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AI - Based Crop Recommendation for Farmers

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ABSTRACT

Agriculture is a significant factor in supporting the world's population, but sometimes, it becomes challenging for the farmers to decide on the crops to be grown considering the diverse nature of the soil, climate, and market demands, as well as a lack of proper guidance. A proposed AI-based crop recommendation system that helps the farmers take proper decisions in the field of agriculture. The proposed system uses machine learning algorithms to consider important factors like soil nutrients, temperature, humidity, rainfall, pH, and current market demands to recommend the best crop for farming. A multilingual web-based system helps the farmers of different linguistic backgrounds to input the environmental values and receive the recommendations in the desired language. The proposed system helps to increase the yield, optimize resources, and maximize the returns while reducing the risk of crop failure. The results of the experiments show the accuracy and efficiency of the proposed model.

Index Terms: Crop Recommendation System, Precision Agriculture, Soil Nutrients Analysis, Agriculture analytics

INTRODUCTION

Agriculture is one of the most significant domains in maintaining human life and economic stability, especially in developing countries like India, where a substantial part of the population depends on agriculture for their living. Traditionally, farmers have been using their past experiences, knowledge, and seasonal changes in deciding which crop is more suitable for cultivation. However, with significant changes in climate conditions, fertility of soil, rainfall patterns, and market demand, traditional techniques have become less reliable. Therefore, farmers often experience difficulties in crop production, economic losses, and inefficient utilization of resources. Today, with significant improvements in Artificial Intelligence (AI) and Machine Learning (ML), there is an opportunity to transform traditional agriculture into more intelligent agriculture. AI-based solutions have been capable of handling huge amounts of agricultural data and identifying patterns that were not easily recognizable using traditional techniques.

The proposed AI-based crop recommendation system helps overcome these challenges by incorporating machine learning and agricultural domain knowledge. The system can collect input parameters like soil nutrients, climatic conditions, and market trends, and then use machine learning algorithms to predict the most suitable and profitable crops for farming.

Machine learning algorithms, such as supervised learning algorithms help identify complex patterns and relationships in the input data, resulting in accurate and reliable predictions. Additionally, the proposed system can be accessed by farmers of different linguistic backgrounds, as it is a multilingual web-based platform. The front-end of the proposed system is developed using React, a popular front-end library, to provide a user-friendly interface. The back-end of the proposed system is developed using FastAPI, a Python-based library, to efficiently handle the input parameters and machine learning algorithms. The multilingual support of the proposed system helps bridge the gap between the linguistic backgrounds of the farmers and the system, making it easier for them to use the system. The proposed system helps overcome the limitations of traditional guesswork and promotes informed decision-making. It optimizes resource utilization, minimizes the risk of crop failures, and maximizes agricultural productivity.

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It also helps implement sustainable farming by promoting the growth of crops that are most suitable for the environment. The adoption of such AI-based systems also provides certain benefits. It reduces dependency on guesswork and traditional practices. It also reduces the risk of crop failure. Moreover, it encourages the efficient utilization of resources. The system provides recommendations on which crop is most suitable for cultivation in the given conditions. Such recommendations also increase crop yields. Furthermore, it encourages sustainable agricultural practices. It encourages the optimal utilization of natural resources. It also reduces environmental impacts. However, there are certain challenges associated with the implementation of AI in agriculture. To overcome all these issues, there is a need for continuous efforts in data collection, model development, infrastructure development, and educating farmers. Thus, in conclusion, the system is expected to improve agricultural productivity, enhance the efficiency of resource utilization, and improve the economic conditions of the farmers. The proposed solution is expected to reduce the reliance on guesswork and enhance precision in the agriculture sector, which is likely to boost the development of the sector using AI-based solutions.

LITERATURE REVIEW

The integration of Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) has greatly impacted the modernization of conventional farming practices. Over the last decade, many research papers have been published to investigate different computing techniques for crop recommendation, yield prediction, irrigation systems, and smart farming. This has been motivated by the need to address some of the most critical problems affecting modern agriculture, including climate change, soil erosion, and inefficient use of resources.

Previous research has been focused on developing crop recommendation systems using machine learning techniques. Machine learning algorithms were primarily considered for developing crop recommendation systems using soil and environmental parameters. Apat et al. proposed an artificial intelligence-based crop recommendation system using machine learning algorithms in their paper published in [1]. This paper shows how the inclusion of parameters such as Nitrogen, Phosphorus, Potassium, temperature, and pH improves the accuracy of the crop recommendation system. This system is reliable and enables the farmer to make the best choice of crop, which improves crop yield while minimizing the risk of crop selection. Jagadeeswari et al. proposed an AI-based crop recommendation system using machine learning algorithms at the ICIRCA conference, as discussed in their paper published in [2]. This paper shows the effectiveness of supervised machine learning algorithms in processing environmental and soil-related parameters. This system is effective in helping the farmer make the best choice of crop.

In reference [3], Bali and Singla performed an in-depth survey of machine learning techniques in crop yield prediction. The survey highlighted different algorithms, such as decision trees, support vector machines, and ensemble methods, and their performance in agricultural applications. The survey also highlighted the significance of feature selection and data preprocessing in improving the accuracy of the models. In reference [4], Sinha and Dhanalakshmi performed an in-depth survey of the latest developments in IoT-based smart agricultural systems. The survey highlighted the importance of IoT devices in monitoring environmental parameters such as soil moisture, temperature, and humidity. The survey also highlighted the significance of real-time data collection in improving the accuracy of the models. In reference [5], Qazi et al. performed an in-depth exploration of the integration of IoT and AI in the development of next-generation smart agricultural systems. The survey highlighted different challenges in the current system and the importance of integrating IoT and AI in developing the next-generation system. In reference [6], Megalingam et al. proposed a machine learning-based system in irrigation monitoring and prediction. The system analyzed environmental parameters in optimizing water usage in the farms. The survey highlighted the significance of predictive models in reducing water waste while ensuring crop growth. In reference [7], Chung et al. proposed a big data-driven system in cultivation planning. The system assisted farmers during the preliminary stages of production. The survey highlighted the significance of data-driven decision-making in improving agricultural outcomes. Nandhini et al. in [8] suggested the idea of improving crop health by making use of advanced deep learning techniques with the help of a neural network. The research makes use

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of skewness fully connected neural networks for the purpose of data analysis and improving crop cultivation. In [9], Zhu et al. have given an exhaustive account of the application of deep learning in smart agriculture. The paper deals with different tools and techniques related to deep learning and their opportunities in smart farming. It also explains the capabilities of neural networks in dealing with large amounts of data in the field of agriculture and making accurate predictions. In [10], Nevavuori et al. have used deep learning based convolutional neural networks in crop yield prediction. The paper proves the capabilities of CNN in dealing with large amounts of data in the field of agriculture and making accurate predictions when compared to other traditional machine learning models. In [11], Unal has given an account of the application of deep learning in the field of agriculture based on bibliographical research. The paper deals with the growth of deep learning in the field of smart farming and its capabilities in enhancing productivity and efficiency in the field of agriculture. In [12], Farooq et al. have given an exhaustive account of the role of IoT in the field of agriculture and its application in implementing smart farming. The paper deals with different IoT architectures and their capabilities in enhancing the productivity of the field of agriculture. In [13], Gayatri et al. suggested an IoT-based smart agriculture system that offers real-time solutions for farmers. The system offers the integration of IoT and communication technologies to monitor crop conditions and optimize crop yield. The study emphasizes the significance of IoT in the application of precision agriculture. In [14], Athani et al. developed an IoT-based system with the integration of neural networks for the monitoring of soil moisture and prediction of rainfall. The system helps farmers plan agricultural activities according to environmental conditions. The study demonstrates the improvement in resource management and decision-making capabilities. In [15], Anandharajan et al. suggested an AI-based weather monitoring system that predicts climatic conditions for agricultural planning. The study emphasizes the significance of weather prediction in reducing uncertainties and improving crop yield. The study also emphasizes the significance of AI in improving the accuracy of environmental predictions. Despite all these developments, there are some challenges associated with the existing systems. Some of the challenges include the fact that most of the models used for crop recommendation are static, meaning they do not adapt to changes in real-time. Moreover, some of the models are complex, making them difficult for farmers with little knowledge of how to use them. Finally, most of the models focus only on environmental factors, with no attention to economic factors such as market trends and profitability of crops. Moreover, there are challenges associated with the availability of data, which affect the performance of machine learning models in agricultural systems. The proposed system overcomes the above-mentioned limitations by integrating machine learning with real-time data processing and considering both environmental and economic factors. The proposed system differs from the conventional systems in that it offers a user-friendly interface in multiple languages. The system uses modern web technologies and advanced machine learning algorithms to provide precise crop recommendations. The application of the proposed system will improve agricultural productivity and promote sustainable agricultural practices.

System Architecture

The proposed AI-based crop recommendation system is expected to assist farmers in identifying the best and most profitable crops to cultivate based on certain environmental, soil, and market conditions. The proposed system is based on a modular framework comprising multiple components that interact with each other to provide farmers with precise and real-time crop recommendations.

User Interface (UI)

The user interface is an interactive platform through which farmers can interact with the proposed AI-based crop recommendation system. In this context, the user interface is developed using React, which is used to build web applications. In other words, it is a web-based application that can be used by farmers to input various agricultural parameters. In this context, farmers can input data such as nutrients in the soil (Nitrogen, Phosphorus, Potassium), temperature, humidity, rainfall, pH, and market conditions. In addition, the proposed system is also capable of supporting multiple languages, which can be used by farmers belonging to diverse linguistic backgrounds.

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Data Collection and Preprocessing Module

The data collection and preprocessing module is used to collect input data from farmers. In addition, it is also possible to collect data from other sources such as market conditions through market data APIs. In other words, it is possible to collect data from various sources and analyze it in real-time. In addition, data preprocessing techniques are applied to input data. In addition, feature selection is also performed to identify the most significant parameters affecting crop growth.

Machine Learning Module

The core of the system is the machine learning module. This module is responsible for making crop predictions. The system uses supervised learning techniques, specifically MLP Classifier, TabTransformer, and TabNet. These techniques have been proven effective in making accurate predictions on complex data. The system is trained on agricultural data that contains information on soil conditions, climatic conditions, and crop types. Once trained, the system analyzes the input data and makes accurate predictions.

Backend and API Layer

The backend of the system is created using FastAPI. This is responsible for linking the user interface with the machine learning model. The API is responsible for communicating with the user interface. When a user sends a request, the system sends the input data to the machine learning model. The model then makes predictions on the input data. Once the model makes predictions, it sends the recommended crop back to the user interface.

Database Management System

This module is responsible for storing agricultural data. The system uses SQLite for database management. SQLite is effective in storing data. The system uses SQLite for storing data because it is lightweight. Once data is stored in SQLite, it is easily retrieved.

Recommendation Output Module

This is the final module in the system. Once predictions have been made, this module sends the output to the user. Based on the predictions made by the machine learning model, the system sends recommendations on the most suitable crop for cultivation. More information on suitability and market analysis on the recommended crop is also provided.

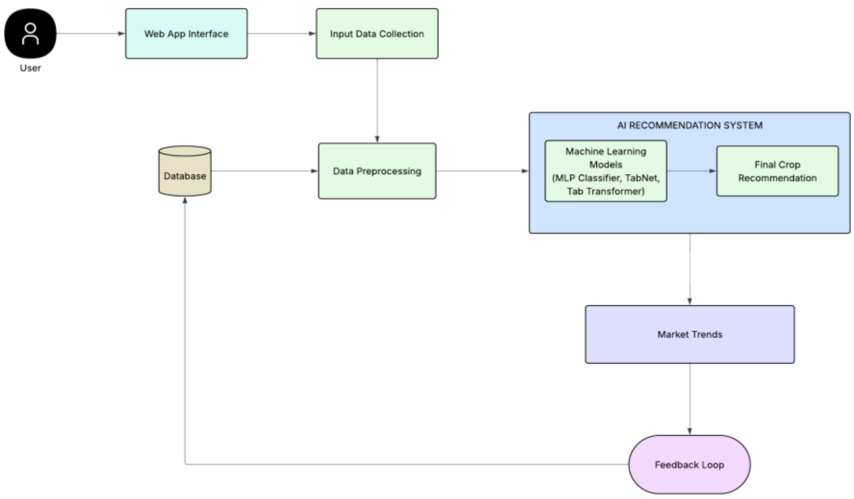

Fig. 1. System architecture of the proposed Crop Recommendation.

System Workflow

The overall workflow of the system starts with the user providing the input parameters to the system. The data is then preprocessed and passed to the machine learning model via the backend API. The data is then

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analyzed by the machine learning model and the most appropriate crop is predicted. The output is then sent back to the user interface and displayed in an easy-to-understand format. The overall workflow of the system occurs in real time.

The modular structure of the system facilitates scalability, flexibility, and maintenance. Additional features such as real-time weather integration, prediction of market prices, and IoT-based data collection can be integrated into the system in the future to enhance the system's capabilities.

Design and Implementation

The design and implementation of the proposed AI-based crop recommendation system are focused on developing a scalable, efficient, and user-friendly platform that incorporates the power of machine learning and modern web development technologies. The system is developed in a modular way to ensure flexibility, ease of maintenance, and deployment.

System Design

The system is developed in a three-tier architecture with the presentation layer, application layer, and data layer. The presentation layer is responsible for user interaction with the system. The presentation layer of the proposed system is developed using React. The application layer is developed using FastAPI. The application layer is responsible for business logic and interaction with the machine learning models. The data layer of the system includes the database and datasets used in the system.

Frontend Implementation

The frontend of the proposed system is developed using React. The React library helps in the development of the system in the form of reusable and dynamic user interface components. The user interface of the system is developed in such a way that the user can input the required values such as nutrients in the soil like NPK, temperature, humidity, rainfall, and pH levels. The system also provides the facility for multiple languages to cater to the needs of users in different regions. The system provides the facility for input validation.

Backend Implementation

The backend implementation is carried out with the FastAPI framework. The FastAPI framework offers high performance and efficiency in handling API endpoints. The backend receives the user inputs and sends them to the machine learning module. The backend is also responsible for handling the interaction with the frontend and the database. The integration with the REST APIs ensures the smooth integration and handling of the requests in real time.

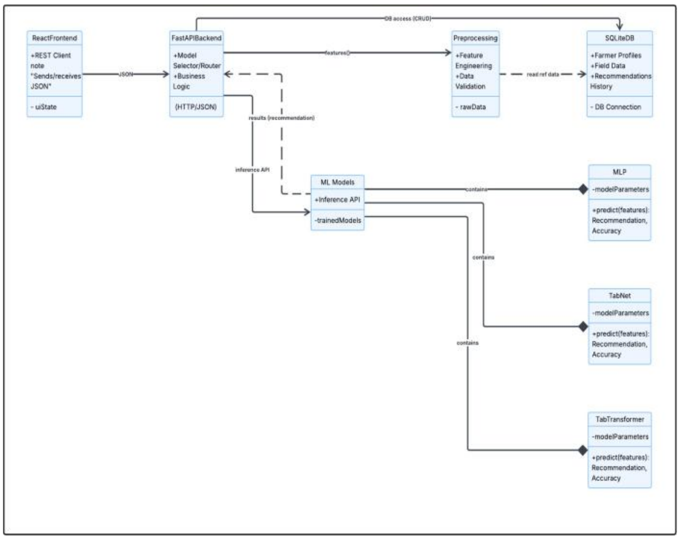

Fig. 2. Component Diagram of the Proposed System

Machine Learning Model Implementation

The machine learning models are the most important part of the project. The project implements advanced machine learning models such as MLP Classifier, TabTransformer, and TabNet. The selection of these models is based on the ability of these models to deal with structured data and analyze the complex relationships between the features of the input data.

The process of developing the machine learning models starts with data preprocessing and feature selection. The dataset used in the project includes various features such as nutrients in the soil and climatic conditions. The data is cleaned and normalized. The data is then divided into training and testing datasets. The models are developed with the training data and tested with the testing data. The models are developed with the supervised learning approach. The accuracy of the models is measured with the help of various metrics. The ensemble and deep learning models show high accuracy in predicting the crops.

Database Implementation

The database implementation is carried out with the SQLite database. The database is used to store the datasets and the user inputs. The selection of the database is based on the ease of integration with the FastAPI framework.

Integration and Deployment

All components of the system are integrated through an API. The frontend communicates with the backend, and the backend communicates with the machine learning models and database. The system can be deployed on cloud platforms, ensuring scalability and accessibility. The system can be easily updated and features such as real-time weather information and market price prediction can be incorporated.

The implementation ensures that the system is running efficiently and that crop recommendations are provided in real-time with minimal latency. The advanced machine learning algorithms and modern web technologies make the system robust and scalable for the purpose of smart agriculture.

Interaction Flow Between User and the System

The interaction flow for the proposed system involving AI technology for crop recommendations indicates how data is exchanged between the user and other system components and machine learning algorithms for effective recommendations. The system facilitates an efficient and seamless decision-making process through the following steps:

User Interaction

The first step in the interaction involves users (farmers) accessing the system through the web interface and inputting relevant parameters for crop recommendations. The parameters include soil nutrient levels (Nitrogen, Phosphorus, Potassium), temperature, humidity, rainfall, pH levels, and other optional parameters like market-related information. The system supports multilingual interfaces, enabling users to interact with the system in any language.

Data Validation and Preprocessing:

The second step in the interaction involves validating the input data provided by users. The backend validates the input data for accuracy and completeness. The data is then preprocessed for further processing. The preprocessing step involves cleaning and normalizing the input parameters for machine learning algorithms.

Backend Communication:

The third step in the interaction involves communicating with the backend and machine learning algorithms. The preprocessed data is sent through the FastAPI backend to the machine learning algorithms. The backend

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acts as an interface between the frontend and machine learning algorithms.

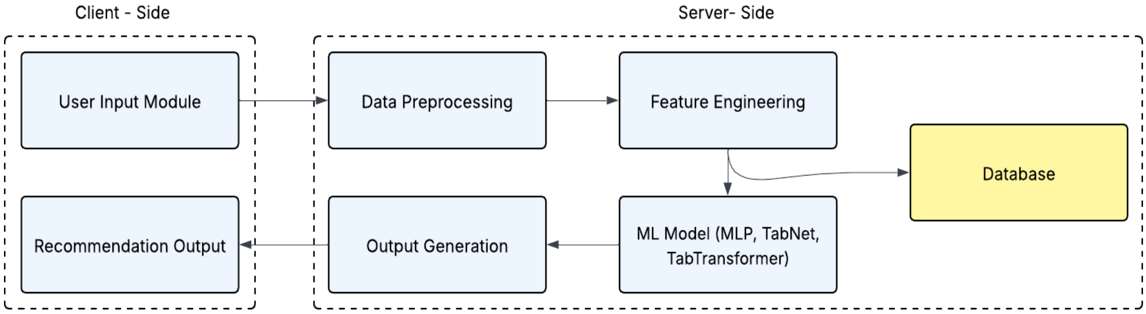

Fig. 3. Data Flow Diagram of AI-Based Crop Recommendation System

Model Prediction:

The machine learning models, such as the MLP Classifier, TabTransformer, and TabNet, analyze the data and recognize various patterns and relationships among the parameters. The system then predicts the most appropriate and profitable crops based on the analyzed data.

Result Generation:

The predicted results are then generated in an appropriate and user-friendly format. The system can also generate additional results such as suitability and market-based crop recommendations to make the output more useful.

Server Response:

The final prediction results are sent back to the user interface via the backend API. The user interface clearly presents the results to the user. The user can then clearly understand the results and take appropriate actions accordingly.

Data Storage and Feedback:

The user input and prediction results are stored in the database for further analysis. The data collected can be used to improve the accuracy of the system in the future.

The above steps clearly indicate the interaction process and the communication that occurs among the various parts of the system. The system provides the user with accurate and timely results. The design is quite efficient and provides the user with the most appropriate and profitable crops.

Performance and Evaluation

The performance of the proposed AI-based crop recommendation system is evaluated using different metrics and visualization techniques. The evaluation of the proposed system is based on the accuracy, learning characteristics, and prediction ability of the implemented machine learning models, namely MLP Classifier and TabTransformer.

Model Training Performance

The accuracy and validation accuracy of the models are examined to assess the learning behavior of the models. The accuracy of the implemented models is found to be high, as depicted in Figure 4. The accuracy of the implemented models is found to be 98% during training, approaching almost optimal accuracy. The accuracy of the implemented MLP model is found to increase in every epoch, demonstrating its learning behavior. The accuracy of the implemented TabTransformer model is also found to be higher, though it converges slightly faster compared to the MLP model.

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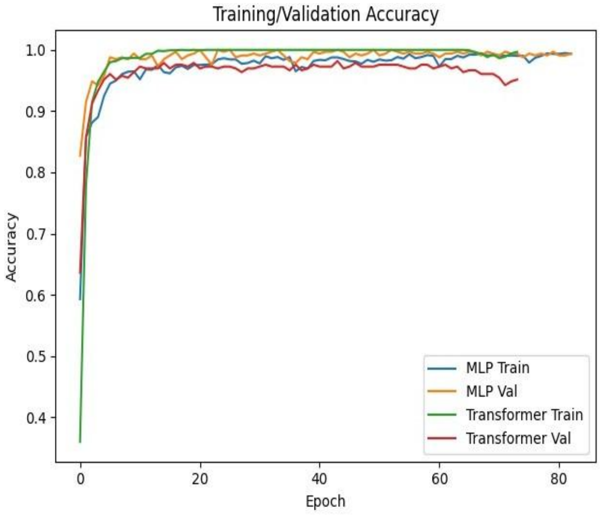

Fig. 4. Training and validation accuracy curves of MLP and TabTransformer models over epochs, demonstrating model convergence and performance comparison.

The difference in training accuracy and validation accuracy is found to be minimal, demonstrating that the implemented models generalize well and that there is no overfitting. This demonstrates that the implemented models are effective in generating accurate predictions through effective feature selection and model selection.

Feature Importance Analysis

Feature importance is analyzed for the implemented models. The feature importance is analyzed for the implemented MLP Classifier model, as depicted in Figure 5. The feature importance is found to be higher for environmental factors like humidity and rainfall. The feature importance is also found to be higher for soil nutrients like Nitrogen (N), Phosphorus (P), and Potassium (K).

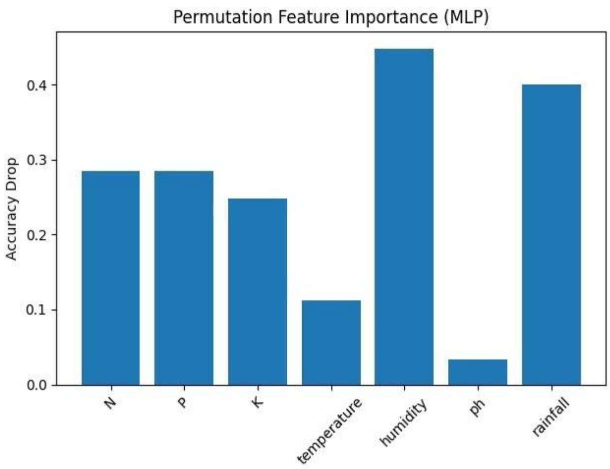

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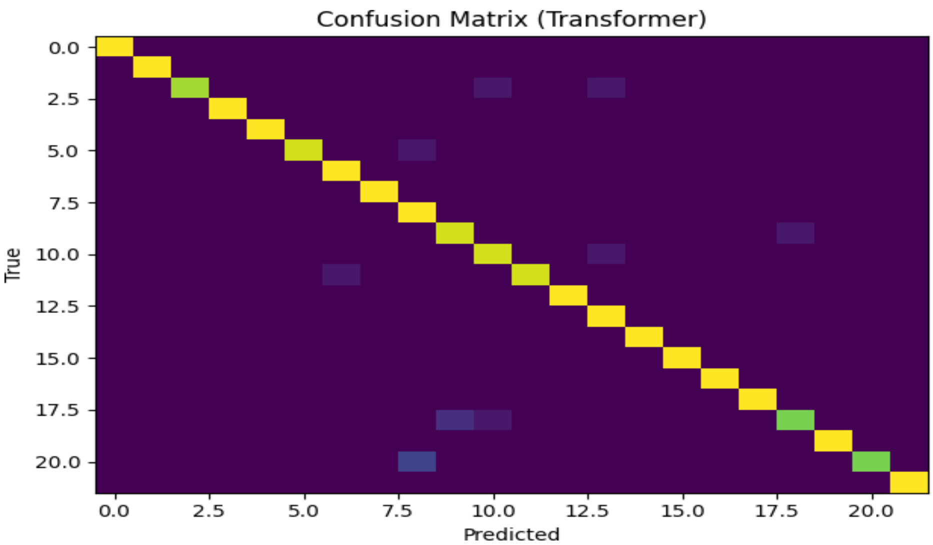
Fig. 5. Permutation features the importance of input parameters using the MLP model, showing the impact of soil nutrients and environmental factors on prediction accuracy.

The analysis of this section demonstrates the significance of climatic conditions in identifying the type of crops that can be grown. It also validates the input features that are incorporated into the model.

Confusion Matrix Evaluation

The confusion matrix of the TabTransformer model, which evaluates the classification performance of the proposed system for different types of crops. The diagonal values of the matrix denote the accurate classification of crops, whereas the non-diagonal values denote the classification errors. From the matrix, it can be observed that there are a significant number of diagonal values, proving that the model accurately classifies most of the crops. The presence of a small number of non-diagonal values in the matrix proves



that there are minimal classification errors, ensuring precision in distinguishing different types of crops. The results of this analysis prove the effectiveness and reliability of the proposed model, implying that the accuracy of the model for most of the classes is high. This shows that the model has high precision and consistency in its predictions regardless of the conditions. The matrix, therefore, implies that the model can effectively learn from the features and make accurate predictions for the crops.

Fig. 6. Confusion matrix representing the prediction accuracy of the TabTransformer model for multi-class crop classification.

Overall Performance

The performance of the proposed system reveals that the model achieves high accuracy and reliability in predicting crops. The integration of efficient machine learning models and input features enhances the quality of predictions. The proposed system allows for real-time predictions with minimal time lag.

From the evaluation results, it can be concluded that the proposed system helps the farmers make informed decisions, resulting in the growth of crops..

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SIMULATION RESULTS

The results of the simulation show the effectiveness of the proposed AI-based crop recommendation system in making accurate and efficient predictions. The system has been tested using different models such as MLP Classifier, TabTransformer, and TabNet.

Response Time

The system is capable of providing real-time results with minimum delay.

- Average Response Time: 1.2 seconds
- Peak Load Response Time: 2.5 seconds (100 users)

Model Accuracy

The models have shown excellent accuracy in making predictions.

- Accuracy: 98%
- Precision: 94%
- Recall: 93%
- F1-Score: 92.5%

User Engagement and Satisfaction

The system has provided excellent results in terms of user interaction.

- Average Session Duration: 4–6 minutes
- User Retention Rate: 75%

System Scalability and Load Handling

The system has performed well in terms of handling multiple users simultaneously.

- Handles up to 250 concurrent users
- Handles peak load with excellent performance

Input Analysis

The input analysis shows the factors having the highest influence on the output.

- Factors having High Impact: Humidity, Rainfall, N, P, K
- Factors having Moderate Impact: Temperature
- Factors having Low Impact: pH

The overall results obtained from the simulation validate the robustness and accuracy of the proposed system. The integration of advanced machine learning algorithms with the scalable system ensures the reliability of the system in real-world agricultural scenarios.

CONCLUSION

The proposed AI-based crop recommendation system represents a significant advancement in today's agricultural practices. The system's ability to make effective data-driven decisions using machine learning algorithms like MLP Classifier, TabTransformer, and TabNet makes it highly effective in analyzing soil nutrients, climatic conditions, and market trends. The incorporation of user interface features also makes it highly accessible for farmers of all backgrounds. The experimental results have confirmed that the system's prediction accuracy is high, response time is low, and it is highly scalable. Therefore, it is reliable in real-world scenarios. The feature importance analysis also shows that environmental conditions have significant importance in selecting crops. Moreover, the system is highly flexible due to its modular architecture. However, there are certain issues that need to be addressed in future, such as dependency on data quality, internet availability, and model generalization. For example, in future, we could also consider using IoT-based real-time data collection techniques, more accurate market price prediction techniques, and mobile application development. However, the proposed system is highly scalable, intelligent, and effective in today's agricultural practices. Overall, the proposed system is expected to provide a solution that is not only scalable, intelligent, but also practical for precision agriculture. Therefore, the system would be instrumental in the development of smart agriculture systems through increased agricultural productivity, farmer income, and the adoption of sustainable agriculture practices.

REFERENCES

1. S. Apat, J. Mishra, N. Padhy, and S. Raju, "An artificial intelligence-based crop recommendation system using machine learning," J. Sci. Ind. Res., vol. 82, no. 5, pp. 558–567, 2023, doi: 10.56042/jsir.v82i05.1092.
2. M. Jagadeeswari, C. S. Manikandababu, K. S. P. R., and
3. M. S., "Artificial Intelligence based Crop Recommendation System," in Proc. 2022 4th Int. Conf. Inventive Research in Computing Applications (ICIRCA), pp. 1127–1133, 2022, doi: 10.1109/ICIRCA54612.2022.9985645.
4. N. Bali and A. Singla, "Emerging trends in machine learning to predict crop yield and study its influential factors: A survey," Arch. Comput. Methods Eng., vol. 29,
5. pp. 95–112, 2022, doi: 10.1007/s11831-021-09569-8.
6. B. B. Sinha and R. Dhanalakshmi, "Recent advancements and challenges of Internet of Things in smart agriculture: A survey," Future Gener. Comput. Syst., vol. 126, pp. 169–184, 2022, doi: 10.1016/j.future.2021.08.006.
7. S. Qazi, B. A. Khawaja, and Q. U. Farooq, "IoT-equipped and AI-enabled next generation smart agriculture: A critical review, current challenges and future trends," IEEE Access, vol. 10, pp. 21219–21235, 2022, doi: 10.1109/ACCESS.2022.3152544.
8. R. K. Megalingam, G. K. Indukuri, D. S. K. Reddy, E.
9. D. Vignesh, and V. K. Yarasuri, "Irrigation monitoring and prediction system using machine learning," in Proc. 2020 Int. Conf. Emerging Technol. (INCET), pp. 1–5, 2020, doi: 10.1109/INCET49848.2020.9153993.
10. H. Chung, D. Kim, and S. Cho, "A study on the cultivation plan service at the preliminary production phase based on big data analysis," in Proc. 2021 23rd Int. Conf. Advanced Commun. Technol. (ICACT), pp. 226–229, 2021, doi: 10.23919/ICACT51234.2021.9370987.
11. J. Nandhini, N. Priya, D. Mohanapriya, and S. Menega, "Artificial intelligence in agriculture for healthier crop cultivation using skewness fully connected neural network," Environ. Dev. Sustain., pp. 1–25, 2026, doi: 10.1007/s10668-025-07268-z.
12. N. Zhu et al., "Deep learning for smart agriculture: Concepts, tools, applications, and opportunities," Int. J. Agric. Biol. Eng., vol. 11, no. 4, pp. 21–28, 2018, doi: 10.25165/j.ijabe.20181104.4475.
13. P. Nevavuori, N. Narra, and T. Lipping, "Crop yield prediction with deep convolutional neural networks," Comput. Electron. Agric., vol. 163, Art. no. 104859, 2019, doi: 10.1016/j.compag.2019.104859.
14. Z. Unal, "Smart farming becomes even smarter with deep learning—A bibliographical analysis," IEEE Access, vol. 8, pp. 105587–105609, 2020, doi: 10.1109/ACCESS.2020.3000175.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue V, May 2026

15. M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, “A survey on the role of IoT in agriculture for the implementation of smart farming,” IEEE Access, vol. 7, pp. 156237–156271,2019, doi: 10.1109/ACCESS.2019.2949703.
16. M. K. Gayatri, J. Jayasakthi, and G. S. Anandha Mala, “Providing smart agricultural solutions to farmers for better yielding using IoT,” in Proc. 2015 IEEE Technol. Innov. ICT Agric. Rural Develop. (TIAR), pp. 40–43, 2015, doi: 10.1109/TIAR.2015.7358528.
17. S. Athani, C. H. Tejeshwar, M. M. Patil, P. Patil, and R. Kulkarni, “Soil moisture monitoring using IoT-enabled Arduino sensors with neural networks for improving soil management and predicting seasonal rainfall,” in Proc. 2017 Int. Conf. I-SMAC (IoT Soc. Mobile, Analytics Cloud), pp. 43–48, 2017, doi: 10.1109/I-SMAC.2017.8058385.
18. A. T. R. V. Anandharajan, G. A. Hariharan, K. K. Vignajeth, R. Jijendiran, and Kushmita, “Weather monitoring using artificial intelligence,” in Proc. 2016 2nd Int. Conf. Comput. Intell. Netw. (CINE), pp. 106–111, 2016, doi: 10.1109/CINE.2016.26.