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Research Article

Machine Learning Algorithm for Soil Analysis and Classification of Micronutrients in IoT-Enabled Automated Farms

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The available nutrient status of the mulberry gardens in the districts of Tamil Nadu is analyzed and evaluated to find the status. In this work, the soil is classified based on the test report to a number of features with fertility indices for boron (B), organic carbon (OC), potassium (K), phosphorus (P), and available boron (B), along with the parameter soil reaction (pH). A total of 10 steps are used for cross-validation purposes wherein in every step, the data involves 10% for validation and the remaining for training data. A fast learning classification methodology known as extreme learning method (ELM) is trained using the data to identify the micronutrients present in the soil. Activation functions such as hard limit, triangular basis, hyperbolic tangent, sine-squared, and Gaussian radial basis are used to optimize the methodology. Based on the analysis performed, the nutrients are classified and the optimal soil conditions are proposed for different regions that are analyzed. Based on the study conducted, it is found that the soils in Tamil Nadu have normal electrical conductivity and are red in colour. They are found to be rich in potassium (35% of the samples), nitrogen (80% of the samples), and sulphur (75% of the sample) and sufficient or poor in magnesium, boron, zinc, and copper.

1. Introduction

One of the primary occupations and sources of income for a large population in India is Agriculture. There has been an exponential increase in the demand for production over time. However, with the increase in industrialization, there has also been a huge reduction in the number of farmlands. In order to make accurate decisions based on the type of crops to be planted and to achieve a good harvest, data such as use of pesticides, fertilizers, meteorological, and soil information must be made available to the farmers in an accurate and timely manner [1]. Better crop productivity can be achieved by farmers through analysis of the suitable conditions, thereby reducing the damage and loss of crops that occur due to unfavorable conditions. Every day, several hybrid varieties of plants are produced. However, when compared to the naturally produced crop, these varieties lack essential nutrients. The quality of soil is often spoiled by these artificial techniques causing further environmental degradation [2]. Prevention of losses is the key consideration of most of these artificial techniques. However, crop loss can be minimized and yield can be increased by the farmers with accurate knowledge of various factors.

About 16-20% of total crops produced in India suffer wastage annually according to survey [3]. Over 215.6 million acres (82.6 million hectare) of farmland is used for agriculture, and crops are cultivated annually in India, of which 48.92 lakh hectares is in Tamil Nadu. Here, around 46,570.25 acres is used for mulberry cultivation. Followed by Karnataka, Tamil Nadu is the second largest producer of silk cocoons. For maintaining a sustainable crop production level, one of the key factors is soil fertility management. This enables ensuring the ability of the soil to provide the required nutrients to the plants at the right time and in the right quantity in the available form. The presence or absence of micro- and macro nutrients helps in determining the fertility level of the soil. Rajkumar et al. [4] discuss the 16 nutrients that are required in medium or large quantities for plant growth along with the micronutrients needed for the plant enzymatic systems that should be available in traces (mg/kg).

The micronutrients are crucial throughout the plant life cycle. Complete crop failure may occur due to abnormal plant growth when there is a deficiency of micronutrients in the soil. Sheeja et al. [5] analyzed the sensitivity of soil environment to the variation in micronutrients in correlation with organic matter, lime, soil pH content, and other such factors. Development of sustainable sericulture is gaining widespread interest in recent days as its dependency on external inputs is less and can help overcome the serious issue of soil erosion. The deficiency symptoms are evident if any specific nutrient is not available in the soil. In such scenarios, the nutrient has to be fed to the plant to achieve optimum yield according to Rana et al. [6]. When considering the cultivation of mulberry for silkworms, the quality of leaves greatly influences the stability of the worm. As mulberry leaves are the sole food for silkworm, the observations are crucial as indicated by Subbaswamy et al. [7]. In this work, the major objectives include assessment of micro- and macro nutrients of the soil in four major districts of Tamil Nadu, where mulberry is cultivated by automating the farms with IoT sensors and processing the data through a machine learning algorithm for enhancing the soil quality.

Improvement and maintenance of the dynamic soil parameters so as to enhance the crop productivity are the key motivation of soil management. Decline of traditional techniques of soil management, terrestrial limitations, and population stresses have caused deterioration in the soil fertility especially in developing countries like India. In modern agriculture, a highly productive system is ensured mainly by crop health, which is directly dependent on the soil quality. Adoption of suitable strategies for management of crop health can help in achieving a stable increase in crop yield. Enhancing the soil quality by introducing micronutrients as corrective measures and effective management of soil resources help in achieving an increased productivity. The issues related to crop yield pointers can be addressed by timely detection and control by the agricultural experts, decision-makers, and farmers for appropriate crop environment and soil resource management.

In recent days, several machine learning (ML) algorithms and models are used for effectively addressing the classification and prediction issues. The challenges faced by experts in the agricultural domain are also overcome largely by the introduction of ML techniques. Agricultural yield prediction can be performed efficiently by means of the classification and regression algorithms. Estimation, yield mapping, supply and demand matching, and overall crop management can be performed with the help of these models [8, 9]. Livestock prediction, water management, soil management, crop failure detection, and various other agricultural and farming applications are greatly benefitted by the machine learning algorithms.

A private online repository is used where real-time data is collected from the soil and crop. The values in the dataset are used for training and validating the model and then assessing and computing the results. For this purpose, the dataset is categorized into training data and testing data while building the model. The soil is analyzed, and the fertility of the soil is classified by applying various machine learning algorithms based on the chemical features and the micronutrients present in the soil. ML models are used for analyzing the crop sowing and yield as well. The existing systems make use of machine learning techniques [10] such as linear regression, Naïve Bayes, decision tree, artificial neural network (ANN), and support vector machine (SVM). In recent research work carried out, the authors from [11] have used clay soil expansion using machine learning algorithms to determine the quality of soil that is used. Similarly, in [12], the authors have incorporated SVD concatenation to determine the organic content present in the soil.

2. Literature Survey

Some of the existing literatures related to crop yield production and soil analysis using machine learning models are analyzed and discussed in this section. Issues that can be modelled from data and numerical parameters can be solved using the decision-making models like machine learning, deep learning, and neural networks. Soil Resources Development Institute- (SRDI-) based dataset is used by Zaminur et al. [13], for implementation of SVM, bagged trees, and KNN models. There are 11 classes consisting of 495 samples in this dataset. For any specific soil, the soil series prediction and suggestion of suitable crop yield can be performed using the ML model that is designed. In terms of soil classification, the highest accuracy is observed with SVM classification in this work. SVM, Naïve Bayes, decision trees, neural

Table 1: Threshold value for soil fertility indices.

Fertility level	Fertility index
High	>2.35
Medium	1-.5-2.35
Low	<1.65

Table 2: Rating of primary nutrient potassium.

Rating	Potassium
Very high	>300
High	200-300
Medium	151-200
Low	101-150
Very low	<100

Table 3: Rating of pH [34].

Rating	pH (1 : 2.5)
Very strongly alkaline	>10
Strongly alkaline	9.1-10
Moderately alkaline	8.1-9
Slightly alkaline	1.7-8
Neutral	7
Slightly acidic	6.5-6.9
Moderately acidic	5.5-6.4
Highly acidic	4.5-5.4
Strongly acidic	<4.5

networks, and several other ML algorithms are used by Pramudyana et al. [14]. Over 70% accuracy is achieved by the algorithm for automating the classification of soil type.

Organic agricultural crop protection has been the major goal in the research proposed by Patil and Umarji [15]. Convolution Neural Network (CNN) architectures are used for developing the deep learning model in this work. Assistance is provided to the farmer by identification of various crop diseases using this technique. Various scientific features and parameters are used for grading and classification of soil samples using the approach proposed by Ashwini et al. [16]. Texture, color, and other such features of soil are extracted using various algorithms. The real-time operation of the model is implemented using Digital Signal Processing (DSP) boards and commercial imaging libraries. Digital image processing as well as pattern recognition models are integrated in this model. A CNN algorithm is used for prediction of various crop yields in a precision agriculture model by Alex and Kanavalli [17]. Fertilizer level, temperature, rainfall, and other such parameters are observed for optimizing the decision and obtaining P values for crop testing in this research.

An advanced soil moisture prediction model using machine learning techniques is introduced by Prakash et al. [18]. Soil prediction is performed using several ML algorithms such as recurrent neural networks, support vector regression, and multiple linear regression. Multiple databases obtained from various online repositories are used, and the models were implemented. Coefficient of determination (R^2) and mean squared error (MSE) techniques are used for evaluation of the prediction performance. Based on the results and comparison, the values 0.975 and 0.14 are attained for R^2 and MSE, respectively, using the multiple regression model which is superior to the other models. From three regions of Pune, India, namely, Velhe, Bhor and Khed, soil datasets were used by Gholap et al. [19]. Nine attributes of 1988 instances are available in this dataset. JRip, Naïve Bayes, and J48 algorithms are applied for classification in this work. The J48 algorithm works with the C4.5 decision tree algorithm and is an open-source Java implementation. Various clustering techniques are described by Gudavalli et al. [20]. The seed dataset is used for implementing various clustering techniques in this work. Length of the kernel groove, width of the kernel asymmetric coefficient, length, compactness, perimeter, area, and other such parameters are considered for enhancing the clustering approach.

Conventionally, soil fertility prediction was performed using the artificial neural networks (ANNs) with backpropagation model based on Levenberg-Marquardt technique in certain machine learning models [21]. The available soil bulk density, soil OC, sandy loam soils, slit loam, clay loam, electrical conductivity (EC), and water capacity are used for forecasting the soil fertility based on partial least square regression model [22]. Water, required nutrient level supply, soil fertility prediction, and various other solutions that can use ML techniques are identified by several researchers in various studies to address the issues related to soil [23]. The phenotypic plant traits are used as inputs for the implementation of Apriori classifier, One-R, K-nearest neighbors (KNN), and J48 models for prediction and classification of wheat yield [24]. Quantification of wheat yield into low, medium, and high categories is performed using counterpropagation neural networks and supervised Kohonen model [25].

In kiwi fruit cultivation, for the leafroller pest monitoring and decision-making on the application of insecticides, Logistic Regression (LR), AdaBoost, support vector machine (SVM), random forests (RF), decision tree (DT), and Naive Bayes classifier were used [26]. The soil organic carbon prediction is performed using an unbiased linear predictor [27]. Boosted regression tree model is used for the analysis of Sicilian soil and prediction of the presence of organic carbon in them [28]. In the eastern Australian soil, the presence of organic carbon is predicted using genetic algorithm-based feature selection technique combined with random forest algorithm [29]. Partial least square technique is used for prediction of various soil types from midinfrared spectra of the Cation Exchange Capacity (CEC) and soil acidity (pH) in the presence of organic carbon [30]. Based on the presence of zinc, organic carbon, phosphorous, potassium, iron, copper, nitrogen, and such soil nutrients and the soil pH value, the soil fertility rating is performed by applying the Bayesian network [31]. The forming of wind speed is analyzed and evaluated using machine learning algorithms for geographic portability. Crop growth and precision farming are directly

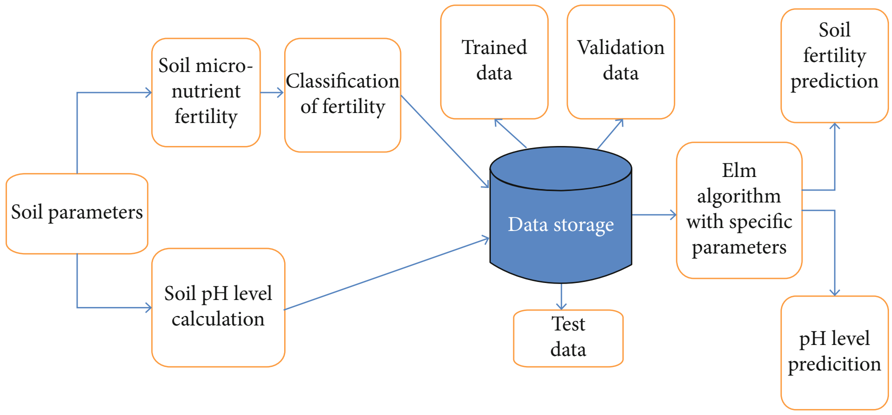

Figure 1: Workflow of the proposed methodology to predict pH content and soil fertility.

impacted by climate and soil parameters that are effectively analyzed using ANN, Bayesian networks, SVM, RF, and DT models [32].

Soil moisture, soil type, and soil nutrient content are predicted by means of various machine learning techniques. Bagging, neural networks, SVM, AdaBoost, RF, and twenty such classifiers are used for categorizing the soil nutrient levels and fertility indices village wise. Based on the numeric values, the soil is categorized into labels of low, medium, and high scales [33]. The fertility indices of the soil village wise can be foretold straightly based on the numerical values and generation of pseudotransfer functions through several regression models. Huang et al. [34] presented a promising machine learning technique, the extreme learning machine (ELM), which is extensively used for their extremely fast learning speed and advanced generalization performance over the past few years. The unrelated variables must be eliminated in most datasets where several spectral variables are present in large numbers. This helps in estimating the soil properties and performs predictions based on the important wavelengths that can provide appropriate insights. District- and block-level categorization of the soil fertility data in India is summarized. Fertilizer distribution procedure, fertility level consumptions and variations, utilization of appropriate quantity of fertilizers, and other crucial decision-making are supported using this information.

3. Proposed Methodology

3.1. Site of the Study. In recent years, there has been heavy loss in soil quality due to incorrect crop and soil management strategies. This is primarily because of the amount of chemical fertilizers used, disturbing the balance of the soil nutrients [33]. These factors have a major impact on the productivity of Tamil Nadu soils. Due to the nature of soil, the presence or absence of specific elements will lead to soil erosion, soil imbalance, and other soil issues. This will limit production in agricultural land. Hence, there is much emphasis on management and conservation of soil in systematic models. It is identified that the gaps in previous methodologies are addressed by identifying the integrating information technology with supporting inputs and services. The agricultural sector can be revived by using this technological advancement of plant health management [35], multiple nutrient deficiencies, and soil acidity treatment.

Table 4: Micronutrients composition in the soil sample.

Parameters	Salem	Coimbatore	Tirupur	Erode
Cu (ppm)	1.32	1.35	1.12	1.42
Mn (ppm)	2.08	6.82	2.2	8.7
Fe (ppm)	2.34	2.96	2.64	3.46
B (ppm)	0.35	0.19	0.46	0.35
Zn (ppm)	0.45	0.36	0.	0.7
S (ppm)	10.12	18.65	38.05	46.72
K (kg/ha)	275.82	294	267	397
P (kg/ha)	32.6	38	14	17.84
N (kg/ha)	521	382	394	798
OC (%)	0.5	0.42	0.38	1.6
EC (millimhos/cm)	0.18	0.09	0.082	0.2
pH	8.2	8.3	8.04	8.4

Samples of the soil have been collected from four mulberry cultivation districts, namely, Salem, Tirupur, Coimbatore, and Erode. From each district, 250 samples have been gathered amounting to a total of 1000 samples. The following are the chemical properties analyzed:

(i) Micronutrients like Fe, Mn, Cu, and Zn are analyzed using atomic absorption spectrophotometer-DTPA (diethylenetriaminepentacetate)

(ii) Sulphur (S) by Black

(iii) Potassium (K) by flame photometer methodology

(iv) Nitrogen (N) content using Kjeldahl's digestion

(v) Carbon (C) content using titration

(vi) EC and pH analyzed in ratio of soil : water (1 : 25)

A survey of the soil in the five districts indicates the level of soil nutrients in the soil, and based on this, the natural deficiency or excess in the content can be identified.

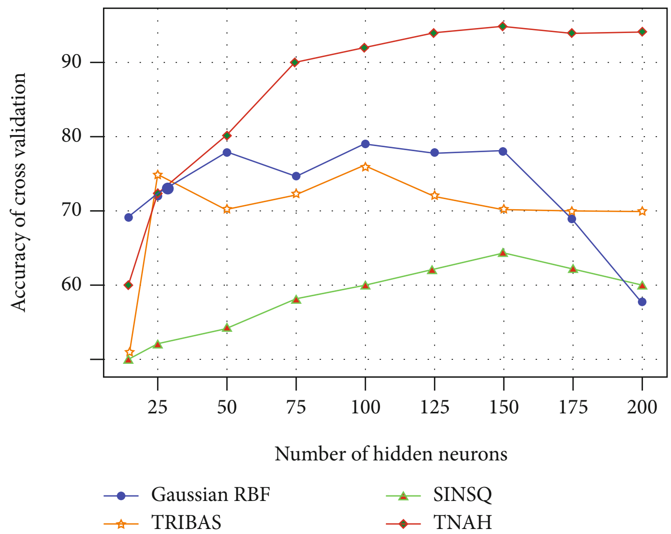

Figure 2: Cross-validation accuracy (%) vs. number of hidden neurons for identifying the pH content in the soil.

3.2. Soil Fertility Indices. Using Parker's nutrient diet, the fertility index of the soil is calculated for a particular area under study. Accordingly, the soil fertility index (F1) can be calculated using the formula shown:

$$\mathrm{F1} = \frac{(\mathrm{VL} * 0.5) + (L * 1) + (M * 1.5) + (M.H * 2) + (H * 2.5) + (\mathrm{VH} * 3)}{\text{total number of cultivation lands}}, \tag{1}$$

where VL, L, M, H, and VH represent the cultivation lands present in very low, low, medium, high, and very high groups of the district. Depending on the chemical characteristics of the cultivation land, the soil is categorized as shown in Tables 1 and 2.

3.3. Soil pH Content. In general, the soil in humid tropics has high acidity due to loss of basic cations and intense leaching conditions. This will result in a stressed environment for plant growth. Further, the use of fertilizers without the use of lime has led to further increase the acidity of the soil. Based on the micronutrients present in the soil, it is possible to classify the pH content. In general, the different ratings of pH classification come under slightly acidic, moderately acidic, highly acidic, and strongly acidic. Further, to identify the microbial nutrients present in the soil, the pH is classified as shown in Table 3.

3.4. Classification of Soil. Figure 1 represents the basic workflow for soil parameter classification and prediction used in this proposed work. For training and cross-validation, the samples are collected using IoT-based smart farming and details regarding the samples are passed between the farms and with the farmers within a matter of seconds. The samples obtained are rearranged arbitrarily, and 75% of them are used while 25% of the remaining is used for testing. A total of 10 steps are used for cross-validation purposes wherein in every step, the data involves 10% for validation and the remaining for training data. A fast learning classification methodology known as extreme learning method (ELM) is trained using the data to identify the micronutrients present in the soil. The parameters involved are total number of hidden nodes and training functions. The best parameters are chosen from the training set and are further used to test data. On an average of 10 trials, the final test result is obtained and the micronutrients are classified. In this work, the ELM classifier uses the hidden neuron parameter to identify soil nutrients and pH classification by assigning a value of 50 and 150, respectively. Accordingly, tuning is performed within the values [10,150] and [10,200], respectively. Similarly activation functions such as hard limit, triangular basis, hyperbolic tangent, sine-squared, and Gaussian radial basis are used to optimize the model.

4. Result and Discussion

According to the analysis performed, the available micronutrients are classified and the soil samples are categorized in four districts of Tamil Nadu.

4.1. Salem. The results analyzed indicate that majority of soils in Salem district are found to be deficient in sulphur content with <10 ppm, moderately high in potassium content with 245-295 kg k_2O/ha), medium in phosphorus content with 20-53 kg P_2O_2/ha, moderately high in nitrogen with 250-550 kg/ha), and medium in organic carbon (>0.5%). The overall texture of the soil is neutral in salinity and an alkaline reaction of over 8.2. The DTPA extracted micronutrients were found to be satisfactory in Cu and Fe while in the case of Mn, B, and Zn, the soil was deficient.

4.2. Coimbatore. The results analyzed indicate that majority of soils in Coimbatore district are found to be satisfactory in sulphur content with >12 ppm, moderately high in potassium content with 245-295 kg k_2O/ha), medium in phosphorus content with 20-53 kg P_2O_2/ha, moderately high in nitrogen with 250-550 kg/ha), and low in organic carbon (<0.5%). The overall texture of the soil is neutral in salinity. The DTPA extracted micronutrients were found to be satisfactory in Cu, Mn, and Fe while in the case of B and Zn, the soil was deficient. The soil also showed a moderately high pH of 8.04.

4.3. Tirupur. The results analyzed indicate that majority of soils in Tirupur district are found to be deficient in sulphur content with <10 ppm, moderately high in potassium content with 245-295 kg k_2O/ha), low in phosphorus content with less than 20 kg P_2O_2/ha, moderately high in nitrogen, with 250-550 kg/ha), low in organic carbon (<0.5%), and neutral in electrical conductivity (<1.0 mmhos/cm). The overall texture of the soil is neutral in salinity and an alkaline reaction of over 8.2. The DTPA extracted micronutrients were found to be satisfactory in Cu, B, and Mn while in the case of Fe and Zn, the soil was deficient. The soil also showed a moderately high pH of 8.24 and neutral salinity of below 1 mmhos/cm.

4.4. Erode. The results analyzed indicate that majority of soils in Erode district are found to be high in sulphur content with >15 ppm, high in potassium content with >295 kg k2O/ha), low in phosphorus content with <20 kg P2O2/ha, high in nitrogen with over 550 kg/ha), and high in organic carbon (>0.9%). The overall texture of the soil is neutral in salinity and an alkaline reaction of 8.23. The DTPA extracted micronutrients were found to be satisfactory in Cu and Fe while in the case of Mn, B, and Zn, the soil was deficient.

Based on the study conducted, it is found that the soils in Tamil Nadu have normal electrical conductivity and are red in colour. About 35% of the samples have high potassium content with another 65% showing moderately high content. The available nitrogen is steadily identified moderately high 80% and high 20% of the samples. The sulphur is measured as medium in 75% and low in the remaining 25% of the samples. On the other hand, DTPA extractable micronutrients such as boron and magnesium are found to be low in 80% and 40% of the samples and sufficient in 20% and 60%, respectively. However, 100% of the samples were found to be either sufficient or deficient in Cu and Zn availability. Table 4 shows that the overall composition of the soil is identified and the corresponding parameters for the four districts studied, namely, Erode, Tirupur, Coimbatore, and Salem.

Figure 2 represents the cross-validated accuracy score with respect to the hidden neurons that are used for determining high accuracy. It is identified that the pH classification is optimal at 150 for classification of soil nutrients. Based on the observation, it is seen that hyperbolic tangent function (tanh) shows optimal performance.

5. Conclusions

The primary reason for loss in quality of the soil is primarily due to the incorrect crop management and soil management methodologies [11, 12]. The level of fertility in the soil is determined with the help of the ELM algorithm. This methodology serves as the base for developing a neural network that enables prediction of soil fertility based on the soil samples and their nature observed using IoT in farming. This methodology will be useful for the Government of Tamil Nadu to manage the soil and address the nutrient deficiency issues faced. This methodology will also be useful to create soil fertility maps and in identifying the fertility indices of other similar nutrients. It can be further incorporated in agroecological regions in order to diagnose the soil parameters. Thus, a detailed study is conducted on the soils in four districts of Tamil Nadu. The results thus obtained are recorded for further reference and necessary action. It is observed that the soil is overall rich in potassium (35% of the samples), nitrogen (80% of the samples), and sulphur (75% of the sample) and sufficient or poor in magnesium, boron, zinc, and copper.

Data Availability

All the data supporting the results of this study have been included in the article.

Disclosure

The publication of this research work is only for the academic purpose of Addis Ababa Science and Technology, Ethiopia.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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