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" Intelligent Fertilizer Management System Using Optimized Artificial Neural Network Approach for Enhance Prediction”

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Abstract:

In agriculture, maximizing crop yields and advancing sustainable farming methods depend on efficient fertilizer management. Artificial intelligence (AI) devices have created tools in agriculture to assist farmers in obtaining precise and regulated cultivation. The right way to predict fertilizer is more important in order to satisfy farmer demands, improve yield output, and manage agricultural operations. This research uses deep learning (DL) models to provide a new introduces an innovative Automated Fertilizer Management System (AFMS) employing an Optimized Artificial Neural Network (OANN) model, enhanced through back propagation and chain rule techniques. The suggested approach makes use of sophisticated optimization techniques, including hyper parameter tuning and regularization, to refine the back propagation process and improve learning efficiency. By leveraging the chain rule for gradient computation, the model ensures accurate and efficient weight updates during training. The ANN is trained on a diverse dataset that includes soil nutrient levels and climatic conditions, specific to the Indian agricultural context. Subsequently, these characteristics are sent into an "Optimized Artificial Neural Network (OANN)" that predicts fertilizer outcomes based on information already known. In particular, the weights of OANN are adjusted using back propagation and chain rule techniques to improve the classifier's prediction accuracy.

Keywords: Optimized Artificial Neural Network, Backpropagation, Deep Learning, Fertilizer, Soil Nutrient, BPCR.

1. Introduction

Agriculture is the main source of income for the majority of people in India [16]. A sizable section of the population depends on agriculture for their livelihood, which also boosts the economy. However, the effective use of fertilizers remains a critical challenge for maximizing crop yields and ensuring sustainable farming practices [6]. Conventional fertilizer application techniques frequently result in either excessive or insufficient use, which can have a negative impact on crop output, soil health, and the environment. There is increasing interest in using cutting-edge technologies for accurate fertilizer forecast in order to overcome these issues.

The most crucial element to guaranteeing maximum field productivity is agronomy. Crop production and management comprise a number of processes in the majority of agricultural techniques. In agriculture, turning and loosening the soil is the first step. After the soil has been sufficiently loosened and aerated, it is prepared for crop cultivation. Depending on the soil's requirements, fertilizers and manures are added to raise the soil's nutritional content. However, excessive fertilizer application harms the soil, while insufficient fertilizer causes crop nutrition deficiencies [25]. Using Artificial Neural Networks (ANNs), especially with the backpropagation method, is one potential strategy [17]. This technique makes it possible to model intricate interactions between different crop growth-influencing elements, such as crop types, soil characteristics, and climatic circumstances. The backpropagation technique effectively updates the neural network's weights by utilizing the chain rule, which enhances the neural network's capacity to forecast the ideal fertilizer requirements. Using artificial neural networks (ANN) to anticipate fertilizer can greatly improve farmers' decision-making in the Indian environment, which has a variety of agroclimatic variables.

Artificial neural network (ANN) models can be taught to make customized fertilizer recommendations by combining data from multiple sources, including soil testing, remote sensing, and historical yield data. In addition to maximizing resource utilization, this strategy encourages sustainable farming methods, which support both environmental preservation and food security.The application of deep learning methods, especially ANN backpropagation, is a viable solution to enhance fertilizer management and improve crop results as India's agricultural environment develops. New prediction techniques utilizing OANN are proposed in order to address the shortcomings of traditional methods and correct the factors influencing the soil. An effective optimization algorithm is also presented. Through the implementation of new, crucial challenges in fertilizer prediction analysis, this study contributes to its certainty. With the least amount of computational complexity, it aids in the establishment of an efficiency model for fertilizer forecast in all meteorological aspects. Deep learning algorithms and emerging and growing features in agronomy are expected to be discovered in this work[15], offering a solid foundation for developing methods in fertilizer prediction algorithms.

2. Related Work

Sivasan karan et. al.[1] study examines a suggested model for forecasting the nutrient composition of soil and suggesting the best fertilizers for growing groundnut crops in a sustainable manner. The model is evaluated against current machine learning classifiers and is based on an Enhanced 1D-CNN deep learning methodology. It seeks to enhance generalization, accuracy, and performance while addressing the shortcomings of the existing soil nutrient prediction models. The suggested model performs better than current models when tested utilizing nutrient datasets from a particular region. The significance of soil fertility for crop production and the influence of technology on precision-based agriculture are also highlighted in the document. It also highlights the need of soil nutrients like potassium, phosphorus, and nitrogen for crop growth and talks about the difficulties in predicting nutrients and soil fertility.

Jion Gao et.al.[5] the study, emphasizing the value of swarm intelligence and machine learning in creating efficient fertilization decision models. It provides context for the writers' contributions to the subject by highlighting the necessity of creative methods to maximize fertilizer application for soybean, rice, and maize crops. It also discusses how fertilizer use affects the environment and promotes sustainable methods that reduce harm to ecosystems. In order to support methods that increase output while minimizing environmental damage, the authors situate their study within the larger framework of sustainable agriculture.

Deepak Mane et. al.[7] The study tackles the serious problem of plant infections, which endanger the production of therapeutic herbs, especially basil. To increase the precision of disease identification, the authors suggest a hybrid deep learning model that integrates Convolutional Neural Networks (CNN) with Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) algorithms. A hybrid model for the early identification of diseases in basil plants—which are significant in traditional medicine—is the main goal of this work.

Amilia Nongbet et. al. [18] investigates the potential benefits of applying nano fertilizers in modern farming. Increased crop yield, reduced nutrient losses, and enhanced nutrient uptake efficiency are the goals of nano fertilizers. They offer advantages like regulated nutrient release, targeted nutrition delivery to plants, and less environmental effect.

Takashi S. et.al. [2] explains how to forecast crop yield and make fertilizer recommendations using machine learning models. The study assesses how yield and economically optimal input rates (EOIRs) are affected by various machine learning techniques and covariate selection. It emphasizes the need for caution when using machine learning for fertilizer recommendations by highlighting how sensitive predicted EOIRs and profits are to algorithm and covariate selection. The difficulties with model uncertainty and the significance of taking temporal and regional variability into account when modeling crop yield response are also covered in the study. All things considered, it highlights the necessity of giving careful thought to model uncertainty and the limitations of machine learning techniques in order to produce trustworthy site-specific input management suggestions.

Pratik kr et. al. [9] explains how deep learning models can be used to identify plant leaf deficiency and suggest suitable fertilizers. It describes the data used, the methodology, data pretreatment methods, and the outcomes. Image processing, classification using the ResNet-50 architecture, and comparing the model's performance to that of other pre-trained models are the main topics of the study. The usefulness of the suggested approach in obtaining high accuracy in identifying malnutrition in photos of plant leaves is highlighted in the text. It also emphasizes how the study could be expanded in the future to anticipate further plant leaf picture classifications.

Dr. T. Venkat Narayana Rao et. al. [17] The use of artificial neural networks (ANN) in agriculture is its main area of interest. The key concepts include employing artificial neural networks (ANN) to estimate agricultural production and soil quality, suggesting appropriate fertilizers, and solving the difficulties faced by farmers. The potential of machine learning to enhance farming methods and lower the suicide incidence among farmers is highlighted in the research. The design of the suggested system and the backpropagation algorithm's application to neural network model training are also covered. Overall, the study emphasizes how important it is to use technology to solve problems in agriculture.

Thilina Abekoon a et. al. [15] explains the creation of a deep learning model to forecast the concentrations of the three main soil nutrients—potassium, phosphorus, and nitrogen—that are essential for cabbage growth. The algorithm analyses and forecasts soil nutrient content based on plant growth factors. The study describes the process, which includes gathering data and training the model with various transfer functions. The findings show that the deep learning model accurately predicts soil nutrient levels, especially when the tangent sigmoid transfer function is used. With possible uses in sustainable agriculture, the study highlights the importance of this strategy for maximizing fertilizer use and improving soil nutrition.

Vani, et al. [14] created a PLMDC strategy to improve clustering accuracy for both deeply allocated and sparse agricultural large data. To clean the data, a logical linear regression approach is employed. A genetic algorithm (GA) was used to extract features. In order to forecast crop yields based on their characteristics, the A-FP growth algorithm was introduced. This technique improved clustering performance.

2.1 Gap Analysis

Fertilizer prediction employs a number of methods and algorithms to forecast fertilizer and overcome obstacles. However, there are still certain disadvantages, such as the need for additional fertilizers, the maximum manpower costs for small-holder farmers, and crop nutrition deficiencies. There were certain difficulties in evaluating different kinds of study. However, The limitations of traditional modeling approaches, the significance of thorough data utilization, the potential of advanced modeling techniques, the need for regionally adaptable models, and the need for more focused research on the relationship between crop yield and fertilization management are all highlighted [5]. The cloud cover must be automated, and image capture is a dangerous procedure. In order to achieve more clustering accuracy with less complexity, the PLMDC scheme was created in [14], and GA was used for the feature extraction genetic algorithm. The crop management approach was offering increased yields along with improved soil aggregation and less soil moisture losses. However, it costs small-holder farmers more in effort and is ineffective for agronomic water management techniques. linear regression (LR) analysis, which boosts soybean yield and lessens the climate impact of crop cultivation; however, it necessitates a lengthy growing season with high thermal requirements.

3. Proposed Work

3.1 Proposed Architecture

In order to predict the kind and amount of fertilizer needed for the best crop growth, the suggested deep learning-based fertilizer prediction model makes use of a multi-input architecture that analyses a variety of agricultural data sources, including soil parameters (such as pH, nitrogen, potassium and phosphorus) and meteorological factors (such as temperature, humidity, and rainfall) [25]. Three essential steps are part of the applied prediction approach: "pre-processing, feature extraction, and fertilizer forecast." The pre-processing step is where the data cleansing procedure is completed. By identifying and removing outliers from the fresh training dataset, the data cleaning method [25] is used to enhance the quality of training data.

These characteristics are then predicted using an optimized ANN, which forecasts the fertilizer as the yield information. The backpropogation chain rule (BPCR) is suggested as a way to adjust the OANN weights during training in order to improve prediction accuracy. The created backpropogation_chain rule (BPCR) prediction framework is demonstrated in Figure 1.

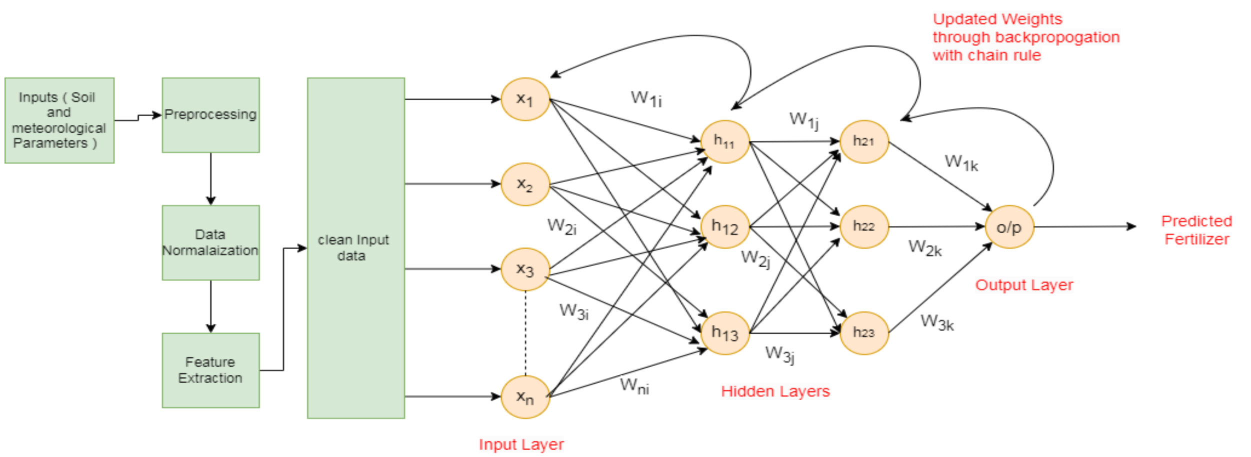

Fig1. Fertilizer prediction system block diagram

Precision agriculture is made possible by this model, which offers customized fertilizer suggestions that maximize crop output, reduce environmental effect, and conform to local farming methods. It also continuously updates and receives feedback to adjust to changing environmental conditions.

3.2 Dataset Description

Dataset is very important factor for using deep learning model in modern agriculture from which dataset we can predict fertilizer accurately. There are total 8 features in dataset out of that 7 features are in-depended and 1 is depended. Total 2230 samples are in dataset. This dataset can be found from various sources such as Agricultural Colleges, Soil Testing Labs, Government websites. We have visited Vasant Dada Sugar Institute Pune, Rajarambapu sugar factory Islampur, Sangliand Agriculture College Karad and collected datasets from them. Also we have generated our own dataset using different sensors. Fertilizer prediction is based on two sets of data weather and soil nutrients parameters. In this case, dataset1 is the public dataset, and dataset2 is the self-sensor-based dataset.

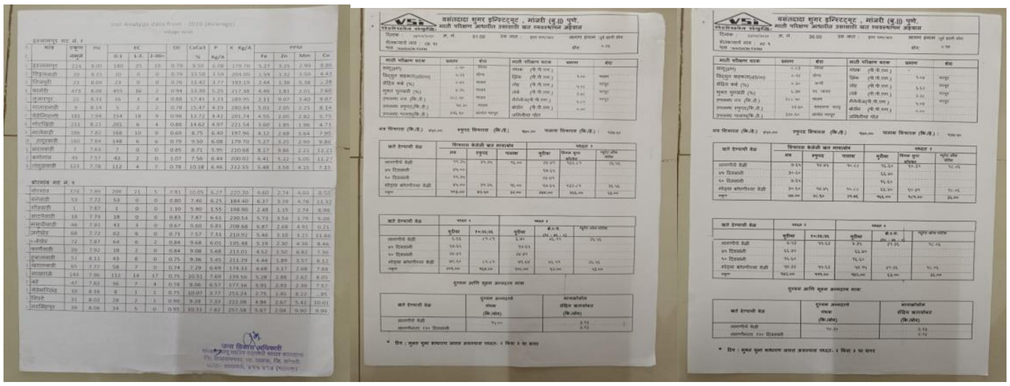

Fig2. Sample dataset images

N	P	K	pH	EC	Temp	Moisture	Target
138	8.6	560	7.46	0.62	26	38	Urea
213	7.5	338	7.62	0.75	29	45	DAP
163	9.6	718	7.59	0.51	34	62	10-26-26
157	6.8	475	7.64	0.58	32	34	Urea
270	9.9	444	7.63	0.4	28	46	10-26-26
220	8.6	444	7.43	0.65	26	35	Urea
220	7.2	222	7.62	0.43	25	64	DAP
207	7	401	7.63	0.59	33	50	Urea
289	8.6	560	7.58	0.44	30	42	Urea
138	8.1	739	7.55	0.33	29	33	10-26-26

Table 1. Data samples from dataset

3.3 EDA

Once the data is collected, it needs to be cleaned and transformed into a format that is suitable for feeding into a deep learning model.

3.3.1 Data Cleaning

Handle Missing Values: Either remove rows or columns with a high number of missing values, or use imputation (such as substituting the mean or median for missing data).Finding and handling outliers that could skew model training is known as outlier detection. Methods such as IQR (Interquartile Range) can be applied. Noise Reduction: If sensor data (such as NPK, soil moisture or temperature) is noisy, use smoothing techniques. Normalization to scale continuous

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numerical features such (soil NPK, pH, temperature, and moisture) to fall within a comparable range [0,1] mean (μw) of 0 and standard deviation (σw) of 1 use Z-score normalization.

$$Z' = \frac{X-\mu_w}{\sigma_w} \tag{1}$$

In Eq.1 Z' denotes new value, X is the value from the dataset, μ_w denotes mean and σ_w denotes standard deviation. One method for transforming category variables into numerical values is label encoding. Label encoding is frequently used for categorical information, such as fertilizer type, in fertilizer prediction. Each distinct value of a categorical feature in label encoding is substituted with an integer, usually beginning with 0 for the first category, 1 for the second, and so forth.

3.4 Algorithmic Details

A number of essential procedures, algorithms, and mathematical concepts are concerned in creating an optimised artificial neural network (OANN) with backpropagation chain rule (OANN+BPCR). By modifying the weights using optimization methods like Gradient Descent and minimizing a loss function through backpropagation, the optimization procedure aims to get better network's performance. First assign the neural networks including how many layers there are, how many neurones there are in each layer, and which activation functions are in use. Assign the initial biases b and weights w at random. Define an activation function f(x) like (ReLU, Sigmoid and Tanh) for every layer. Now next step is forward propagation to calculate the output for each input sample through the network. Once the network's output has been obtained, compute the loss function L, which measures the discrepancy between the actual target and the projected output is the Mean Squared Error (MSE). Using the chain rule of calculus, backpropagation's primary goal is to calculate the gradients of the loss function in relation to the weights and biases. The gradients instruct us on how to modify the settings to lower the error. Beginning at the output layer and working backward through the network, the procedure entails calculating the gradient of the loss function with regard to the weights and biases as shown in Fig.3.

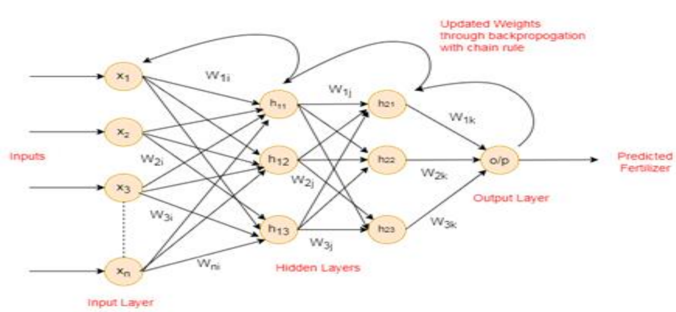

Fig.3 Backpropogation Framework

4. OANN Model for Fertilizer prediction using Back-Propagation with Chain-Rule algorithm (OANN+BPCR)

An Optimized Artificial Neural Network (OANN) is a kind of neural network model that uses optimization strategies and cutting-edge learning algorithms to produce predictions with high efficiency and accuracy. Based on dataset an OANN can be used to predict the type and quantity of fertilizer that will be best appropriate for a particular soil nutrients, and weather circumstances. The Backpropagation Algorithm with the Chain Rule (BPCR) is a powerful technique used in training neural networks, including OANNs, by updating the weights of the network during the training process. This process minimizes the error between the model's predicted output and the actual target output fertilizer requirement using a gradient descent-based optimization technique. In the context of agriculture, predicting the type and quantity of fertilizer needed based on various soil and environmental conditions is crucial. It leverages the backpropagation algorithm, employing the chain rule to compute gradients efficiently, thereby updating the network's weights and biases to improve accuracy. By training the model on a dataset of soil and environmental conditions, it learns to predict the appropriate fertilizer type or quantity needed.

Let's define the input features for the fertilizer prediction problem as follows:

X=[x_1, x_2,....., x_n] is input vector representing soil properties**,** weather conditions**,** etc**.** x_1-Nitrogen(N), x_2- Phosphorus(P), x_3-Potassium(K), x_4-Soil pH, x_5-Temperature, x_6-Humidity. To predict the fertilizer denoted as y_{pred} , which could be the fertilizer type.Consider a Artificial neural network with theInput layer Consists of n features x_1, x_2,....., x_n.Hidden layer(s)contains *h* neurons, output layerproduces a prediction y_{pred} .Let the weights between the input layer and the hidden layer be denoted by W_1 and the biases by b_1. For the hidden layer, the output can be expressed as Eq.2

$$z_1^{(i)} =_{j=1}^{n} W_1^{(i,j)} x_j + b_1^{(i)} \tag{2}$$

Where i represents the i^{th} neuron in the hidden layer.$W_1^{(i,j)}$ are the weights connecting the j^{th} input feature to the i^{th} hidden neuron.$b_1^{(i)}$ is the bias term for the i^{th} hidden neuron.$z_1^{(i)}$ is the weighted sum of inputs to the i^{th} hidden neuron. The activation function transforms the weighted sumin Eq.3

$$a_1^{(i)} = f\left(z_1^{(i)}\right) \tag{3}$$

where f(z) is a non-linear sigmoid activation function ($f(z) = \frac{1}{1+e^{-z}}$) Similarly, for the output layer with weights W_2 and bias b_2 Eq.4

$$z_2 =_{i=1}^{h} W_2^{(i)} a_1^{(i)} + b_2 \tag{4}$$

The final output y_{pred} is Eq.5

$$y_{pred} = f_{output}(z_2) \tag{5}$$

where f_{output} is the activation function for the output layer

The neural network's ability to estimate the amount of fertilizer needed is measured by the OANN's loss function. OANN loss function was indicated as loss and is denoted the Eq. 6

$$L = \frac{1}{N}\sum_{K=1}^{N} (y_{pred,k} - y_{true,k})^2 \tag{6}$$

where N is the number of training samples. y_{pred}, k is the predicted fertilizer value for sample k. y_{true},k is the true fertilizer requirement for sample k.Here, the OANN weights with the best performance are selected through backpropagation algorithm using the chain rule method. To reduce the loss L, the weights W_1 and W_2 are updated by backpropagation. The gradients of the loss function with respect to each weight are calculated throughout the update phase using the chain rule.

Step 1: Determine the Output Layer Gradients:

In relation to the output layer, the gradient of the loss L is Eq.7

$$\frac{\partial L}{\partial z_2} = \frac{\partial L}{\partial y_{pred}} \cdot \frac{\partial y_{pred}}{\partial z_2} \tag{7}$$

so $y_{pred} = f_{output}(z_2)$ we have Eq. 8

$$\frac{\partial y_{pred}}{\partial z_2} = f'_{output}(z_2) \tag{8}$$

Consequently, the output layer's gradient is represent the Eq. 9

$$\frac{\partial L}{\partial z_2} = (y_{pred} - y_{true}) \cdot f'_{output}(z_2) \tag{9}$$

Next, Eq. 10 is determine the gradients in relation to the output layer's weights

$$\frac{\partial L}{\partial W_2^{(i)}} = \frac{\partial L}{\partial z_2} \cdot a_1^{(i)} \tag{10}$$

Eq. 11 is calculate the output layer's bias gradient

$$\frac{\partial L}{\partial b_2} = \frac{\partial L}{\partial z_2} \tag{11}$$

Step 2:Determine the Hidden Layer's Gradients:

Now, Eq. 12 we backpropagate to the hidden layerusing the chain rule, the gradient of the loss with respect to the activations of the hidden layer neurons

$$\frac{\partial L}{\partial a_1^{(i)}} = \frac{\partial L}{\partial z_2} \cdot W_2^{(i)} \cdot f'_1(z_1^{(i)}) \tag{12}$$

Where $f'_1(z_1^{(i)})$ is the derivative of the activation function used in the hidden layer? Then, compute the gradient with respect to the weights in the hidden layer Eq. 13

$$\frac{\partial L}{\partial W_1^{(i,j)}} = \frac{\partial L}{\partial a_1^{(i)}} \cdot x_j \tag{13}$$

And the Eq. 14 is bias gradient for the hidden layer:

$$\frac{\partial L}{\partial b_1^{(i)}} = \frac{\partial L}{\partial a_1^{(i)}} \tag{14}$$

Step 3: Update the Weights:

Finally, the weights are updated using an optimization algorithm, such as **Gradient Descent**:

$$W_1^{(i,j)} \leftarrow W_1^{(i,j)} - \eta \cdot \frac{\partial L}{\partial W_1^{(i,j)}} \tag{15}$$

$$W_2^{(i)} \leftarrow W_2^{(i)} - \eta \cdot \frac{\partial L}{\partial W_2^{(i)}} \tag{16}$$

$$b_1^{(i)} \leftarrow b_1^{(i)} - \eta \cdot \frac{\partial L}{\partial b_1^{(i)}} \tag{17}$$

$$b_2 \leftarrow b_2 - \eta \cdot \frac{\partial L}{\partial b_2} \tag{18}$$

where η is the learning rate. After training the model through multiple iterations (epochs), the optimized weights W_1 and W_2 are used to predict the fertilizer requirements for new input data:

$$y_{pred} = f_{output} \,{}_{i=1}^{h} W_2^{(i)} a_1^{(i)} + b_2 \tag{19}$$

where $a_1^{(i)}$ is the output of the hidden layer neurons, computed using the learned weights and activation functions.

This mathematical model describes how an artificial neural network (ANN) uses backpropagation with the chain rule to forecast fertilizer needs. After specifying the input features, the weighted sums at each layer are calculated, activation functions are applied, the loss is calculated, and the weights are updated using the chain rule to minimize the loss. Through iterative weight optimization,

5. Result and Discussion

Python was used to implement a recommended fertilizer prediction method utilizing the OANN+BPCR model. The fertilizer prediction in this work, as previously indicated. This covers the soil's temperature, moisture content, nutrients, and a few other characteristics. Furthermore, the suggested model's efficacy was assessed in comparison to conventional models with learning rates of 70, 80, and 90. Furthermore, it was established that the OANN+BPCR model that was presented in terms of error analysis of MAE, MSE, RMSE, and RMAE. Performance was assessed using a dataset of prepared soil nutrients. Fig.4 shows the training and validation loss performance graph. The validation accuracy is quite low at first, but it tends to grow as the number of epochs increases. After a given number of epochs, the value tends to reach saturation.

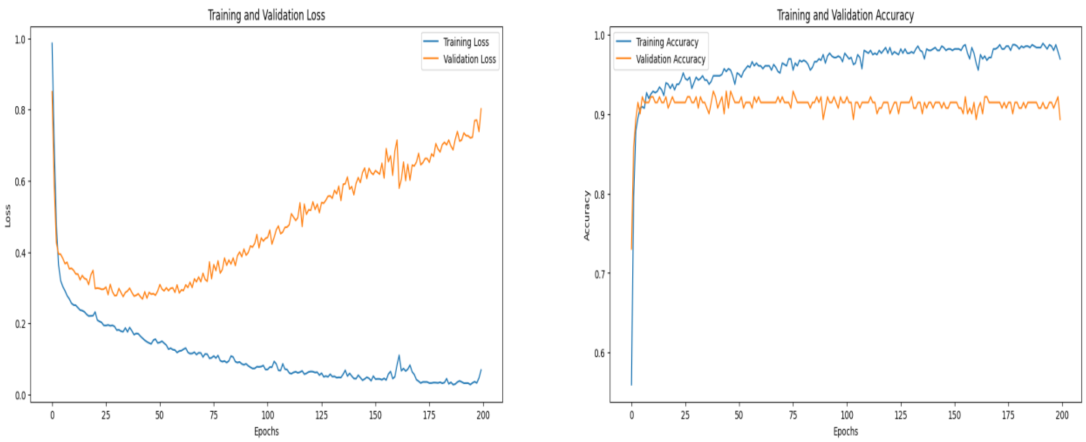

Fig.4 Validation and Training Performance graph

The error between the actual target and anticipated results for a number of error variables, including MAE, MSE, RMSE, and RMAE for Public dataset (dataset1) and self dataset (dataset2), for the fertilizer prediction method that was applied using OANN+BPCR over conventional models. Table1 and Table2 presents the study of the MAE, MARE, MSE and RMSE metrics for dataset1 and dataset2

Metrics	SVM	KNN	RF	Ensemble	OANN+BPCR
MAE	0.91169	0.33931	0.59603	0.50046	0.30684
MSE	4.86211	3.76131	7.62914	4.07404	2.97945
RMAE	0.06262	0.53277	0.54649	0.21736	0.10791
RMSE	2.20502	1.93941	2.76209	2.01843	1.72611

Table1. Proposed vs. Conventional Error Analysis for Dataset1

Metrics	SVM	KNN	RF	Ensemble	OANN+BPCR
MAE	1.960265	0.911692	1.339312	1.500463	0.726837
MSE	8.139073	5.290068	4.001305	4.784043	3.539574
RMAE	2.91209	2.905019	3.293941	2.928491	2.872609
RMSE	2.091644	1.982618	1.989277	1.917364	0.980796

Table1. Proposed vs. Conventional Error Analysis for Dataset2

The overall error analysis of the approved OANN+BPCR model compared to traditional schemes for the dataset. Error analysis was therefore performed for measures such as MAE, MSE, RMSE, and RMAE. The accepted OANN+BPCR model has achieved minimal error (MAE: 0.306837) when compared to existing methods shown in Fig.5.

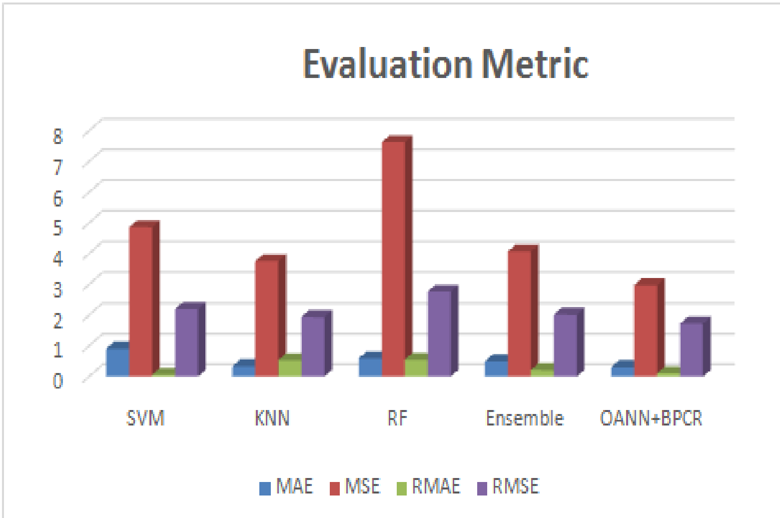

Fig.5 Error Analysis Graph

In order to predict fertilizer, various models (OANN+BPCR, Ensemble, RF, KNN, and SVM) were applied to the soil nutrients dataset. Fig.6 the OANN+BPCR based sigmoid function had the highest accuracy of 95.02% when compared to all other models.

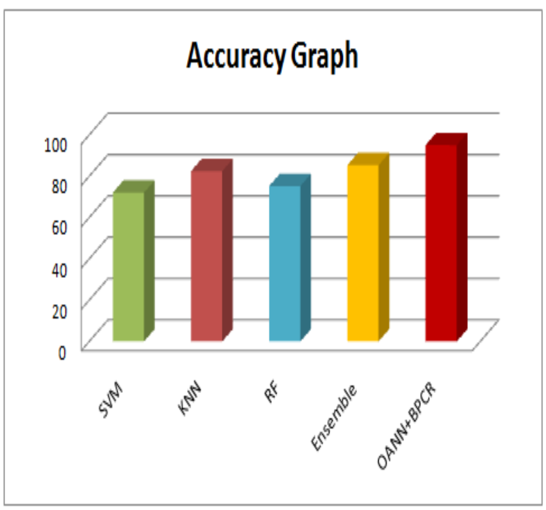

Fig.6 Overall Accuracy Graph

6. Conclusion

This study used the OANN+BPCR algorithm to create a new fertilizer prediction model. Prior to deriving the "soil parameters, metrological parameters, statistical features, and higher order statistical features," preprocessing was completed. The characteristics were then provided as input to OANN for prediction, where the OANN+BPCR model was used to fine-tune the OANN weights. The provided system was ultimately found to be superior to the conventional schemes in a number of aspects. For all learning rates, the error output of the proposed method mainly reaches minimal values. The most widely used acceptable scheme has a learning rate of 70 and a minimum MAE value of 0.247. Stated otherwise, the created OANN+BPCR technique outperformed 95.02% the existing SVM, RF, KNN, and Ensemble (SVM+RF+KNN) models by 72%, 78.4%, 82.5%, and 85.4% when learning rates were 70. Consequently, the efficacy of the introduced OANN+BPCR technique effectively established its superiority. Some of the constraints of the proposed research include its inability to manage large amounts of fertilizer data, also known as big data or high dimensional data. Furthermore, a few restrictions, including soil and metrological factors, can be used to anticipate fertilizer. Therefore, the study will be expanded in the future to include various meteorological conditions or soil factors related to micronutrients. To increase the system's accuracy, research can concentrate on investigating different deep learning models or implementing more sophisticated strategies.

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