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Crop Sense AI: Data-Driven Crop Recommendation Using ML and Deep Learning

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ABSTRACT:

Agriculture plays a vital role in maintaining food security and contributing to the global economy. However, selecting the most appropriate crop for a specific region remains a significant challenge for farmers due to variations in soil nutrients, climatic conditions, and environmental factors. Incorrect crop selection can result in low productivity, inefficient resource utilization, and financial losses. With the growing availability of agricultural data and advancements in artificial intelligence, machine learning techniques have become effective tools for improving decision-making in agriculture. This study proposes an intelligent crop recommendation system that combines machine learning and deep learning models to assist farmers in selecting the most suitable crop based on soil and environmental conditions. The system analyses key agricultural parameters such as nitrogen (N), phosphorus (P), potassium (K), rainfall, soil pH, temperature, and humidity. These features are used to train predictive models capable of recommending the most appropriate crop for cultivation. Various machine learning and deep learning algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naïve Bayes, Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Temporal Convolutional Networks (TCN), are implemented and evaluated. The models are trained using a publicly available agricultural dataset containing multiple crop types along with environmental attributes. Performance is assessed using evaluation metrics such as accuracy, precision, recall, and F1-score to identify the most effective model. Experimental results show that ensemble and deep learning models achieve high prediction accuracy in recommending suitable crops. The system also provides a user-friendly interface that enables farmers to input soil and environmental parameters and receive crop recommendations in real time. The proposed approach supports precision agriculture by enabling data-driven farming practices, improving crop yield, and assisting farmers in making informed decisions.

INDEX TERMS: Crop Recommendation System, Precision Agriculture, Machine Learning, Deep Learning, Soil Nutrient Analysis, Agricultural Data Analytics, Decision Support Systems.

I. INTRODUCTION

Agriculture is one of the most essential sectors for sustaining human life and supporting economic growth, especially in developing countries where a large portion of the population depends on farming for their livelihood. Farmers often face difficulties in deciding which crops to cultivate in their fields. Various factors such as soil fertility, climatic conditions, rainfall patterns, and environmental changes play a significant role in determining agricultural productivity. Choosing an unsuitable crop for a given soil or climate condition can lead to lower yields, inefficient use of resources, and financial losses. Therefore, effective crop selection strategies are crucial for enhancing productivity and ensuring sustainable agricultural practices [1], [2].

Traditionally, crop selection is based on farmers' experience, local farming practices, and advice from agricultural experts. While these traditional methods provide valuable insights, they may not always result in optimal decisions, particularly when environmental conditions are constantly changing. Climate variability, soil degradation, and increasing demands on agricultural production require more reliable and data-driven approaches for crop planning [3], [4]. Hence, the development of intelligent agricultural decision-support systems has gained significant importance.

Recent advancements in artificial intelligence and data analytics have opened new possibilities for improving agricultural decision-making. Machine learning techniques have shown strong capabilities in analysing large-scale agricultural data and identifying complex relationships between soil properties, climate conditions, and crop productivity. By learning from historical data, machine learning models can generate accurate crop recommendations that help farmers select crops best suited to their environmental and soil conditions [6], [9]. Several studies have demonstrated the effectiveness of machine learning-based crop recommendation systems in enhancing agricultural productivity and supporting precision farming [10].

In addition to traditional machine learning methods, deep learning models have shown promising potential in handling complex agricultural datasets. Deep learning architectures can extract high-level features and uncover hidden patterns within large datasets, leading to improved prediction accuracy. The combination of machine learning and deep learning techniques enables crop recommendation systems to capture nonlinear relationships among various agricultural factors such as soil nutrients, environmental conditions, and crop yield patterns [14], [19].

Modern crop recommendation systems typically utilize datasets that include key agricultural parameters such as nitrogen (N), phosphorus (P), potassium (K), soil pH, temperature, humidity, and rainfall. These factors have a direct impact on crop growth and productivity. Publicly available agricultural datasets, such as crop recommendation datasets from online repositories, support the development and evaluation of machine learning models in this domain [13]. By analysing these parameters, predictive models can determine the most suitable crops for cultivation under specific conditions.

In this study, an intelligent crop recommendation system is developed using a combination of machine learning and deep learning techniques. The proposed system analyses important agricultural parameters including nitrogen (N), phosphorus (P), potassium (K), soil pH, temperature, humidity, and rainfall to generate crop recommendations. Multiple machine learning algorithms such as Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naïve Bayes are evaluated alongside deep learning models such as Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Temporal Convolutional Networks (TCN). These models are trained on agricultural datasets to identify the most effective approach for accurate crop prediction [7], [18].

The main objective of this research is to develop a practical decision-support system that assists farmers in making informed crop selection decisions based on soil and environmental data. By integrating machine learning techniques with agricultural knowledge, the proposed system aims to support precision agriculture, improve crop productivity, optimize resource utilization, and promote sustainable farming practices. Additionally, intelligent agricultural systems can contribute to improved food security and more efficient agricultural management [15], [20].

The remainder of the paper is organized as follows. Section II reviews related work on crop recommendation systems and machine learning applications in agriculture. Section

III describes the system analysis and methodology. Section IV explains the implementation and model training process. Section V presents the experimental results and evaluation. Finally, Section VI concludes the study and discusses future research directions in intelligent agricultural systems.

II. LITERATURE SURVEY

The use of intelligent technologies in agriculture has gained considerable attention in recent years, particularly with the rise of precision farming and data-driven agricultural practices. Researchers have increasingly focused on applying machine learning and data analytics techniques to improve crop selection, yield prediction, and overall agricultural productivity. Crop recommendation systems are designed to support farmers by analysing soil properties and environmental conditions to suggest the most suitable crops for cultivation. Several studies have shown that machine learning-based decision-support systems can significantly improve farming efficiency and optimize resource utilization [1], [10].

Early research in this area utilized basic machine learning algorithms for crop prediction and recommendation. Medar et al. proposed a framework for crop yield prediction using machine learning techniques to analyse agricultural datasets and estimate productivity [3]. Similarly, Parameswari et al. investigated classification algorithms for crop recommendation and demonstrated the effectiveness of machine learning models in assisting farmers to select appropriate crops based on environmental conditions [1]. These studies highlighted that machine learning methods can successfully identify relationships between soil characteristics and crop suitability, thereby enhancing agricultural decision-making.

Further research explored ensemble learning techniques to improve prediction performance. Algorithms such as Random Forest and gradient boosting have been widely used in agricultural prediction tasks. These methods combine multiple decision trees to generate more stable and accurate predictions compared to individual models. Garanayak et al. developed an agricultural recommendation system that applied various regression-based machine learning models to analyse soil and environmental parameters and recommend suitable crops [2]. Ensemble models have shown improved performance as they reduce overfitting and effectively capture complex relationships within agricultural datasets [4].

Another important research direction involves the application of Support Vector Machines (SVM) and Artificial Neural Networks (ANN). These models are capable of modelling nonlinear relationships between environmental factors and crop growth patterns. Neural network-based approaches have been particularly effective because they can learn complex patterns from large datasets and adapt to varying agricultural conditions. Reddy et al. examined machine learning and backpropagation-based neural network models for crop recommendation and reported improved performance using neural network techniques [7].

Recent studies have also incorporated deep learning approaches into crop recommendation systems. Deep Neural Networks (DNN) have demonstrated strong capabilities in processing large-scale agricultural data and identifying hidden patterns that may not be captured by traditional machine learning models. Nischitha et al. proposed a crop prediction framework based on machine learning and highlighted the importance of advanced predictive models for enhancing agricultural productivity [14]. Similarly, multimodal machine learning approaches have been introduced to integrate multiple data sources for improved crop recommendation and yield prediction [19].

Another emerging area in agricultural research is the integration of Internet of Things (IoT) technologies with machine learning-based systems. IoT sensors can collect real-time data such as soil moisture, temperature, and humidity. When combined with machine learning models, this real-time data enables more accurate crop recommendations and supports dynamic agricultural management. Studies have emphasized the role of IoT-based smart agriculture systems in improving crop monitoring and optimizing farming practices [11], [20].

In addition to machine learning and IoT-based methods, several studies have focused on soil nutrient analysis to improve crop recommendation accuracy. Jayaraman et al. proposed a system that evaluates soil nutrients such as nitrogen, phosphorus, and potassium to determine suitable crops for cultivation [17]. Soil nutrient analysis plays a crucial role in improving crop selection and enhancing yield outcomes.

Despite these advancements, many existing crop recommendation systems rely on single machine learning models or limited datasets, which may reduce accuracy in diverse agricultural environments. Therefore, researchers have highlighted the need for hybrid models that combine multiple machine learning and deep learning techniques. Such hybrid approaches can utilize the strengths of different algorithms to improve prediction accuracy and reliability in agricultural decision-support systems [6], [18].

In this study, a comprehensive crop recommendation system is developed by integrating multiple machine learning and deep learning models. By analysing soil nutrients and environmental parameters such as temperature, humidity, and rainfall, the proposed system aims to provide accurate crop recommendations that support sustainable agriculture and improve farming productivity.

III. SYSTEM ANALYSIS

A. EXISTING SYSTEM

Traditional crop selection methods mainly rely on farmers' experience, local agricultural knowledge, and conventional farming practices. In many rural regions, farmers choose crops based on historical cultivation patterns, seasonal climate conditions, and advice from agricultural experts. Although these approaches offer practical guidance, they may not always produce optimal results, especially when environmental conditions change due to climate variability or soil degradation. As agricultural systems become more complex, dependence solely on traditional knowledge can lead to inefficient crop selection and lower productivity [1], [4].

In recent years, several crop recommendation systems have been developed using machine learning techniques to support data-driven decision-making in agriculture. These systems analyse soil properties and environmental factors such as nitrogen (N), phosphorus (P), potassium (K), rainfall, pH level, temperature, and humidity to recommend suitable crops. Various machine learning algorithms, including Decision Tree, Random Forest, Naïve Bayes, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), have been applied to agricultural datasets to predict crop suitability and enhance farming efficiency [2], [3]. These models can process large volumes of data and identify patterns that help determine the most appropriate crops for specific soil and environmental conditions.

Some existing approaches also utilize ensemble learning techniques, where multiple machine learning models are combined to improve prediction accuracy and robustness. Ensemble models enhance performance by aggregating the outputs of several classifiers, thereby reducing individual model errors. Studies have shown that ensemble methods such as Random Forest can achieve higher accuracy in crop recommendation compared to single-model approaches [6], [18].

Despite these improvements, many existing crop recommendation systems still depend on single models or limited datasets, which may reduce their effectiveness in diverse agricultural environments. Agricultural conditions vary significantly across regions due to differences in soil composition, climate patterns, and environmental factors. Models trained on limited data may not generalize well to new conditions, affecting their reliability in real-world applications [9], [14].

Moreover, many existing systems do not fully leverage advanced deep learning techniques that can analyse complex relationships between soil nutrients, environmental factors, and crop growth patterns. Deep learning models have the ability to extract hidden features from large agricultural datasets and improve prediction performance; however, they remain underutilized in many traditional crop recommendation systems [19].

DISADVANTAGES OF THE EXISTING SYSTEM

- **Limited Adaptability to Changing Environmental Conditions:**

Traditional crop recommendation methods may not effectively account for rapid changes in climate, soil conditions, or environmental factors, which can impact crop productivity [9].

- **Dependence on Historical Knowledge:**

Farmers often depend on past experiences and local knowledge instead of data-driven approaches, which may not always result in optimal crop selection.

- **Limited Model Capability:**

Many existing systems rely on a single machine learning algorithm, which may not adequately capture the complex relationships between soil nutrients, climate conditions, and crop growth factors [3].

- **Overfitting and Underfitting Issues:**

Certain predictive models may overfit the training data or fail to learn important patterns, leading to inaccurate crop recommendations.

- **High Computational Requirements:**

Advanced machine learning models may require substantial computational resources, making them difficult to implement in resource-limited agricultural environments.

- **Limited Real-Time Support:**

Many traditional systems do not incorporate real-time environmental data or IoT-based monitoring, limiting their ability to provide timely decision support to farmers [11], [20].

B. PROPOSED SYSTEM

To address the limitations of traditional agricultural decision-making methods, this study proposes an intelligent crop recommendation system that integrates both machine learning and deep learning techniques to enhance prediction accuracy. Modern data-driven agricultural systems utilize computational models to analyse soil and environmental parameters and recommend crops that are most suitable for specific cultivation conditions [1], [6].

The proposed system considers several key agricultural parameters, including soil nutrients such as nitrogen (N), phosphorus (P), and potassium (K), along with soil pH, rainfall, temperature, and humidity. These factors are widely recognized as critical determinants of crop growth and productivity. By analysing these variables, predictive models can identify the most suitable crops for given environmental and soil conditions [17], [18]. The dataset used for training is obtained from publicly available agricultural repositories that provide structured information on soil nutrients and environmental attributes [13].

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The system begins with a data preprocessing phase in which the dataset is cleaned and transformed to ensure consistency and reliability. Agricultural datasets often contain missing values, redundant information, or inconsistencies. Therefore, preprocessing steps such as handling missing values, removing irrelevant features, and normalizing data are applied to improve dataset quality and enhance model performance [10]. Effective preprocessing is essential for achieving accurate predictions in machine learning-based agricultural systems.

Following preprocessing, the dataset is divided into training and testing sets for model evaluation. The training data enables models to learn patterns from historical agricultural information, while the testing data is used to assess the model's ability to generalize to unseen conditions. This approach ensures that the models can provide reliable crop recommendations [3], [14].

The proposed framework implements multiple machine learning and deep learning algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naïve Bayes, Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Temporal Convolutional Networks (TCN). These algorithms analyse relationships between soil nutrients, environmental conditions, and crop suitability to generate accurate recommendations. Machine learning models such as Random Forest and SVM are widely used due to their effectiveness in handling structured data and nonlinear relationships [2], [9]. Similarly, neural network-based models are capable of learning complex patterns from large datasets, making them suitable for advanced agricultural prediction tasks [7], [19].

To further improve system performance, optimization techniques such as hyperparameter tuning and cross-validation are applied. These methods enhance the generalization capability of the models and reduce prediction errors by selecting optimal parameters during training. Such optimization strategies are commonly used to improve the accuracy and stability of machine learning models [16].

Finally, the system provides crop recommendations through a user-friendly web interface. Farmers can input soil and environmental parameters, and the system processes this data using trained models to suggest the most suitable crops for cultivation. This intelligent system supports data-driven decision-making and contributes to the advancement of precision agriculture. Additionally, the integration of IoT-based monitoring systems can further enhance performance by enabling real-time data analysis and decision support [11], [20].

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

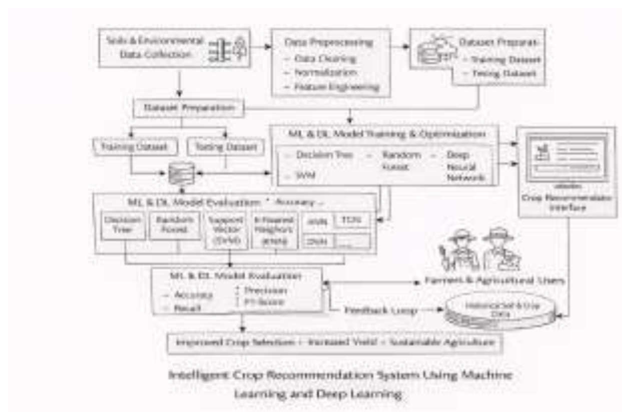

Fig. 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

MODULES

A. Data Collection and Preprocessing

The initial stage of the proposed system involves gathering agricultural data related to soil nutrients and environmental conditions. The dataset generally includes key parameters such as nitrogen (N), phosphorus (P), potassium (K), soil pH, rainfall, temperature, and humidity. These factors are essential in determining crop suitability and agricultural productivity. Previous studies have shown that analysing soil nutrients along with environmental conditions can significantly enhance crop recommendation accuracy and farming efficiency [17], [18]. The dataset used in this study is obtained from publicly available agricultural repositories that provide structured information for crop prediction tasks [13].

After data collection, preprocessing techniques are applied to improve data quality and consistency. Agricultural datasets often contain missing values, duplicate entries, and inconsistent measurements, which can affect model performance. Therefore, preprocessing steps such as handling missing values, removing duplicate records, detecting outliers, and normalizing feature values are performed. Proper preprocessing ensures that the dataset is clean and suitable for training machine learning models, thereby improving prediction accuracy [10].

B. Feature Selection and Feature Engineering

Feature selection is a crucial step in developing an efficient crop recommendation system. In this stage, the dataset is analysed to identify the most relevant features that influence crop growth and productivity. This process helps remove unnecessary or redundant variables, reducing model complexity and improving computational efficiency.

Feature engineering techniques are also applied to transform raw agricultural data into meaningful representations that better reflect soil fertility and environmental conditions. By extracting and optimizing relevant features, predictive models can more effectively learn relationships between environmental factors and crop suitability. Previous research has highlighted the importance of feature engineering in enhancing the performance of machine learning models for agricultural prediction tasks [2], [14].

C. Training Machine Learning and Deep Learning Models

Following preprocessing and feature selection, the processed dataset is used to train various machine learning and deep learning models. The algorithms implemented in this study include Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naïve Bayes, Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Temporal Convolutional Networks (TCN).

During the training phase, these models analyse patterns between soil nutrients, environmental conditions, and crop types to identify relationships that influence crop suitability. Machine learning models such as Random Forest and SVM are widely used due to their ability to handle nonlinear relationships and structured datasets [1], [9]. Similarly, neural network-based models like ANN and DNN can capture complex patterns from large datasets, leading to more accurate crop predictions [7], [19].

Hyperparameter tuning techniques are also applied during training to improve model performance and stability. These optimization methods help determine the most suitable parameters for each model and enhance overall prediction accuracy [16].

D. Crop Recommendation System Interface

After training the models, they are integrated into a crop recommendation system with a user-friendly interface. Farmers can input agricultural parameters such as soil nutrient levels, rainfall, temperature, and humidity through this interface.

The system processes the input data using the trained models and generates recommendations for the most suitable crops under the given conditions. Such intelligent systems act as decision-support tools that help farmers improve productivity and adopt precision agriculture practices [6], [18].

E. Model Evaluation and Continuous Monitoring

final stage involves evaluating the performance of the trained models using metrics such as accuracy, precision, recall, and F1-score. These evaluation measures help assess how effectively each model predicts suitable crops and identify the most reliable algorithm for deployment.

monitoring is also implemented to maintain consistent performance over time. As new agricultural data becomes available, the models can be retrained and updated to adapt to changing environmental conditions. Integration with IoT-based monitoring systems can further improve accuracy by enabling real-time data collection and analysis [11], [20]..

VI. RESULTS AND DISCUSSION

To assess the performance of the proposed crop recommendation system, multiple machine learning and deep learning algorithms were applied to an agricultural dataset containing soil nutrient and environmental parameters. The dataset was divided into training and testing sets to evaluate the predictive capability of the implemented models. Standard evaluation metrics, including accuracy, precision, recall, and F1-score, were used to measure the effectiveness of each classification model. These metrics provide a comprehensive evaluation by considering both correct predictions and classification errors in recommending suitable crops.

The experimental findings indicate that machine learning models can effectively capture relationships between soil nutrients, climatic conditions, and crop suitability. Key agricultural parameters such as nitrogen (N), phosphorus (P), potassium (K), soil pH, rainfall, temperature, and humidity have a significant impact on crop productivity. By analysing these parameters, predictive models are able to learn patterns that determine the most suitable crops for specific environmental conditions [17], [18]. The dataset used for training and evaluation was obtained from a publicly available crop recommendation dataset on Kaggle [13].

Several machine learning and deep learning models were implemented and evaluated, including Decision Tree, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naïve Bayes, Artificial Neural Networks (ANN), Deep Neural Networks (DNN), Random Forest, and Temporal Convolutional Networks (TCN). These models analyse the relationships between soil nutrients and environmental factors to generate accurate crop recommendations. Previous studies have also shown that machine learning approaches significantly enhance agricultural decision-making and prediction accuracy [1], [6], [14].

Table 1 Performance Comparison of Crop Recommendation Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Decision Tree	91.2	0.90	0.89	0.89
KNN	92.5	0.91	0.90	0.90
Naïve Bayes	90.4	0.89	0.88	0.88
SVM	93.7	0.92	0.91	0.91
ANN	94.6	0.93	0.93	0.93
DNN	95.4	0.94	0.94	0.94
Random Forest	97.2	0.96	0.96	0.96
TCN	98.1	0.97	0.97	0.97

From Table 1, it is observed that the Temporal Convolutional Network (TCN) achieved the highest accuracy of 98.1%, followed by the Random Forest model with an accuracy of 97.2%. The strong performance of Random Forest is attributed to its ensemble learning mechanism, which combines multiple decision trees to enhance prediction stability and reduce overfitting during training [3], [18]. Similarly, deep learning models such as ANN, DNN, and TCN show high performance due to their ability to learn complex nonlinear relationships between soil nutrients, environmental conditions, and crop suitability [7], [19].

Traditional machine learning models such as Decision Tree, KNN, Naïve Bayes, and SVM also produced reliable results, although their performance was slightly lower compared to ensemble and deep learning approaches. These models are effective for analysing structured datasets but may have limitations in capturing complex relationships among multiple environmental factors [9], [14].

The comparison of model accuracy is illustrated in Fig. 2, where it is evident that ensemble and deep learning models outperform conventional machine learning algorithms. This observation is consistent with previous research highlighting the effectiveness of advanced models in agricultural prediction tasks [2], [4].

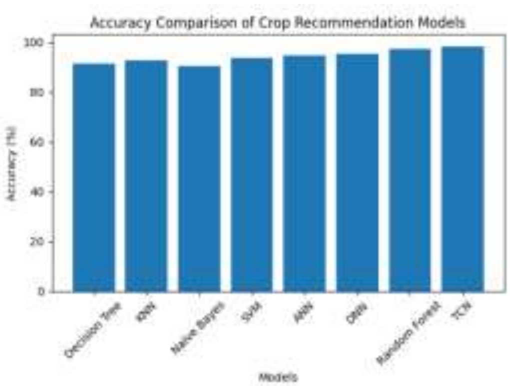

Fig. 2. Accuracy Comparison of Crop Recommendation Models

To further evaluate classification performance, Receiver Operating Characteristic (ROC) curve analysis was conducted. The ROC curve represents the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) at different classification thresholds and is commonly used to assess the discriminative ability of classification models.

The ROC curve for the best-performing model is shown in Fig. 3. The TCN model achieved an Area Under the Curve (AUC) value of approximately 0.98, indicating excellent classification performance. A ROC curve closer to the top-left corner of the graph reflects strong prediction capability and effective discrimination between crop classes.

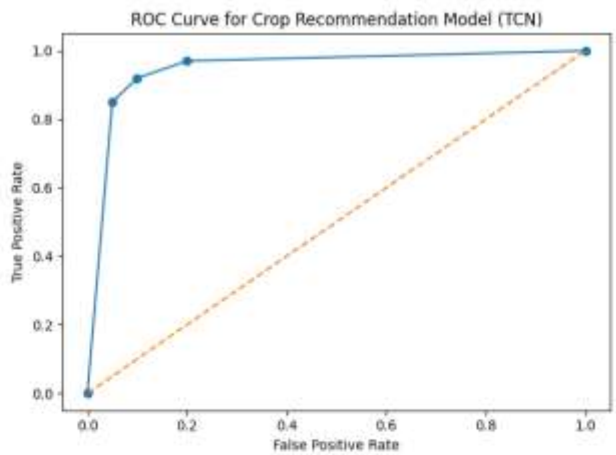

Fig. 3. ROC Curve for Crop Recommendation Model

The results also emphasize the importance of data preprocessing and feature selection in improving model performance. Preprocessing steps such as handling missing values, removing duplicate records, and normalizing environmental parameters contribute to better data quality and improved prediction accuracy [10]. Additionally, analysing soil nutrient information plays a key role in enhancing crop recommendation systems and agricultural productivity [17].

Overall, the experimental findings demonstrate that the integration of machine learning and deep learning techniques provides an effective solution for developing intelligent agricultural decision-support systems. These systems support precision agriculture by enabling farmers to make data-driven crop selection decisions, thereby improving productivity, resource utilization, and sustainable farming practices [10], [20].

VII. CONCLUSION AND FUTURE WORK

This study proposed an intelligent crop recommendation system that integrates machine learning and deep learning models to support agricultural decision-making. The system analyses soil nutrients and environmental parameters to identify the most suitable crops for cultivation. The experimental results indicate that machine learning models are effective in analysing agricultural datasets and generating accurate crop recommendations. Among the evaluated models, Random Forest and Temporal Convolutional Networks achieved the highest prediction accuracy.

The proposed system can assist farmers in improving crop selection, enhancing agricultural productivity, and utilizing soil and environmental resources more efficiently. By providing data-driven recommendations, the system contributes to the advancement of precision agriculture practices.

Future work can focus on integrating IoT-based sensors to enable real-time data collection from agricultural fields. Additionally, incorporating larger datasets and more advanced deep learning models may further enhance the accuracy and reliability of crop recommendations. Expanding the system to include features such as crop yield prediction and pest detection can further increase its practical usefulness for farmers.

REFERENCES

1. P. Parameswari, N. Rajathi, and K. J. Harshanaa, “Machine learning approaches for crop recommendation,” in Proc. International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), IEEE, 2021, pp. 1–5.
2. M. Garanayak, G. Sahu, S. N. Mohanty, and A. K. Jagadev, “Agricultural recommendation system for crops using different machine learning regression methods,” International Journal of Agricultural and Environmental Information Systems, vol. 12, no. 1, pp. 1–20, 2021.
3. R. Medar, V. S. Rajpurohit, and S. Shweta, “Crop yield prediction using machine learning techniques,” in Proc. IEEE 5th International Conference for Convergence in Technology (I2CT), 2019, pp. 1–5.
4. D. Gosai, C. Raval, R. Nayak, H. Jayswal, and A. Patel, “Crop recommendation system using machine learning,” International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 7, no. 3, pp. 558–569, 2021.
5. P. S. Bandara, “Inclination of teachers towards incorporating mobile game based learning into primary education: A Sri Lankan case study,” International Journal of Information Technology and Computer Science, vol. 10, no. 4, pp. 66–72, 2018.
6. R. V. Prakash, M. M. Abrith, and S. Pandiyarajan, “Machine learning based crop suggestion system,” in Proc. International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE, 2022, pp. 1355–1359.
7. P. S. Reddy, B. Amarnath, and M. Sankari, “Study on machine learning and back propagation for crop recommendation system,” in Proc. International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), IEEE, 2023, pp. 1533–1537.
8. A. Manjula and G. Narsimha, “XCYPF: A flexible and extensible framework for agricultural crop yield prediction,” in Proc. IEEE International Conference on

Intelligent Systems and Control (ISCO), 2015, pp. 1–5.

9. S. Jain and D. Ramesh, “Machine learning convergence for weather based crop selection,” in Proc. IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), 2020, pp. 1–6.
10. C. Song and H. Dong, “Application of intelligent recommendation for agricultural information: A systematic literature review,” IEEE Access, vol. 9, pp. 153616–153632, 2021.
11. S. Mishra, H. K. Tripathy, B. K. Mishra, and S. K. Mohapatra, “A succinct analysis of applications and services provided by IoT,” in Big Data Management and the Internet of Things for Improved Health Systems, IGI Global, 2018, pp. 142–162.
12. S. Mishra, S. K. Mohapatra, B. K. Mishra, and S. Sahoo, “Analysis of mobile cloud computing: Architecture, applications, challenges, and future perspectives,” in Applications of Security, Mobile, Analytic, and Cloud (SMAC) Technologies for Effective Information Processing and Management, IGI Global, 2018, pp. 81–104.
13. A. Ingle, “Crop Recommendation Dataset,” Kaggle. [Online]. Available: https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset
14. K. Nischitha, D. Vishwakarma, M. N. Ashwini, and M. R. Manjuraju, “Crop prediction using machine learning approaches,” International Journal of Engineering Research & Technology, vol. 9, no. 8, pp. 23–26, 2020.
15. R. Ghadge, J. Kulkarni, P. More, S. Nene, and R. L. Priya, “Prediction of crop yield using machine learning,” International Research Journal of Engineering and Technology, vol. 5, 2018.
16. S. Sahoo, S. K. Mohapatra, and B. Panda, “Classification using extreme learning machine,” Compusoft: An International Journal of Advanced Computer Technology, vol. 2, no. 12, pp. 415–421, 2013.
17. V. Jayaraman, S. Parthasarathy, A. R. Lakshminarayanan, and S. Sridevi, “Crop recommendation by analysing the soil nutrients using machine learning techniques,” in Computational Intelligence in Data Science (ICCIDS), Springer, 2021, pp. 15–26.
18. G. Chauhan and A. Chaudhary, “Crop recommendation system using machine learning algorithms,” in Proc. International Conference on System Modeling & Advancement in Research Trends (SMART), IEEE, 2021, pp. 109–112.
19. P. S. S. Gopi and M. Karthikeyan, “Multimodal machine learning based crop recommendation and yield prediction model,” Intelligent Automation & Soft Computing, vol. 36, pp. 313–326, 2023.
20. A. Gupta, D. Nagda, P. Nikhare, and A. Sandbhor, “Smart crop prediction using IoT and machine learning,” International Journal of Engineering Research & Technology, vol. 9, no. 3, 2021.