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The Prediction of Soil Texture Properties Using Hybrid CNN-LMO Algorithm

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Abstract—The prediction of soil texture using their properties helps to find the soil type to determine the patterns of cropping and agriculture. The convolutional neural network used for training the data which makes easy understood about the pattern of hyperspectral data. This paper is discussed about the prediction of eight properties present in the soil for identifying the soil type. The existing work predicts six properties as organic carbon, cation exchange capacity, nitrogen (N), pH level, clay and sand in the soil particle. This Proposed paper enhanced by predicting two more properties of soil P, K with existing six properties along as terrain factor, Potassium level and vertical slope position. These properties are predicted using hybrid optimization algorithm called Levenberg Marquardt optimization(LMO) algorithm, which execute the prediction result faster and more stable. Here the error rate is decreased by adjusting the weight of connections in Convolution neural network.

Keywords*:* Soil properties; Convolutional Neural Network, Levenberg Marquardt optimizer, Hyperspectral Data, Soil Texture, Deep Learning.

1. Introduction

Soil texture plays an important role in land for soil degradation and transportation of water, quality of soil control and productivity in soil. To predict the texture of soil, it is necessary to college huge samples for analysis to estimate the soil texture variability. There are several methods to develop the estimation of soil samples but the field surveys are currently taken to develop the indirect estimation based on remote sensors. Techniques like chemometrics are used to estimate the soil properties by infrared waves and shortwave infrared domains.in past decades such methods are used because it considered as low-cost method implemented for the prediction of soil variables based on their reflectance range of 400 to 2500nm wavelength [1] [2] [3].

Neural networks are used for training the data to understand and learn the bonding between more data sets. Neural network plays as computational model for processing information with simple nodes. It helps to build mathematical model like human brain to perform various functions. The weights are adjusted or trained for particular values to execute the expected output. Neural network consists of input, hidden units and output units used widely in soil science for prediction of soil properties. The classification process helps to gather more information about chemical and physical properties which need more analysis for their property values. Based on the colour the soil texture can identify the organic matters.

An objective of this study was developed with convolution neural network with hybrid algorithm called Levenberg Marquardt optimization algorithm for better prediction of soil properties with minimum error rate and higher accuracy is reached by CNN model. LUCAS dataset is collected and train the data with CNN based on selected attributes and parameters the expected results was executed successfully.

2. Related works

Zhengyong, et.al., proposed model using digital elevation model with resilient back propagation algorithm for soil texture prediction using artificial neural network model and concluded that the proposed algorithm was executed higher and reduce the error rate using the data taken from southern east NB from the black brook watershed [4].

Parameswari, et.al., implemented their research with feed forward neural network model for soil texture prediction using artificial neural network. Subsequently compare the proposed model with self-organizing map using the data from remote sensors field. The model predicts the properties like sandy loam, clay, silt based on the properties of soil type and concluded that feed forward neural network executed the prediction with higher accuracy than self-organizing map [5].

Xiaogang, et.al.,done a case study at south china based on soil depth for predicting the properties of soil to determine the soil type. They used artificial neural network for train the data to predict the clay and sand properties to identify the soil texture [6].

Curcio, et.al., proposed VNIR-SWIR reflectance method for soil texture prediction using PLSR technique for higher accuracy and minimum error rate for different soil properties like sand and clay. They used key wavelength method to investigate the spectrum range for predicting the soil texture using satellite sensors [7].

Manikandan, et.al., implemented their research by collecting the soil of local area was surveyed at scale of 10,000 hector acre of agricultural land and the properties like sand and clay was analysed based on the texture of soil sample using lab analysis. They designed a unique method to predict the properties using soil depth and layers for texture prediction and stated that the soil texture was varied from properties like clay and sand predicted.

3. Methodology

In agriculture the prediction of soil texture is main factor and it have difficult characters to predict the type of soil. With the help of hyperspectral data, properties of soil are determined and it require more process for better understanding of the prediction. The proposed research is implemented with convolution neural network with hybrid algorithm called as Levenberg Marquardt optimization algorithm.

There are 6 soil properties were identified in existing methodology such as organic carbon, cation exchange capacity, clay and sand particles, pH level and nitrogen content. In this proposed model we enhanced with two more soil properties such as terrain factors, potassium level and vertical slope position as properties to predict the texture of the soil.

3.1 Convolution neural network

Convolution neural network is the deep learning algorithm processed for working with video and images. Features are extracted from the image for better understanding to classify the features.

It has more than one convolutional layer for image processing, classification, segmentation, etc. the input data will be given for pre-processing of hyperspectral data for prediction and filters are applied on every pixel of an image to get detailed information about the image.

The below figure explains about the basic architecture of convolution neural network (CNN).

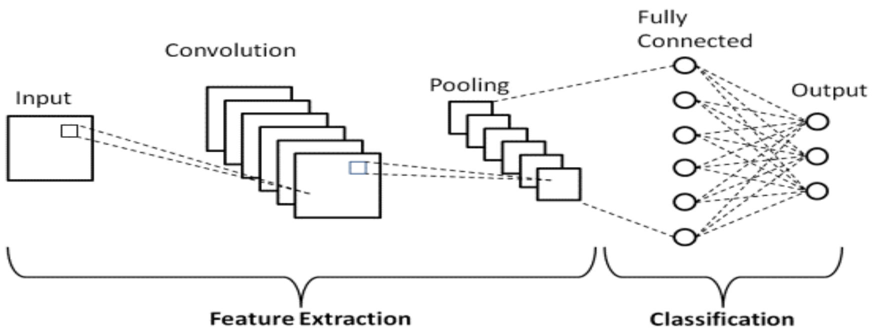

Figure 1. Architecture of Convolution neural network

There are two major sections in convolution neural network as feature extraction and classification. The tool divides the layer to identify the features from an image for better analysis called feature extraction section. And the layers connected together will use the output values from previous section prediction at classification section [10].Convolution neural network was implemented for several research because it can be used to map the point which was discontinued between the input and output layers. The back propagation algorithms like LMO were trained by adjusting the bias and weight of the nodes with gradient descent method to reduce the mean square error between input and output layers while training the data. Adjusting the weight and bias using trained data was known as epoch values, which helps to calculate the error values between the predicted value and target value by using each different epoch values. Process of training the data was stopped when the error rates cannot be reduced further. Both the input and output layers are connected with hidden layers and the model complexity will be determined by the number of nodes connected with hidden layers.

$$\mathbf{o = f\ (-T + \Sigma\ w_i x_i) \ldots\ldots\ldots\ldots(1)}$$

here, ‘f’ denotes non-linear function

‘T’ denotes threshold value for each node.

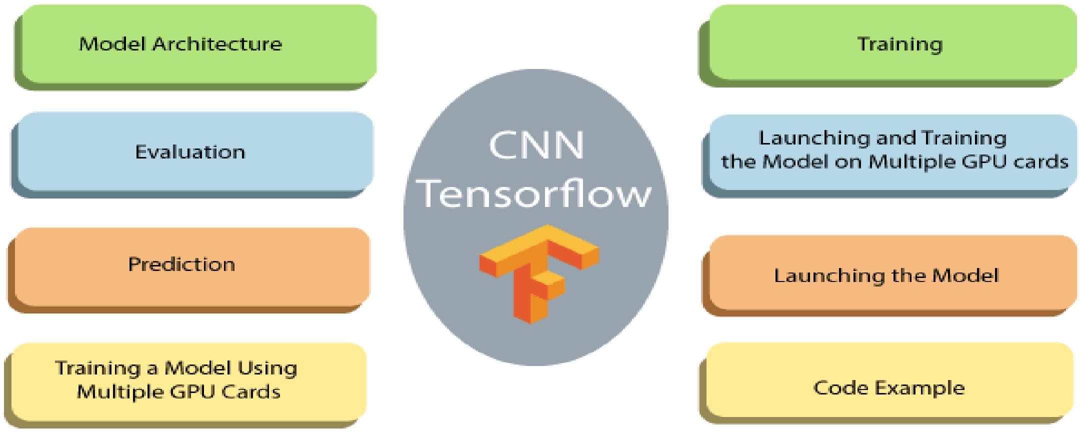

Figure 2. Train the data using Convolution neural network

Training neural network have two phases as forward and backward. The forward phase will receive the input data through the network and backward phase where gradients are backpropagation and weights are added.

3.2 Levenberg Marquardt algorithm

Levenberg Marquardt algorithm is used for optimization to detect the minimum functions over a huge parameter. It will process like gradient descent method for processing the values when the parameters are far away from the optimal value. It will execute the numerical solution with low the errors of non- linear functions. This algorithm will process faster and execute the stable results.

It will occupy more space and consider as supervised algorithm which is fastest backpropagation method using trainlm.The below equation helps to avoid increasing the error rates by regularizing the gauss newton method,

$$\mathbf{P^{k+1} = P^{k} + (X^{Tk}.W.X^{k})\text{-}1\ .\ X^{Tk}.W.(y\text{-}i^{k})} \quad \text{………………}(2)$$

It will update the weight and bias values for best optimization process and reduce the error rates. By increasing the nodes in hidden layer will helps to reduce the mean square error by Levenberg Marquardt optimization, but the relative overall accuracy ±5 will reach the high value by 25 nodes in hidden layers.

The proposed model designed with CNN model helps to predict the properties of potassium and terrain factor to identify the soil texture was 2-25-2 net. When the number of nodes lesser than 25 in hidden layer will produce the low accuracy. When the model was over fitted with high nodes greater than 25, will produce the high accuracy in training but the prediction results was too low.

The bonding between training time and accuracy are shown in table 4, by setting epoch value as 50 will execute the accuracy higher reduce the error rates.

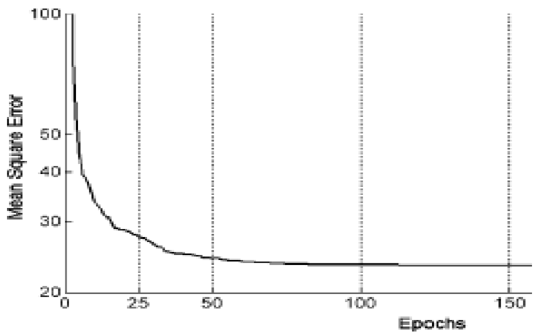

Figure 3. MSE cure for 6-25-2 neural network using LMO for 150 epochs.

The prediction accuracy for the network model 6-25-2 using Levenberg Marquardt optimization training method with 25, 50, 100, 150 epochs values. The value of relative overall accuracy ± 5% will reached the maximum value after 100 epochs, which means the performance of CNN model will helps to predict the accuracy of the properties like potassium, terrain factors and vertical slope positions are trained using LMO algorithm at 100 training times.

When the epoch values are increased for training the error rates reduced randomly and accuracy in prediction increased.

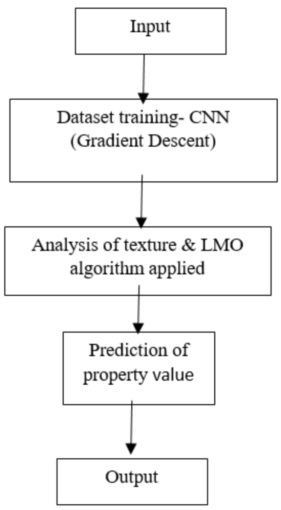

Fig 4. Flow chart of proposed method working principle

The above figure, explained about the proposed work flow. The input data is given for training using convolution neural network like gradient descents method and soil texture was analysed by implementing Levenberg Marquardt optimization algorithm. The property values are predicted from the trained data using neural network and properties in the soil are predicted to determine the soil texture more accurately.

3.3 Architecture of NN

The proposed research done with neural network concept with LMO algorithm and the network architecture was consisted of n input units with one hidden layer and output layer. The neuron in the neural network model will produce their outputs based on the input values.

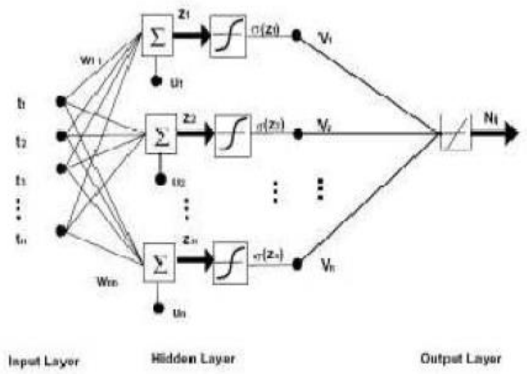

Fig 5. Neural network architecture

While training the model, weight and bias of network will adjusted and processed for prediction using Levenberg Marquardt algorithm. The training was done based on the following method as, each node weight will be initialized and randomly the vector is chosen from the training dataset to analyze the weight of each node and identify which is similar like input node. The nodes which presence within the radius is taken to calculate the other neighbour node which is located near the radius and its weight was adjusted for higher accuracy rates.

3.4Algorithm for neural network

Step 1: Input vector$t_j$loaded.

Step 2: randomized weight W_{ij} and bias U_i initialized.

Step 3: Compute $Z_i = W_{ij}t_j + U_i$

Step 4:Weight vector initialized from hidden layer to output layer.

Step 5: calculate $N_{ij} = \varphi_i\ \sigma(Z_i)$

Step 6: Neural network training will be repeated until error reduced and execution of expected output.

4. Result and Discussion

The datasets are collected from LUCAS database with 12,000 data points with limited attributes for training with neural network. There are some attributes are selected for processing like pH level, organic carbon, carbonate content, nitrogen value, sand and silt values, terrain factors and vertical slope positions. Such datasets are considered as hyperspectral data which has data values of reflectance spectrum ranges from 400nm to 2500nm.

The proposed research can be calculated with error rate as root mean square error (RMSE). The gradient descent method used to calculate the weight rates during training the datasets. The Levenberg Marquardt optimization algorithm were implemented for better execution with low error rate and higher accuracy rate.

Table 1. Parameter values of CNN

Parameter	***Values***
No of epoch	50
Algorithm to train	Gradient descent
Error function	Mean absolute error
Optimization algorithm	Levenberg Marquardt

The proposed research was trained with 50 epoch value for training using gradient descent algorithm for training the datasets using neural network. The error functions are calculated using root mean square error (RMSE) and mean square error (MSE).

Table 2. Comparison of Error rate (RMSE) between proposed vs existing

S. No	***pH***	***OC***	***CEC***	***Clay***	***sand***	***N***	***P***	***K***
Pro.	**.48**	**6.11**	**3.81**	**4.75**	**8.6**	**.55**	**3.6**	**2.87**
Exis.	.30	5.98	3.57	2.70	9	.47	-	-

Table 3. Algorithm comparison

	Algorithm / method	**Error rate %**	**Accuracy**
Existing	CNN	5.68	95%
	VNIR-SWIR	7.7	95.2%
	SOM	6	87%
	FFNN	3-6	92%
Proposed	**Levenberg Marquardt algorithm**	**2.6**	**96.7%**

In table 2 and 3, the comparison of predicted properties from soil to identify the texture type was discussed. In table 2, the properties like pH level in soil, organic carbon, clay, sand particles, nitrogen and potassium levels are predicted and compared with existing model. By comparison, the proposed model was highly predicted using LMO algorithm by reducing the error rates. In table 3, the different algorithms and methods implemented in existing research was compared with proposed model and compare the error rate and accuracy rate. By comparing all these models, it finally concluded that the proposed model with hybrid back propagation algorithm call Levenberg Marquardt executed with higher accuracy around 96.7%.

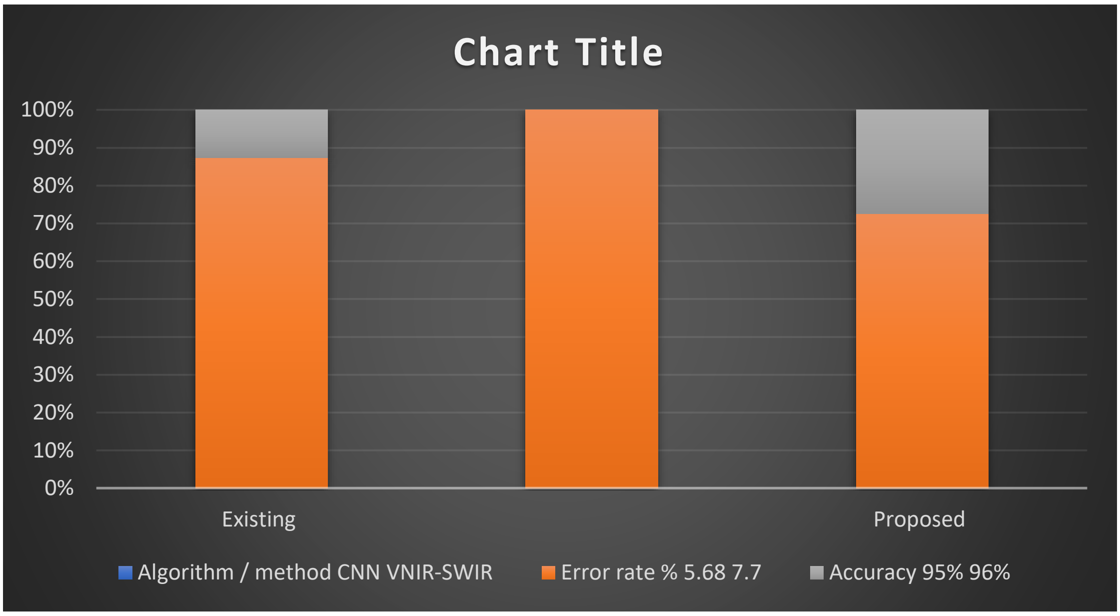

Figure 6. Comparison chart of error rates between existing and proposed system

The above chart state that the comparison between existing research and proposed system by comparing with different algorithm and method proposed to predict the properties of soil to predict the soil texture and concluded that the proposed research is executed with higher accuracy with lower error rate by implementing Levenberg Marquardt optimization algorithm for prediction.

4.1 Assessment of accuracy

In the proposed research, texture of soil was identified by the assessment of field and categorized into various types. There are some relative values of clay, silt, sand, terrain factor and vertical slope positions and some chemical properties which can be used for the prediction of soil texture and measure the property

values using relative overall accuracy (ROA) method. This method can work based on the prediction value which relatively similar with assess value of such properties. ROA ± 5 was measured based on overall prediction values which comes under the range of 5% is measured and considered as soil texture content.

The accuracy also compared based on the error rates RMSE and ME for better model accuracy. Such method will be used more for prediction of higher ROA and lower error rates for better model.

The below table compare the error rate as mean error and root mean square error and time taken for assess the model with different epoch values and predict the accuracy of terrain factor and vertical slope position.

Table 4. Predicted terrain factor and vertical slope position using LMO method with different epoch values.

Epoch	***Training***			***Predicted terrain factor and VSP***	
	ME	***Time (min.)***	***RMSE***	***Relative overall accuracy (ROA)***	
25	29	3	4.2	Terrain VSP Potassium	86 76 86
50	22	11	4.3	Terrain VSP Potassium	80 72 88
100	19	15	4	Terrain VSP Potassium	87 81 91
150	23	19	3.8	Terrain VSP Potassium	84 80 94

In table 4 the proposed model was trained with four different epoch values for better prediction in the proposed model as 25, 50, 100, 150. While training the proposed system, time taken for execution of the predicted result is differed by some error rates as mean error (ME) and root mean square error (RMSE).

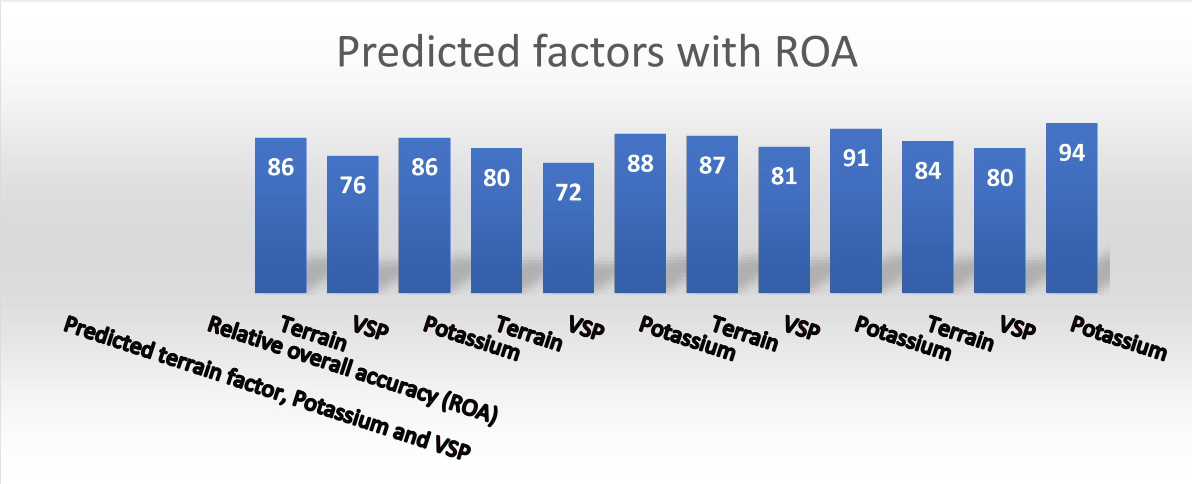

Figure 7. Prediction of properties with ROA

This chart shows the prediction level of proposed properties to predict the soil texture using LMO algorithm. The prediction of terrain factor, potassium level and vertical slope position is calculated with relative overall accuracy as mentioned in table 1.

4.2 Performance of LMO algorithm

The performance of proposed convolution neural network model has trained with Levenberg Marquardt optimization back propagation algorithm with the hidden layers and training epochs value from 25 to 150. The accuracy of proposed model was predicted using Levenberg Marquardt Optimization algorithm has reached higher accuracy than the existing algorithms with low error rates of root mean square error using the same hidden layer nodes by adjusting the weights and bias values in neural network layers. Moreover, LMO algorithm predicts the properties of potassium, vertical slope positions and terrain factor with higher accuracy as 96.7% and lower error as 2.6% by taking longer time for predictions using ANN model.

5. Conclusion

Convolution neural network model was developed and trained to get higher prediction values of eight different soil properties as organic carbon, cation exchange capacity, N,P,K, pH level, clay particles, soil particles, terrain factor, potassium level and vertical slope position. Levenberg Marquardt back propagation optimization algorithm was implemented for better accuracy prediction with low error rates and the proposed model executed successfully with 2.6% and 96.8% of accuracy by comparing with existing works. In future research, the time taken for train the model is reduced with more datasets.

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