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Improving the Prediction Accuracy of Soil Nutrient Classification by Optimizing Extreme Learning Machine Parameters

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Abstract: Agriculture is a non-technical sector where in technology can be incorporated for the betterment. In this paper, the soil test report values are used to classify several significant soil features like village wise soil fertility indices of Available Phosphorus (P), Available Potassium (K), Organic Carbon (OC) and Boron (B), as well as the parameter Soil Reaction (pH). The classification and prediction of the village wise soil parameters aids in reducing wasteful expenditure on fertilizer inputs, increase profitability, save the time of chemical soil analysis experts, improves soil health and environmental quality. These five classification problems are solved using the fast learning classification technique known as Extreme Learning Machine (ELM) with different activation functions like Gaussian radial basis, sine-squared, hyperbolic tangent, triangular basis, and hard limit.
Keywords: Extreme Learning Machines, Activation functions, Soil, Confusion matrix and Parameters

I. INTRODUCTION

In society the population is increasing at a high rate, people are not aware of the advancement of technologies. Machine learning can be used to increase the crop yield and quality of crops in the agriculture sector. India is a country which has huge no. of natural as well as human resources, and its economy is growing at a rapid rate. A large part of Indian economy is dependent upon agriculture sector and to improve agricultural practices it is necessary to accurately predict responses of the crop yield which can be done with the help of Machine Learning. Agricultural soil quality depends on the soil macro as well as micro nutrient content like S, K, pH, C, Mg, P, Ca, B etc.,.

The soil, Soul of Infinite Life, is the entity responsible for sustaining life on earth. In spite of significant advances in the service sector, agriculture remains the major provider of employment and source of revenue in India. Soil testing is a valuable tool for evaluating the available nutrient status of soil and helps to determine the proper amount of nutrients to be added to a given soil based on its fertility and crop needs. The major focus for soil management in agriculture for enhancing crop productivity is on the maintenance and improvement of dynamic soil parameters. The population stresses, terrestrial limitations and the decline of traditional soil management methods have directed to deterioration in the fertility of the soil in developing countries like India.

Crop health is a major element in the highly productive system of modern agriculture. A substantial increase in crop production can be attained by adopting the suitable crop health management strategy. The increased productivity could be achieved through effective soil resource management and corrective measures to apply micronutrients. Timely detection and controlling of problems connected with crop yield pointers enables the decision makers (agricultural experts) and farmers to decide on appropriate soil resource management and crop environment management. Nowadays the prediction and classification problems are effectively handled by Machine Learning (ML) techniques. The exposure of ML methods in the areaof agriculture definitely reduces the challenges faced by the domain experts.

II. METHODOLOGY

An easy way to comply with IJRASET paper formatting requirements is to use this document as a template and simply type your text into it. The fundamental point is to structure a framework which is proficient and which give Soil nutrients grading as quick as conceivable. For that reason we utilize two stages: first is training stage and second is testing stage. In first stage: Data procurement, Data Pre-preparing and ELM based preparing. In second stage Data procurement, Data Pre-preparing, classification and soil nutrients rating identification. For experimentation reason we have utilized Davangere district locally collected datasets. The block diagram is shown in below figure 1.1.

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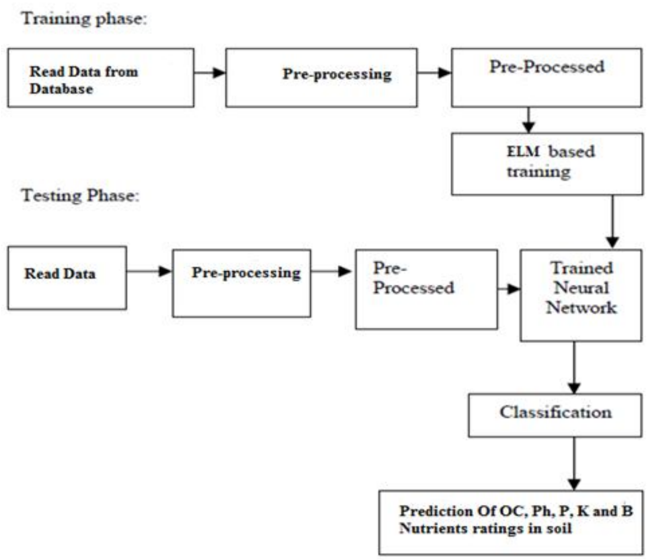

Figure 1.1: Block diagram of proposed methodology

The samples of each classification problem are arbitrarily rearranged and 80% of them are used for training and cross-validation and the remaining 20% for testing. Hence the tenfold cross-validation strategy is used here for training and validation, wherein each fold, 90% of training data is devoted for training and 10% of the same for validation. Each ELM classifier is trained on the training set using a different combination of parameters i.e., training function and the number of hidden nodes, and then it is verified on the validation sets. The best parameters are calculated and selected from the training set and are then used for testing the data. The final test result obtained is considered as the output of the corresponding classifier for the analysis, which is averaged over ten trials.
The classifier used is selected based on the learning algorithm which can learn much quicker than commonly used learning algorithms i.e., Extreme Learning Machine. The best generalization performance is achieved in this learning algorithm for feedforward neural networks. Even though this algorithm is not complicated, at the same time it is a highly efficient learning algorithm for single hidden layer feedforward neural networks (SLFNs). It can choose the input weights randomly without any preconceived notion and analytically decides the output weights of SLFNs.
Our implemented ELM tends to achieve the smallest norm of weights and the smallest training error. In this proeject the classification problems are implemented by ELMs with different activation functions. A part from that, the performance of each classification is compared with the other.

III.RESULTS AND DISCUSSION

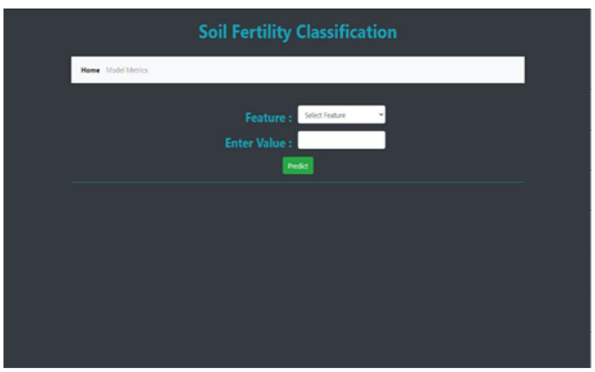

Figure: Home page

The figure above shows the home page of our proposed system. It includes Feature field to enter the feature name i.e., nutrients and also enter value field to enter the value of nutrients to test.

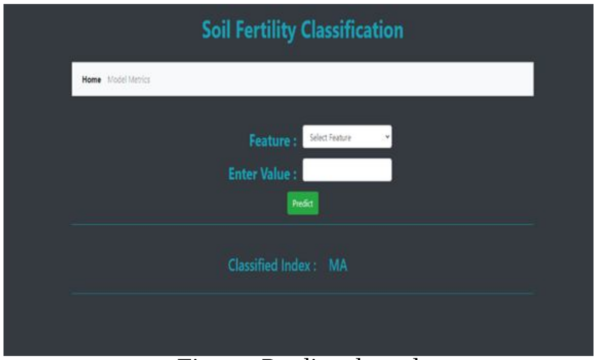

Figure: Predicted result

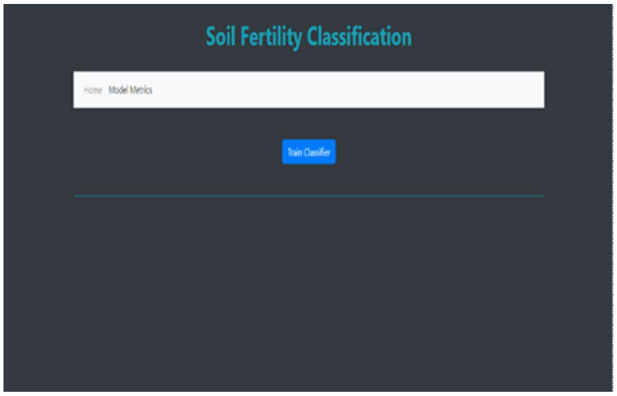

Figure: Model metrics page

In model metrics page we have train classifier button to train the model with the datasets stored in the backend database.

More Performance evaluation was obtained, in Boron parameter of activation function of tan hyperbolic_25_confusion matrix as compared to other activation functions like Gaussian radial basis, hard limit, sine square and triangular basis, in Potassium parameter of sine square_35_confusion matrix, in organic carbon of sine square_45_confusion_matrix, Phosphorus of sine square_45_confusion_matrix and PH of sinesq_35_confusion_matrix.

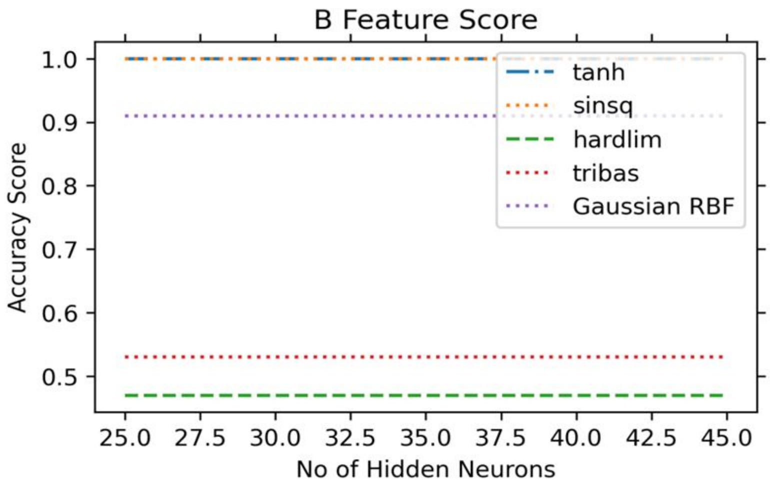

Figure 3.1(a): Boron feature score

The peak value of graph in fig.3.1 (a) indicate the best value that can be used as the number of hidden neurons for obtaining the maximum trained accuracy.

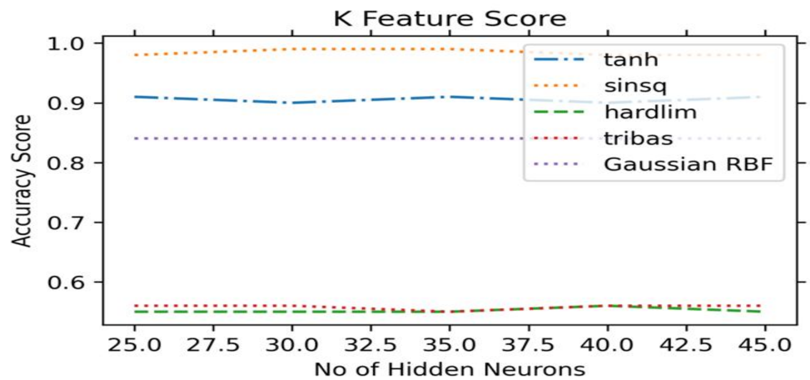

Figure 3.1 (b): Potassium feature score

The cross-validated accuracy score achieved by each classifier for 5 classification problems is illustrated in Fig. 3.1(b). 35 is the optimal number of hidden neurons for PH classification.

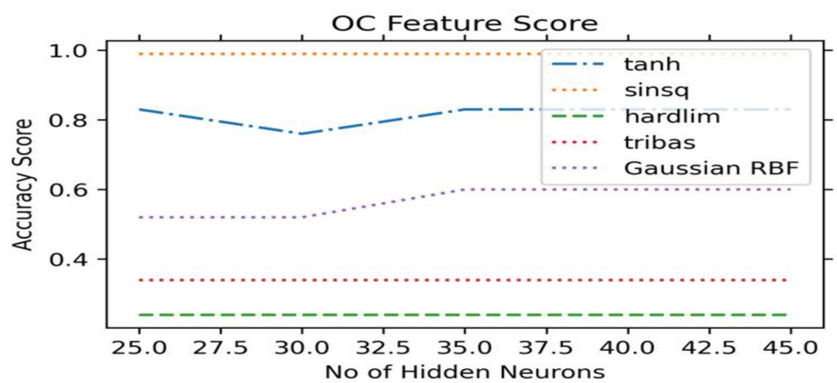

Figure 3.1(c): Organic carbon feature score

The accuracy score obtained for the testing data by using the optimized meta-parameter values is indicated in Table 1. 45 is the optimal number of hidden neurons for soil nutrient classification.

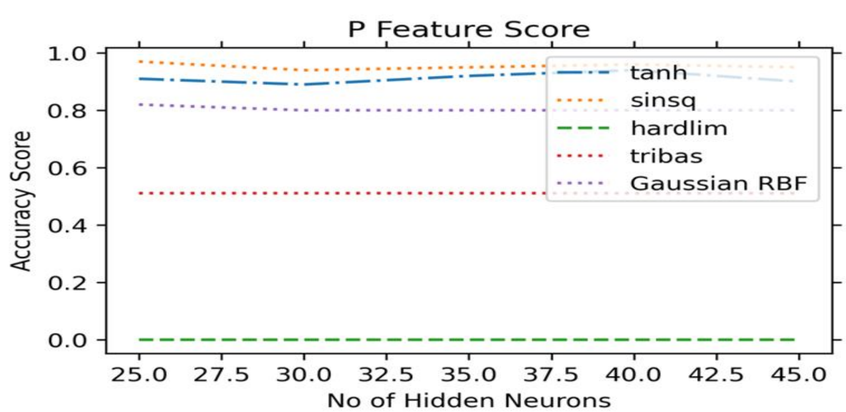

Figure 3.1(d): Phosphorus feature score

Figure 3.1(d) shows the graphical plotting of each cross validated classification accuracy (in %) with a different number of hidden nodes and for different ELM activation functions.

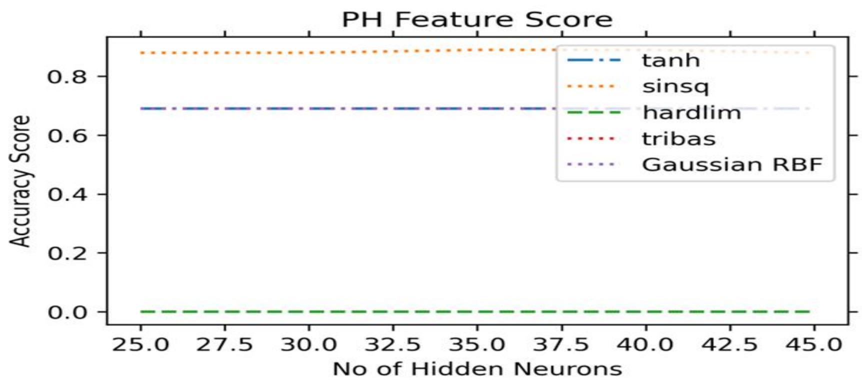

Figure 3.1(e): PH feature score

The dotted line is drawn at the peak which indicates the optimal number of hidden neurons. The cross-validated results of different classification problems are plotted in Fig. 3.1(e)

Table1: Performance evaluation for various parameters of various activation function

		Boron parameter	Potassium parameter	Organic carbon parameter	Phosphorus parameter	Potential of hydrogen parameter
Transfer function		Tan hyperbolic	Sine square	Sine square	Sine square	Sine square
No. of neurons		25	35	45	45	35
Accuracy		0.9996	0.9895	0.9945	0.9574	0.8887
Sensitivity		1	0.9895	0.9945	0.9574	0.8887
Specificity		0.9992	0.9895	0.9945	0.9574	0.8887
Precision		0.9991	0.9895	0.9945	0.9574	0.8887
F-Score		0.9995	0.9895	0.9945	0.9574	0.8887
AUC		0.9996	0.9895	0.9945	0.9574	0.8887
Youden's index		0.9992	0.9790	0.9890	0.9148	0.7774
Likelihoods	Rho+	1250	94.2381	180.8182	22.4742	7.9847
	Rho-	0	0.0106	0.0055	0.0445	0.1252
Discriminant Power		∞	2.1769	2.4890	1.4904	0.9949
ROC		1148.5	93.8269	181.6296	22.4810	7.9818

Table 1 shows the performance evaluation for various parameters of various activation function. More Performance evaluation was obtained, in Boron parameter of activation function of tan hyperbolic_25_confusion matrix as compared to other activation functions like Gaussian radial basis, hard limit, sine square and triangular basis, in Potassium parameter of sine square_35_confusion matrix, in organic carbon of sine square_45_confusion_matrix, Phosphorus of sine square_45_confusion_matrix and PH of sinesq_35_confusion_matrix.

IV. CONCLUSIONS

The work is to develop a neural network model to classify and predict soil fertility indices and pH values. The outcomes of this work might help to make a machine learning decision system to manage the soil nutrient deficiency problems. Results showed that optimization of ELM parameters helps to create a suitable model for soil fertility index classification. The very fast and simple learning algorithm called ELM classifier with its different activation functions are used to predict the fertility levels as low, medium and high using the soil parameters as input values; and to predict the pH levels of the corresponding soil.

V. ACKNOWLEDGMENT

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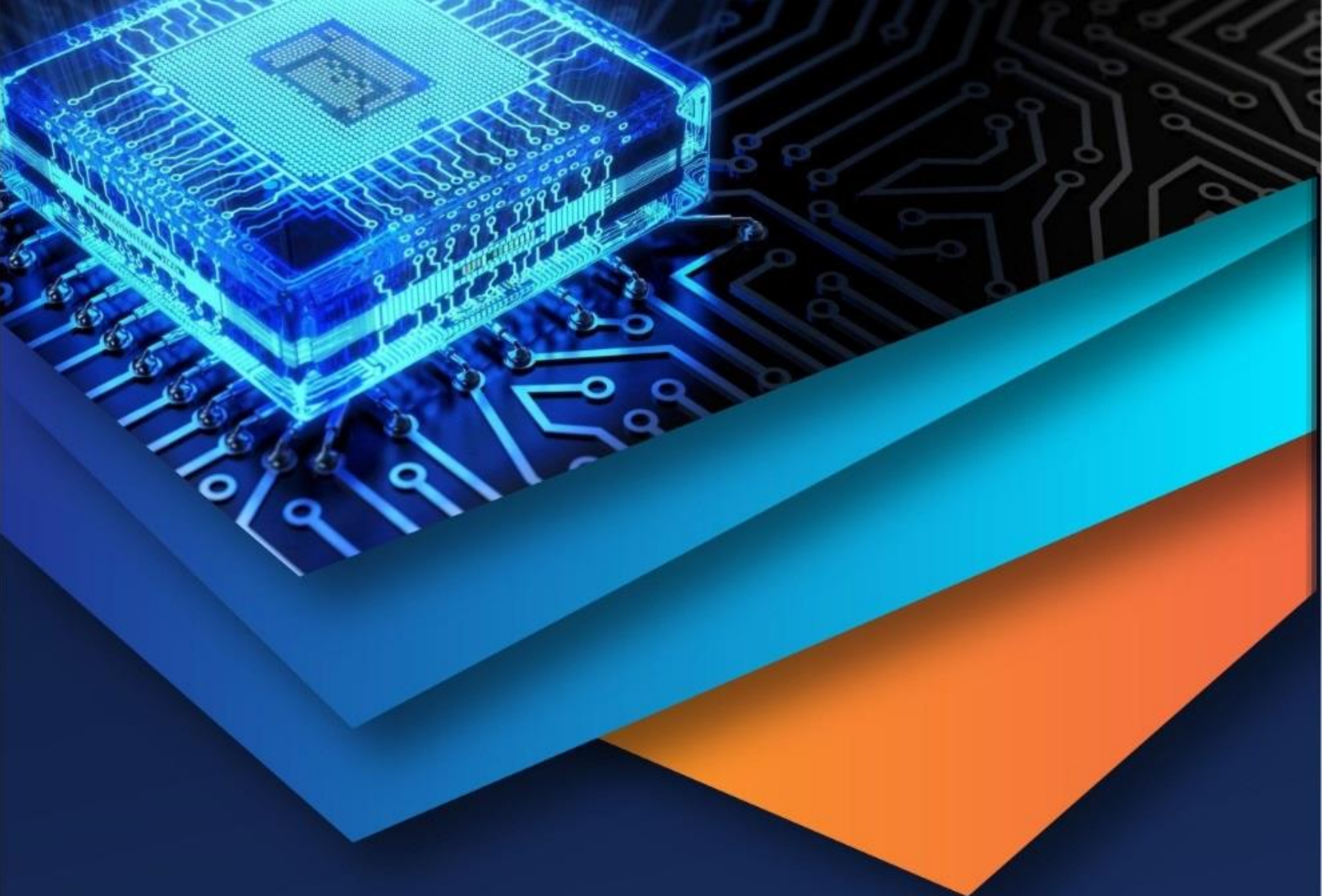

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