JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Predictive persistence learning on Soil Fertility Slant using IOT

S.Janakiraman [1], Dr.K.Rajeswari [2]

Ph.D Research Scholar, Department of Computer Science, Tiruppur Kumaran College for Women, Tiruppur, Tamil Nadu, India [1]

Associate Professor, Department of Computer Science, Tiruppur Kumaran College for Women, Tiruppur, Tamil Nadu, India[2]

ABSTRACT

Agriculture plays a major role in wealth formation, addressing food security needs and generating employment, thereby contributing significantly to a country's growth. The integration of IoT in the agriculture domain is utilized for smart farming, enabling the automatic monitoring of farmlands and enhancing overall operational efficiency. Soil fertility is a crucial aspect of agriculture, influencing the growth and health of crop production. It refers to the soil's ability to provide essential nutrients to plants. Therefore, maintaining proper soil fertility is essential for sustainable and precision agriculture. Machine learning techniques are used for addressing challenges in soil fertility prediction problems in agriculture. The challenges include achieving accurate and timely predictions.

***Keywords*: IoT, Soil fertility prediction, preprocessing, Gower's proximity hot deck imputation, maximum normalized residual test.**

1. INTRODUCTION

Agriculture is the largest sector in India, significantly influencing the economy. Precision and smart agriculture have emerged as new models for achieving better productivity through optimal resource utilization. The advanced development of Internet-of-Things (IoT) based systems is referred to as 'smart agriculture.' Soil fertility, indicating the concentration of nutrients essential for plant growth and it plays a pivotal role in the smart agriculture. The level of soil fertility is directly linked to the growth of plants. The integration of IoT with machine learning technologies has proven effective for soil fertility management. Accurate predictions of soil fertility are crucial for optimizing agricultural practices, guiding farmers in making decisions about nutrient management, and finally enhancing crop yield. Various machine learning methods have been developed for soil fertility prediction in the context of smart agriculture

A deep learning approach, known as Long Short-Term Memory (LSTM), was developed in [1] to analyze soil moisture for smart farming. However, the designed approach faced challenges in creating a more robust model to enhance the accuracy of the learning process. A Deep Learning Multi-Layer Perceptron (DLMLP) neural network was developed in [2] for crop yield forecasting using remotely sensed soil data. However, the accuracy did not improved when utilizing a larger set of soil health parameters.

Machine learning algorithms were introduced in [3] to analyse the collected data and generate customized recommendations for improving crop yield. However, these algorithms failed to enhance the capabilities required for achieving precision agriculture. An automated 1D-CNN was developed in [4] to simultaneously predict soil texture properties. However, it encountered challenges in integrating multi-source data for soil mapping.

1.1 IMPORTANT CONTRIBUTIONS OF THE PAPER

In order to overcome the issues from the existing methods, a novel FPNI-IELM technique is developed with the following contribution,

- A novel FPNI-IELM technique is introduced to enhance the soil fertility prediction incorporating preprocessing and feature selection.
- To minimize time and space complexity, the FPNI-IELM technique involves preprocessing the data. This is achieved through Gower's proximity hot deck imputation for handling missing data. A maximum normalized residual test is performed to detect outlier data.

2. RELATED WORKS

An Explainable Artificial Intelligence (XAI) model, based on a Random Forest classifier, was introduced in reference [11] for predicting the relative soil fertility using a range of its physiochemical properties. An artificial intelligence (AI), deep learning (DL), and machine learning (ML) system was developed in [12] to achieve robust, accurate, and rapid soil analysis and soil texture analysis. However, the approach employed was insufficient for ensuring robustness in soil texture analysis.

An extreme learning method (ELM) was introduced in [13] for soil fertility prediction based on classification. However, the method faced challenges in accurately predicting fertility maps and addressing nutrient deficiency issues. Several Extreme Learning Mechanisms (ELMs) were developed in [14] to classify nutrients for predicting soil fertility. But the time and space complexity in the soil fertility remained unsolved.

2. PROPOSAL METHODOLOGY

Soil fertility prediction in the agriculture field is crucial, as it refers to the soil's ability in a specific area to provide optimal chemical, physical, and biological qualities that contribute to enhancing crop growth and productivity. This section presents a detailed description of the proposed FPNI-IELM technique, outlining its different processes. The architecture design of the proposed FPNI-IELM technique is illustrated in Figure 1 and consists of three main phases.

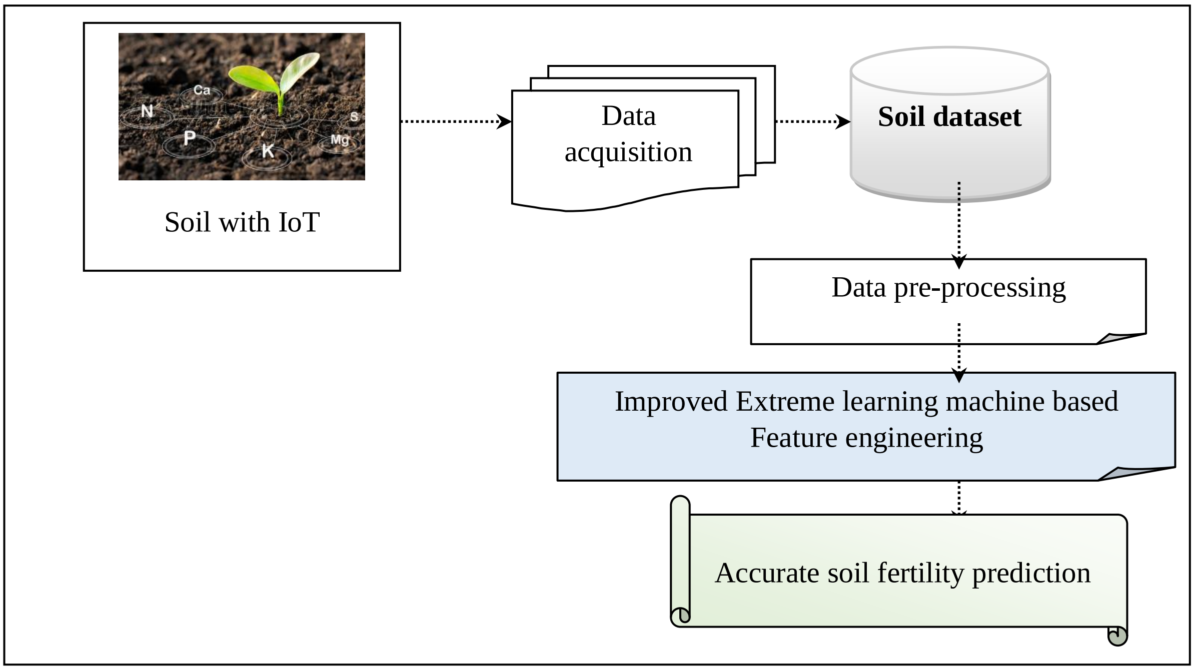

Figure 1 Architecture of the proposed FPNI-IELM technique

Figure 1 illustrates the architecture of the proposed FPNI-IELM technique that consists of three phases namely data acquisition, pre-processing and feature engineering. In the data acquisition phase, IoT (Internet of Things) involves collecting information from physical devices equipped with sensors in the agriculture domain.

These devices often are embedded in soil of the agricultural ground to gather data and transmitted for further analysis. Pre-processing is a fundamental step in the proposed FPNI-IELM technique. It involves cleaning, transforming, and organizing raw data into a suitable format for analysis. Feature engineering involves choosing the most important features to improve model performance and reduce dimensionality. The explanation of these three phases of the proposed FPNI-IELM technique is given below.

3.1 DATA ACQUISITION PHASE

In this phase, deploy a network of IoT sensors in the agricultural field. These sensors may comprise soil sensors, weather stations, and other environmental sensors designed to collect information such as moisture content, pH level, and nutrient levels like Nitrogen, Phosphorous, Potassium, Iron, copper, Manganese etc. Utilize the Soil Fertility Dataset obtained from https://www.kaggle.com/datasets/rahuljaiswalonkaggle/soil-fertility-dataset to assess soil fertility. The dataset comprises of a soil data organized in rows and columns. Each column signifies a feature or attribute, while each row represents a record of data or an instance.

4. EXPERIMENTAL SETUP

In this section, the proposed FPNI-IELM technique with existing LSTM [1] and DLMLP [2] are implemented in Python using the Soil Fertility Dataset collected from https://www.kaggle.com/datasets/rahuljaiswalonkaggle/soil-fertility-dataset/. This dataset is used to predict Soil Fertility based on different features. The dataset consists of 13 features and 880 instances. The features are listed in table 1.

Table 1 dataset description

S.No	Features	Description
1.	N	Ratio of Nitrogen (NH4+) content in soil
2.	P	Ratio of Phosphorous (P) content in soil
3.	K	ratio of Potassium (K) content in soil
4.	Ph	soil acidity (pH)
5.	Ec	electrical conductivity
6.	Oc	organic carbon

7.	S	sulfur (S)
8.	Zn	Zinc (Zn)
9.	fe	Iron (Fe)
10.	cu	Copper (Cu)
11.	Mn	Manganese (Mn)
12.	B	Boron (B)
13.	Class fertility	0 "Less Fertile", 1 "Fertile" 2 "Highly Fertile"

5.COMPARATIVE PERFORMANCE ANALYSIS

In this section, a comparative analysis of proposed FPNI-IELM technique with existing LSTM [1] and DLMLP [2], is discussed with different evaluation metrics such as prediction accuracy, error rate, soil fertility prediction time and space complexity.

Accuracy: The accuracy is measured as the number of accurately predicted data samples divided by the total number of data samples, based on selected features. It is measured as follows,

$$AC = \sum_{i=1}^{n} \left(\frac{predicted\ Ds}{Ds_i}\right) * 100 \qquad (1)$$

Where AC indicates an accuracy, Ds_i indicates a number of data samples, $predicted\ Ds$ indicates a number of data samples correctly predicted. It is measured in percentage (%).

TABLE 2 COMPARISON OF ACCURACY

Number of data samples	Accuracy (%)		
	FPNI-IELM	LSTM	DLMLP
80	91.25	87.5	85
160	90.62	86.25	83.75
240	91.66	88.75	85.41
320	90.31	87.5	85.62
400	91.5	88.75	86.25
480	90.62	87.08	85.83
560	91.96	86.60	84.82

640	91.40	87.96	85.93
720	90.97	88.19	86.80
800	91.87	87.87	85.62

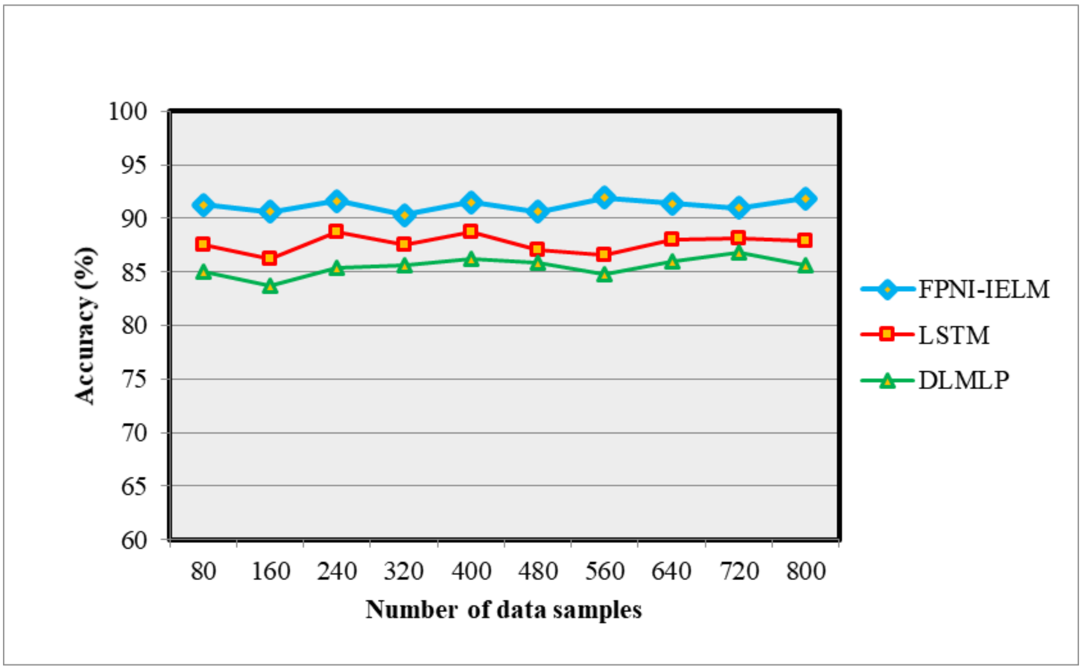

FIGURE 4 COMPARISON OF THE ACCURACY BETWEEN THE PROPOSED AND EXISTING METHODS

Figure 4 depicts a performance comparison analysis of accuracy using three different methods namely FPNI-IELM technique, the existing LSTM [1], and DLMLP [2]. The horizontal axis represents the input data samples, while the vertical axis illustrates the performance analysis of accuracy. The soil fertility prediction accuracy of the three techniques is denoted by blue, red, and green colors, respectively. The graphical representation indicates that the proposed FPNI-IELM technique achieved higher prediction accuracy compared to the other existing methods. Let us consider the 80 data samples in the first iteration, the application of the FPNI-IELM technique resulted in a soil fertility prediction accuracy of 91.25%. In comparison, the accuracy of the existing methods [1] and [2] was found to be 87.5% and 85%, respectively. For each method, ten different sets of results were observed and compared. The average of these ten comparison results indicates that the prediction accuracy of the FPNI-IELM technique improved significantly by 4% and 7% compared to existing methods [1] and [2], respectively. This is because of the efficient feature selection process employed by the FPNI-IELM technique. Additionally, with the preprocessed dataset, feature engineering is carried out by applying an improved extreme learning machine. Sokal–Michener's simple matching is employed to perform feature learning and select relevant features from the dataset for accurate soil fertility prediction.

Error rate: it is measured as the number of incorrectly predicted data samples divided by the total number of data samples, based on selected features. It is estimated as follows,

$$RE = \sum_{i=1}^{n} \left(\frac{IC\ Ds}{Ds_i}\right) * 100 \qquad (13)$$

Where RE indicates an error rate, Ds_i indicates a number of data samples, $IC\ Ds$ ndicates a number of data samples incorrectly predicted. It is measured in percentage (%).

Table 3 comparison of error rate

Number of data samples	Error rate (%)		
	FPNI-IELM	LSTM	DLMLP
80	8.75	12.5	15
160	9.37	13.75	16.25
240	8.33	11.25	14.58
320	9.68	12.5	14.37
400	8.5	11.25	13.75
480	9.37	12.91	14.16
560	8.03	13.39	15.17
640	8.59	12.03	14.06
720	9.02	11.80	13.19
800	8.12	12.12	14.37

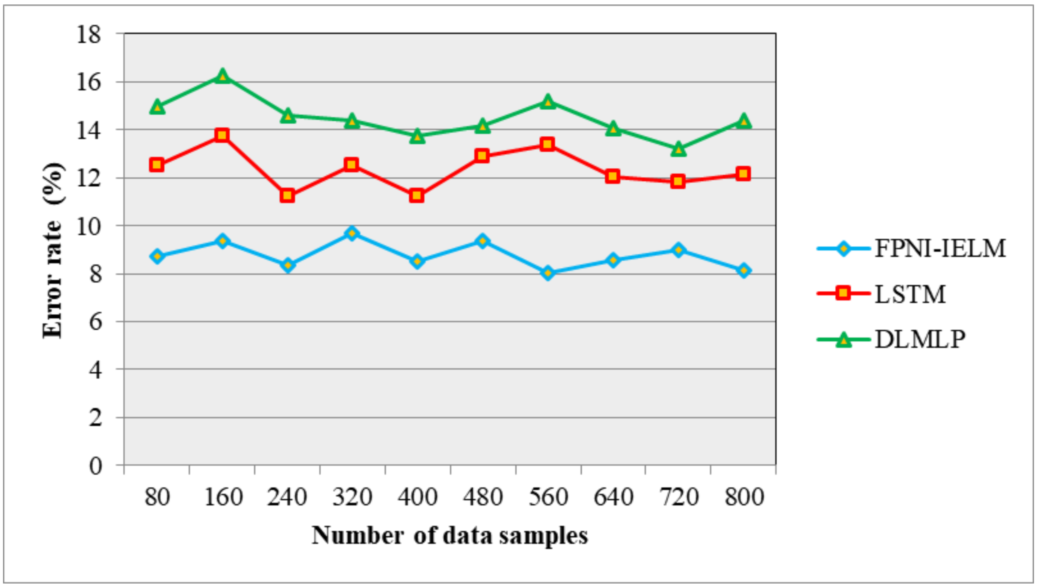

FIGURE 5 COMPARISON OF THE ERROR RATE BETWEEN THE PROPOSED AND EXISTING METHODS

Figure 5 illustrates the assessment of error rate analysis for soil fertility prediction using three techniques namely FPNI-IELM technique, existing LSTM [1], and DLMLP [2]. The observed performance results in Figure 5 demonstrate that the error rate using the FPNI-IELM technique is lower compared to the other two existing techniques. When applying 80 data samples as input in the first iteration, the error rate of the FPNI-IELM technique was found to be 8.75%, whereas the error rates for the existing methods [1] and [2] were found to be 12.5% and 15%, respectively. Similarly, nine varieties of results were observed with varying numbers of data samples. Finally, the observed results of the proposed technique were compared to the results of existing methods. The average of ten results indicates that the error rate of the FPNI-IELM technique is reduced by 29% and 39% compared to the existing methods. This reduction achieved to the FPNI-IELM technique has the ability to select more relevant features and remove others from the dataset. Consequently, these selected significant features provide more accurate information for soil fertility prediction and reduction in the error rate. Additionally, the removal of outlier data from the dataset contributes to minimize the error rates in identifying fertility prediction.

6. CONCLUSION

Monitoring soil health is crucial for sustainable agriculture practices as it provides valuable information about soil properties. Agriculture's role in addressing global food concerns highlight the importance of tackling issues related to soil fertility. This article focuses on accurate soil fertility prediction for smart farming applications, employing the FPNI-IELM technique, which involves key steps in data preprocessing and feature selection. In the data preprocessing phase, the FPNI-IELM technique addresses missing data imputation and identifies outliers to ensure the quality of the dataset.

REFERENCES

[1] Gabriele Patrizi , Alessandro Bartolini , Lorenzo Ciani , Vincenzo Gallo , Paolo Sommella , and Marco Carratù, “A Virtual Soil Moisture Sensor for Smart Farming Using Deep Learning”, IEEE Transactions on Instrumentation and Measurement , Volume 71, 2022, **DOI:** 10.1109/TIM.2022.3196446

[2] Akshar Tripathi, Reet Kamal Tiwari, Surya Prakash Tiwari, “A deep learning multi-layer perceptron and remote sensing approach for soil health based crop yield estimation”, International Journal of Applied Earth Observation and Geoinformation, Elsevier, Volume 113, 2022, Pages 1-12. https://doi.org/10.1016/j.jag.2022.102959

[3] Md Reazul Islam, Khondokar Oliullah, Md Mohsin Kabir, Munzirul Alom, M.F. Mridha, "Machine learning enabled IoT system for soil nutrients monitoring and crop recommendation", Journal of Agriculture and Food Research, Elsevier, Volume 14, 2023, Pages 1-12. https://doi.org/10.1016/j.jafr.2023.100880

[4] Osayande Pascal Omondiagbe, Linda Lilburne, Sherlock A. Licorish, Stephen G. MacDonell, "Soil texture prediction with automated deep convolutional neural networks and population-based learning", Geoderma, Elsevier, Volume 436, August 2023, Pages 1-12. https://doi.org/10.1016/j.geoderma.2023.116521

[5] Usman Ahmed, Jerry Chun-Wei Lin, Gautam Srivastava, Youcef Djenouri, "A nutrient recommendation system for soil fertilization based on evolutionary computation", Computers and Electronics in Agriculture, Elsevier, Volume 189, 2021, Pages 1-7. https://doi.org/10.1016/j.compag.2021.106407

[6] Pingki Datta, Salah A. Faroughi, "A multihead LSTM technique for prognostic prediction of soil moisture", Geoderma, Elsevier, Volume 433, 2023, Pages 1-13. https://doi.org/10.1016/j.geoderma.2023.116452

[7] Francesco Reyes, Raffaele Casa, Massimo Tolomio, Michele Dalponte, Nada Mzid, "Soil properties zoning of agricultural fields based on a climate-driven spatial clustering of remote sensing time series data", European Journal of Agronomy, Elsevier, Volume 150, October 2023, Pages 1-13. https://doi.org/10.1016/j.eja.2023.126930

[8] Qian Liu, Bin Du, Li He, Yun Zeng, Yu Tian, Zihong Zhang, Ran Wang, Tiezhu Shi, "Digital soil mapping of heavy metals using multiple geospatial data: Feature identification and deep neural network", Ecological Indicators, Elsevier, Volume 154, 2023, Pages 1-11. https://doi.org/10.1016/j.ecolind.2023.110863

[9] Maiara Pusch, Alessandro Samuel-Rosa, Paulo Sergio Graziano Magalhaes, Lucas Rios do Amaral, "Covariates in sample planning optimization for digital soil fertility mapping in agricultural areas", Geoderma, Elsevier, Volume 429, 2023, Pages 1-14. https://doi.org/10.1016/j.geoderma.2022.116252

[10] Shubhadip Dasgupta, Santonu Debnath, Ayan Das, Asim Biswas , David C. Weindorf, Bin Li, Arvind Kumar Shukla, Shreya Das, Sushanta Saha, Somsubhra Chakraborty, "Developing regional soil micronutrient management strategies through ensemble learning based digital soil mapping", Geoderma, Elsevier, Volume 433, May 2023, Pages 1-20. https://doi.org/10.1016/j.geoderma.2023.116457