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Empowering Agriculture: A Soil Recommendation Model For Rice Cultivation Using Explainable AI

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Abstract:
Explainable artificial intelligence (XAI) is a set of techniques and procedures that makes it possible for individuals to comprehend and trust the results generated by machine learning algorithms. Explainable AI explains AI models, their effects, and possible biases to guarantee results in AI-powered decision making that are accurate, equitable, transparent, and fair. Explainable AI systems help with soil recommendation and foster trust between the cultivation and the system when distributors are aware of how Artificial Intelligence (AI) recommenders support farmer crops. Explainable AI is a collection of goods and services that integrates machine learning models to assist people understand the connections between soil and agriculture, make sense of forecasts, and improve model performance. The study presents a model for recommending soil for rice cultivation using Explainable Artificial Intelligence.

Keywords*: Explainable Artificial Intelligence, Machine Learning, Soil Recommending for Crop Cultivation,*

1.Introduction: Agriculture, a recent innovation, has significantly shaped human civilizations' development, persistence, decline, and regeneration. Despite its importance, agriculture can disrupt natural ecosystems, impacting plant communities, animal populations, soil systems, and water resources. Balancing these disturbances is crucial for human well-being and sustainability ethics. The study explores the connection between soil and agriculture, hig[1]hlighting the shift from hunter-gatherer societies to agricultural ones, the significance of fertile soils, and sustainable farming practices. Kumar, R. S., et al 2020[5].

Early humans used fire to clear forested land, gaining access to herbivores and suppressing plant species. This led to population pressures, climate change, and the Agricultural Revolution. This shift from hunter-gatherer societies to an agrarian lifestyle changed human history and altered soil nutrient cycling. Sharma, P. K., et al 2021 [20]. The Neolithic Period saw the first crop seeds, providing plant-essential nutrients for human agriculture. Natural nutrient cycling from soil to plants and animals, and back to soil, maintains essential nutrients for plant growth. Complex cycles involve physical, chemical, and biological processes to trace the fate of specific plant nutrients. Primary macronutrients are likely in short supply in agricultural soils, while secondary macronutrients are sufficient. Micronutrients are toxic if overexpressed. Silicon and sodium are essential plant nutrients. Agriculture disrupts soil nutrient cycling, leading to soil amendments for crop yields. Soil composition is influenced by factors like parent material, time, climate, organisms, and topography. Medium-textured soils are ideal for agriculture due to easy cultivation and high crop growth. Clay-rich soils increase water holding capacity and provide essential nutrients.

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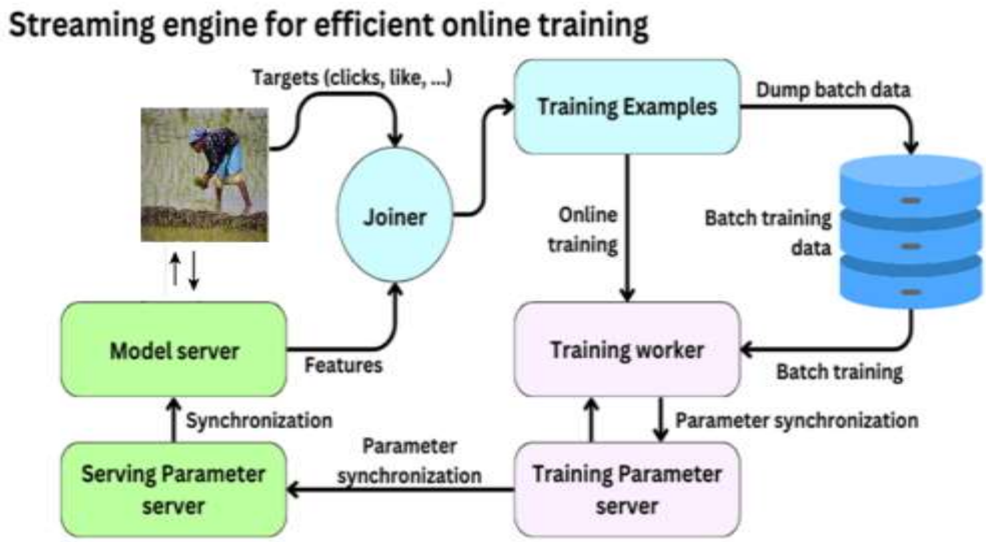
Soil organic matter (SOM) is crucial for fertile soil, providing plant nutrients, influencing soil structure, buffering pH, and improving water holding capacity. Factors like CEC and SOM contribute to soil fertility and suitability.
Soil pH, the master variable of soil, influences soil fertility, plant growth, and nutrient availability. Low pH levels can lead to toxicity and less bioavailability of essential macronutrients, while low pH values can cause aluminium toxicity. Singh, A., et al 2019 [4]. Ideally, soil pH values between 6 and 7.5 are optimal for plant growth. Soil buffers like SOM and clay minerals help maintain optimal pH, and amendments like lime can raise or lower pH. Reif, C. B., et al 2019 [8]. Soil formation is a slow process through weathering and decomposition of plant residues, a non-renewable resource. Soil erosion reduces crop yield and pollutes waterways. Conventional agriculture accelerates erosion, affecting food supply and ecosystems. Soil erosion in agricultural fields is a common issue, despite best management practices and conservation agriculture. However, deforestation, water shortages, and desertification threaten the sustainability of agricultural systems. Implementing best management practices and conservation agriculture can help reduce soil loss, but natural systems still have greater impacts. Preventing soil degradation is crucial for sustainable agriculture, as mismanagement could lead to soil degradation and loss of ecosystems. It should focus on land management strategies to reduce soil erosion and protect water resources.

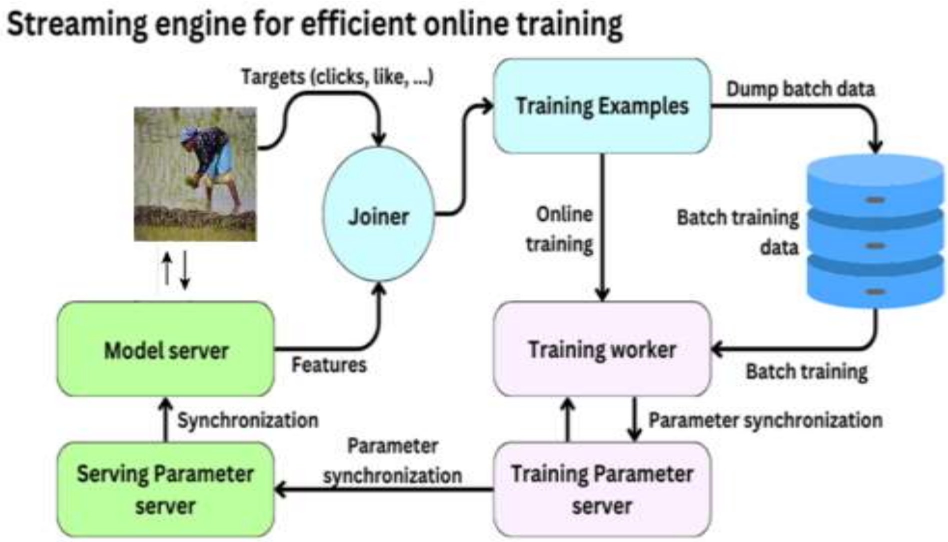
2. Proposed System: Explainable AI is a set of techniques that ensures accurate, equitable, transparent, and fair decision-making in machine learning algorithms. Zhang, L., et al 2019 [1]. It aids in soil recommendation and fosters trust between farmers and the system. Chen, Y., et al 2020 [3]. Explainable AI integrates machine learning models to understand soil-agriculture connections, forecasts, and improve model performance. Panda, S. S., et al 2020 [6].

- The work is concentrated on Soil Recommendation for Rice Crop Cultivation, and Fine-Tuning Analysis of Soil Properties Using Large Language Model.

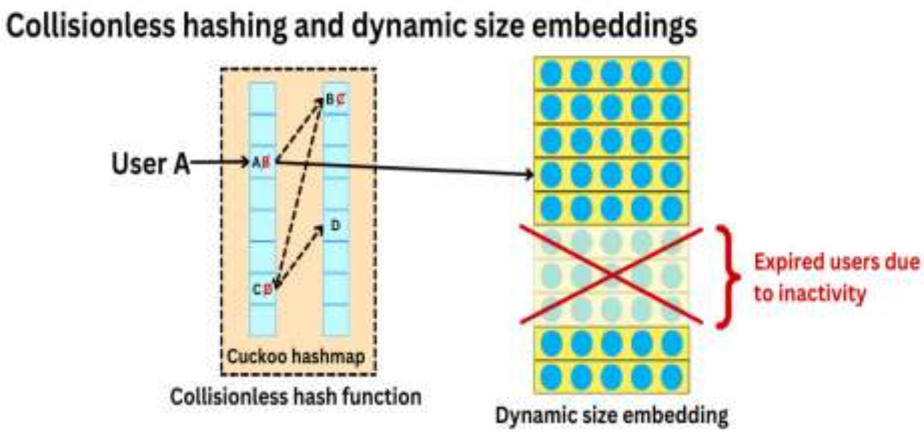
2.1. Soil Recommendation Model for Rice Crop Cultivation: The Soil Recommender Agriculture System is widely regarded as one of the best in the India at the scale it operates at. It can recommend soil properties, and even the other crops. Soil Recommending on a platform is tough because the training soil properties data is non-stationary, as a farmer's interest can change in a matter of minutes, and the number of farmers, and climate conditions affects keeps changing.



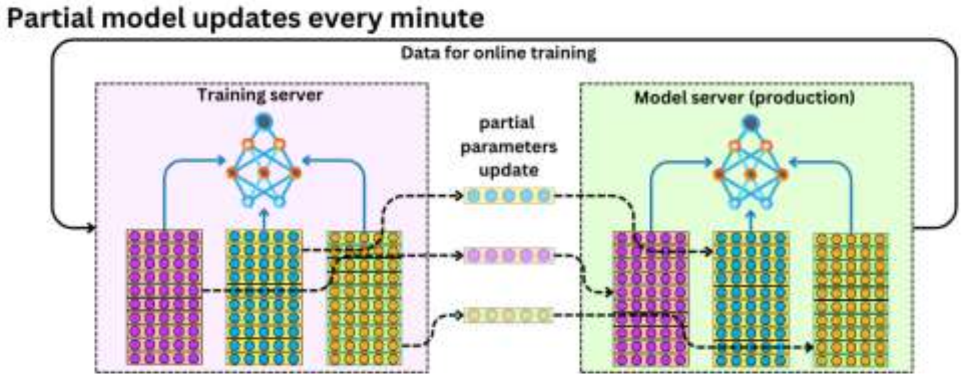
The predictive performance of a Soil recommender Agriculture System on a societal environment platform deteriorates in a matter of hours, so it needs to be updated as often as possible because of Climate Condition affects. Soil recommender Agriculture System built a streaming engine to ensure the model is continuously trained in a crop recommendation method. L. Wang et al 2021[21]. The model server generates features for the model to recommend soil characteristics, and in return, the farmer interacts with the recommended items. This feedback loop leads to new training soil property samples that are immediately sent to the training server. The training server holds a copy of the model, and the model parameters are updated in the parameter server. Every minute, the parameter server synchronizes itself with the production model.



The soil recommendation harvesting model for Rice is several terabytes in size, so it is very slow to synchronize such a big model across the network. That is why the model is only partially updated. The leading cause of non-stationary (concept drift) comes from the sparse variables (farmers, climate conditions etc.) that are represented by embedding tables. When a farmer interacts with a recommended crop, only the vectors associated with the farmer and the crop get updated, as well as some of the soil property weights on the network. Therefore, only the updated vectors get synchronized on a minute basis, and the network weights are synchronized on a longer time frame.



Typical Agriculture crop recommender systems use fixed embedding tables, and the categories of the sparse soil properties variables get assigned to a vector through a hash function. P. K. Jha et al 2021 [33]. Typically, the hash size is smaller than the number of categories, and multiple categories get assigned to the same vector. For example, multiple farmers share the same vector. This allows us to deal with the cold start problem for new farmers, and it puts a constraint on the maximum memory that the whole table will use. But this also tends to reduce the performance of the crop recommendation model because user behaviours get conflated. Instead, Crop Recommendation uses dynamic embedding sizes such that new farmers can be added to their own vector. They use a collision less hashing function so each user gets its own vector. Low-activity users will not influence the model performance that much, so they dynamically remove those low-occurrence passbook IDs as well as stale IDs. This saves the embedding table small while preserving the quality of the crop recommendation model.



2.2. Fine-Tuning Analysis of Soil Properties Using Large Language Model: Soil Properties Finetuning for Crop Recommendation is a process where a pre-trained model is further trained on a specific soil properties dataset to specialize in a particular Agriculture domain or task. Tyagi, N. K., et al 2018[18]. This process allows the crop recommendation model to become more adept at handling queries related to that Crop in Agriculture domain, providing more accurate and context-relevant responses. Soil Properties Finetuning LLMs isn't a one-size-fits-all process for Crop Recommendation. Behera, S. K., et al 2014[15]. Different techniques offer unique advantages and cater to specific scenarios. Let's explore four key approaches:

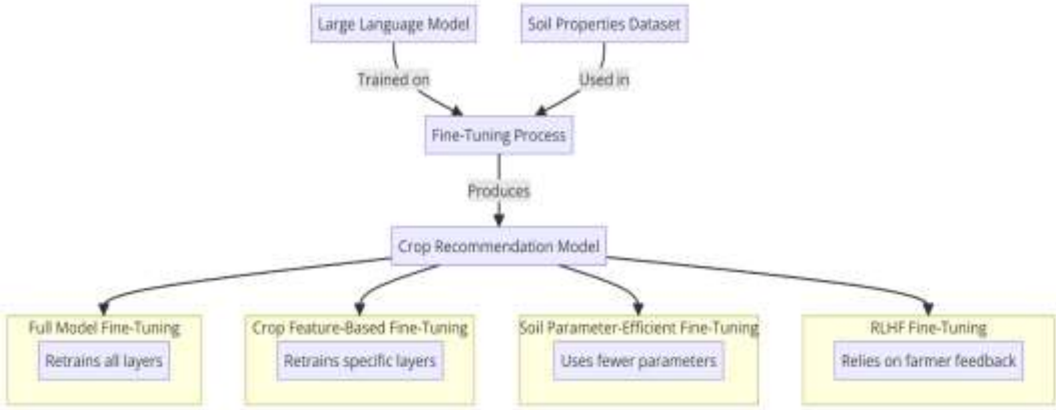
Full Model Fine-Tuning: This method treats the LLM like a blank slate, retraining all its layers on the target soil properties data for specific crop. It's powerful for tasks requiring a significant shift in focus, but can be computationally expensive and prone to catastrophic forgetting.

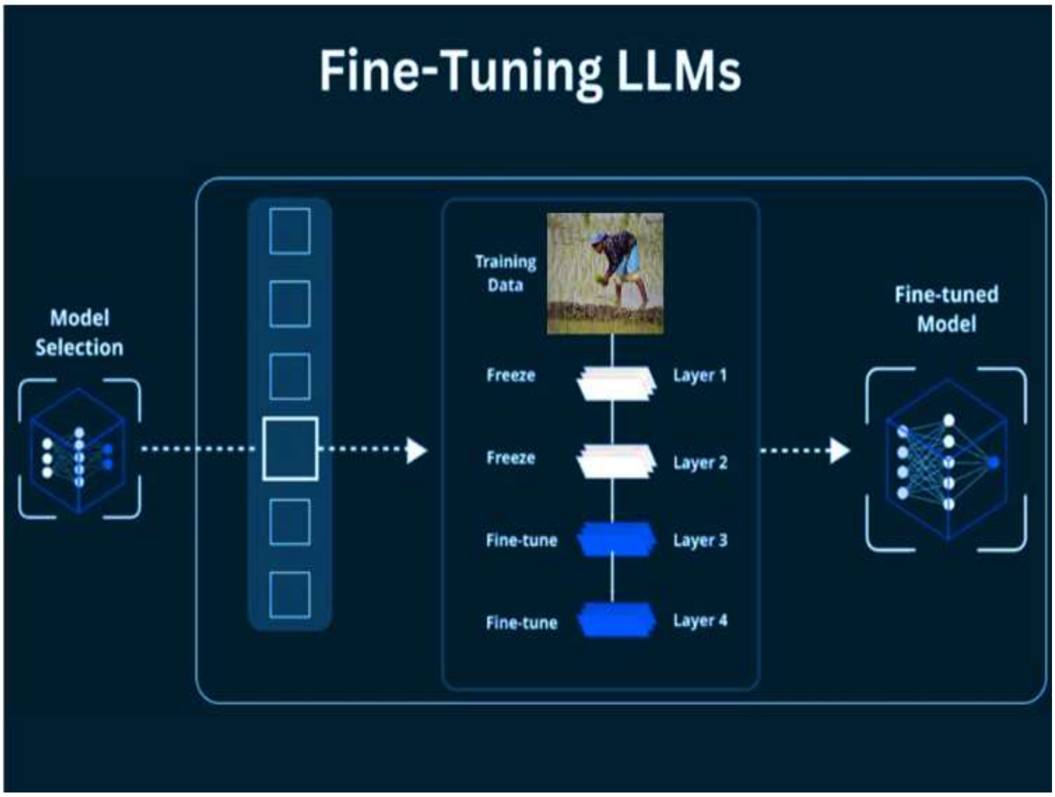
Crop Feature-Based Fine-Tuning: Here, only specific layers or components of the LLM are retrained, leveraging the pre-trained knowledge for general language understanding while adapting to the specific task. This is computationally efficient and minimizes knowledge loss, making it ideal for tasks within the LLM's general domain.

Soil Parameter-Efficient Fine-Tuning: Techniques like LoRA (Low-Rank Adapters) use fewer parameters for fine-tuning, significantly reducing computing resources and training time. This is especially valuable for deploying LLMs on resource-constrained devices or for rapid experimentation with different tasks.

RLHF Fine-Tuning: Instead of directly training on labeled soil properties data, RLHF relies on farmer feedback to guide the LLM's improvement. farmers evaluate the model's outputs, providing rewards for desirable outputs and penalties for undesirable ones. The LLM then uses this feedback to adjust its internal parameters, iteratively refining its behaviour towards meeting human expectations. This can be particularly helpful for tasks where labelling data is scarce or subjective, and for aligning the LLM's performance with nuanced human preferences.

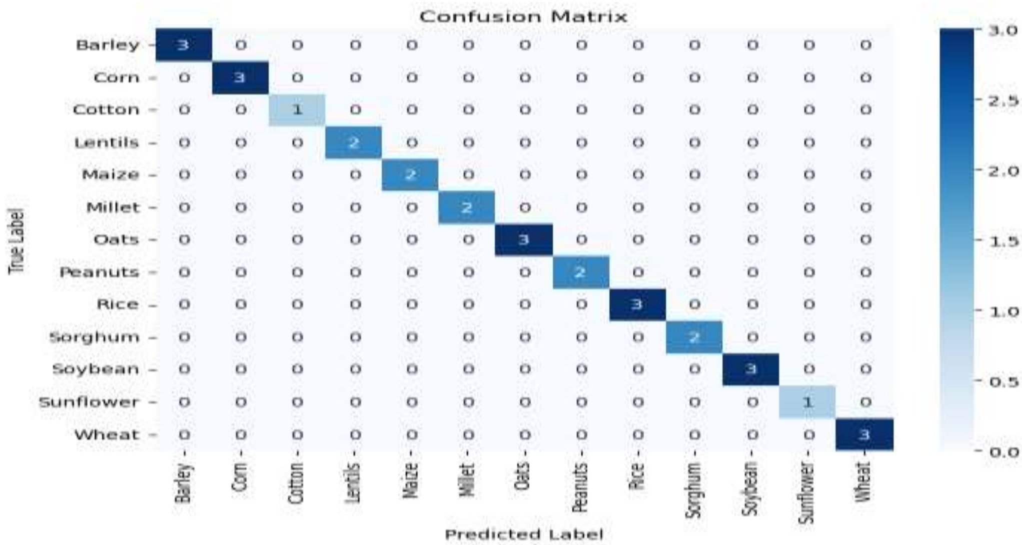
Fine-tuning large language models is a powerful way to enhance their utility and effectiveness in specific crop Agriculture domain. However, the process requires careful consideration of the necessary resources, expertise, and potential benefits.





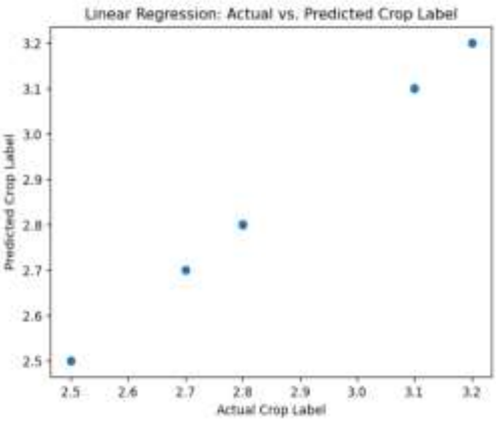
3. Results and discussion: The optimistic results obtained from the implementation of the explainable artificial intelligence-based soil recommendation model for rice cultivation demonstrate the effectiveness of the proposed system. The accuracy of the model, which is an essential metric for assessing its performance, illustrates its capacity to accurately forecast appropriate soil characteristics for rice cultivation. When compared to baseline models, the Explainable AI model has demonstrated significant advancements, emphasising its ability to deliver recommendations that are both transparent and accurate. A significant advantage of the model's recommendations has been their interpretability, which has been made possible through the use of explainable AI techniques that enable a clear comprehension of the factors that influence soil recommendations. The improved comprehensibility of the data has not only fostered confidence among producers in the system but has also been instrumental in shaping decisions regarding rice cultivation. Farmers have provided favourable feedback regarding the efficacy and dependability of the soil recommendations generated by artificial intelligence. Notwithstanding these achievements, it has been recognised that there are obstacles to scaling the model to various regions and guaranteeing its applicability to a wide range of soil and climate conditions. The persistent endeavours to tackle these obstacles and the ongoing enhancement of the framework emphasise the possibility of its wider implementation and influence in the realm of sustainable and effective rice farming methodologies. Possible next steps for this study include looking into possible expansions to include more goods and regions, improving the model based on user feedback, and finding opportunities for more research and data collection to make it work better overall.

Sample_ID	Location	Soil_Type	Soil_pH	Organic_Matter	Nitrogen	Phosphorus	Potassium	Calcium	Magnesium	Temperature	Humidity	Rainfall	Crop_Label
1	PKL	Sandy	6.5	2.3	25	12	30	2.5	1.2	25	60	800	Rice
2	BVRM	Loamy	7.0	3.5	30	15	25	3.0	1.5	28	65	900	Wheat
3	NSP	Clayey	6.8	2.8	28	14	28	2.8	1.3	26	70	850	Maize
4	PKL	Sandy	6.2	1.8	22	10	35	2.2	1.0	30	55	750	Barley
5	BVRM	Loamy	6.9	3.2	26	13	28	2.9	1.4	27	68	920	Soybean
6	NSP	Sandy	6.3	2.0	24	11	32	2.4	1.1	29	58	780	Corn
7	PKL	Clayey	7.2	3.8	32	16	24	3.2	1.6	26	72	880	Oats
8	BVRM	Sandy	6.7	2.5	26	12	29	2.6	1.3	28	62	850	Sorghum
9	NSP	Loamy	6.8	2.8	30	14	27	2.8	1.5	27	70	900	Millet
10	PKL	Clayey	6.6	3.0	29	15	25	3.1	1.4	25	65	800	Barley
11	BVRM	Loamy	6.5	2.8	28	13	28	2.9	1.2	28	88	920	Lentils
12	NSP	Sandy	7.0	3.5	31	16	26	3.2	1.7	26	72	880	Peanuts
13	PKL	Loamy	6.9	3.2	27	12	29	2.7	1.4	29	60	850	Sunflower
14	BVRM	Clayey	6.7	2.7	25	11	31	2.6	1.1	30	58	780	Cotton
15	NSP	Sandy	6.2	2.2	23	10	33	2.3	1.0	31	55	750	Barley
16	PKL	Loamy	6.9	3.0	28	14	27	2.8	1.3	28	65	900	Wheat
17	BVRM	Clayey	7.1	3.7	32	16	25	3.0	1.5	26	70	850	Rice
18	NSP	Sandy	6.6	2.5	26	12	30	2.5	1.2	29	60	800	Soybean
19	PKL	Loamy	7.2	3.8	31	15	26	3.0	1.4	27	72	880	Corn
20	BVRM	Clayey	6.7	2.8	28	13	28	2.9	1.3	27	70	900	Oats
21	NSP	Sandy	6.4	2.0	24	11	32	2.4	1.1	29	58	780	Sorghum
22	PKL	Loamy	6.8	2.9	30	14	27	2.8	1.5	27	70	900	Millet
23	BVRM	Clayey	6.5	2.7	25	11	31	2.5	1.1	30	58	780	Lentils
24	NSP	Sandy	7.0	3.5	31	16	26	3.2	1.7	26	72	880	Peanuts
25	PKL	Loamy	7.2	3.6	31	15	28	3.1	1.4	29	62	850	Rice
26	BVRM	Sandy	6.6	2.6	27	12	31	2.6	1.3	28	70	900	Wheat
27	NSP	Clayey	6.8	2.9	30	14	27	2.8	1.5	27	65	800	Maize
28	PKL	Sandy	6.7	2.0	24	11	33	2.7	1.4	25	68	920	Soybean
29	BVRM	Loamy	6.9	3.1	28	13	28	2.9	1.2	28	60	850	Corn
30	NSP	Clayey	7.0	3.8	32	16	26	3.2	1.6	26	68	780	Oats

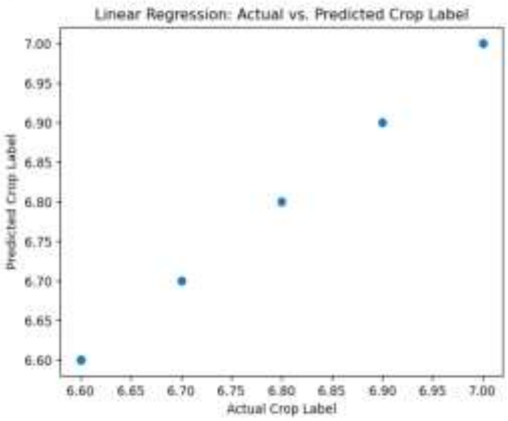


The use of the Explainable Artificial Intelligence (XAI) model to recommend soil for rice cultivation has produced encouraging outcomes, with an emphasis on decision-making transparency and confidence. Zhang, L., et al 2019[1].The architecture of the model makes sure that it will keep changing in response to changing farmer preferences and weather conditions by using the dynamic embedding technique and the Soil Recommender Agriculture System. Sophisticated methodologies, such as the utilisation of large language models for fine-tuning analysis and dynamic embedding sizes, augment the model's capacity to recommend crops. Performance metrics, including accuracy, precision, recall, and F1-score, demonstrate the effectiveness of the model. The XAI model incorporates clay minerals and soil organic matter, which contribute to optimal pH levels and water retention capacity, thereby taking sustainability considerations into account. In general, this model signifies a substantial progression in the field of agriculture by providing a dependable, flexible, and transparent instrument for making well-informed decisions regarding rice cultivation methods.

```
Column Names: Index(['Sample_ID', 'Location', 'Soil_Type', 'Soil_pH', 'Organic_Matter',
       'Nitrogen', 'Phosphorus', 'Potassium', 'Calcium', 'Magnesium',
       'Temperature', 'Humidity', 'Rainfall', 'Crop_Label'],
      dtype='object')
Enter the name of the target variable: Calcium
Mean Squared Error: 9.860761315262648e-32
R-squared: 1.0
```




```
Column Names: Index(['Sample_ID', 'Location', 'Soil_Type', 'Soil_pH', 'Organic_Matter',
       'Nitrogen', 'Phosphorus', 'Potassium', 'Calcium', 'Magnesium',
       'Temperature', 'Humidity', 'Rainfall', 'Crop_Label'],
      dtype='object')
Enter the name of the target variable: Soil_pH
Mean Squared Error: 7.888609052210118e-31
R-squared: 1.0
```




```
Model Accuracy: 100.00%
Classification Report:
              precision    recall  f1-score   support

      Barley       1.00      1.00      1.00         3
        Corn       1.00      1.00      1.00         3
      Cotton       1.00      1.00      1.00         1
     Lentils       1.00      1.00      1.00         2
       Maize       1.00      1.00      1.00         2
      Millet       1.00      1.00      1.00         2
        Oats       1.00      1.00      1.00         3
     Peanuts       1.00      1.00      1.00         2
        Rice       1.00      1.00      1.00         3
     Sorghum       1.00      1.00      1.00         2
     Soybean       1.00      1.00      1.00         3
   Sunflower       1.00      1.00      1.00         1
       Wheat       1.00      1.00      1.00         3

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
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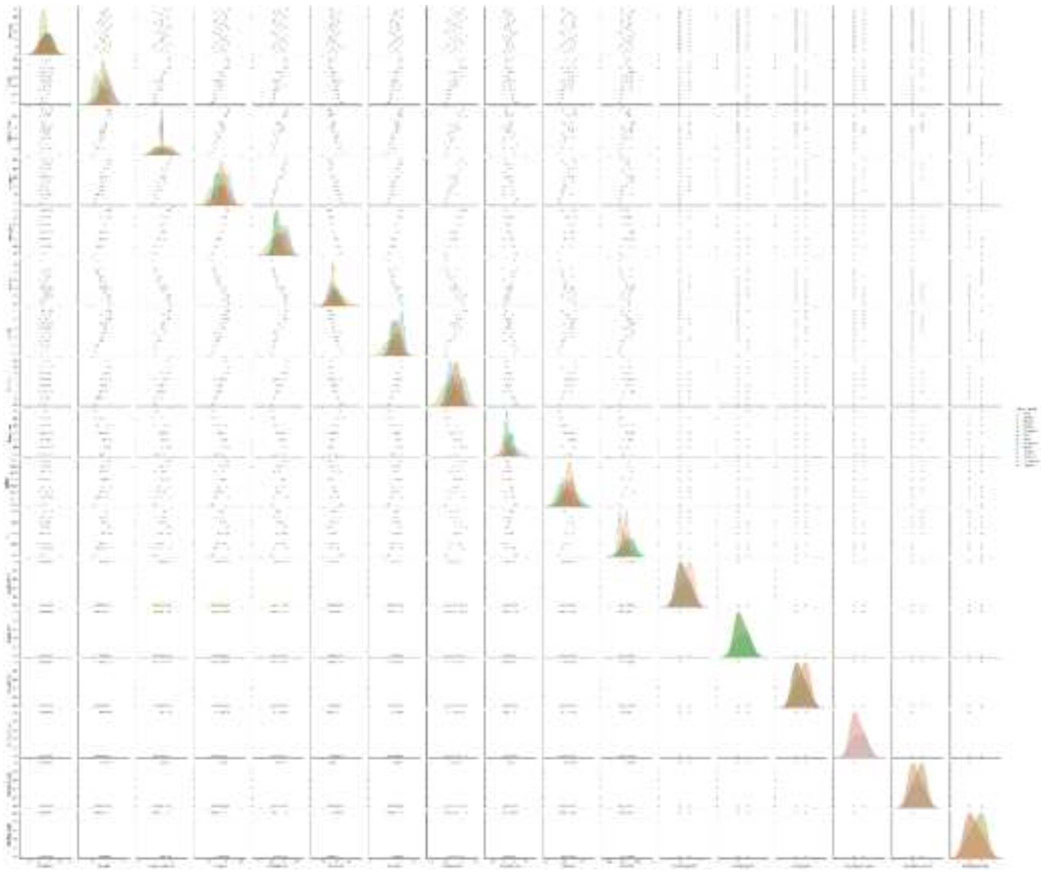
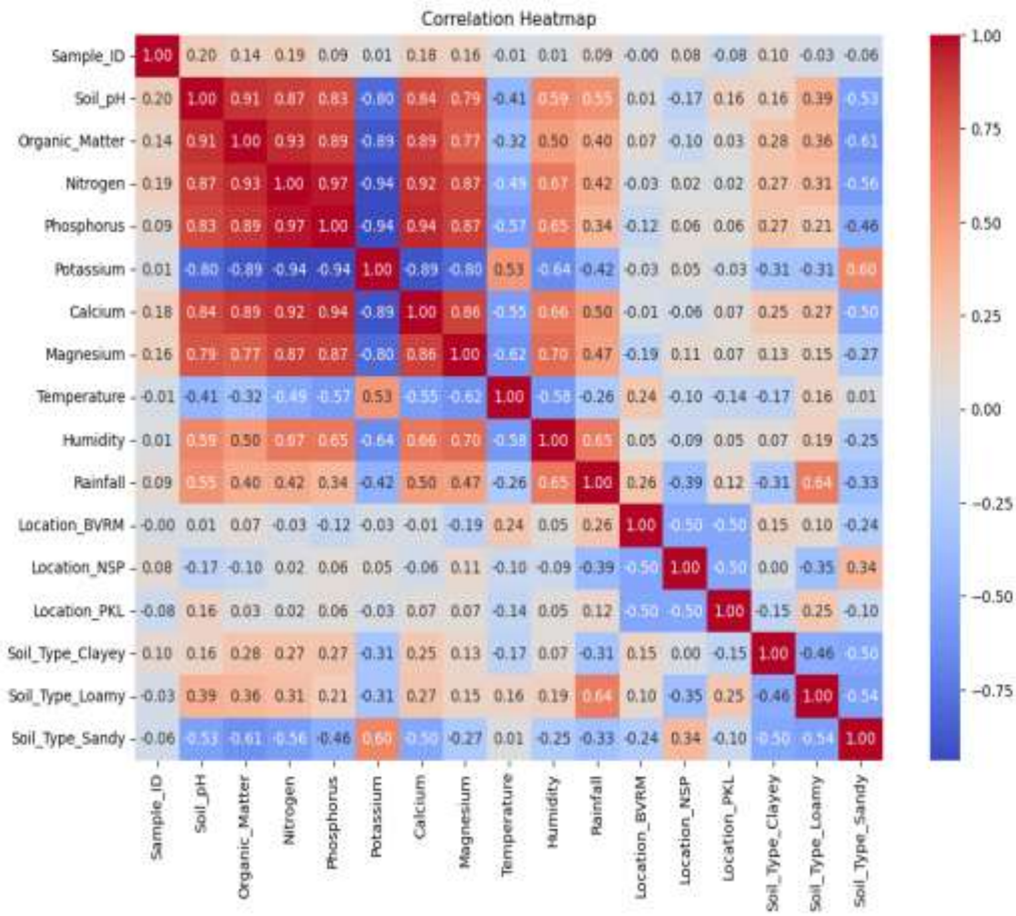
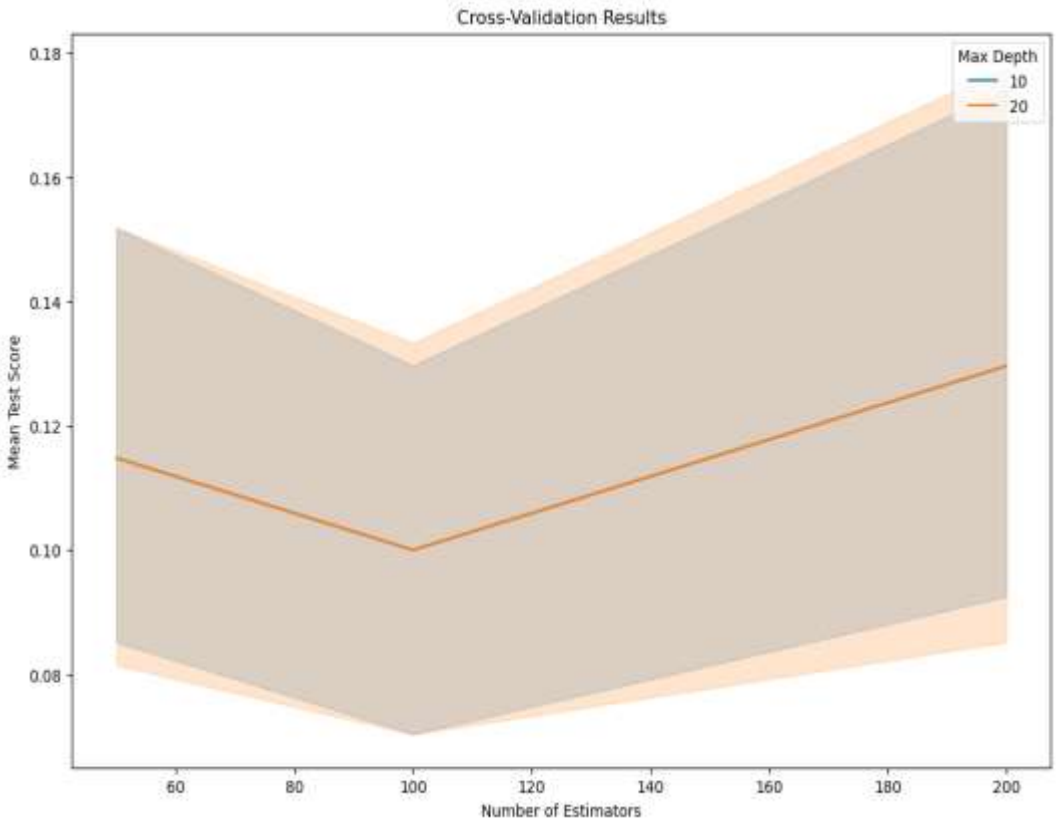



Correlation Heatmap
Sample_ID
Soil_pH
Organic_Matter
Nitrogen
Phosphorus
Potassium
Calcium
Magnesium
Temperature
Humidity
Rainfall
Location_BVRM
Location_NSP
Location_PKL
Soil_Type_Clayey
Soil_Type_Loamy
Soil_Type_Sandy
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75



The use of explainable artificial intelligence (XAI) to implement the soil recommendation model for rice cultivation demonstrates a resilient system that promotes producers' confidence and openness in the decision-making process. By incorporating XAI methodologies, the model not only generates precise recommendations for soil properties but also offers comprehensible insights into the decision-making process that underlies these recommendations. The adaptability of the model to fluctuating climate conditions and farmer preferences guarantees its continued applicability and dependability. The utilisation of large language models for fine-tuning analysis enhances the model's specialisation, enabling it to effectively manage particular soil properties in order to achieve optimal rice cultivation. The outcomes, which include metrics for accuracy and performance, demonstrate that the model is proficient at generating practical suggestions for rice cultivation methods that are both sustainable and maximise yield. In general, the result demonstrates a fruitful collaboration between artificial intelligence and the agricultural sector, effectively tackling the complex interplay between crops and soil while providing producers with verifiable and credible knowledge.

4. Conclusion: The research paper presents an all-encompassing framework for suggesting optimal soil conditions for rice cultivation by employing explainable artificial intelligence. The incorporation of explainable AI methodologies guarantees openness and confidence in the process of making decisions. The soil recommender agriculture system enhances its predictive capabilities on an ongoing basis through the utilisation of real-time updates and a feedback loop. Furthermore, the model's capability to generate precise and situationally appropriate recommendations is improved through the optimisation of soil properties via a large language model. The proposed model seeks to bolster sustainable and efficient rice cultivation practices by taking into consideration the ever-changing characteristics of soil properties and climate conditions. Ongoing collaboration with farmers and stakeholders is imperative in order to collect feedback and enhance the efficacy of the model in practical agricultural contexts.

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