, we compute a correlation matrix (corr = crop.corr()). This matrix quantifies the strength and direction of linear relationships between pairs of numerical variables, with values ranging from -0.2 to 1. Visualizing the correlation matrix using a heatmap (sns.heatmap(corr, annot=True, cbar=True, cmap='coolwarm')) reveals patterns and relationships between variables. Warmer colors indicate stronger positive correlations, while cooler colors signify stronger negative correlations, with white representing no correlation. Analyzing this heatmap helps identify variables that influence each other; for example, a strong negative correlation between temperature and rainfall suggests that higher temperatures are associated with lower rainfall. Understanding these relationships is crucial for effective data exploration and feature selection, enabling the identification of key patterns, potential outliers, and the most relevant variables for crop recommendations [13]. This insight enhances the performance of machine learning models used in crop recommendation tasks.

```
[9]: import seaborn as sns
sns.heatmap(corr,annot=True,cbar=True, cmap='coolwarm')
```

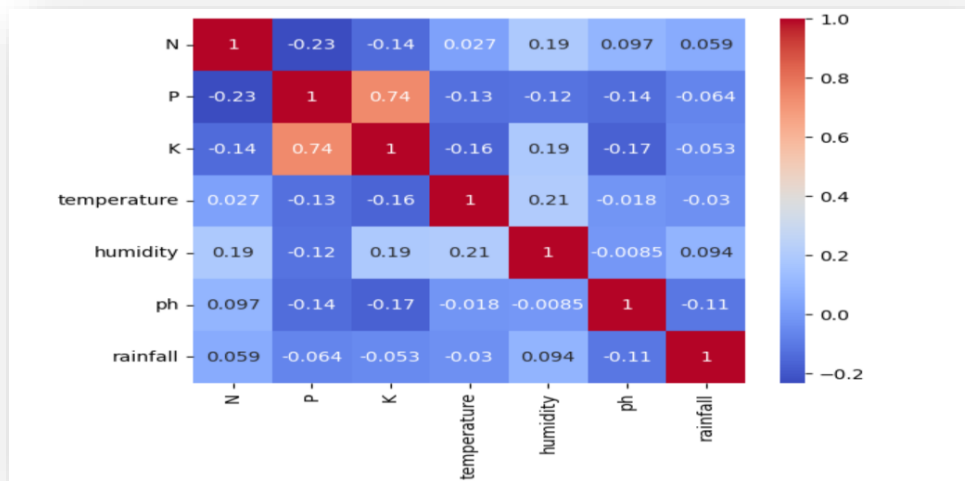


Figure 3. Correlation Matrix Plot Diagram

The Correlation Matrix Plot for crop categorization using a Random Forest-based approach presents a comprehensive analysis of the relationships between the different variables within the dataset to discern

patterns and dependencies. In this context, the dataset comprises various agricultural parameters such as environmental factors like temperature and humidity, and historical crop yields obtained from Kaggle. Each variable is quantified, and a correlation matrix is generated to measure the strength and direction of linear relationships between pairs of numerical variables, ranging from -0.2 to 1. The Correlation Matrix Plot, typically depicted as a heatmap in Figure 3, visually represents these correlations, with warmer colors indicating stronger positive correlations and cooler colors indicating stronger negative correlations. By analyzing this plot, insights into the interdependencies between variables can be gleaned, aiding in feature selection, model optimization, and ultimately, accurate crop categorization using the Random Forest algorithm [16]. Additionally, the Correlation Matrix Plot facilitates the identification of multicollinearity issues and redundant features, allowing for the refinement of predictive models and the enhancement of their performance in crop classification tasks.

Model Building

In the model-building process, the goal is to develop a predictive system that recommends the most suitable crop based on given environmental conditions [16]. This begins with thorough data preprocessing, which includes importing the dataset, performing exploratory data analysis to understand its structure and characteristics, and encoding categorical variables into numerical values for modeling. Feature scaling is applied to standardize the range of input variables, ensuring consistency during model training. Various classification models are considered, with the Random Forest Classifier ultimately chosen for its robustness and performance. Model accuracy is evaluated using test data, and the predictive system is implemented to provide crop recommendations based on input environmental conditions. The trained Random Forest model and scaling transformers are then serialized for future use, completing the process. This comprehensive approach, from data preprocessing to model selection, training, evaluation, and deployment culminates in the development of an effective crop recommendation system.

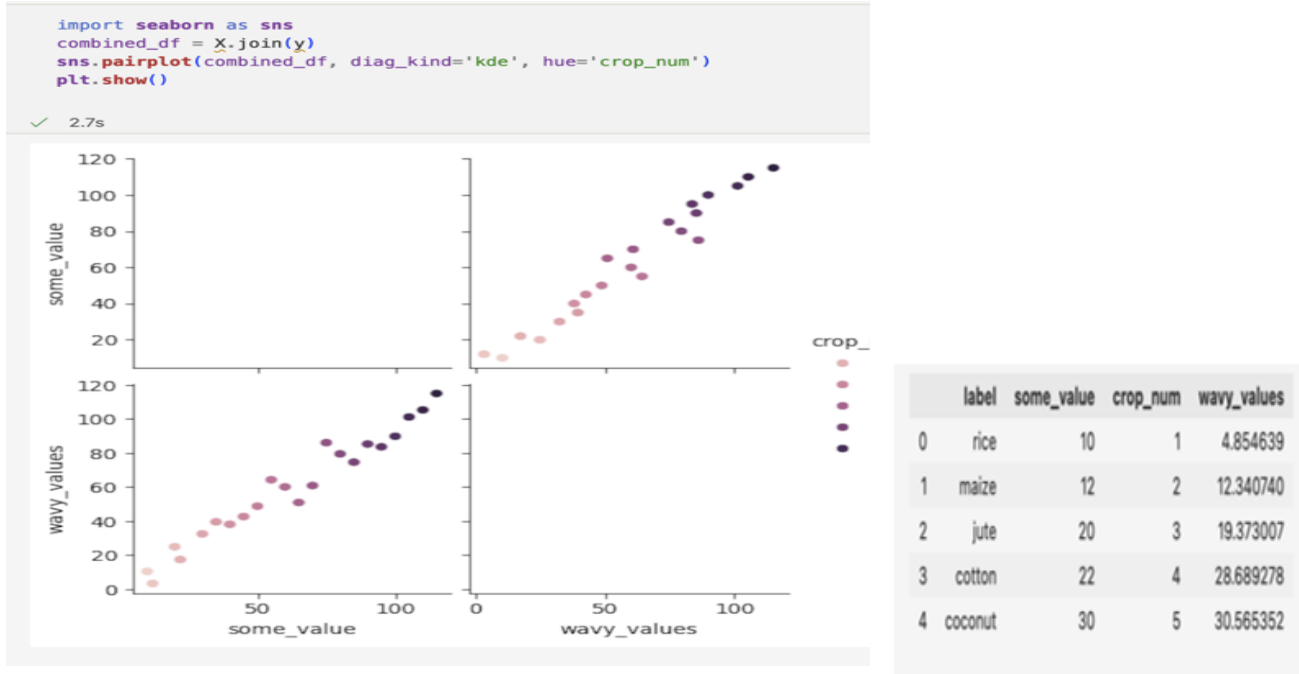


Figure 4. Correlation Matrix Plot Diagram

In the context of Crop Categorization using a Random Forest-Based Approach, the wavy line plot and its associated values depict the decision boundaries and prediction probabilities generated by the Random Forest algorithm [17]. In Figure 4, each wavy line represents a decision boundary separating different crop categories, with the amplitude of the wave indicating the model's confidence in its predictions. Higher amplitudes indicated by crop-num signify greater certainty in classification, while lower amplitudes suggest ambiguity. The plot showcases how the algorithm partitions the feature space to classify crops based on input variables such as soil composition, environmental factors, and historical yields. Additionally, the values associated with each data point on the plot represent the probability assigned by the Random Forest model to each crop category, offering insights into the model's confidence level for each classification decision. Analyzing the wavy line plot and its accompanying values enables stakeholders to interpret the model's classification boundaries, assess prediction uncertainty, and refine the model's performance for more accurate crop categorization.

DISCUSSION

This study presents a comprehensive design and implementation of a data-driven crop classification and cultivation advisory system that leverages machine learning algorithms and agricultural data to automate and enhance traditional manual processes. Key aspects include data preprocessing, which involves handling missing values and normalizing features to ensure quality and reliability for model training [18]. The system employs various machine learning models, such as random forests, Bagging

Classifier, and AdaBoost Classifier, trained on labeled data incorporating spectral, temporal, weather data, soil characteristics, and historical crop yields. Model performance evaluation reveals high accuracy rates (>90%) for crop classification tasks, outperforming traditional methods reliant on manual observation or remote sensing techniques. Cultivation recommendations are tailored to individual farmers, considering soil quality, climate conditions, and market demand, helping optimize crop selection, planting schedules, and resource management [19]. The study underscores the efficacy of the proposed approach, with experimental results demonstrating its practical application and superiority. Temporal features and ensemble models are highlighted as crucial for improving system performance [19], enhancing crop classification, and yield prediction accuracy by capturing complex relationships between input variables and output labels.

Implication to Research and Practice

This research contributes significantly to agriculture by introducing a data-driven approach to crop classification and cultivation advisory systems. Utilizing machine learning algorithms [20] and agricultural data, the study automates and enhances processes traditionally dependent on manual expertise. The proposed system addresses critical challenges in agriculture, such as improving crop productivity, optimizing cultivation practices, and promoting sustainable development. By integrating data-driven models [20], the study provides actionable insights tailored to specific crop requirements, soil conditions, and environmental factors, thus enhancing the precision and effectiveness of agricultural advisories.

Based on the study's findings, several recommendations are made. Firstly, tailored advisory services should be implemented to customize support for individual farmers, addressing their unique needs and optimizing cultivation practices. Secondly, the enhancement of decision support tools is essential. These tools should integrate real-time data on weather patterns, market trends, and profitability analysis, aiding farmers in making informed decisions about crop selection, planting schedules, and resource allocation. Lastly, introducing incentive programs and value-added services can increase farmer engagement with the advisory system. Incentives such as discounts on agricultural inputs, access to premium features, and rewards for adherence to recommended practices can foster user loyalty and long-term engagement, thereby enhancing the system's overall impact.

CONCLUSION

The research work focused on three key objectives to optimize crop cultivation practices. Firstly, it identified the primary factors influencing crop classification and cultivation decisions by analyzing historical agricultural data, recognizing variables such as soil nutrient levels (Nitrogen, Phosphorus, Potassium), Temperature, Humidity, pH, and Rainfall as significant determinants of crop growth and yield. Secondly, the project aimed to propose tailored cultivation advisory strategies based on these insights. Personalized recommendations were provided, including optimal fertilizer application rates tailored to soil nutrient levels, climate-sensitive planting schedules adjusted for temperature, humidity, and rainfall patterns, and pH-balancing measures, all designed to enhance crop yield and promote agricultural sustainability. Overall, the project underscores the importance of data-driven approaches

[21] in understanding agricultural dynamics, guiding strategic decision-making [21], and implementing targeted interventions to improve crop productivity and farming outcomes.

Future areas of study for this project include integrating real-time weather data to improve recommendation accuracy, incorporating crop market prices and profitability analysis for economically viable decision-making, developing a mobile application for convenient access on smartphones and tablets, and integrating user feedback and data collection to continuously enhance the system's performance. These enhancements aim to create a more responsive and effective crop recommendation system that adapts to evolving agricultural conditions and farmer needs.

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