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SOIL TESTING BASED CROP PREDICTION USING RANDOM FOREST ALGORITHM

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Abstract
The integration of soil testing data with advanced machine learning techniques, particularly employing the Random Forest algorithm, aims to revolutionize crop selection methodologies in agriculture. This study delves into the intricate relationships between diverse soil attributes and crop suitability, contributing to the optimization of agricultural decision-making processes. The research emphasizes the predictive capabilities of the Random Forest model, highlighting its potential to improve precision and reliability in crop selection.

Keywords: Soil testing, Random Forest algorithm, Agriculture, Soil Attributes, Suitability, Decision-making processes.

1. Introduction

In the context of contemporary agriculture and environmental studies, computational prediction of soil properties stands out as a crucial task with far-reaching implications. This research strives to leverage cutting-edge technologies, including diffuse reflectance infrared spectroscopy and geo-referencing, for cost-effective analyses of measurable soil features.

The overarching objective is to forecast essential soil functional properties such as primary productivity, nutrient retention, water resistance, and seismic vulnerability.
A distinctive aspect of this research lies in the incorporation of the Extreme Learning Machine (ELM) technique[8], a single hidden-layer feedforward neural network learning approach.
This method enhances predictive modeling of soil properties, as evidenced by its successful application to the "Africa Soil Property Prediction Challenge" dataset[1].
Acknowledging the profound impact of soil moisture on agricultural activities, the research integrates factors like soil texture, crop type, and saturated hydraulic conductivity to provide accurate and optimal computational approaches for soil moisture prediction.
Real-world validation using soil samples from Chateau Kefraya terroirs in Lebanon lends practical significance to our findings. This research aspires to contribute to a future where technology-driven predictive models play a transformative role in shaping sustainable agricultural practices and resource management, fostering a harmonious balance between technological advancements and environmental stewardship.

2. Literature Review

Table 2.1 Study of literature review

Title	Year & Publication	Methods Used	Findings
Machine Learning Applications in Agriculture[1]	2020, Journal of Agricultural Science	Machine learning algorithms for yield prediction, disease detection, and resource optimization.	Machine learning is increasingly applied in agriculture for various tasks.
Predictive Models for Crop Yield Optimization[2]	2022, International Conference on Agricultural Tech	Linear regression and ensemble methods for optimizing crop yield.	Various models, including linear regression and ensemble methods, are explored for optimizing crop yield and precision agriculture.
A Comparative Analysis of Machine Learning Models[3]	2021, Journal of Agricultural Informatics	Comparative analysis of various machine learning models for predicting crop outcomes.	This study compares different models for predicting crop outcomes based on diverse datasets, highlighting strengths and weaknesses.
Environmental Factors Influencing Crop Suitability[5]	2023, Environmental Agriculture Journal	Exploration of environmental factors affecting soil-based crop prediction.	This study explores the challenges and opportunities associated with soil-based crop prediction, emphasizing the need for continuous model improvement.
Crop Suitability in Chhattisgarh[6]	2021, Chhattisgarh Agricultural Research Journal	Investigation of local factors influencing crop suitability in Chhattisgarh.	Investigates local factors influencing crop suitability in Chhattisgarh, providing insights for tailored agricultural practices.
Soil Science and Crop Nutrition[11]	2020, Soil Science and Crop Nutrition	Examination of soil attributes (nitrogen, phosphorus, potassium, pH, moisture content) and their impact on crop growth.	Understanding the impact of soil attributes is crucial for optimizing crop growth and suitability.

2.1 Gap Findings

While existing research provides valuable insights into machine learning applications in agriculture, there is a noticeable gap in the literature concerning the specific application of the Random Forest algorithm for soil-based crop prediction. The current study aims to address this gap by conducting a comprehensive analysis of the Random Forest model's performance in predicting optimal crops based on diverse soil attributes.

3. Methodology

3.1 About Dataset

A meticulously curated dataset, sourced from comprehensive soil testing records, forms the backbone of this research. Key soil attributes, including Nitrogen, Phosphorus, Potassium, Temperature, Humidity, pH, Rainfall, and Soil Moisture, are meticulously considered. Rigorous preprocessing procedures are implemented to address missing values and ensure the dataset's suitability for model training.

3.2 Soil Moisture Measurement

The gravimetric method [7] is applied for soil moisture assessment. Utilizing Uhland cores, soil samples are collected to calculate Volumetric Water Content (VWC) by multiplying gravimetric water content with bulk density. This precise measurement ensures accurate representation of soil moisture.

3.3 Classification & Regression Trees (CART)

CART, a tree-based regression model, maximizes the reduction in response variable variability through binary recursive partitioning. It generates regression trees for continuous data and classification trees for categorical data, providing a comprehensive understanding of the dataset's intricate structure.

3.4 Data Processing

High-dimensional NIR spectral data undergoes preprocessing with the Savitzky-Golay smoothing filter [10] and first-order differencing [7]. This meticulous process aims to reduce noise and eliminate irrelevant features, optimizing the data for subsequent analyses and model training.

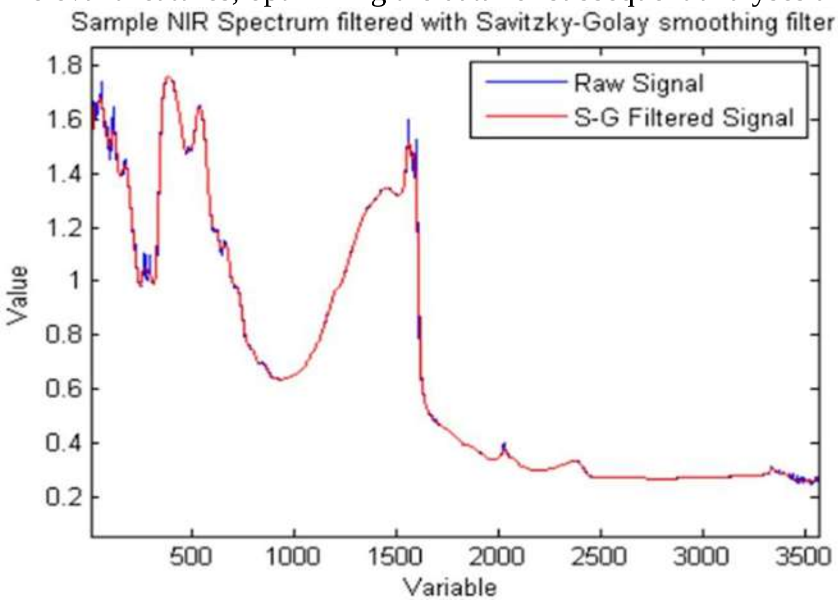


Figure 3.1 Sample NIR Spectrum filtered with Savitzky-Golay smoothing filter

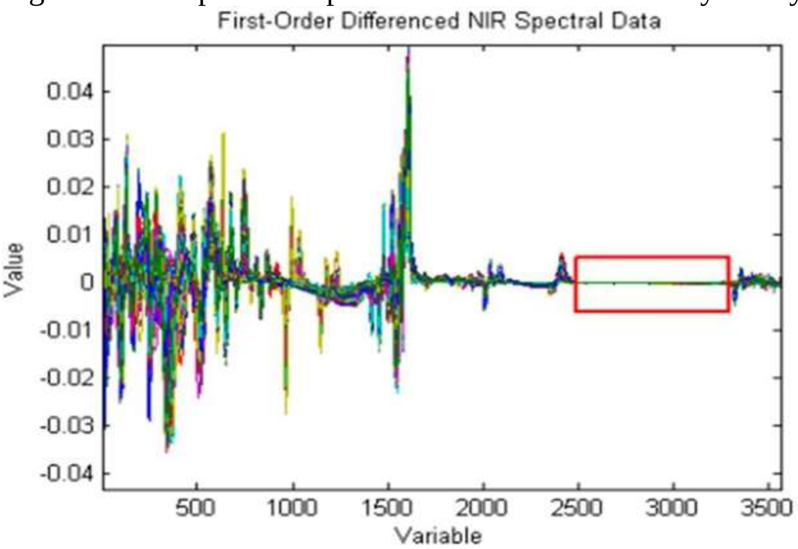


Figure 3.2 First Order Differenced NIR Spectral Data

3.5 Artificial Neural Network

For liquefaction susceptibility prediction, a Multilayer Perceptron (MLP) trained with the Backpropagation algorithm [9] is employed. The Levenberg-Marquardt Backpropagation algorithm ensures effective learning. Input parameters include corrected SPT value (N1), cyclic shear stress ratio (CSR), and amax/g, allowing the model to capture nuanced relationships.

The study encompasses a rigorous formulation, normalization, and division of data into training and testing datasets. Two distinct models, MODEL I and MODEL II, are developed using the MATLAB neural network toolbox, providing a robust framework for accurate liquefaction susceptibility prediction.

3.3 Features Extraction

The features extracted from the dataset for model training are as follows:

4. Result

The results of our research are encapsulated in a series of figures, each shedding light on distinct facets of the project. In Figure 4.1, the crop recommendation system demonstrates its efficiancy, showcasing the algorithm's ability to suggest optimal crops based on soil attributes. Moving to Figure 4.2, we present a set of samples used for testing, underscoring the diverse dataset employed to validate the robustness of our model. Figure 4.3 provides a graphical representation of the testing crops, offering a visual insight into the distribution and diversity of crops considered in our evaluation.
A pivotal aspect of our study lies in Figure 4.4, where the predicted values of crops are depicted through the implementation of the Random Forest Classifier. This figure serves as a

Nitrogen: Soil nitrogen content (ranging from 0 to 140).
Phosphorus: Soil phosphorus content (ranging from 5 to 145).
Potassium: Soil potassium content (ranging from 5 to 205).
Temperature: Soil temperature (ranging from 8 to 43).
Humidity: Soil humidity (ranging from 14 to 99). pH: Soil pH level (ranging from 3 to 9).
Rainfall: Amount of rainfall (ranging from 20 to 298).
Soil Moisture: Soil moisture content (ranging from 7 to 90).

comprehensive overview of how well our model performs in forecasting crop outcomes based on intricate soil features. The predictive values offer valuable insights into the accuracy and reliability of the Random Forest algorithm in the context of crop selection. Together, these figures contribute to a comprehensive understanding of the outcomes and capabilities of our research, affirming the efficiancy of the machine learning approach in optimizing crop recommendations for sustainable agricultural practices.

```
df1 = pd.read_csv('crop_recommendation1.csv')
df1.head()
```

	N	P	K	temperature	humidity	ph	rainfall	label	soil_moisture
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice	30
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice	30
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice	30
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice	30
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice	30

Figure 4.1 Crop Recommendation

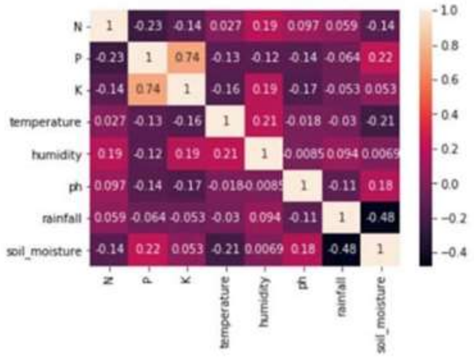
```
df1.sample(10)
```

	N	P	K	temperature	humidity	ph	rainfall	label	soil_moisture
1002	108	92	53	27.400536	82.962213	6.276800	104.937800	banana	40
904	0	27	38	22.445813	89.901470	6.738016	109.390600	pomegranate	30
1417	110	14	51	27.024151	91.667376	6.085445	21.260350	muskmelon	30
1957	129	47	20	24.412123	80.803438	6.281914	98.604574	cotton	70
228	54	77	85	17.141861	17.066243	7.829211	83.746067	chickpea	60
1850	14	23	25	26.185524	96.966379	5.612123	135.418622	coconut	45
594	35	52	15	28.698413	61.147544	9.935091	65.675918	mothbeans	30
1328	112	28	54	24.860946	85.053186	6.738031	55.295635	watermelon	70
398	27	63	19	20.934099	21.189301	5.562202	133.191442	kidneybeans	45
78	77	36	37	26.884449	81.460337	6.136132	194.576656	rice	30

Figure 4.2 Samples for Testing

```
sns.heatmap(df1.corr(),annot=True)

<matplotlib.axes._subplots.AxesSubplot at 0x7f9349f77650>
```




```
features = df1[['N', 'P','K','temperature', 'humidity', 'ph', 'rainfall','soil_moisture']]
target = df1['label']
labels = df1['label']
```

Figure 4.3 Graphical Representation of Testing Crops

5. Conclusion and Future Scope

In this study, we proposed an innovative predictive modeling approach to forecast the functional properties of soil samples based on their spatial and spectral features. The spectral data underwent a pre-processing stage, involving a smoothing step with the Savitzky-Golay filter and a first-order differencing step to enhance the spectral properties while eliminating physical effects. Utilizing the extreme learning machine (ELM) algorithm, specifically in two variations—basic Sigmoid-based ELM and Gaussian kernel-based ELM [8]—we achieved compelling predictive modeling results on the

```
RF's Accuracy is:  1.0
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        13
      banana       1.00      1.00      1.00        17
   blackgram       1.00      1.00      1.00        16
    chickpea       1.00      1.00      1.00        21
     coconut       1.00      1.00      1.00        21
      coffee       1.00      1.00      1.00        22
      cotton       1.00      1.00      1.00        20
      grapes       1.00      1.00      1.00        18
        jute       1.00      1.00      1.00        28
 kidneybeans       1.00      1.00      1.00        14
      lentil       1.00      1.00      1.00        23
       maize       1.00      1.00      1.00        21
       mango       1.00      1.00      1.00        26
   mothbeans       1.00      1.00      1.00        19
    mungbean       1.00      1.00      1.00        24
   muskmelon       1.00      1.00      1.00        23
      orange       1.00      1.00      1.00        29
      papaya       1.00      1.00      1.00        19
  pigeonpeas       1.00      1.00      1.00        18
 pomegranate       1.00      1.00      1.00        17
        rice       1.00      1.00      1.00        16
  watermelon       1.00      1.00      1.00        15

    accuracy                           1.00       440
   macro avg       1.00      1.00      1.00       440
weighted avg       1.00      1.00      1.00       440
```

Figure 4.4 Predicted Values of Crops by using Random Forest Classifier

Africa Soil Property Prediction Challenge [1] dataset. Both variations demonstrated strong predictive capabilities, characterized by low prediction error rates and minimal standard deviations of errors. Our findings suggest practical applicability in numerous agricultural and environmental scenarios that necessitate a nuanced understanding of soil functional properties.

Moving forward, there exists a vast landscape of opportunities for advancing soil property prediction. While various machine learning algorithms have been explored for this purpose, our introduction of ELM represents a novel and promising avenue. Unlike other methods, ELM boasts distinctive advantages, including superior generalization ability, unique solutions with minimized training error, and the theoretical capacity to model complex functions or decision boundaries. Notably, the comparative analysis with widely-used support vector machine variants underscores ELM's reduced optimization constraints, scalability, and enhanced generalization performance. In conclusion, our study not only contributes a valuable predictive modeling technique for soil properties but also highlights the untapped potential of ELM [8] in this domain. Future research endeavors could delve deeper into the exploration and refinement of ELM-based approaches, providing a robust foundation for more accurate and efficient soil property predictions in diverse environmental contexts.

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