A MACHINE LEARNING APPROACH FOR RECOMMENDING SOIL NUTRIENT LEVELS

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Abstract— India's coastal state of Tamil Nadu is confronted with difficulties in agriculture as a result of climate-related variables and unpredictability. Even though both the people and the area are expanding, there is no way to achieve the desired rise in productivity. The expansion of the information technology industry has resulted in the creation of a system that allows farmers to get suggestions about the production of crops. The recommendation of crops is based on the amount and meteorological conditions of the area, and data analytics makes it possible to extract meaningful information from large agricultural datasets. An analysis of the crop dataset has been performed, and suggestions have been given depending on the season and the level of production.

Keywords— Recommendation, Crop, Agriculture, Data Analysis, Machine Learning

I. INTRODUCTION

The presence of nutrients in the soil has a crucial role in influencing the fertility and productivity of agricultural land. Understanding the identity and mechanisms of action of these nutrients is crucial for Optimal soil management practices to provide sustainable crop productivity over an extended period. This research article seeks to investigate the use of machine learning techniques for predicting soil nutrient levels as a viable alternative to traditional approaches.

For plants to thrive, they need a diverse range of nutrients, including both macronutrients and micronutrients. Macronutrients such as potassium (K), sulfur (S), and phosphorus (P) are essential. Essential for the well-being of plants are small quantities of the micronutrients copper (Cu), zinc (Zn), iron (Fe), sulfur (S), calcium (Ca), molybdenum (Mo), boron (B), zinc (Cl), and manganese (Mn) [1].

The use of conventional techniques for soil nutrient prediction has been extensively adopted in agricultural practices [2]. The collection of operations includes techniques for extracting nutrients, kits for testing soil, and laboratory examination of soil samples. Although these approaches are valuable for assessing soil nutrient levels, they are not devoid of shortcomings. An inherent drawback of traditional soil nutrient prediction methods is their time- consuming nature.

The results obtained by these procedures may need substantial laboratory analysis and might potentially take many days, if not weeks, to get. Additionally, they are costly because of the need for specialized equipment and skilled workers. Furthermore, the data obtained from these approaches is inherently restricted, therefore rendering them incapable of encompassing the whole spectrum of soil nutrient levels seen throughout various locales.

While soil nutrient prediction has some drawbacks, machine learning (ML) techniques have emerged as a viable alternative. Their various advantages make them superior to more traditional procedures. They provide more cost efficiency, require less effort, and deliver immediate forecasts. Moreover, these models possess the capability to illustrate the intricate connections among soil features, nutrient levels, and other variables, so improving comprehension and control of soil nourishment. The primary objective is to use machine learning techniques to predict soil nutrient levels. Additionally, the performance of MLR and KNN regression models in accomplishing this job will be evaluated.

A. Objective

The primary purpose of this research is to provide recommendations about the soil based on the levels of nitrogen, phosphorus, and potassium. To put into practice several machine learning techniques, such as the Decision tree and the KNN algorithm. To provide a prediction on the soil nutrient values for the crop in question. To improve the performance and make it more efficient.

II.RELATED WORKS

The purpose of this study is to conduct a comparative analysis of the prediction of agricultural output by using Artificial Neural Networks (ANN) in combination with Independent Component Analysis (ICA) and Genetic Wolf Optimization (GWO). To provide accurate and reliable projections of crop yield, the purpose of this research is to identify the strategy that is the most effective among these possible approaches [1]. By integrating information obtained from proximal sensing with techniques from machine learning, the purpose of this study is to make projections on agricultural productivity. Through the use of data collected near the crops, the project hopes to increase the accuracy of agricultural production predictions and the understanding of the factors that impact variations in output [2].

Through the use of a Deep Reinforcement Learning model,

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this article proposes a novel approach to the prediction of agricultural production. There is a greater concern for ecologically friendly and resource-efficient agricultural practices in the prediction models, which is shown by the fact that the emphasis is on the development of sustainable agrarian applications [3]. Deep Convolutional Neural Networks (CNNs) are the subject of this research, which analyzes its potential use in estimating agricultural production. The ability of Convolutional Neural Networks, sometimes known as CNNs, to capture spatial properties has contributed to their widespread popularity. The purpose of this research is to make use of these traits to improve the accuracy of crop production forecasts [4].

To anticipate agricultural production, the purpose of this project is to develop a framework that incorporates both convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Through the incorporation of geographical and temporal elements, the research endeavors to enhance the predictive capabilities of the model to provide more accurate projections of crop production outcomes [5]. Specifically focusing on Dacrydium pectinatum species in China, the purpose of this research is to evaluate the quantities of nutrients present in the soil via the use of machine learning techniques. Through the use of advanced computer tools, the study endeavors to get an understanding of the current condition of soil health and the range of nutrients present [6].

The project investigates the transition from approaches based in the laboratory to proximal sensing spectroscopy to estimate the amount of organic carbon found in soil. In this review, a complete analysis of the most recent advancements in soil analytical methodologies is presented. These advancements have substantially improved our understanding of the dynamics of soil carbon that have been observed [7].

The objective of this study is to investigate the use of laser-induced breakdown spectroscopy for characterization of soil. In particular, it focuses on the classification of various kinds of soil as well as the examination of the components that are present in the soil. The findings of this work contribute to the exploration of advanced spectroscopic approaches for the thorough characterization of soil [8]. Through the use of X-ray fluorescence data and machine learning algorithms, the research proposes a method that may increase the speed with which soil fertility can be predicted. The purpose of this study is to develop a system that is both efficient and straightforward for determining the levels of soil fertility by using advanced analytical techniques [9].

The variability of soil organic carbon is evaluated in this work via the use of machine learning techniques, with environmental conditions and soil nutritional indicators being taken into consideration too. This study contributes to a better understanding of the relationships that exist between the carbon content of soil and the environmental factors that are present in alluvial soils [10]. Through the use of visible near infrared ray spectroscopy and boosting algorithms that make use of a variety of pretreatment modifications, the study is centered on the prediction of the potassium content that is accessible in the soil. The problem of accurately detecting critically important soil nutrient levels to improve agricultural practices is the primary emphasis of this work [11].

The purpose of this research is to examine the use of learning algorithms in conjunction with visible and near- infrared (Vis-NIR) spectra to assess the presence of potentially hazardous components in forest soils. The purpose of this effort is to improve our understanding of the occurrence and dispersion of harmful compounds in forest soils, with the end goal of reducing the environmental dangers that are associated with these substances [12]. In this study, a new approach for performing liver segmentation in threedimensional computed tomography (3DCT) is presented. This method integrates the U-Net algorithm with the ADAM algorithm. To increase the accuracy of diagnosis, the study focuses on the challenges that are faced in medical imaging and segmentation methodologies [13].

Through the use of Artificial Intelligence, this research presents a Mobile Ad-Hoc Network (MANET) that is both hybrid and efficient, and in addition, it guarantees the secure transmission of data. The project's primary objective is to solve the security concerns that are present in Mobile Ad hoc Networks (MANETs) by using trust mechanisms and Artificial Intelligence (AI) strategies to guarantee secure communication [14].

The purpose of this paper is to provide a unique technique for providing an energy-efficient adaptive cluster fuzzy- based controller in wireless sensor networks. The strategy makes use of sparse Long Short-Term Memory (LSTM). The purpose of the research is to improve the energy efficiency of sensor networks, with the end goal of making a significant contribution to the creation of wireless communication systems that are both sustainable and efficient [15].

In this article, ideas for smartphone applications are provided, depending on the feedback and features provided by customers. This study focuses on the problem of personalized app recommendations, which attempts to improve the overall experience of using apps and make it easier for users to find new apps [16]. This research is being conducted with the main purpose of protecting the frequency count of Bitcoin from any efforts to double-spend their funds. The purpose of the project is to improve the reliability and trustworthiness of digital transactions [17]. The project's primary emphasis is on fixing security vulnerabilities that exist inside crypto currency systems

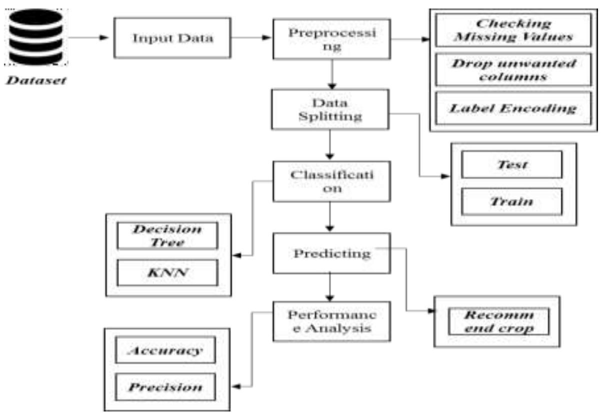

Fig. 1. System Architecture

III.PROPOSED METHODOLOGY

The process of constructing the crop recommendation system begins with the acquisition of a relevant dataset from a source. This is the first phase in the process. It is quite likely that this information contains significant factors such as the kind of soil, the peculiarities of the climate, and the success of the crop in the past. The subsequent step is the pre- processing of the data,

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which is a vital phase that must be finished to ensure that the model is of high quality and meets all of the necessary criteria. At this point in the process, it is very essential to begin addressing the problem of missing data to prevent the production of inaccurate projections. When there is a lack of data, it may lead to models that are biased and incorrect recommendations. This underscores the need to use data imputation strategies that are dependable. The emphasis shifts to the implementation of machine learning algorithms as soon as the pre-processing of the data is completed. In particular, Decision Trees and K-nearest neighbors (KNN) are the algorithms that are being focused on. The capacity of decision trees to be interpreted, in addition to their flexibility for categorical and numerical data, is only one of the many reasons why they are useful. In contrast, the KNN method is constructed on the concept of similarity, which allows it to successfully recommend crops based on examples in the dataset that are equivalent to one another. This is made possible by the fact that it is built on the notion of similarity. To put these algorithms into operation, it is required to train them on a component of the dataset, while at the same time reserving another portion of the dataset for testing and validation. The findings of the tests shed light on the performance measures that are capable of performing the role of acting as indicators of the success of the models. The confusion matrix, accuracy, precision, and recall are some of the metrics that are considered to be among the most essential among them. On the other hand, recall is a method that evaluates the ability of the models to identify significant occurrences, while accuracy provides an overall measurement of correctness. Precision is a useful tool for analyzing the accuracy of positive forecasts, while accuracy is a measure of correctness that offers an overall perspective. A detailed study of model predictions is offered by the confusion matrix, which classifies situations into true positives, true negatives, false positives, and false negatives. This matrix also provides a breakdown of model predictions. This methodical approach ensures that the crop recommendation system not only makes use of a relevant dataset but also undergoes severe data preprocessing to address any values that are lacking. In summary, this methodology assures that the crop recommendation system also makes use of a relevant dataset. By using Decision Trees and KNN, the system is made more complex. Additionally, the comprehensive evaluation that is carried out via performance metrics provides a nuanced understanding of the strengths and limits of the models in terms of picking crops that are suitable for the system. Figure 1 shows

proposed work is designed and enrolled

Dataset:

If the dataset is named "Crop Recommendation" and originates from an online platform such as Kaggle, it is likely to be available in Kaggle's data repository. Kaggle, a well-liked platform for data science and machine learning competitions, provides a diverse selection of datasets catering to many sectors, including agriculture. The key aspects include crucial environmental variables that are essential for crop growth and yield. These elements include fluctuations in temperature and the commencement and conclusion of seasons, with soil-related attributes such as pH and humidity levels. A more thorough evaluation of the environmental elements that impact crop development is achieved by considering these features.

Soil moisture level: The moisture content in the soil is likely determined by the value of this variable. The moisture content of the soil directly impacts the amount of water that plants uptake and the accessibility of nutrients, thereby influencing the overall well-being and production of the crop.

The soil's pH level is a quantitative measure that may be used to determine if the soil is alkaline or acidic. Maintaining the optimal pH level of the soil is crucial for facilitating nutrient absorption by plants. This is because different crop species need specific pH ranges for optimum development.

Thermal condition: The dataset has data about temperature variables. Temperature is a crucial environmental component that may greatly influence plant growth and development. Each crop necessitates certain temperature conditions for the processes of germination, flowering, and overall growth and development.

Season: To comprehend the climatic aspects that contribute to the cultivation of certain crops, one must possess knowledge of seasonal data. The choice of crops, the development patterns, and the overall organization of agricultural operations are significantly impacted by seasonal variations.

The dataset's copious amount of information facilitates a more profound understanding of the correlation between crop performance and environmental conditions. This information may be used to develop recommendation systems and prediction models that maximize crop selections according to current conditions. Agricultural scientists and practitioners may use this information to examine correlations, discern trends, and enhance the methodologies employed in formulating efficient and sustainable crop management strategies.

Data preprocessing

Data preparation is essential for successful crop recommendation machine learning model training. This method requires numerous steps to ensure data correctness, consistency, and analytic readiness. Missing data may affect recommendation model performance, thus addressing it is important. First, find and fix missing data in the dataset. Data may be missing owing to poor data collection or sensor faults. Imputation may be used to preserve dataset integrity. This entails substituting missing values with data-derived predictions. Imputation processes may involve replacing the mode for categorical variables and the mean or median for numerical features to obtain a complete and accurate dataset. Category data like crop kinds is encoded using label encoding. This strategy helps machine learning algorithms interpret and handle data by labeling categories with numbers. Label encoding simplifies category data modeling without adding complexity. To guarantee consistency over a large range of values, numerical properties may need to be scaled. Scaling prevents some features from dominating during model training. Normalization and standardization are popular scaling methods. Normalization sets the findings to a defined range, usually between 0 and 1, while standardization places the mean at 0 and the standard deviation at 1. To preserve consistency, the dataset may undergo outlier control, duplicate deletion, and data type alteration. These measures improve the dataset, making crop recommendation algorithms more robust and reliable.

Data Split:

When creating data for crop prediction, it is common to utilize a 70:30 split for training and testing datasets. The dataset will be randomly divided into two subsets: 70% of the data will be allocated for training the machine learning model, while the remaining 30% will be reserved for assessing the model's performance. The testing set serves as a separate set to evaluate

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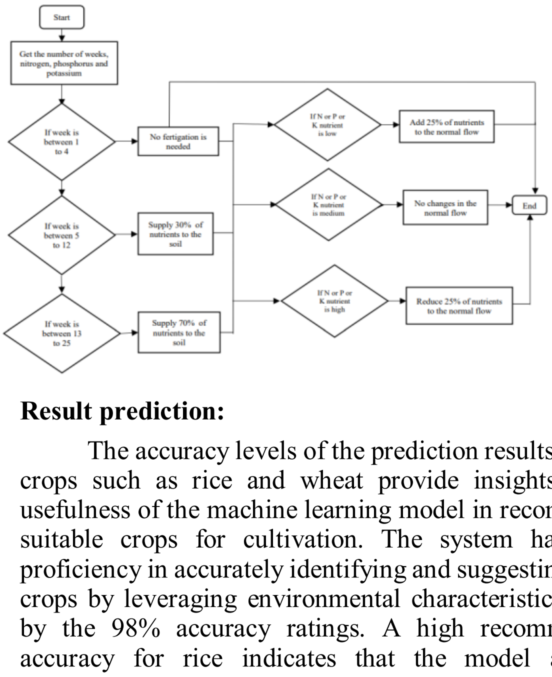
the model's ability to generalize on new examples that it has not seen before, while the training set aids the model in identifying patterns and relationships within the data. This split ratio facilitates the development of an effective crop recommendation system by finding a balance between supplying sufficient data for model training and ensuring a comprehensive evaluation of its predictive capabilities on new data.

Data Classification:

Utilizing machine learning algorithms like K-Nearest Neighbors (KNN) and Decision Trees (DT) is crucial for crop recommendation as it enables the delivery of tailored suggestions based on agricultural variables. KNN operates based on the concept of proximity, recommending crops based on the similarity of their environmental conditions to those of neighboring instances in the dataset. This method is very effective in discovering regional patterns and relationships within the data. On the other hand, Decision Trees are used to repeatedly divide the data based on significant attributes to create a predictive model that identifies the optimal crop choices. The hierarchical arrangement formed by these divisions enables comprehension of decision-making processes. A crop recommendation system that combines the advantages of both KNN (K-Nearest Neighbors) and DT (Decision Tree) algorithms may examine several factors such as temperature, humidity, soil quality, and seasonality. This will enable farmers to make educated decisions on sustainable and productive farming practices. By combining these algorithms, the accuracy and flexibility of crop recommendations are enhanced, enabling farmers to embrace resource-conscious and productive agricultural techniques.



Result prediction:

The accuracy levels of the prediction results for staple crops such as rice and wheat provide insights into the usefulness of the machine learning model in recommending suitable crops for cultivation. The system has a high proficiency in accurately identifying and suggesting suitable crops by leveraging environmental characteristics, as seen by the 98% accuracy ratings. A high recommendation accuracy for rice indicates that the model accurately identifies the optimal environmental factors for rice cultivation, such as soil pH, temperature, and humidity. Similarly, the model's excellent accuracy in suggesting wheat demonstrates its ability to consider specific requirements for wheat growth, such as appropriate soil and climatic conditions. Farmers may use the accuracy values as a measurable measure of the model's reliability in offering precise crop recommendations, enabling them to make educated decisions about crop selection and land utilization. The findings emphasize the potential of machine learning algorithms in promoting sustainable agricultural practices and precision agriculture. These algorithms may optimize crop selection based on the prevailing environmental circumstances, hence enhancing crop production and resource use efficiency.

IV.EXPERIMENTAL RESULTS

By analyzing Figures 2 to 9, one might likely discover various aspects of the crop recommendation model's efficacy concerning different crops. The outputs are crucial for understanding the effectiveness of the model and shedding light on its practical applicability. The statistics' accuracy values may indicate the machine learning model's ability to accurately anticipate suitable crops under different environmental conditions. Begin by presenting a concise overview of the primary findings shown in each visual representation, highlighting any consistent trends or inconsistencies in precision across the different crops. Analyze the factors that influence the observed results in the discussion section. Analyze the impact of certain variables on the precision of the model, such as soil characteristics, meteorological patterns, or seasonal fluctuations. Select crops that consistently demonstrate a high level of precision, and thereafter analyze the environmental factors that contribute to their precise forecasting. Discuss any challenges or limitations encountered in the functioning of the model. This entails examining instances when precision is diminished and exploring potential factors contributing to these disparities. Consider the potential impact of these findings on practical agricultural decision-making. Analyze the results shown in the figures, emphasizing the strengths and weaknesses of the model. Discuss any discernible patterns or regularities and elucidate how the crop suggestions might be used in practical contexts. Consider the broader implications for enhancing agricultural productivity, implementing sustainable farming techniques, and advancing precision agriculture. Provide a concise summary of the key findings shown in Figures 2 through 9, emphasizing the significance of the model's precision in offering valuable insights for crop selection as you conclude. This part should include a comprehensive analysis of the model's performance and its implications for agricultural operations, while also providing the research results.

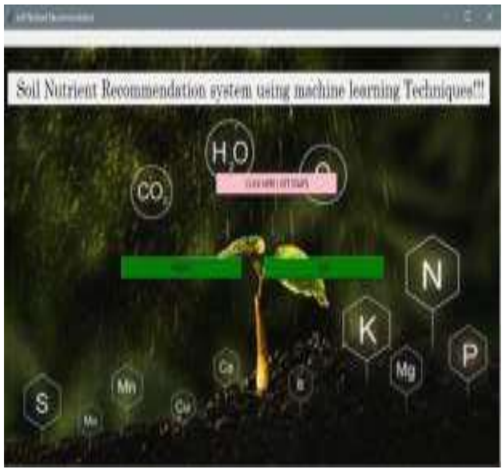


Fig. 2. Welcome Page

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Precision=TP/(TP+FP) Recall=TP/(TP+FN)

Abbreviations:

TP-True Positive

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FP-False Positive

TN-True Negative

FN-False Negative

```
Input Data ---> Soil Nutrient Recommendation

Data Selection
```

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice
5	69	37	42	23.058049	83.370118	7.073454	251.055000	rice
6	69	55	38	22.708838	82.639414	5.700806	271.324860	rice
7	94	53	40	20.277744	82.894086	5.718627	241.974195	rice
8	89	54	38	24.515881	83.535216	6.685346	230.446236	rice
9	68	58	38	23.223974	83.033227	6.336254	221.209196	rice
10	91	53	40	26.527235	81.417538	5.386168	264.614870	rice
11	90	46	42	23.978982	81.450616	7.502834	250.083234	rice
12	78	58	44	26.800796	80.886848	5.108682	284.436457	rice
13	93	56	36	24.014976	82.056872	6.984354	185.277339	rice
14	94	50	37	25.665852	80.663850	6.948020	209.586971	rice

Fig.3. Data Selection

```
Handling Missing Values
N              0
P              0
K              0
temperature    0
humidity       0
ph             0
rainfall       0
label          0
dtype: int64
```

Fig.4. Dataset Missing Values

```
Before Label Encoding

0     rice
1     rice
2     rice
3     rice
4     rice
5     rice
6     rice
7     rice
8     rice
9     rice
10    rice
11    rice
12    rice
13    rice
14    rice
Name: label, dtype: object
```

Fig.5. Encode the label

```
ML --> Decision Tree Classifier

1) Accuracy =  99.0909090909091 %

2) Classification Report

              precision    recall  f1-score   support

           0       1.00      1.00      1.00        33
           1       1.00      1.00      1.00        31
           2       1.00      0.96      0.98        28
           3       1.00      1.00      1.00        32
           4       1.00      1.00      1.00        35
           5       1.00      1.00      1.00        32
           6       0.94      1.00      0.97        31
           7       1.00      1.00      1.00        30
           8       1.00      0.97      0.98        33
           9       1.00      1.00      1.00        32
          10       1.00      0.94      0.97        33
          11       0.97      0.94      0.95        32
          12       1.00      1.00      1.00        28
          13       0.94      1.00      0.97        31
          14       1.00      1.00      1.00        29
```

Fig.6. Decision Tree Classifier Result

```
ML --> K Nearest Neighbour Classifier

1) Accuracy =  97.27272727272728 %

2) Classification Report

              precision    recall  f1-score   support

           0       1.00      1.00      1.00        33
           1       1.00      1.00      1.00        31
           2       0.97      1.00      0.98        28
           3       1.00      1.00      1.00        32
           4       1.00      1.00      1.00        35
           5       1.00      0.97      0.98        32
           6       0.97      1.00      0.98        31
           7       1.00      1.00      1.00        30
           8       0.80      0.85      0.82        33
           9       0.97      1.00      0.98        32
          10       0.92      1.00      0.96        33
          11       1.00      0.97      0.98        32
          12       1.00      1.00      1.00        28
          13       1.00      0.90      0.95        31
```

Fig.7. KNN Classifier Result

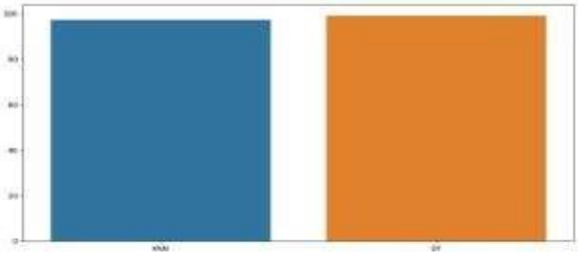

Fig.8. Compare between KNN and DT Classifier Results

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Fig.9. Predictive Result

```
The Identified Crop =  rice
The Recommendated Nitrogen =  65
The Recommendated Phosphorous =  37
The Recommendated Potassium =  40
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V.CONCLUSION AND FUTURE WORK

In conclusion, the use of Decision Trees (DT) and K-nearest neighbors (KNN) in machine learning has shown potential to enhance the precision of agricultural predictions for soil nutrient levels. These algorithms enable reliable prediction of optimal soil nutrient levels based on various environmental conditions. The efficiency of the model is primarily attributable to the use of the KNN algorithm, which leverages the similarity principle, and the DT algorithm, which may provide decision structures that are easily comprehensible. The results demonstrate that the machine learning model has the potential to significantly enhance informed decision making in soil management, ensuring optimal crop growth by providing accurate nutrient allocation. There are several prospects for enhancement and expansion in future endeavors. To enhance the predictive capability of the model, additional information such as historical nutrient levels, crop rotation patterns, and climate data may be included. Moreover, exploring ensemble methodologies that combine the strengths of many algorithms might improve overall robustness and precision.

To enhance the model's effectiveness, it is advisable to include temporal variations in soil conditions and use dynamic models capable of adapting to changing environmental elements. Furthermore, the practical use of the model in real agricultural settings and the collection of feedback from farmers would provide valuable data about its efficacy. Iterative modifications may be guided by this user-centric approach, ensuring that the model closely aligns with the expectations and challenges faced by individuals in the agricultural sector. The current machine learning method has shown promise in suggesting soil nutrient levels, more efforts are required to enhance the model, include additional characteristics, and validate its effectiveness in real-world scenarios. This study not only enhances the field of precision agriculture but also demonstrates the use of data-driven solutions to address existing challenges in sustainable and efficient farming practices.

VI.REFERENCES

[1]Saeed Nosratabadi, Karoly Szell, Bertalan Beszedes, Felde Imre, Sina Ardabili, Amir Mosavi. "Comparative Analysis of ANN-ICA and ANN-GWO for Crop Yield Prediction." 2020.

[2]Farhat Abbas, Hassan Afzaal, Aitazaz A. Farooque, Skylar Tang. "Crop Yield Prediction through Proximal Sensing and Machine Learning Algorithms." 2020.

[3]Dhivya Elavarasan, P. M. Durairaj Vincent. "Crop Yield Prediction Using Deep Reinforcement Learning Model for Sustainable Agrarian Applications." 2019.

[4]Petteri Nevavuori, Nathaniel Narra, Tarmo Lipping. "Crop Yield Prediction with Deep Convolutional Neural Networks." 2019. [5] Saeed Khaki, Lizhi Wang, Sotirios V. Archontoulis. "A CNN-RNN Framework for Crop Yield Prediction." 2020.

[6]Wu, C.; Chen, Y.; Hong, X.; Liu, Z.; Peng, C. Evaluating soil nutrients of Dacrydium pectinatum in China using machine learning techniques. For. Ecosyst. 2020

[7]Angelopoulou, T.; Balafoutis, A.; Zalidis, G.; Bochtis, D. From Laboratory to Proximal Sensing Spectroscopy for Soil Organic Carbon Estimation—A Review. Sustainability 2020

[8]Villas-Boas, P.R.; Franco, M.A.; Martin-Neto, L.; Gollany, H.T.; Milori, D.M.B.P. Applications of laser-induced breakdown spectroscopy for soil characterization, part II: Review of elemental analysis and soil classification. Eur. J. Soil Sci. 2020

[9]Benedet, L.; Acuña-Guzman, S.F.; Faria, W.M.; Silva, S.H.G.; Mancini, M.; dos Teixeira, A.F.S.; Pierangeli, L.M.P.; Acerbi, F.W., Jr.; Gomide, L.R.; Pádua, A.L., Jr.; et al. Rapid soil fertility prediction using X-ray fluorescence data and machine learning algorithms. Catena 2021

[10]John, K.; Isong, I.; Kebonye, N.; Ayito, E.; Agyeman, P.; Afu, S. Using Machine Learning Algorithms to Estimate Soil Organic Carbon Variability with Environmental Variables and Soil Nutrient Indicators in an Alluvial Soil. Land 2020

[11]Jin, X.; Li, S.; Zhang, W.; Zhu, J.; Sun, J. Prediction of Soil-Available Potassium Content with Visible Near-Infrared Ray Spectroscopy of Different Pretreatment Transformations by the Boosting Algorithms. Appl. Sci. 2020

[12]Gholizadeh, A.; Saberioon, M.; Ben-Dor, E.; Rossel, R.V.; Boruvka,L. Modelling potentially toxic elements in forest soils with vis–NIR spectra and learning algorithms. Environ. Pollut. 2022.

[13]Hybrid U-Net and ADAM Algorithm for 3DCT Liver Segmentation, Ramesh, S., Kanchana, J.S., David Neels Ponkumar, D. 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), I-SMAC 2023 - Proceedings, 2023, pp. 752– 757

[14]Uma Maheswari, G., Gnana Jeslin, J., RajaSuguna, M., Jayabharathi,R. (2023). "A Hybrid Effective Trusted Manet Based On Secure Data Transmission Using Artificial Intelligence." Proceedings of 8th IEEE International Conference on Science, Technology, Engineering and Mathematics, ICONSTEM 2023.

[15]Ramanan, K., Ramesh, S.P., Kingsly, C.S., Ponkumar, D.D.N., Vargheese, M. (2023). "Sparse Long Short-Term Memory Approach for Energy-Efficient Adaptive Cluster Fuzzy-based Controller in Wireless Sensor Network." Proceedings - 5th International Conference on Smart Systems and Inventive Technology, ICSSIT 2023, pp. 211–219.

[16]Ramnath, M., Rubavathi,C.Y. (2023). "Recommendations of Smartphone Applications According to Customer Reviews and Capabilities." Proceedings of the 2023 2nd International Conference on Augmented Intelligence and Sustainable Systems, ICAISS 2023, pp. 821–825.

[17]Nisha, M.S., Rajakumar, G., Jenifer, P., Benita, B. (2023). "Protecting Bitcoins Frequency Count Against Double-Spend Attacks." Proceedings - 5th International Conference on Smart Systems and Inventive Technology, ICSSIT 2023, pp. 725–731

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