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Intelligent Crop Recommendation System Using Machine Learning and Deep Learning for Precision Agriculture

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Abstract- — Agriculture plays a crucial role in ensuring food security and supporting the global economy. However, selecting the most suitable crop for a particular region remains a major challenge for many farmers due to variations in soil nutrients, climate conditions, and environmental factors. Incorrect crop selection can lead to reduced productivity, inefficient use of resources, and financial losses. With the increasing availability of agricultural data and advances in artificial intelligence, machine learning techniques have emerged as powerful tools for improving agricultural decision-making.This study presents an intelligent crop recommendation system that integrates machine learning and deep learning models to assist farmers in selecting the most suitable crop based on soil and environmental conditions. The proposed system analyses important agricultural parameters such as nitrogen (N), phosphorus (P), potassium (K), rainfall, soil pH, temperature, and humidity. These features are used to train predictive models that can recommend the optimal crop for cultivation.Several 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 and environmental attributes. Performance evaluation is conducted using metrics such as accuracy, precision, recall, and F1-score to determine the most effective model.Experimental results demonstrate that ensemble and deep learning models achieve high prediction accuracy in recommending suitable crops. The system also includes a user-friendly interface that allows farmers to input soil and environmental parameters and receive crop recommendations in real time.The proposed approach contributes to the development of precision agriculture systems by supporting data-driven farming practices, improving crop productivity, and helping farmers make more informed agricultural decisions.

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

I. INTRODUCTION

Agriculture remains one of the most important sectors for sustaining human life and supporting economic development, particularly in developing countries where a significant portion of the population depends on farming for their livelihood. Farmers frequently face challenges when deciding which crops to cultivate in their fields. Several factors, including soil fertility, climate conditions, rainfall patterns, and environmental changes, play a crucial role in determining agricultural productivity. Selecting an unsuitable crop for a particular soil or climate condition may lead to reduced yield, inefficient utilization of agricultural resources, and economic losses for farmers. Therefore, effective crop selection strategies are essential for improving productivity and ensuring sustainable agricultural practices [1], [2].

Traditionally, farmers rely on personal experience, regional farming practices, and guidance from agricultural experts when selecting crops. Although these conventional approaches can provide useful insights, they may not always yield optimal results, particularly in situations where environmental conditions change frequently. Climate variability, soil degradation, and increasing pressure on agricultural production systems require more reliable and data-driven decision-making approaches for crop cultivation [3], [4]. As a result, the development of intelligent agricultural decision-support systems has become an important area of research.

Recent advancements in artificial intelligence and data analytics have introduced new opportunities to enhance agricultural decision-making processes. Machine learning techniques have demonstrated strong capabilities in analysing large volumes of agricultural data and identifying complex relationships between soil characteristics, climatic conditions, and crop productivity. By learning patterns from historical agricultural datasets, machine learning models can provide accurate crop recommendations that assist farmers in selecting crops best suited for their environmental and soil conditions [6], [9]. Several studies have highlighted the effectiveness of machine learning-based crop recommendation systems in improving agricultural productivity and supporting precision farming practices [10].

In addition to conventional machine learning approaches, deep learning models have shown promising potential for analysing complex agricultural datasets. Deep learning architectures are capable of extracting high-level features and identifying hidden patterns within large datasets, thereby improving prediction accuracy in agricultural applications. The integration of machine learning and deep learning techniques can enhance crop recommendation systems by enabling them to capture nonlinear relationships between multiple agricultural variables such as soil nutrients, environmental conditions, and crop yield patterns [14], [19].

Modern crop recommendation systems often utilize datasets containing important agricultural parameters such as nitrogen (N), phosphorus (P), potassium (K), soil pH, temperature, humidity, and rainfall. These parameters significantly influence crop growth and productivity. Several publicly available agricultural datasets, such as the crop recommendation dataset provided through online repositories, support the development and evaluation of machine learning-based agricultural models [13]. By analysing these parameters, predictive models can identify the most suitable crops for cultivation under specific environmental conditions.

In this study, an intelligent crop recommendation system is developed using a combination of machine learning and deep learning algorithms. The proposed system analyses key agricultural parameters including nitrogen (N), phosphorus (P), potassium (K), soil pH, temperature, humidity, and rainfall to generate crop recommendations. Various 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 approaches such as Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Temporal Convolutional Networks (TCN). These models are trained using agricultural datasets to determine the most effective algorithm for accurate crop recommendation [7], [18].

The primary objective of this research is to develop a practical decision-support system capable of assisting 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 and improve crop productivity, resource utilization, and long-term sustainability in farming practices. Furthermore, intelligent agricultural systems can contribute to enhancing food security and improving the efficiency of modern agricultural management strategies [15], [20].

The remainder of this paper is organized as follows. Section II reviews existing research related to crop recommendation systems and machine learning applications in agriculture. Section III describes the system analysis and methodology used for crop prediction. Section IV explains the implementation process and model training procedures. Section V presents the experimental results and performance evaluation of the models. Finally, Section VI concludes the study and discusses potential directions for future improvements in intelligent agricultural systems.

II. LITERATURESURVEY

The application of intelligent technologies in agriculture has gained significant attention in recent years, particularly with the emergence of precision farming and data-driven agricultural practices. Researchers have increasingly explored machine learning and data analytics techniques to improve crop selection, yield prediction, and agricultural productivity. Crop recommendation systems are designed to assist farmers by analysing soil properties and environmental parameters and recommending the most suitable crop for cultivation. Several studies have demonstrated that machine learning-based agricultural decision-support systems can significantly enhance farming efficiency and resource utilization [1], [10].

One of the early approaches in this domain involved the use of basic machine learning algorithms for crop prediction and recommendation. Medar et al. proposed a crop yield prediction framework that utilized machine learning techniques to analyse agricultural datasets and estimate crop productivity [3]. Similarly, Parameswari et al. explored the use of classification algorithms for crop recommendation and highlighted the potential of machine learning models to support farmers in selecting appropriate crops based on environmental conditions [1]. These studies demonstrated that machine learning algorithms could effectively identify relationships between soil properties and crop suitability, thereby improving agricultural decision-making.

Further research explored the use of ensemble learning techniques to improve prediction accuracy. Algorithms such as Random Forest and gradient boosting methods have been widely applied for agricultural prediction tasks. These models combine multiple decision trees to produce more reliable and stable predictions compared to single classifiers. Garanayak et al. proposed an agricultural recommendation system that applied various machine learning regression models to analyse soil and environmental attributes and generate crop suggestions [2]. Ensemble-based models have shown improved performance because they reduce overfitting and capture complex relationships within agricultural datasets [4].

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

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

Another emerging trend in agricultural research is the integration of Internet of Things (IoT) technologies with machine learning-based decision-support systems. IoT sensors can collect real-time environmental data such as soil moisture, temperature, and humidity. When integrated with machine learning models, this real-time data enables more accurate crop recommendations and supports dynamic agricultural management strategies. Studies have highlighted 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 approaches, several studies have focused on the analysis of soil nutrients to improve crop recommendation accuracy. Jayaraman et al. proposed a crop recommendation system that analyses soil nutrient levels such as nitrogen, phosphorus, and potassium to identify suitable crops for cultivation [17]. Soil nutrient analysis plays a critical role in determining crop suitability and improving yield outcomes.

Despite these advancements, many existing crop recommendation systems still rely on single machine learning models or limited datasets, which may reduce prediction accuracy in diverse agricultural environments. Researchers have therefore emphasized the importance of developing hybrid models that combine multiple machine learning and deep learning algorithms. Hybrid frameworks can leverage 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 several 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 agricultural practices and enhance farming productivity.

III.SYSTEM ANALYSIS

A. Existing System

Traditional crop selection methods primarily depend on farmers' experience, local agricultural knowledge, and conventional farming practices. In many rural areas, farmers decide which crops to cultivate based on historical cultivation patterns, seasonal climate conditions, and guidance from agricultural experts. Although these approaches can provide practical insights, they may not always yield optimal results, particularly when environmental conditions change due to climate variability or soil degradation. As agricultural systems become increasingly complex, relying solely on traditional knowledge may lead to inefficient crop selection and reduced productivity [1], [4].

In recent years, several crop recommendation systems have been developed using machine learning algorithms to support data-driven agricultural decision-making. These systems analyse soil characteristics and environmental parameters such as nitrogen (N), phosphorus (P), potassium (K), rainfall, pH level, temperature, and humidity to recommend suitable crops for cultivation. 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 improve farming efficiency [2], [3]. These models can analyse large datasets and identify patterns that help determine which crops are best suited for specific environmental and soil conditions.

Some existing systems also employ ensemble learning techniques in which multiple machine learning algorithms are combined to improve prediction accuracy and robustness. Ensemble-based models can enhance prediction performance by aggregating the outputs of multiple classifiers and reducing the impact of individual model errors. Several studies have demonstrated that ensemble models such as Random Forest can improve crop recommendation accuracy compared to single-algorithm approaches [6], [18].

Despite these advancements, many existing agricultural recommendation systems still rely on single machine learning models or limited datasets, which may reduce prediction accuracy in diverse agricultural environments. Agricultural conditions vary widely across regions due to differences in soil composition, climate patterns, and environmental factors. Models trained on limited datasets may not generalize well to new environments, thereby affecting their reliability in real-world farming scenarios [9], [14].

Furthermore, many existing agricultural recommendation systems do not fully utilize advanced deep learning techniques that can analyse complex relationships between soil nutrients, environmental variables, and crop growth patterns. Deep learning models have the potential to extract hidden features from large agricultural datasets and improve prediction performance, but they are still underutilized in many traditional crop recommendation frameworks [19].

Disadvantages Of The Existing System

Limited Adaptability to Changing Environmental Conditions:
Traditional crop recommendation methods may not accurately reflect rapid changes in climate patterns, soil conditions, or environmental factors, which can affect crop productivity [9].

- **Dependence on Historical Knowledge:**
Farmers often rely on past experiences and local knowledge rather than data-driven analysis, which may not always lead to optimal crop selection decisions.

- **Limited Model Capability:**
Many existing systems rely on a single machine learning algorithm, which may fail to capture complex relationships among soil nutrients, climate conditions, and crop growth factors [3].

- **Overfitting and Underfitting Issues:**
Some predictive models may overfit the training dataset or fail to capture important patterns in agricultural data, resulting in inaccurate crop recommendations.

- **High Computational Requirements:**
Advanced machine learning models may require significant computational resources, which can make them difficult to deploy in resource-constrained agricultural environments.

- **Limited Real-Time Support:**
Many traditional crop recommendation systems do not incorporate real-time environmental data or IoT-based monitoring systems, which limits their ability to provide timely decision support for farmers [11], [20].
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B. Proposed System

To overcome 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 improve crop prediction accuracy. Modern data-driven agricultural systems utilize computational models to analyse environmental and soil parameters in order to recommend crops that are most suitable for cultivation under specific conditions [1], [6].

The proposed system analyses several important agricultural parameters including soil nutrients such as nitrogen (N), phosphorus (P), and potassium (K), along with soil pH level, rainfall, temperature, and humidity. These parameters are widely recognized as critical factors that influence crop growth and agricultural productivity. By analysing these variables, predictive models can identify optimal crop choices for specific environmental and soil conditions [17], [18]. The dataset used for training the models is obtained from publicly available agricultural repositories that provide structured information related to soil nutrients and environmental conditions [13].

The system begins with a data preprocessing stage where the dataset is cleaned and transformed to ensure data consistency and reliability. Environmental datasets often contain missing values, redundant information, or inconsistent measurements. Therefore, preprocessing techniques such as handling missing values, removing irrelevant features, and normalizing feature

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values are applied to improve the quality of the dataset and enhance model performance [10]. Proper preprocessing is essential for improving the accuracy of machine learning models in agricultural applications.

After preprocessing, the dataset is divided into training and testing subsets to evaluate the performance of the predictive models. The training dataset allows the models to learn patterns from historical agricultural data, while the testing dataset is used to measure the model's ability to generalize and predict crop suitability for unseen conditions. Such evaluation techniques help ensure that the developed models provide reliable crop recommendations [3], [14].

The proposed framework implements multiple machine learning and deep learning models 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). Each of these algorithms analyses the relationships between soil nutrients, environmental variables, and crop suitability in order to generate accurate crop recommendations. Machine learning algorithms such as Random Forest and SVM have been widely used in agricultural prediction systems due to their strong performance in handling structured datasets 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 enhance the reliability of the system, model optimization techniques such as hyperparameter tuning and cross-validation are applied. These techniques help improve the generalization capability of the models and reduce prediction errors by selecting optimal model parameters during the training process. Optimization methods are commonly used in machine learning applications to improve model accuracy and stability [16].

Finally, the system generates crop recommendations through a user-friendly web interface. Farmers can input soil and environmental parameters, and the system analyses the data using the trained models to recommend the most suitable crops for cultivation. Such intelligent agricultural systems support farmers in making data-driven decisions and contribute to the development of precision agriculture practices. Additionally, integrating advanced technologies such as IoT-based environmental monitoring can further enhance the effectiveness of crop recommendation systems by enabling real-time data analysis and decision support [11], [20].

IV. SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

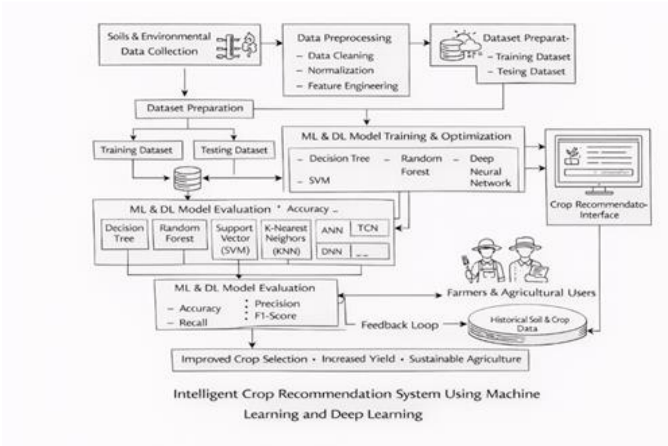

Fig. 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

1. Data Collection and Preprocessing

The first stage of the proposed system involves collecting agricultural data related to soil nutrients and environmental conditions. The dataset typically contains important parameters such as nitrogen (N), phosphorus (P), potassium (K), soil pH, rainfall, temperature, and humidity. These parameters play a crucial role in determining crop suitability and agricultural productivity. Several studies have highlighted that analysing soil nutrients and environmental conditions can significantly improve 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 on soil and environmental attributes for crop prediction tasks [13].

After collecting the dataset, preprocessing techniques are applied to improve the quality and reliability of the data. Environmental datasets often contain missing values, duplicate records, and inconsistent measurements that may affect the performance of predictive models. Therefore, preprocessing steps such as handling missing values, removing duplicate records, detecting outliers, and normalizing feature values are performed. Proper data preprocessing ensures that the dataset becomes consistent and suitable for training machine learning models and improves the accuracy of the prediction system [10].

2. Feature Selection and Feature Engineering

Feature selection is an important step in developing an effective crop recommendation system. In this module, the dataset is analysed to identify the most significant features that influence crop growth and agricultural productivity. Feature selection helps eliminate irrelevant or redundant variables, which reduces model complexity and improves computational efficiency.

Feature engineering techniques are also applied to transform raw agricultural data into meaningful features that better represent soil fertility and climate conditions. By extracting relevant features and optimizing the dataset, predictive models can more effectively learn relationships between environmental variables and crop suitability. Previous studies have emphasized that appropriate feature engineering plays a critical role in improving the performance of machine learning models used for agricultural prediction tasks [2], [14].

3. Training Machine Learning and Deep Learning Models

After preprocessing and feature selection, the processed dataset is used to train several machine learning and deep learning models. In this study, algorithms such as 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.

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 algorithms such as Random Forest and SVM are widely used for agricultural prediction because of their ability to handle nonlinear relationships and structured datasets [1], [9]. Similarly, neural network-based models such as ANN and DNN can learn complex patterns from large datasets and provide more accurate predictions for crop recommendation systems [7], [19].

Hyperparameter tuning techniques are also applied during training to improve model performance and stability. Optimization techniques help identify the most suitable parameters for each algorithm and enhance the overall prediction accuracy of the system [16].

4. Crop Recommendation System Interface

Once the models are trained, they are integrated into a crop recommendation system that provides a user-friendly interface for farmers. Through this interface, farmers can input agricultural parameters such as soil nutrient levels, rainfall, temperature, and humidity.

The system processes the input data using trained machine learning models and generates recommendations for the most suitable crops that can be cultivated under those environmental conditions. Intelligent crop recommendation systems provide valuable decision-support tools that help farmers improve productivity and adopt precision agriculture practices [6], [18].

5. Model Evaluation and Continuous Monitoring

The final module focuses on evaluating the performance of the trained models using various evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics measure how effectively each model predicts correct crop recommendations and help identify the most reliable algorithm for the system.

Continuous monitoring is also implemented to ensure that the system maintains high prediction accuracy over time. As new agricultural data becomes available, the models can be retrained and updated to adapt to changing environmental conditions. Integrating advanced technologies such as IoT-based monitoring systems can further enhance the accuracy of crop recommendation systems by enabling real-time data collection and analysis [11], [20].

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VI. RESULTS AND DISCUSSION

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

The experimental results demonstrate that machine learning algorithms can effectively identify relationships between soil nutrients, climatic conditions, and crop suitability. Agricultural parameters such as nitrogen (N), phosphorus (P), potassium (K), soil pH, rainfall, temperature, and humidity significantly influence crop productivity. By analysing these parameters, predictive models can learn patterns that determine which crops are best suited for specific environmental conditions [17], [18]. The dataset used for model training and evaluation was obtained from the publicly available crop recommendation dataset provided through 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 conditions to generate accurate crop recommendations. Previous studies have also demonstrated that machine learning techniques can significantly improve agricultural decision-making and crop 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 the results shown in Table 1, it can be observed that the Temporal Convolutional Network (TCN) achieved the highest prediction accuracy of 98.1%, followed by the Random Forest model with 97.2% accuracy. The superior performance of Random Forest can be attributed to its ensemble learning mechanism, which combines multiple decision trees to improve prediction stability and reduce overfitting during training [3], [18]. Similarly, deep learning models such as ANN, DNN, and TCN demonstrate strong performance because they are capable of learning complex nonlinear relationships between soil nutrients, environmental variables, and crop suitability [7], [19].

Traditional machine learning algorithms such as Decision Tree, KNN, Naïve Bayes, and SVM also produced reliable predictions, although their performance was slightly lower compared to ensemble and deep learning models. These algorithms are effective in analysing structured agricultural datasets but may have limitations when modelling complex relationships among multiple environmental variables [9], [14]. The accuracy comparison of different models is illustrated in Fig. 2. The graph clearly shows that ensemble and deep learning models achieve higher prediction accuracy compared to conventional machine learning algorithms. This result aligns with previous studies which highlight the effectiveness of advanced machine learning models in agricultural prediction tasks [2], [4].

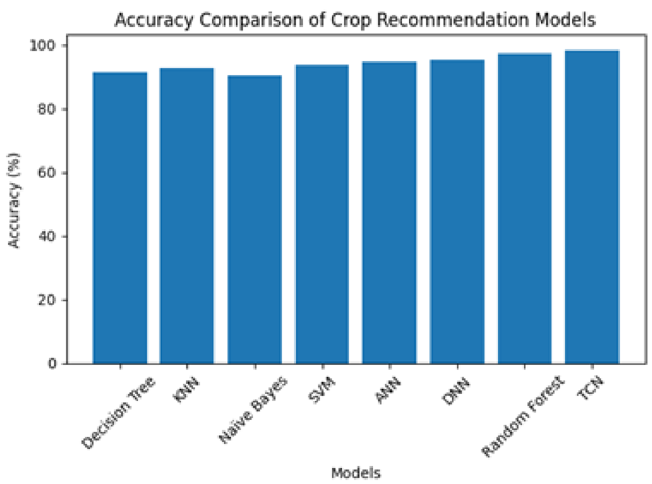

Fig. 2. Accuracy Comparison of Crop Recommendation Models

To further evaluate the classification capability of the proposed system, the Receiver Operating Characteristic (ROC) curve was analysed. The ROC curve represents the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) at different classification thresholds. It is commonly used to evaluate 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 that approaches the top-left corner of the graph represents a model with strong prediction capability and high discrimination between crop classes.

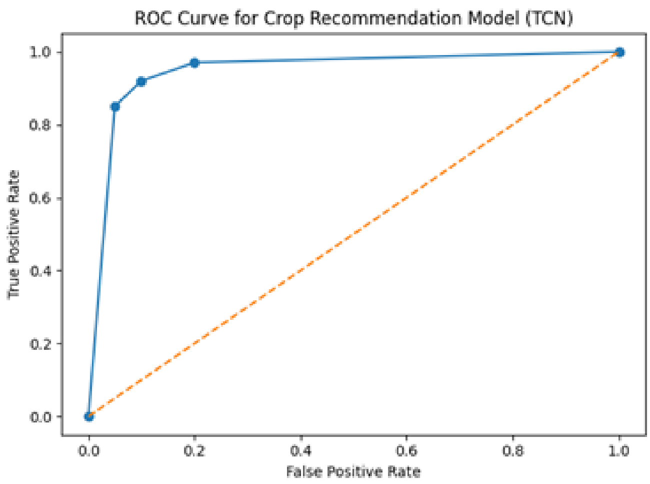

Fig. 3. ROC Curve for Crop Recommendation Model

The results also highlight the importance of data preprocessing and feature selection in improving model performance. Data preprocessing operations such as handling missing values, removing duplicate records, and normalizing environmental parameters help improve the quality of the dataset and enhance prediction accuracy [10]. Furthermore, analysing soil nutrient information plays a crucial role in improving crop recommendation systems and agricultural productivity [17].

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

VII. CONCLUSION AND FUTURE WORK

This study presented 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 recommend the most suitable crops for cultivation.The experimental results demonstrate that machine learning models can effectively analyse agricultural datasets and generate accurate crop recommendations. Among the evaluated models, Random Forest and Temporal Convolutional Networks showed the best performance in terms of prediction accuracy.The proposed system can help farmers improve crop selection, increase agricultural productivity, and make better use of soil and environmental resources. By providing data-driven recommendations, the system supports the development of precision agriculture practices.Future work may focus on integrating IoT-based sensors for real-time data collection from agricultural fields. Additionally, incorporatinglarger agricultural datasets and advanced deep learning models may further improve the accuracy and reliability of crop recommendations. Expanding the system to include crop yield prediction and pest detection features could also enhance its usefulness for farmers.

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