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A Systematic Approach of Classifying Soil & Crop Nutrient Using Machine Learning Algorithms

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Abstract: Agriculture is the foundation of India's economy. Farmers have a limited understanding of soil nutrient content. It is imperative to use the land that is available to the fullest extent possible by planting the right crops and using the right fertilisers. In order to produce the best results in today's world, agriculture needs technological assistance. Traditional farming methods are being replaced by newer, more efficient methods. Fertilizer overuse is a growing concern in the modern era. To help farmers better understand soil fertility and fertiliser application amounts, various machine learning algorithms can be used. Different crops necessitate different fertiliser application amounts, and crop intake also varies. The goal of machine learning (ML) is to develop algorithms that can learn from patterns in data and then use that learning to make predictions about new data. Machine Learning (ML) techniques can effectively solve the prediction and classification problems. Because of the widespread use of machine learning in agriculture, farmers are able to overcome their greatest challenges. In this study, Support vector machine (SVM), Decision Tree (DT), and Multilayer Perceptron (MLP) are three machine learning algorithms that were used to determine how well they analyse soil nutrients. When compared to other algorithms, the results showed that MLP had a 94% accuracy rate.

Keywords: *Agriculture, Accuracy, DT, Machine learning, MLP, Soil nutrient, SVM*

1. Introduction

The World Bank study report of September 2016 indicates, "Agricultural development is one of the most powerful tools to end extreme poverty, boost shared prosperity and feed nine billion people by 2050. [25] Soil nutrients are an important part of soil fertility and other environmental factors. Diverse soil constituents result in diverse soil types with distinct spatiotemporal distribution patterns as a result of natural processes. [1] Due to increase in population and demand for food supply, a large quantity on fertilizers are used in soil, which may result in soil pollution and also degradation of soil quality which may lead to multiple problems for future generations. [26] Plant size, species composition and geographical distribution were all affected by this variation, according to a recent study. [2] Scientific management and sensible application of soil nutrients necessitate the use of soil nutrient evaluation. Soil nutrients may be accurately analysed using BP neural networks, PCA, GRA, fuzzy comprehensive evaluation, and index approaches. [4] There is a significant rate of error with these procedures, which are difficult to implement. Even if the BP neural network outputs are correct, there may be scenarios in which they are erroneous. Soil nutrient levels were analysed with the help of support vector machines (SVM), multiple linear regressions (MLR), and artificial neural networks (ANN). Studying soil nutrient ranking, the dependent variable in the study, was total nitrogen, alkali-hydrolysable nitrogen, fast accessible phosphorus and rapidly available potassium. [4] The statistical learning theory is the foundation for support vector machines (SVMs). Due to sample complexity and models' ability to generalise, this theory makes use of samples' sparse information to help with generalisation. It is SVM's most fundamental idea to find the best hyperplane, a plane that separates all samples by the greatest margin. Classification errors are less likely when the plane and model are used together. The primary goal of this study is to classify soil fertility indices by area using data collected at the village level. To avoid overuse of fertilisers, it also recommended the appropriate amount of fertilisers based on the crop's needs and developed a model using MLP in order to increase the prediction accuracy and carry out a comparative analysis with other Machine Learning algorithms.

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2. Related Study

The primary goal of agricultural soil management is to protect and enhance the unique properties of the soil. [5] Overcrowding and physical constraints on land use have contributed to a decline in soil fertility in emerging countries like India. Modern agriculture's high-yielding system relies heavily on maintaining healthy crops. A successful method for maintaining crop health can have a significant impact on crop productivity. Soil management and remediation strategies that use micronutrients could increase productivity. [6] Problems with crop production tips might help agricultural experts and farmers make better decisions about soil resource management and crop environment management. It is now possible for Machine Learning (ML) systems to accurately predict and classify data. The difficulties that domain experts used to face have been considerably lessened as a result of the introduction of ML techniques to agriculture. Early on in the development of machine learning techniques, ANNs back-propagation utilising the Levenberg-Marquardt approach were initially employed to estimate soil fertility. An alternative method for estimating soil fertility is based on partial least squares regression and a variety of other parameters, such as available water capacity (AWC), electrical conductivity (EC), clay or sandy loam, organic carbon (OC), and bulk soil density (BSD). Soil fertility, nutrients, and water levels can all be predicted using ML. We were able to predict wheat yields using phenotypic plant traits and algorithms like J48 or KNN, along with One-R or Apriori classification techniques. [7] In eastern Australian soils, random forest and feature selection techniques have been used in genetic algorithms to estimate organic carbon. To quantify organic carbon, pH, and CEC, partial least squares models were used to the mid-infrared spectra of diverse soils. An analysis of the soil's pH and pH value, as well as several nutrients such as copper (and zinc), potassium (and phosphorus), nitrate (and other elements), and organic carbon was used to evaluate the soil's fertility.

Machine learning methods have been tested for their capacity to predict wind speed at various locations. [8] Soil and climate analysis for precision farming can be accomplished through a variety of means. A variety of machine learning algorithms were used to predict soil nutrient content, soil type, and soil moisture. [9] The creation of pedotransfer functions, which can be used to quantitatively forecast fertility indices at the village level, has been made possible through the use of a variety of regression methods [10]. In India, data on soil fertility are compiled at the district and block level. Use this information when determining the amount of fertiliser that is needed and how it should be applied. [11] Using data collected at the village level, this study will categorise soil fertility indices. The decision support system may provide village-by-village fertility index analysis reports. These reports can then be utilised to make fertiliser recommendations. Soil fertility indices like organic carbon (OC), phosphorus (P), and potassium (K) must be classified in order to compare levels of soil fertility among communities. [12] In North Kerala, where flooding and drought are common, it is crucial to know the soil's pH in advance so that less chemical fertiliser is needed. [17]

The use of machine learning (ML) algorithms to predict the values of various soil parameters might eliminate excessive fertiliser inputs and evaluate soil and environmental health. For this study, soil fertility and pH levels in the north central laterite region of Kerala will be categorised and linked to soil features. [13] Extreme Learning Machines (ELMs) and other second-generation neural network algorithms can be used to classify and predict data (ELM). The soil nutrient problem categorization model is improved by modifying the ELM meta-parameters. [14] In Kerala agriculture, soil nutrients and pH levels are classified using ELM approaches to increase accuracy. Finally, in order to better classify neural networks, we looked into them. When all factors are considered, neural networks outperform statistical methods in terms of accuracy. The experimental evaluation of Extreme Learning Machine variations with different activation functions was based on their noteworthy behaviour. [15] Kerala's soil classification may now be more accurate thanks to the new ML technique just proposed. In the agricultural arena, early soil status predictions utilising machine learning can yield significant benefits for growers. [16]

It is possible to use Nutrient Expert as a decision-support tool. [17] It is a tool to aid in decision-making for computers or mobile phones developed with the help of QUEFTS and on-site agronomic data. For a smaller or larger area, this method can be utilised to establish a strategy for applying the right amount of nutrients under the same growing conditions. [18] To help farmers improve their crop management practises and maximise the return of fertiliser investments, agricultural extension agents can employ NE. It was created in a participatory approach to meet the demands of both farmers and researchers. Such studies have been limited in SSA farming systems, which are substantially more variable and complex. [19] Prior to convincing agricultural planners and extension advisers that NE and other decision support tools like soil testing are beneficial, these methods must be examined. Obtaining representative samples is difficult for smallholder farmers in Sub-Saharan Africa due to the lack of well-equipped laboratories and the amount of time it takes to get results. [20] There are limits to the interpretation of soil test data. [21]

Soil nutrient restrictions for maize agriculture were examined as part of this study's primary goal of calibrating and confirming the NE model in large maize-based systems in Nigeria, Ethiopia, and Tanzania. Agronomic usage efficiency of N, P, and K is estimated in order to better comprehend the advantages of NE recommendations over soil-test-based and blanket fertiliser recommendations in terms of agronomic and economic considerations. The study focuses on maize as a means of ensuring food security in Sub-Saharan Africa. [22] For the study's conclusion that smallholder agricultural systems in Africa comprise one-third of the continent's human population, research was carried out in Nigeria, Ethiopia, and Tanzania. Traditional evaluation approaches of soil nutrient are quite hard to operate, making great difficulties in practical applications. When it comes to macro nutrients such as nitrogen (N), phosphorus (P), and potassium (K), focus on each crop's specific needs and requirements. Machine learning algorithms and crop fertility indices are used to classify soil. It can be used to create a village-by-village fertility index report, which can then be used to recommend fertiliser. The recommended fertilisers in this study were found to be accurate to within a reasonable margin.

3. Materials and Method

3.1. Data collection

The research work is focused on the southernmost region of Tamil Nadu , area focused are kanyakumari district, tirunelvelli and thoothiukudi districts of Tamil Nadu the soil parameters are collected from this region. The major crops cultivated in the region are focused for the work, Crops such as varieties of banana, Varieties of Rice, Varieties of Maize and Ragi are chosen for the study. Soil data were collected from Department of Soil science, Agricultural University located at trichendur. And additional information's were also collected from soil science laboratory located at kanyakumari district. Major parameters considered for the study are Nitrogen (N), Phosphorous (P), Potassium (K), the prediction is carried out with the NPK values.

This study focused on classifying the soil fertility indices levels of the region and to predict the required amount of fertilizers for each crop. Pre-Processing of data is carried to avoid duplication and missing values, Missing values are replaced as 0s and Label encoder is used to process the data into low high and medium. Village wise soil data are classified as Low, High and Medium. Classification algorithms are used in classification of soil data. Machine learning algorithms such as SVM, DT and MLP are used in classification of given data. Classification of fertilizers N,P and K using Decision tree, SVM, and MLP is carried out. The data set were portioned using K-fold method for testing and training. The comparison of classification models was conducted using 10-fold cross-validation repeated in 100 different iterations, to train the data. By using K-Fold method, each and every values are trained and tested. The range is fixed for classification of soil parameters, as each parameters has different range of values, a limit is set to classify as Low, medium and high (refer Table 1).

Soil parameters	Range	Level
N	X<130	Low
	130<x<200	High
	200<x	Medium
P	X<16	Low
	17<x<23	Medium
	24<x	High
K	X<700	Low
	701<X<1,200	Medium
	1,200<x	High

Table 1. Range of NPK

3.2. Classification using SVM

Classification and regression problems can be solved using the "Support Vector Machine" (SVM) approach. [23] Classification concerns, on the other hand, frequently adopt this strategy. The SVM algorithm plots all characteristics as coordinates in n-dimensional space; each feature's value corresponds to a location in n-dimensional space (n is the number of features present). Classification is accomplished by identifying the hyper-plane that divides the dataset into its several classes based on the nitrogen value. It is feasible to recommend a crop based on the NPK value of this categorization. As one of the most commonly used binary classifier methods, SVM is applied in a wide variety of field, SVM is used in classification of NPK By predicting the nearby values and classifying as Low, High and Medium. A key factor in application of the model is to understand the soil fertility level and crop fertilizer requirement. Train the SVM using the training dataset and verify the validity of the model using the test dataset. From Fig. 1, we can observe the process of classifying the soil upon village wise.

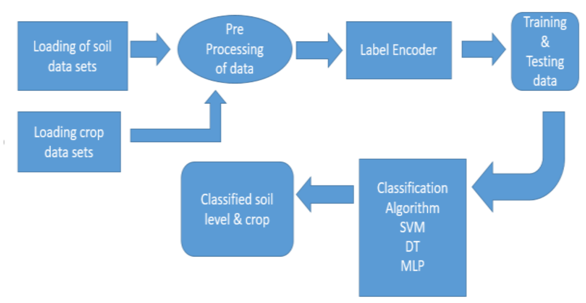

Figure 1. Proposed architecture.

3.3. Decision tree in classification

With a multi-step or hierarchical approach, the decision tree is used (tree structure). For every branch to grow from, it must begin from the root. An observation can be thought of as a root. In terms of decision tree algorithms, CART is the most often utilised. First, the CART algorithm has to prune the trees in order to get the best potential results. [24] CART, an iterative partitioning approach, is used in both regression and classification. CART divides all prediction variables into subgroups and then constructs two consecutive sub-nodes from the entire data set. There should be as little variation in the goal variable as possible. In this experiment, the Gini impurity metric was utilised to determine the best estimate. DT (Decision Tree) is a popular method of machine learning it comprises a tree structured arrangement of a set of attributes to evaluate and predict the output. Each parameters like N, P and K are classified using DT. Here, N, P and k Acts as Root node and the target values Acts as leaf node to classify Low, High and Medium.

3.4. Multilayer perceptron in classification

Multiple-layer perceptron is a method for teaching a function under supervision. *f*(.):*Rx*→*Ro* where x is the number of input dimensions and o is the number of output dimensions, is used for training, The MLP was built with numerous layers of processing units resembling neurons. Each layer's nodes were linked to those in the one before it. A node's strength and weight can be symmetrical or asymmetrical. There is an input layer and an output layer in a network and the data flows between them. Multilayer perceptrons (MLPs) have been used as a classification method for artificial neural networks. Prior to algorithm training, the "Normalizer" node was used to normalise the z-scores of the input data. Afterwards, actual test data was subjected to the same procedure. Nodes in a directed graph form a nonlinear statistical model with each layer connected to the next. Hidden, input, and output are all types of layers that can be found. To put it another way, every node in the network is a nonlinearly activated neuron, except for the input nodes (or processing element).
A set of input data xi (i = 1,2,…,N), Equation y can be used to obtain the output of a neural model (1):

$$y = f\left(W^T x\right) = f\left(\sum_{i=1}^{N} W_i x_i + b\right) \tag{1}$$

A neural network model is formed by multiplying N by the number of neurons (N) (W) (b). The output of a binary classification MLP is a value ranging from 0 to 1, which can be understood as likelihood for the target class to be positive. The model's hyper parameters were fine-tuned using a parameter optimization loop to boost precision and recall. Structural risk reduction is used to a constrained quadratic optimization problem that is addressed by the hyper plane f(x) = zero. The entered information xi (i = 0, 1, 2) Things that are both positive and negative are labelled with separate labels. Xi represents the range of soil indices. Equation yields the village wise soil separating data acquired linearly (2):

$$y = f(x) = W^T x + b = \sum_{i=1}^{N} W_i x_i + b \tag{2}$$

In all, it has three parts: N, P, K. All three parameters are represented as (N), (W), (b) respectively. In this case, the classifying soil is defined by W and b, respectively, which are vectors. The best hyper plane for separating data is one that leaves the most space or margin between the plane and the closest data. Non-linear classification tasks can be handled by SVM's kernel function. No machine learning or standard assessment procedures may be used with this data. Model evaluation in this type of investigation relies heavily on the overall accuracy score, notwithstanding this fact, it is crucial to emphasise that this metric is useless for this type of investigation

True positives (TP) and true negatives (TN) are both true positives if the model correctly classifies them (TP). A false negative occurs when the model incorrectly classifies a result (TN). According to (3), overall accuracy (OA) can be determined.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)} \quad (3)$$

When forecasting a majority class, the model can achieve near-perfect overall accuracy by forecasting the majority class, which is mediated by the other two classes.

To evaluate models in severely unbalanced datasets, F1 (weighted average of precision and recall) is the most useful metric: (4)–(6).

$$\text{Precision} = \frac{TP}{(TP + FP)} \quad (4)$$

$$\text{Recall} = \frac{TP}{(TP + FP)} \quad (5)$$

$$\text{F1 score} = \frac{2. (\text{Precision. Recall})}{\text{Precision + Recall}} \quad (6)$$

Recall and precision over class "1" are chosen as the evaluation metric because the study's goal is to predict if the machine will fail in the future.

In addition to this, confusion matrix is used to determine the performance of classified parameter. In this study, the confusion matrix for NPK using SVM, DT and MLP have been analysed.

4. Results and Discussion

4.1. Support vector machines

By using SVM, the accuracy of soil index has been evaluated. From Table 2, we can observe that the accuracy of P is higher than N and K.

Parameters	Range	Precision	Recall	F1-score	Support
N	O	0.38	1.00	0.55	31
	1	0.00	0.00	0.00	18
	2	000	0.00	0.00	33
Accuracy				0.38	82
P	0	0.00	0.00	0.00	2
	1	0.79	0.67	0.73	61
	2	0.24	032	0.27	19
Accuracy				0.57	82
K	0	0.00	.00	0.00	1
	1	0.50	0.43	0.46	35
	2	0.58	0.61	0.60	46
Accuracy				0.52	82

Table 2. Results of N using SVM

Support vector machines (SVM) have an accuracy of 57% when classifying P, and accuracy rates of 38% and 52% when classifying N and K, respectively. Classifying N, SVM outperforms DT when compared to P&K and the remaining parameters.

Confusion matrix

During the data testing period, the confusion matrices for all ELM classifiers, as well as accuracy scores, precision scores, recall scores, and F scores, are shown in Fig. 2. 3×3 confusion matrix computed for low, medium and high soil indices. The diagonal cells represents correct classification whereas off diagonals represent misclassification.

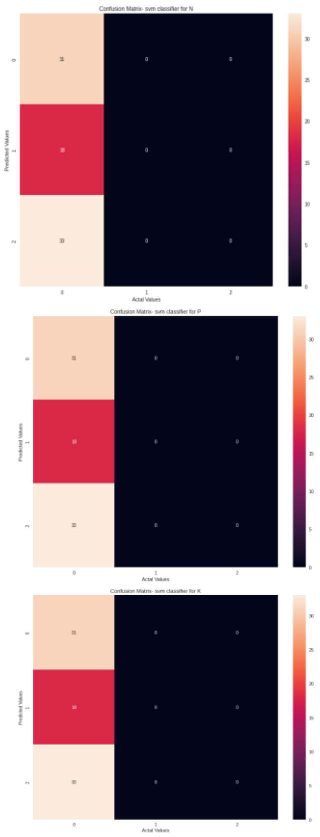

Figure 2. Confusion matrix of NPK using SVM.

In this case, the predicted values denotes the output class. There is no diagonal cells identified in this confusion matrix (refer Fig. 2). It represents that the testing data have incorrect classified observations.

4.2. Decision tree

Like SVM, the soil index of NPK were analyzed by using DT. From Table 3, it is observed that the parameters K and P has high accuracy than N (refer Table 3)

Parameters	Range	Precision	Recall	F1-score	Support
N	0	0.37	0.42	0.39	31
	1	0.17	0.11	0.13	18
	2	0.40	0.42	0.41	33
Accuracy				0.35	82
P	0	0.00	0.00	0.00	2
	1	0.79	0.67	0.73	61
	2	0.24	032	0.27	19
Accuracy				0.57	82
K	0	0.00	0.00	0.00	1
	1	0.52	0.43	0.47	35
	2	0.58	0.61	0.60	46
Accuracy				0.52	82

Table 3. Results of NPK using decision tree

Classification of soil parameters using decision tree provides varying accuracy for each parameters NP&K. DT provides maximum accuracy of 57% in classification of soil parameter P, whereas in classification of N and K it shows the accuracy of 35% and 52% respectively.

Confusion matrix:

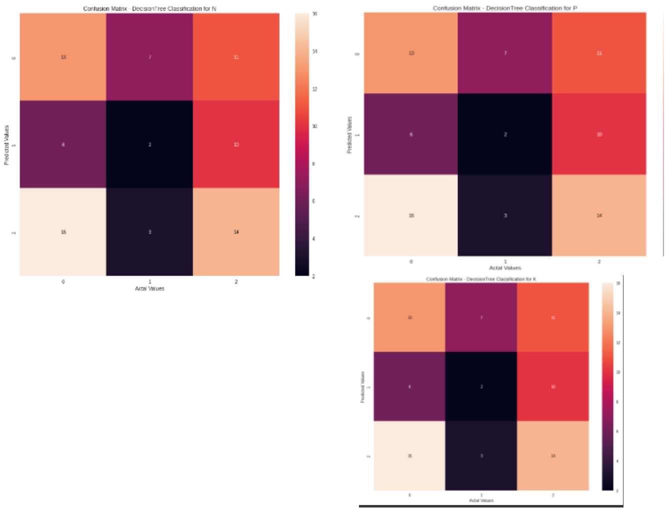

Figure 3. Confusion matrix of NPK using DT.

From Fig. 3, it is observed that all parameters N, P, K have off diagonal cells which represents incorrectly classified observation. In addition to this, the off diagonal cells shows medium range of soil nutrients.

4.3. Multi-layer perceptron

MLP provides maximum accuracy of 94% in classification of N and 74 % in classification of P. whereas, the accuracy of K drops when compared with SVM and DT, MLP provides 23% in classification of N.

Parameters	Range	Precision	Recall	F1-score	Support
N	0	1.00	0.84	0.91	31
	1	1.00	1.00	1.00	18
	2	0.87	1.00	0.93	33
Accuracy				0.94	82
P	0	0.00	0.00	0.00	2
	1	0.74	1.00	0.85	61
	2	0.00	0.00	0.00	19
Accuracy				0.74	82
K	0	0.02	1.00	0.03	1
	1	1.00	0.51	0.68	35
	2	0.00	0.00	0.00	46
Accuracy				0.23	82

Table 4. Results of NPK using MLP

From Table 4, it is observed that Multi-layer Perceptron provides better accuracy when compared with both DT.and SVM. Confusion matrix

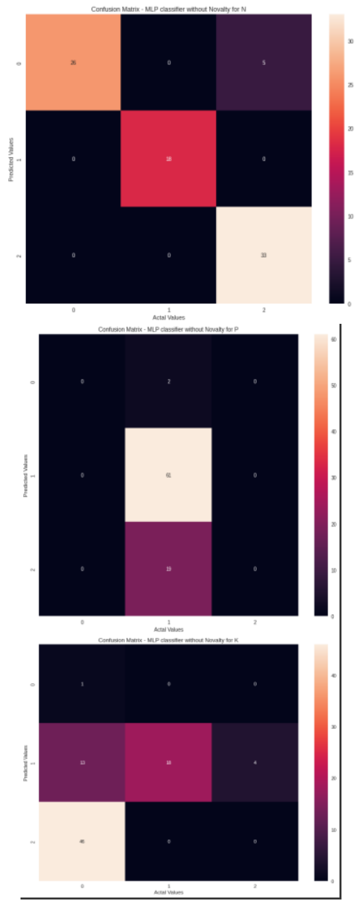

Figure 4. Confusion matrix of NPK using MLP.

From Fig. 4, it is observed that the diagonal cells of N represent to observations which are correctly classified. The off diagonal cells correspond to incorrectly classified observations. In this case, both P and K have off diagonal cells. In addition to this, the confusion matrix explains P has high and K has medium range of soil nutrient. From this confusion matrix, we can conclude that NPK using MLP has provided correctly classified observations.

In this study, different algorithms such as decision tree, SVM and MLP were used in classification of NP and K individually.

Among three classifier algorithms, MLP performs better in classifying N&P, so in further process of the work a Hybrid activation function in MLP will be designed to recommend the crop requirements.

5. Conclusion

The main cause of soil degradation is due to poor soil and crop management practises. As a result of the overuse of chemical fertilisers, soil nutrients are no longer as readily available. Soil degradation must be reversed as a result of this research, which aims to develop a model that can assist farmers. The nutrients in the soil were measured using SVM, DT, and MLP. SVM and DT models for soil nutrient analysis are less accurate than MLP, according to the study results. . In addition, it has been found that MLP can be used to assess soil nutrient levels in practical applications. For future research, it is highly recommended to implement MLP with a hybrid activation function is proposed to improve the accuracy.

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