ISSN: 0369-8963

A Novel Ensemble Fuzzy Neural Network Classifier Simulator Algorithm for Anomaly Detection from Soil Nutrient Sample Experiments

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Abstract:

The problem is that there are no ensemble techniques to solve anomaly detection and classifier simulation. The study focused on developing the novel ensemble fuzzy neural network classifier simulator algorithm (EFNN CSA). The EFNN CSA conducts experiments with very complex data. Here, the used soil parameters are pH, sulfur (S), nitrogen (N), potassium (K), and phosphorus (P). The challenge is to identify an anomaly and simulate the classified scale of changes in the soil parameters. The EFNN CSA integrated the five-soil nutrient computing rules. The five models are the N learning model, P learning model, K learning model, S learning model, and pH learning model. Each integrated model computed the selected soil parameters separately and detected the anomalies level-wise. The EFNN CSA combinedly simulated the integrated EFNN CSA models, which analyzed the result and interpreted it. The EFNN CSA model achieved 98.07% accuracy with a very less error is 8.64%. The EFNN CSA model concluded the derangement soil nutrient anomaly detection simulation, which proved sustainable agriculture practice in complex data.

Keywords: *EFNN CSA, Fuzzy Rule Based models, N learning model, P learning model, K learning model, S learning model, pH learning model, nitrogen (N), phosphorus (P), potassium (K), sulfur (S) and pH*

Literature Review

The former use harmful pesticides (fertilizers) due to the insufficient nutrient content in the soil to cultivate the plant. The farmers use fertilizer in an intensified manner, which affects the agricultural land and pasture. The emergency technologies ML and DL help to solve various agriculture problems (crop diseases, pesticide control, etc.) through neural networks [1]. The soil quality classification helps with sustainable agriculture practices through the data mining technique. Soil physical parameters impact the plan through known factors and unknown factors. Soil fertility balancing is very poor in agricultural practice. Here we enhance the soil fertility management practice by using Texture Triangle-Fuzzy C-Means. Here is soil texture classification and clustering and concludes the same evaluation factor through the texture triangle [2]. The study compares the different types of algorithms for the removal of Cu (II). Cu (II) content is available in water, which is used for agriculture, and it is impacting the soil and environment. Here used ANN, ANFIS, and MLR algorithms to estimate the efficiency of biochar [4].

Soil macro-micronutrients have a big challenge on soil fertility practices, environmental impacts, and agriculture's sustainable development. The study were conducting a low-cost analysis and predicting the soil properties. Here applied PLSR, ANN, fuzzy c-mean applied cluster and used classification techniques to predict and estimate (*sand content accuracy* ($R2 = 0.69–0.77$, *silt accuracy range* ($R2 = 0.56–0.71$), *organic matter accuracy range* ($R2 = 0.54–0.69$), *clay content accuracy range* ($R2 = 0.29–0.65$)) and dealing the heterogeneous soil data [3]. The machine learning used in agriculture 4.0, here, is focused on soil science. The integrated machine learning algorithms support classification and estimation in agriculture [5]. Soil nutrient management is the biggest challenge to farmers. Enhancing the soil fertility practice, which helps in crop productivity. Farmers are not following the recommended fertilizer practice from the laboratories (*chemical analysis, technicians recommend nutrients*). Based on the soil characteristics, here used the fuzzy inference system for recommending the soil fertilizer based on the conditions (MF – fuzzy membership function). The implemented Fuzzy Membership Function gives simulated soil nutrient recommendations [6]. Most of the research focused on soil texture, soil clay classification, and clustering. The most complicated and very essential soil nutrient problems are NPK and S, and these nutrients are fed by farmers to plants. Several methods were developed to test the soil using soft computing. The study focused on fuzzy logic for interpreting the NPK values based on their levels and predicting the possibility of inputs [7]. Artificial intelligence computed the predictive model in plant nutrient analysis. The study implemented MLR and ANN, which evaluated the different plant nutrients with an RMSE of between 0.539 and 0.85, and it was used to find the relationship and estimate the N, K, and Ca parameters [12]. Soil conditions are assessed using pH. More studies are confirming that machine learning techniques give reliable predictions. This study focused on the soil characteristics using an ensemble learning approach. Ensemble learning combines numerous models and predicts the soil properties and extracts the complex relationships among the soil properties. The stacked generalization process filters the best learning model in the heterogeneous ensemble approach [18]. For soil analysis support, machine learning techniques include support vector machines, artificial neural networks, and adaptive neuro-fuzzy inference systems. These machine learning algorithms classify the soil and estimate the cumulative penetration of soil. The data was collected from 106 real-time experiments. For the data

ISSN: 0369-8963

preparation and finalization, 70% is for training and 30% for testing. The analysis concludes that influenced soil parameters are affected by the fertilizer [21]. Soil science narrows artificial intelligence applications to explore research gaps and support decision-making. Machine learning and deep learning techniques are used to analyze the soil data in different dimensions. This study found the research gap in the machine learning method in soil science for creating automatic analytics models to solve the problems in developing countries. The research gaps are soil nutrients, fertilizer management, harvesting, remote sensing, soil carbon analysis, modeling, water contamination, soil erosion, parent material, etc., The past publication is overfitting and does not have strong interpretability, here needs to add strong advanced machine learning models and an understanding of the soil [22]. Agriculture's suitability is improving through artificial intelligence in developing countries. The study's focusing factors are phosphorus (P), potassium (K), organic carbon (OC), boron (B), and the parameter soil reaction (pH). Here used Extreme Learning Machine with different classification techniques for five problems and every problem has been solved with more the 80 to 90% of accuracy [28]. Many studies worked and compared six common techniques: random forest, decision tree, naïve Bayes, support vector machine, Least-square support vector machine, and ANN. The problem is a single-component soil property analysis. That six common algorithms cannot achieve prediction accuracy always. [29]. Machine learning is an emerging field in the agriculture industry. The study focused on feature extraction and classification using K-Nearest Neighbor, bagged tree, support vector machine, and logistic regression [30].

MFIS is applied for decision-making in fruit quality evolution. The used data came from Asia and North Africa. Here the fuzzy system supported 91% accuracy of results for those used in Matlab [8]. The problem-solving techniques are presented with different use cases in different domains. The fuzzy focus is on a data-driven decision-making system. This is enabled through data satisfied by ‘IF’ rule constructions [9]. The most frequently used engineering judgmental technique is the membership function in a fuzzy system. which helps to implement rule-based concepts. As per the study, whenever facing modeling and controlling the factors with computational, MFs are the right choice to solve the model performance analysis. Here focused on non-linear systems to solve the optimization using MFs, to enhance the model performance in a non-linear system [10]. Compared classifier the concepts of extreme learning machine with fuzzification function, neurons formed by density center, and created null neurons allowed if/then fuzzy rules-based. The training has

 https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

been verified by the FNN and uses a single neuron activation function for robustness [15]. This study evaluated the real-time regression and the forecasting problems solved with the FNN and IC-FNN. Here focused on the non-separable and correlation problems using fuzzy rules for the proper optimization and it is proposing the fuzzy sets. Fuzzy rules extract the parameters from the HL-Marquardt learning. Fuzzy deals with the more complex, correlated, and uncorrelated data in a more complex data structure [16]. Fuzzy plays a major role in predictive analysis, here developed the fuzzy logic classifier to analyze weather and animal data sets. The fuzzy logical classifier indicated the results based on the temperature-humidity indexing and it showed the consistency of the animal's response [13]. During the operation, abnormal events occur often in the complex integrated system. The high non-linear data-driven modeling and predicting ability in anomaly detection. The data anomaly detection model provides timely detection and reliability of operations [14]. The RBF is used to predict the various soil complex environments and regression is used to find the soil factor relationship. This study simulated the results-based RBF neural network from the different soil environmental datasets. Here considered the biological regulation is complex, which is solved by ML [11]. The novel fuzzy clustering helps the ensemble predictions in regression models, which creates new regression models for every cluster and solves the forecasting problems. Here used the RBF and cross-validation techniques and handled a four-dimensional data set [25]. The ensemble neural network classification works with the FC-NN and combines the probabilistic theory. The errors were calculated through the cross-entropy and the cost was calculated through the softmax function cost in the output layer. The ensemble consists of C-mean clustering for the connection of networks and the non-linear least squares method. It analyzed the two-dimensional machine learning dataset [26].

Machine learning significantly achieves success in various fields in real-time applications. The most complicated part is handling the complex data (*imbalance, high dimension, nosy, etc.*). Data mining has been constructed to implement efficient knowledge discovery processing in data. Ensemble learning is the hot spot of the research area in artificial intelligence, which aims to extract useful features from complex data. Ensemble learning performs well in predictions and discovering knowledge from different combination models [17]. Ensemble learning helps to improve the integrated models' performance in machine learning and deep learning. This study discusses decision-making using deep neural networks to extract the features. Here handling categorical data with established the Bayesian theory, which found the complex relationship and

 https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

knowledge. The state transition algorithm optimizes the weight of all attributes and compared the DNN, GDM, and EL methods in real-time [19]. The hybrid method used 332 soil samples to estimate the soil parameters using artificial intelligence, which combined the LSSVM and the CSO models. A hybrid method prediction accuracy is 88%, and the hybrid method promises soil quality estimation and utilizes and determines the parameters automatically [20]. The regressive ensemble learning simulates the cloud resources prediction in the cloud environment for the predicted simulated services. The ensemble supports the SVM, DT, LR, RF, and KNN algorithms and improves the performance of the classification techniques. It works on feature selection and reduces duplication intelligently [23]. In parallel, tasks face dynamic execution issues and less efficiency in a complex system to make simulations. The study focused first on selecting the features and executing the computing resources through ensemble learning. Secondly, it simulates all entities with imbalanced data. Through Metis, Chacos, and multi-weight graph models compared, it was found that models performed 26% faster in the ensemble approach [24]. The ensemble methodology is forecasted to detect the UB and LB at the operation level. Compared to the several benchmark methods by the MSE, MAE, and loss function. The study improved the forecasting accuracy with a decrease of 22.3% mean squared error and a 33.1% mean absolute percentage error. Ensemble learning improved the model's accuracy and here used ANN, fuzzy inference system model, and adaptive neuro-fuzzy inference system [27].

The Research gap: The literature review concludes that the existing techniques, like ANN, CNN, FNN, FIS, NFI, ML, etc., can solve most common and specific problems. The existing techniques only classify and predict, but not anomalies in the soil. In general, the problem is that most of the research analyzed all soil parameters into one or two models with all soil parameters. The research gap is, not existing ensemble learning algorithms to solve the anomaly detection for the soil parameter scalable changes. Here, the problem is that all nutrients are used for the different purposes of the plant, and soil nutrient resources are all different. So, while combinedly analyzing all soil parameters using machine learning, the machine learning model cannot give a sensible research outcome. So, our study needs to focus on this particular problem, and develop ensemble techniques to forecast soil nutrients separately and simulate all forecasted soil nutrients to detect anomalies.

 https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

Proposed Research Methodology

The proposed novel ensemble fuzzy neural network classifier simulation algorithm (EFNN CSA) was simulated with 48,756 soil sample results.

Figure 1 shows the Ensemble Fuzzy Neural Network Classifier Simulator Algorithm (EFNN CSA) process follow.

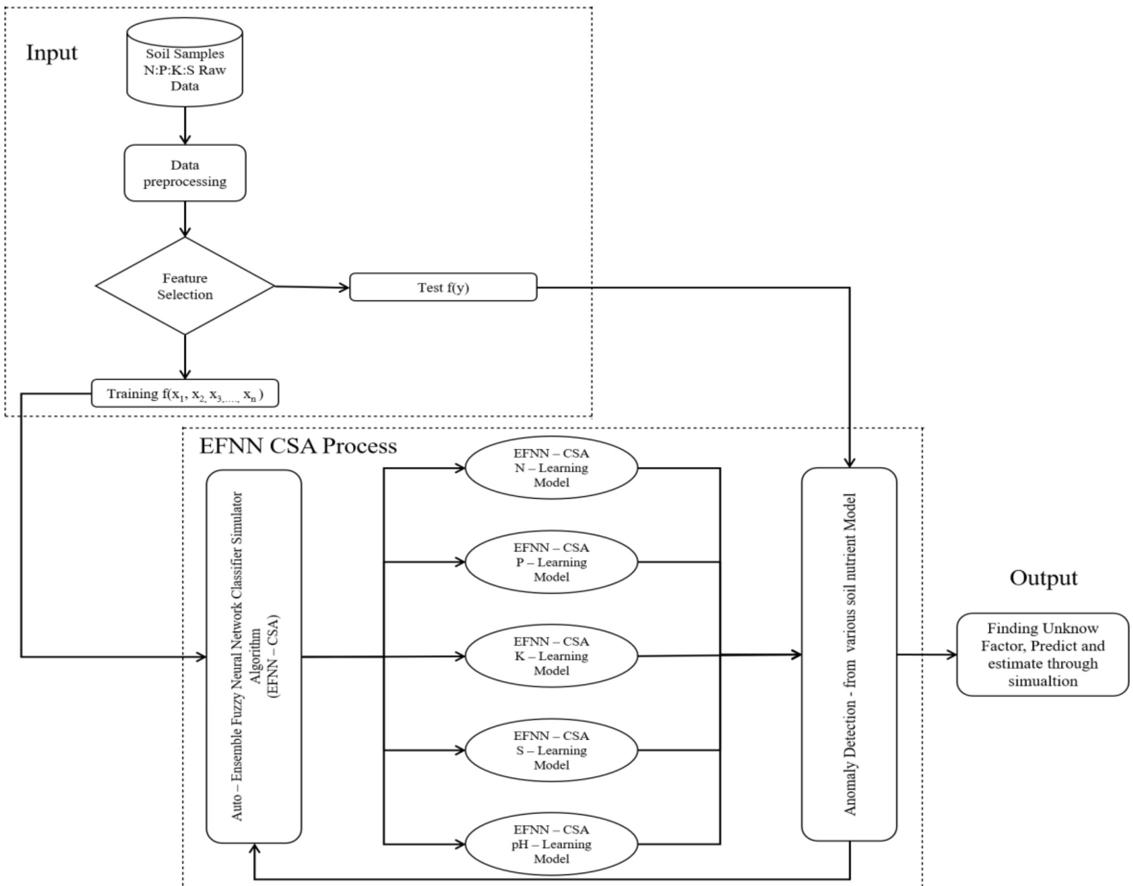

Figure 1. Ensemble Fuzzy Neural Network Classifier Simulator Algorithm (EFNN CSA)

Figure 1. explains the EFNN-CSA execution of five integrated models with anomaly detection, which helps to find the unknown factor and simulate the results. Before starting EFNN-CSA, the study collected soil samples and conducted a data preprocessing step. After that, the most important thing here is the feature selection, which is conducted based on the available nutrients $f(x_1, x_2, x_3, \ldots, x_n)$ and $f(y)$.

https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

The integrated ensemble models are the N learning model, P learning model, K learning model, S learning model, and pH learning model. Except for the S learning model, all learning models will support multi-class classifier simulation. S learning model supports binary classifier simulation.

EFNN CSA procedure,

Ensemble Fuzzy Neural Network Classifier Simulator Algorithm for Anomaly detection

1: Initialize Correlation feature selections
2: Compute, Auto EFNN-CSA
3: IF input is N
4: Compute N Learning Model
5: ELSE IF input is P
6: Compute P Learning Model
7: ELSE IF Input is K
8: Compute K Learning Model
9: ELSE IF input is S
10: Compute S Learning Model
11: ELSE IF input is pH
12: Compute pH Learning Model
13: END IF
14: Detect the anomaly from Auto EFNN-CSA
15: EFNN-CSA output

When f(y) is to be N, other nutrients will be supported as input f (x1, x2, x3, …., xn) is to be (P, K, S, and pH). EFNN-CSA will select an N Learning model, target as N, detect the anomalies, and simulate the result with a classification report.

When f(y) is to be P, other nutrients will be supported as input f (x1, x2, x3, …., xn) is to be (N, K, S, and pH). EFNN-CSA will select the P Learning model, select the target as P, detect the anomalies, and simulate the result with a classification report.

https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

When f(y) is to be K, other nutrients will be supported as input f (x1, x2, x3, …., xn) is to be (N, K, S, and pH). EFNN-CSA will select the K Learning model, select the target as K, detect the anomalies, and simulate the result with a classification report.

When f(y) is to be S, other nutrients will be supported as input f (x1, x2, x3, …., xn) is to be (N, K, S, and pH). EFNN-CSA will select the S Learning model, select the target as S, detect the anomalies, and simulate the result with a classification report.

When f(y) is to be pH, other nutrients will be supported as input f (x1, x2, x3, …., xn) is to be (N, K, S, and pH). EFNN-CSA will select the pH Learning model, select the target as pH, detect the anomalies, and simulate the result with a classification report.

The integrated model computing algorithm procedure,

EFNN – CSA Integrated Computing N, P, K, S and pH Learning Methods

To Compute the N, P, K, S and pH learning method to detect the anomalies

Input: f (x_1, x_2, x_3, …., x_n)

Output: f(y) Corresponding N classes

1: f (x_1, x_2, x_3, …., x_n) inputs and based on target f(y) classes respectively simulate the classifier results.

2: EFNN-CSA f(y) = [] {Initialize an f (x_1, x_2, x_3, …., x_n) × f(y) dimensional vectors from f(y) classes
to normalize for the confidence score.

3: EFNN-CSA N, EFNN-CSA P, EFNN-CSA K, EFNN-CSA S, EFNN-CSA pH = [], [], [], [] Initialize
f (x_1, x_2, x_3, …., x_n) × f(y) dimensional vector for calculate the ensemble fuzzy score for the µA1
(N), µA1 (P), µA1 (K), µA1 (S) and µA1 (pH).

4: EFNN-CSA = [] {Initialize f (x_1, x_2, x_3, …., x_n) × f(y) dimensional vector for refined ensemble fuzzy
score}

5: N, P, K, S and pH = [], [], [], [] {Initialize f(y) ×1 dimensional to store the gross ranks and gross confidence score of all parameters.

https://doi.org/10.37896/pd91.5/9156

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FOR each target class i do

Compute $\mu_{A}i$ N, $\mu_{A}i$ P, $\mu_{A}i$ K, $\mu_{A}i$ S and, $\mu_{A}i$ pH using computing the values from equations (1), (2) and (3) respectively.

Compute Ni f(N), Pi f(P), Ki f(K), Si f(S) and pHi f(y) using equation (4)

Equate $\mu_{A}i$ N, $\mu_{A}i$ P, $\mu_{A}i$ K and $\mu_{A}i$ S using equations (5) and (6) respectively

Compute, $\mu_{A}i$ pH using equation (7)

END FOR

Predicted Class = Class with minimum N-Learning model, P Learning Model, K Learning model, S

Learning model and pH learning model score.

The computing rules EFNN CSA neural network

Figure 2 Shows the Ensemble fuzzy classification simulation algorithm (EFNN CSA) rules based classifier neural network.

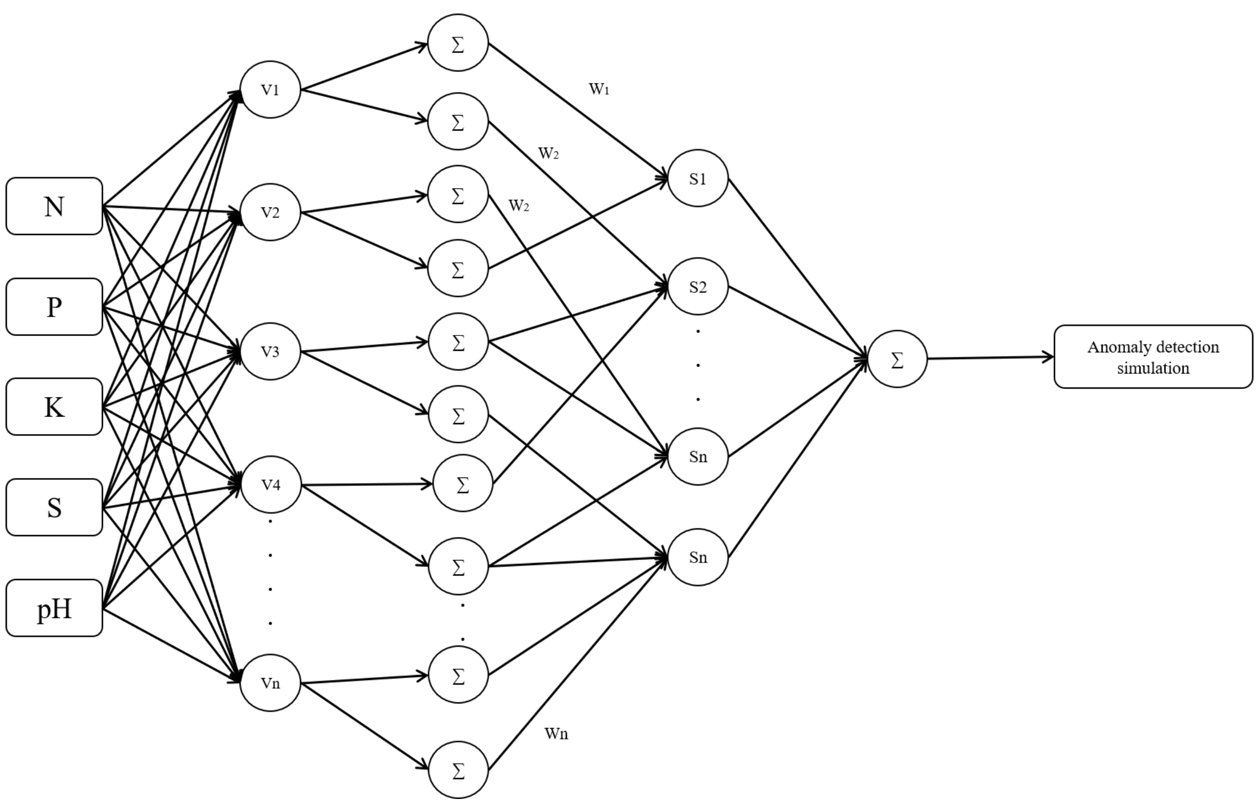

Figure 2. The computing rules EFNN CSA

 https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

Figure 2 explains the computing rules of the EFNN CSA, which computed the 12,18,900 neurons, 68,456 rules, and 90,000 epochs. It stimulates anomaly detection from the N, P, K, S, and pH soil samples. The rules have been created based on if the inputs are *Num*, and each can have different C classes, then the finding of the possible rules by Num^C. The neurons are calculated through the multiplication of the three dimensions of the layer.

Compute N Learning Model

$$\mu_{A1}(N) = \begin{cases} 0 & N \le a1 \\ \frac{N-p1}{q1-p1} & p1 \le N \le q1 \\ \frac{r1-N}{r1-q1} & q1 \le N \le r1 \\ 0 & r1 \le N \end{cases}$$

N learning model EFNN CSA calculation equation (1)

Compute P-Learning Model

$$\mu_{A1}(P) = \begin{cases} 0 & P \le a1 \\ \frac{P-p1}{q1-p1} & p1 \le P \le q1 \\ \frac{r1-P}{r1-q1} & q1 \le P \le r1 \\ 0 & r1 \le P \end{cases}$$

P learning model EFNN CSA calculation equation (2)

Compute K Learning Model

$$\mu_{A1}(K) = \begin{cases} 0 & K \le a1 \\ \frac{K-p1}{q1-p1} & p1 \le K \le q1 \\ \frac{r1-K}{r1-q1} & q1 \le K \le r1 \\ 0 & r1 \le K \end{cases}$$

K learning model EFNN CSA calculation equation (3)

Compute S Learning Model

$$\mu_{A1}(S) = \begin{cases} 0 & S \le a1 \\ \frac{S-p1}{q1-p1} & p1 \le S \le q1 \\ \frac{r1-S}{r1-q1} & q1 \le S \le r1 \\ 0 & r1 \le S \end{cases}$$

https://doi.org/10.37896/pd91.5/9156

S learning model EFNN CSA calculation equation (4)

Compute pH Learning Model

$$\mu_{A1}(pH) = \begin{cases} 0 & pH \le a1 \\ \frac{pH-p1}{q1-p1} & p1 \le pH \le q1 \\ \frac{r1-pH}{r1-q1} & q1 \le pH \le r1 \\ 0 & r1 \le pH \end{cases}$$

pH learning model EFNN CSA calculation equation (5)

Result and Discussion

EFNN CSA Anomalies detection result Table 1.

Table 1 shows the Ensemble Fuzzy classification simulation algorithm anomaly identification of sensitivity, specificity, and AUC results.

E-Fuzzy CSA Models	Training	Testing	Sensitivity	Specificity	AUC
N Learning Model	99.99	98.76	96.18	97.99	99.9
P Learning Model	97.99	97.25	94.65	98.74	99.03
K Learning Model	98.81	98.16	94.33	97.89	94.49
S Learning Model	99.9	96.54	94.49	98.94	98.94
pH Learning Model	98.76	97.34	95.99	96.76	98.01

Table 1. EFNN CSA Anomaly detection test report

Table 1 explains the EFNN CSA anomaly identification performance. The N learning model, P learning model, K learning model, S learning model, and pH learning model face the unattended situation from the N, P, K, S, and pH soil samples. EFNN CSA grate to solve the sensitivity problem with the very larger soil nutrient samples.

The outcomes are given by the models, and it is set as the main unattended circumstance with a large dataset, so the issue with the extremely large number of horticulture supplement tests. The EFNN CSA solves the issues very efficiently and detects the anomalies in each learning model test performed. Here, the accuracy, sensitivity, and specificity are focused on determining the anomalies. The proposed model has different parameters in different generated rules. The E-Fuzzy

CSA can serve as the basis for the training and testing. The best results are presented in table 1 of the accuracy for the N learning model, P learning model, K learning model, S learning model, and pH learning model. EFNN CSA has detected anomalies correctly identified.

Among all the EFNN CSA integrated models, the models presented the best accuracy results. The proposed research methodology works very efficiently to determine the anomalies in a complicated dataset. The EFNN CSA analyses of N, P, K, S, and pH parameters are different learning model approaches. which provides the results with satisfactory accuracy results in the focused parameters are sensitivity, specificity, and AUC. Figure 3 shows the experiments results of the soil samples, which evaluate the anomaly detection. It shows the integrated the Ensemble Fuzzy classification simulation algorithm. It represents the N learning model, P learning model, K learning model, S learning model and pH Learning model accuracy.

EFNN CSA anomaly detection Analysis

Figure 3 shows the EFNN CSA anomaly detection analysis in the different experiments. The five experiments have conducted and measure the EFNN CSA model accuracy.

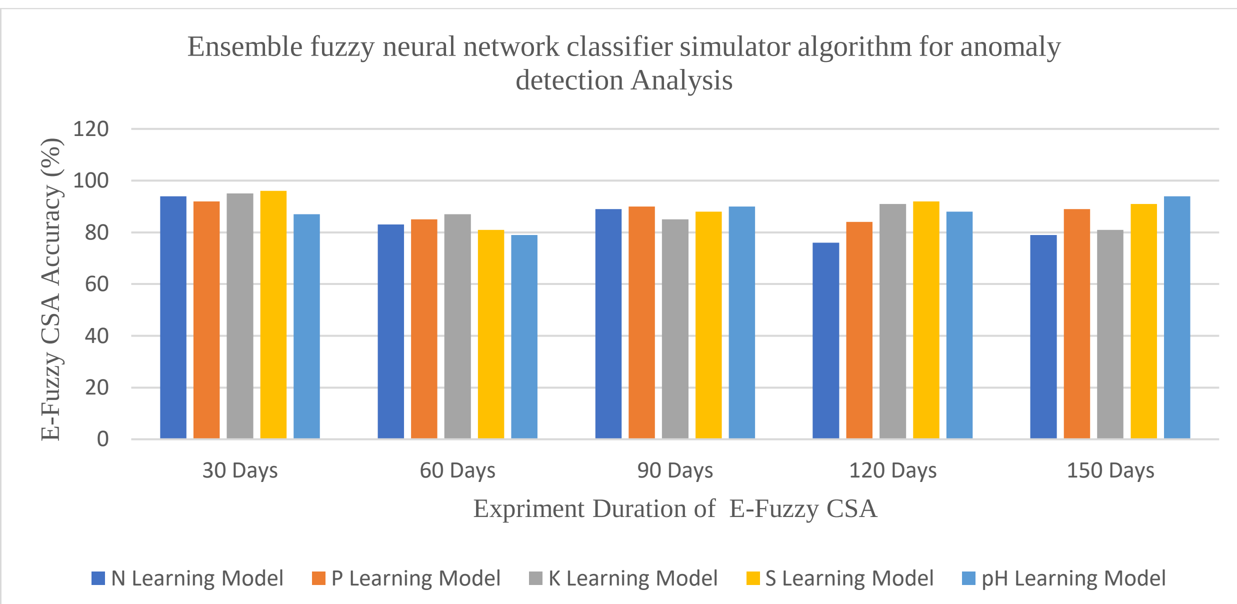

Figure 3. E-FNN CSA Anomaly Detection Analysis

Figure 3 explains the Ensemble Fuzzy Neural Network Classification Simulation Algorithm (EFNN CSA) for anomaly detection analysis with experiments of different durations and different samples of results. In EFNN CSA, the N learning model is given an accuracy range

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from 76% to 94% of accuracy in all experiments; the P learning model is given an accuracy range from 84% to 92% of accuracy in all experiments; the K learning model is given an accuracy range from 81% to 95% of accuracy in all experiments; the S learning model gives an accuracy range between 81% to 96% of accuracy in all experiments, and the pH learning model is given an accuracy range from 79% to 94% in all experiments.

The interpreted EFNN CSA model result is,

N Learning Model

Figure 4 shows the N learning model found the nitrogen anomaly detection level-wise in the different experiments. The issue is to identify the anomalies in nitrogen behavior. It's a complex combination to identify.

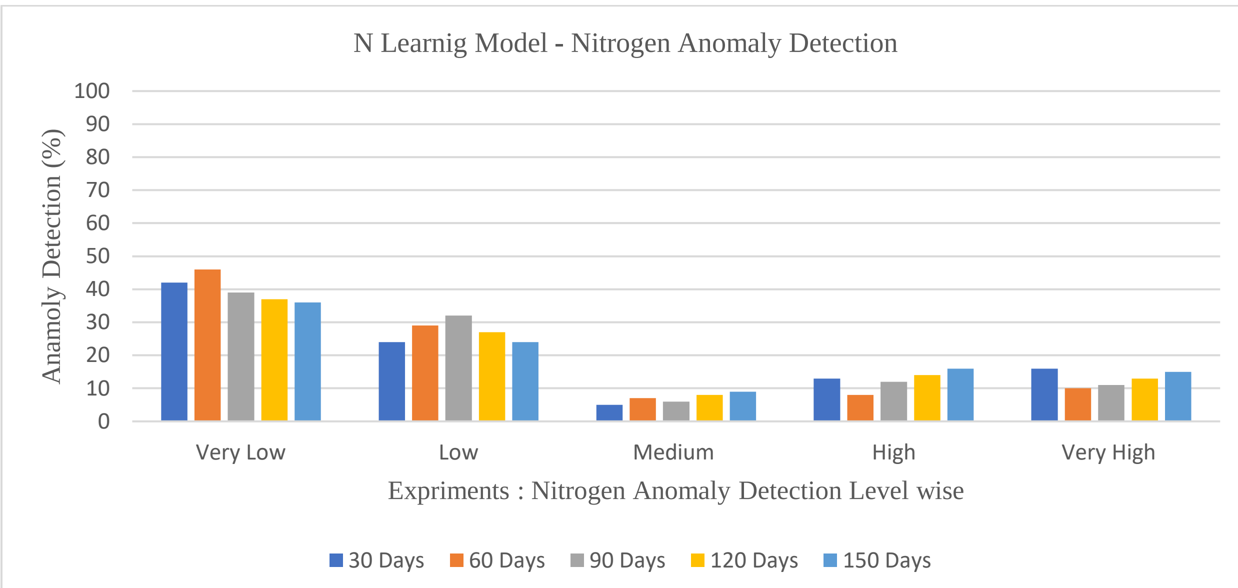

Figure 4. N Learning Model – Nitrogen Anomaly Detection

EFNN CSA anomaly identification integrated the N learning model, P learning model, K learning model, S learning model, and pH learning model. Figure 4 The N Learning Model – Nitrogen Anomaly Detection explains nitrogen behavior analysis in soil. The proposed N learning model works with categorical data from the different experiments and explained nitrogen, level-wise (very low (VL), low (L), medium (M), high (H), and very high (VH)).

In experiment 1 conducted in 30 days, the N learning model classified and predicted the anomalies into five categories in validating the soil nitrogen samples. The N learning model interpreted the

 https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

nitrogen anomalies as very low at 42%, low at 24 %, medium at 5%, high at 13%, and very high at 16%. The N learning model validated result concluded, that the impact of soil from Very Low to Low was 66%, similarly from High to Very High impacted 29% and 5% medium.

In experiment 2, conducted in 60 days, the N learning model interpreted the nitrogen anomalies as very low at 46%, low at 29%, medium at 7%, high at 8%, and very high at 10%. The N learning model validated result concluded that the impact of soil from Very Low to Low was 75%, similarly, from High to Very High impacted 18%, and 7% medium.

In experiment 3, conducted in 90 days, the N learning model interpreted the nitrogen anomalies as very low at 37%, low at 27%, medium at 8%, high at 14%, and very high at 13%. The N learning model validated result concluded, that the impact of soil from Very Low to Low was 71%, similarly from High to Very High impacted 23%, and 6% medium.

In experiment 4, conducted in 120 days, the N learning model interpreted the nitrogen anomalies as very low at 37%, low at 27%, medium at 8%, high at 14%, and very high at 13%. The N learning model validated result concluded, the impact of soil from Very Low to Low was 64%, similarly, from High to Very High was impacted 27%, and 8% medium.

In experiment 5, conducted in 150 days, the N learning model interpreted the nitrogen anomalies as very low at 36%, low at 24%, medium at 9%, high at 16%, and very high at 15%. The N learning model validated result concluded, that the impact of soil from Very Low to Low was 60%, similarly from High to very high was impacted at 31% and 9% medium.

The EFNN CSA is very efficiently simulated into five categories of anomaly detection by the integrated N learning model simulated result (Figure 4). The proposed EFNN CSA forecasted the nitrogen soil samples. The EFNN CSA was proposed to forecast soil nutrients independently. For that, the N learning model created and forecasted the nitrogen only. The EFNN CSA classified, predicted, and simulated the anomalies through the N learning model, and classified and predicted the anomaly detection with 99.9 % accuracy.

P Learning Model

Figure 5 shows the N learning model found the nitrogen anomaly detection level-wise in the different experiments. The issue is to identify the anomalies in phosphorus behavior, it’s complex combination to identify.

 https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

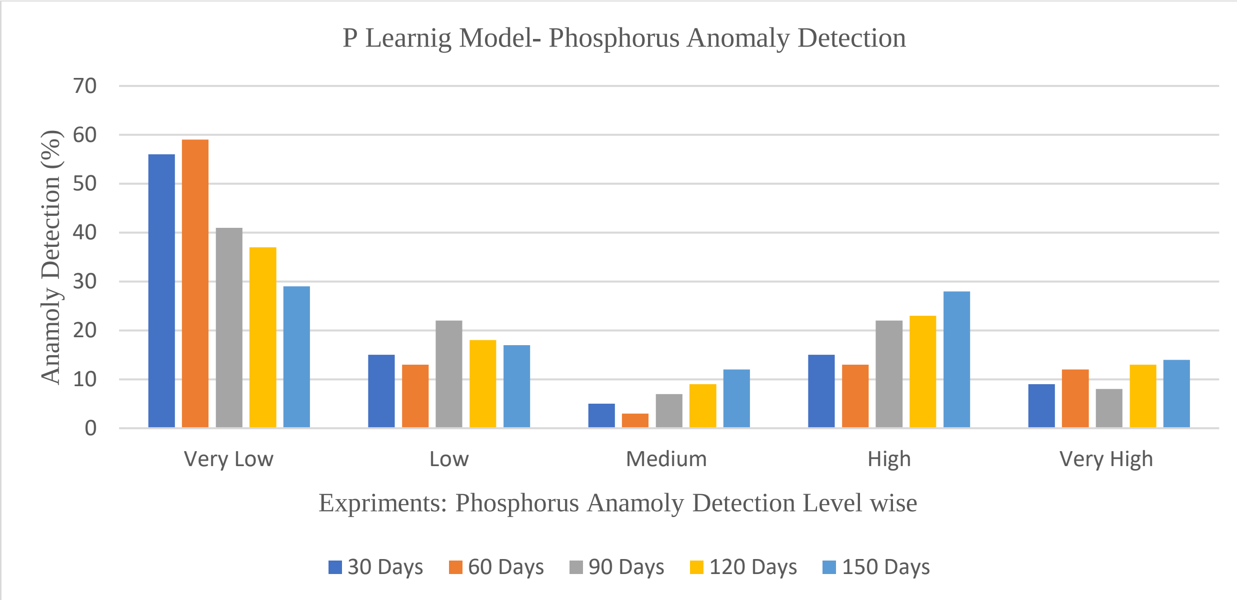

Figure 5. P Learning Model – Phosphorus Anomaly Detection

EFNN CSA anomaly identification integrated the N learning model, P learning model, K learning model, S learning model, and pH learning model. Figure 5 The P Learning Model – Phosphorus Anomaly Detection explains phosphorus behavior analysis in soil. The proposed P learning model works with categorical data from the different experiments and explains the nitrogen level-wise (very low (VL), low (L), medium (M), high (H), and very high (VH)).

In experiment 1, conducted in 30 days, the P learning model classified and predicted the anomalies into five categories in validating the soil phosphorus samples. The P learning model interpreted the phosphorus anomalies as very low at 56%, low at 15%, medium at 5%, high at 15%, and very high at 9%. The P learning model validated result concluded that the impact of soil from very low to low was 71%, similarly, from high to very high impacted 24%, and 5% medium.

In experiment 2, conducted in 60 days, the P learning model interpreted the phosphorus anomalies as very low at 59%, low at 13%, medium at 3%, high at 13%, and very high at 12%. The P learning model validated result concluded that the impact of soil from very low to low was 72%, similarly, from high to very high impacted 25%, and 3% medium.

In experiment 3 conducted in 90 days, the P learning model interpreted the phosphorus anomalies as very low at 41%, low at 22%, medium at 7%, high at 22%, and very high at 8%. The P learning

https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

model validated result concluded that the impact of soil from very low to low was 63%. Similarly, from high to very high, was impacted at 30% and 7% medium.

In experiment 4, conducted in 120 days, the P learning model interpreted the phosphorus anomalies as very low at 37%, low at 18%, medium at 9%, high at 23%, and very high at 13%. The P learning model validated result concluded that the impact of soil from very low to low was 55%, similarly, from high to very high was impacted 36%, and 9% medium.

In experiment 5, conducted in 150 days, the P learning model interpreted the phosphorus anomalies as very low at 29%, low at 17%, medium at 12%, high at 28%, and very high at 14%. The P learning model validated result concluded that the impact of soil from very low to low was 46%, similarly from high to very high was impacted at 42% and 12% for medium.

The EFNN CSA is very efficiently simulated into five categories of anomaly detection by the integrated P learning model simulated result (Figure 5). The proposed EFNN CSA forecasted the phosphorus soil samples. The EFNN CSA was proposed to forecast soil nutrients independently. For that, the P learning model created and forecasted the phosphorus only. The EFNN CSA classified, predicted, and simulated the anomalies through the N learning model, and classified and predicted the anomaly detection with 99.03 % accuracy.

K learning model

Figure 6 shows the K learning model found the potassium anomaly detection in level wise in the different experiments through the K Learning method. The issue is to identify the anomalies in potassium behavior, it’s complex combination to identification anomaly detection.

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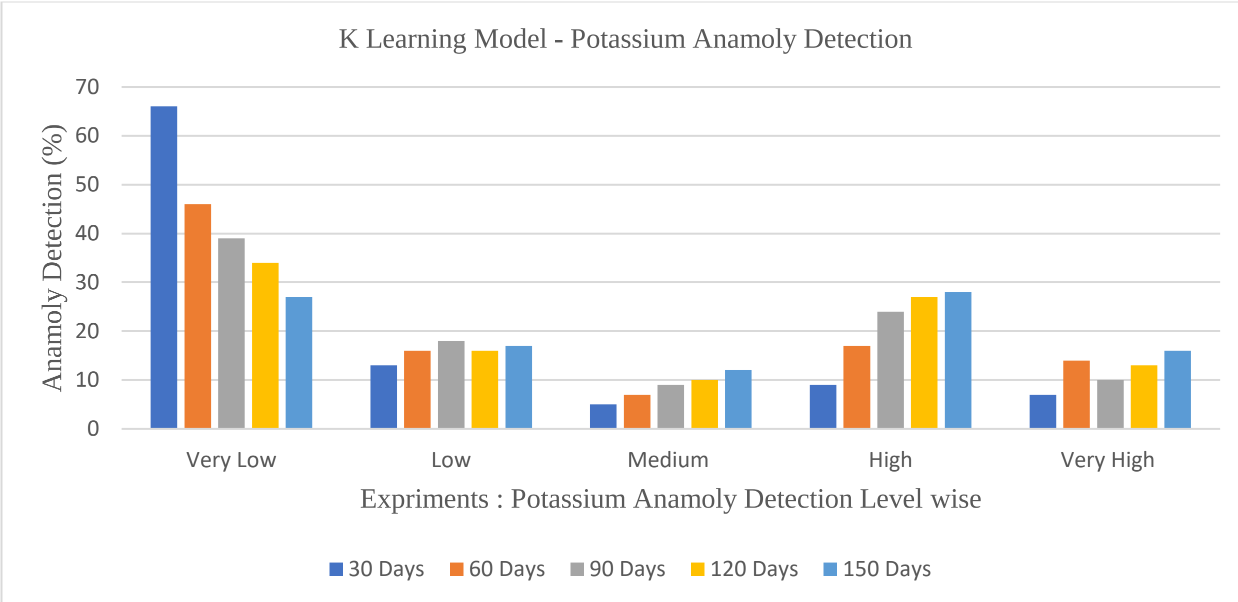

Figure 6. K Learning Model – Potassium Anomaly Detection

EFNN CSA anomaly identification integrated the N learning model, P learning model, K learning model, S learning model, and pH learning model. Figure 6 The K Learning Model – Potassium Anomaly Detection explains potassium behavior analysis in soil. The proposed K learning model works with categorical data from the different experiments and explains the nitrogen level-wise (very low (VL), low (L), medium (M), high (H), and very high (VH)).

In experiment 1, conducted in 30 days, the K learning model classified and predicted the anomalies into five categories in validating the soil potassium samples. The K learning model interpreted the potassium anomalies as very low at 66%, low at 13 %, medium at 5%, high at 9%, and very high at 7%. The K learning model validated result concluded that the impact of soil from very low to low was 79%, similarly, from high to very high impacted 16%, and 5% medium.

In experiment 2, conducted in 60 days, the K learning model interpreted the potassium anomalies as very low at 46%, low at 16%, medium at 7%, high at 17%, and very high at 14%. The K learning model validated result concluded that the impact of soil from very low to low was 62%, similarly from high to very high impacted 31%, and 7% medium.

In experiment 3, conducted in 90 days, the K learning model interpreted the potassium anomalies as very low at 39%, low at 18%, medium at 9%, high at 24%, and very high at 10%. The K learning

 https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

model validated result concluded, that the impact of soil from Very Low to Low was 57%, similarly from High to Very High impacted 34% and 9% medium.

In experiment 4, conducted in 120 days, the K learning model interpreted the potassium anomalies as very low at 34%, low at 16%, medium at 10%, high at 27%, and very high at 13%. The K learning model validated result concluded that the impact of soil from very low to low was 50%, similarly from high to very high impacted 40% and 10% medium.

In experiment 5, conducted over 150 days, the K learning model interpreted the potassium anomalies as very low at 27%, low at 17%, medium at 12%, high at 28%, and very high at 16%. The K learning model validated result concluded, that the impact of soil from very low to low was 44%, similarly from high to very high was impacted at 44% and 12% for medium.

The EFNN CSA is very efficiently simulated into five categories of anomaly detection by the integrated K learning model simulated result (Figure 6). The proposed EFNN CSA forecasted the potassium soil samples. The EFNN CSA was proposed to forecast soil nutrients independently. For that, the K learning model created and forecasted the potassium only. The EFNN CSA classified, predicted, and simulated the anomalies through the K learning model, and classified and predicted the anomaly detection with 94.49 % accuracy.

S Learning Model

Figure 7 shows the S learning model found the sulfur anomaly detection in level wise in the different experiments, to identify the anomalies in sulfur behavior, it’s complex combination to identification anomaly detection.

https://doi.org/10.37896/pd91.5/9156

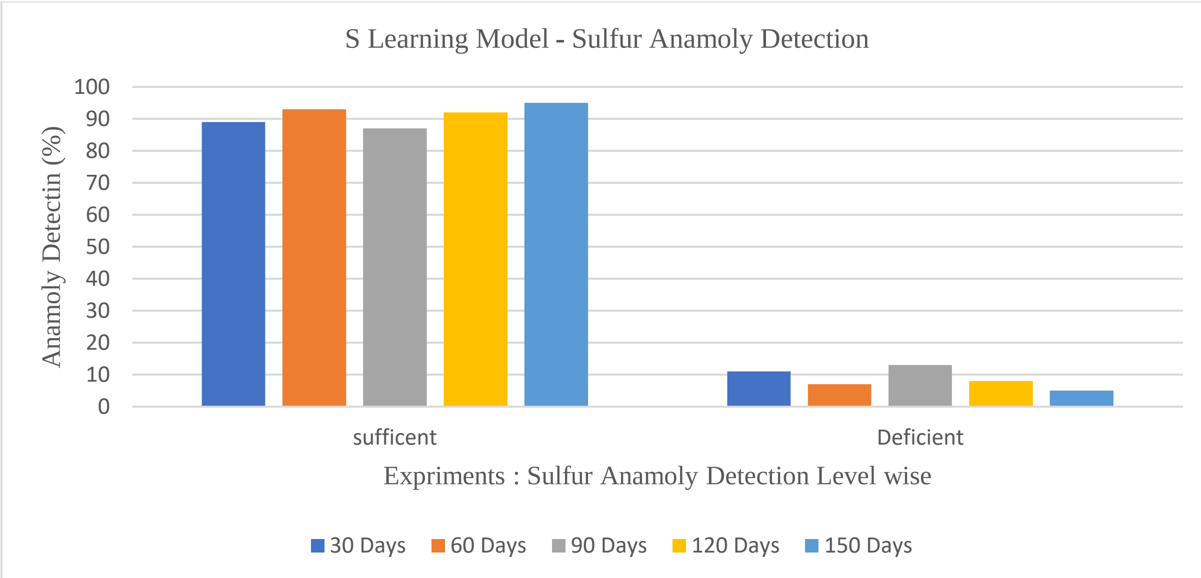

Figure 7. S Learning Model – Sulfur Anomaly Detection

EFNN CSA anomaly identification integrated the N learning model, P learning model, K learning model, S learning model, and pH learning model. Figure 7 The S Learning Model – Sulfur Anomaly Detection explains sulfur behavior analysis in soil. The proposed S learning model works with categorical data from the different experiments and explains the sulfur level-wise (Sufficient (S) and Deficiency (D)).

In experiment 1, conducted in 30 days, the S learning model classified and predicted the anomalies into two categories in validating the soil nutrient sulfur samples. The S learning model interpreted the sulfur anomalies as sufficient at 89% and deficient at 11%. The S learning model validated the result and concluded, that most of the soil samples have sufficient sulfur, but the S learning model identified the anomalies from 11% deficient in experiment 1.

In experiment 2, conducted in 60 days, The S learning model interpreted the sulfur anomalies as sufficient at 93% and deficient at 7%. The S learning model validated the result and concluded, that most of the soil samples have sufficient sulfur, but the S learning model identified the anomalies from 7% deficient in experiment 2.

In experiment 3, conducted in 90 days, The S learning model interpreted the sulfur anomalies as sufficient at 87% and deficient at 13%. The S learning model validated the result and concluded, that most of the soil samples have sufficient sulfur, but the S learning model identified the anomalies from 13% deficient in experiment 3.

 https://doi.org/10.37896/pd91.5/9156

ISSN: 0369-8963

In experiment 4, conducted in 120 days, The S learning model interpreted the sulfur anomalies as sufficient at 92% and deficient at 8%. The S learning model validated the result and concluded, that most of the soil samples have sufficient sulfur, but the S learning model identified the anomalies from 8% deficient in experiment 4.

In experiment 5, conducted in 150 days, The S learning model interpreted the sulfur anomalies as sufficient at 95% and deficient at 5%. The S learning model validated the result and concluded, that most of the soil samples have sufficient sulfur, but the S learning model identified the anomalies from 5% deficient in experiment 5.

The EFNN CSA is very efficiently simulated into two categories of anomaly detection by the integrated S learning model simulated result (Figure 7). The proposed EFNN CSA forecasted the sulfur soil samples. The EFNN CSA was proposed to forecast soil nutrients independently. For that, the S learning model created and forecasted the sulfur only. The EFNN CSA classified, predicted, and simulated the anomalies through the S learning model, and classified and predicted the anomaly detection with 98.94 % accuracy.

pH Learning Model

Figure 8 shows the pH learning model found the sulfur anomaly detection in level wise in the different experiments, to identify the anomalies in pH behavior, it’s complex combination to identification anomaly detection.

 https://doi.org/10.37896/pd91.5/9156

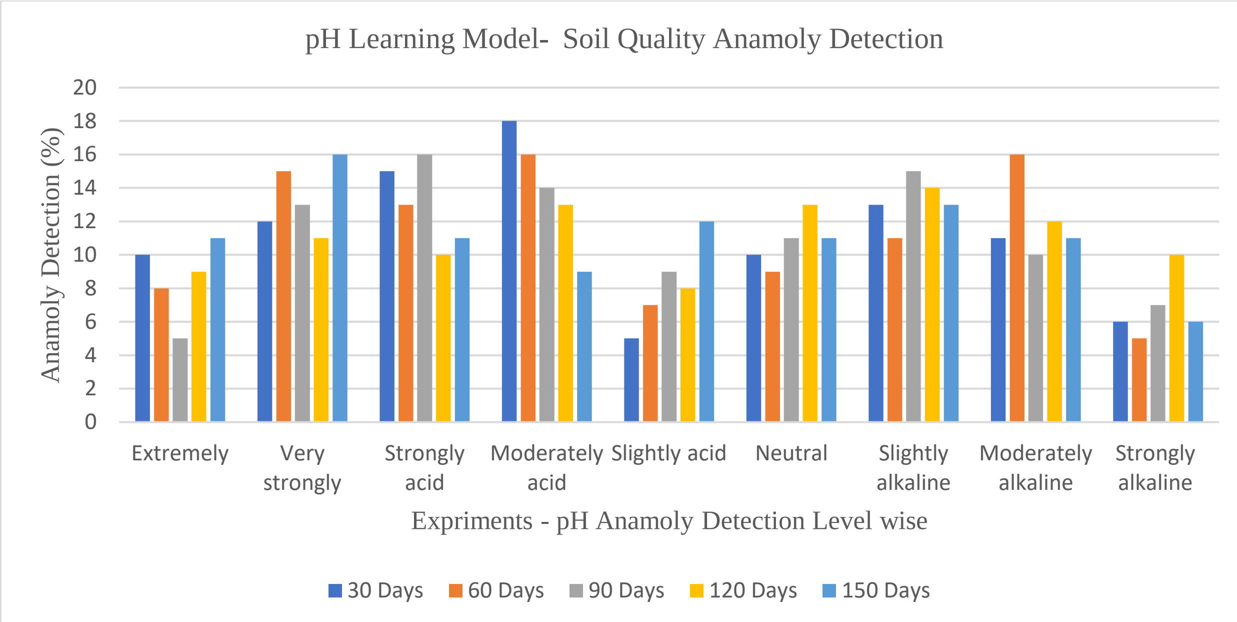

Figure 8. pH Learning Model – pH Anomaly Detection

EFNN CSA anomaly identification integrated the N learning model, P learning model, K learning model, S learning model, and pH learning model. Figure 8 The pH Learning Model – pH Anomaly Detection explains pH behavior analysis in soil. The proposed pH learning model works with categorical data from the different experiments and explains the nitrogen level-wise (Extremely acid (EA), Very strongly acid (VSA), Strongly acid (SA), Moderately acid (MA), Slightly acid(SlA), Neutral (N) Slightly alkaline (SlAl), Moderately alkaline (MAl), Strongly alkaline(SAl)).

In experiment 1, conducted in 30 days, the pH learning model classified and predicted the anomalies into nine categories and interpreted the test soil samples. The pH learning model interpreted results are EA at 10%, VSA at 12%, SA at 15%, MA at 18%, SlA at 5%, N at 10%, SlAl at 13%, MAl at 11%, and SAl at 6%. The pH learning model results concluded that the impact of soil acid levels is 60%, alkaline at 30%, and neutral at 10%.

In experiment 2, conducted in 60 days, the pH learning model classified and predicted the anomalies into nine categories and interpreted the test soil samples. The pH learning model interpreted results are EA at 8%, VSA at 15%, SA at 13%, MA at 16%, SlA at 7%, N at 9%, SlAl at 11%, MAl at 16%, and SAl at 5%. The pH learning model results concluded the impact of soil acid levels was 59%, alkaline at 32%, and neutral at 9%.

 https://doi.org/10.37896/pd91.5/9156

In experiment 3, conducted in 90 days, the pH learning model classified and predicted the anomalies into nine categories and interpreted the test soil samples. The pH learning model interpreted results are EA at 5%, VSA at 13%, SA at 16%, MA at 14%, SlA at 9%, N at 11%, SlAl at 15%, MAl at 10%, and SAl at 7%. The pH learning model results concluded the impact of soil acid levels was 57%, alkaline at 32%, and neutral at 11%.

In experiment 4, conducted in 120 days, the pH learning model classified and predicted the anomalies into nine categories and interpreted the test soil samples. The pH learning model interpreted results are EA at 9%, VSA at 11%, SA at 10%, MA at 13%, SlA at 8%, N at 13%, SlAl at 14%, MAl at 12%, and SAl at 10%. The pH learning model results concluded the impact of soil acid levels was 51%, alkaline at 36%, and neutral at 13%.

In experiment 5, conducted in 150 days, the pH learning model classified and predicted the anomalies into nine categories and interpreted the test soil samples. The pH learning model interpreted results are EA at 11%, VSA at 16%, SA at 11%, MA at 9%, SlA at 12%, N at 11%, SlAl at 13%, MAl at 11%, and SAl at 6%. The pH learning model results concluded the impact of soil acid levels was 59%, alkaline at 30%, and neutral at 11%.

The EFNN CSA is very efficiently simulated into nine categories of anomaly detection by the integrated pH learning model simulated result (Figure 8). The proposed EFNN CSA forecasted the pH soil samples. The EFNN CSA was proposed to forecast soil nutrients independently. For that, the pH learning model created and forecasted the pH only. The EFNN CSA classified, predicted, and simulated the anomalies through the pH learning model, and classified and predicted the anomaly detection with 98.01 % accuracy.

Conclusion

Finally, the novel EFNN CSA performed with 98.07% accuracy and 8.64% error. The study concluded, developed the new novel EFNN CSA proved the soil parameter scalable changes track and detect the anomalies while simulating the predictions with less error. The EFNN CSA works in a more complicated environment. In future studies, enable the integration of all soil nutrient analyses in ensemble learning for sustainable soil practice.

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