An EPSO_CNN Approach to Predict the Soil Texture Properties in Smart Farming

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Abstract: Prediction of soil is one the important factors in smart farming. The use of near infrared spectroscopy that has exclusive benefit in the forecast of soil moisture content is an appropriate and operative method. Convolutional Neural Network (CNN) is a kind of deep learning model with extraordinary performance. Effective attributes can be mined from the complex spectral data and the internal organisation of attributes can be learned with the help of CNN. When a comparison has been made with conventional models, CNN has influential modelling capability since it has objective of attaining better outcomes in soil prediction for hyperspectral data. CNN is proficient to comprehend the arrangement of hyperspectral data by spatial interpolation. The concept of CNN was utilized to forecast the soil humidity content by near infrared spectroscopy. LUCAS dataset have been adopted in this which have nearly 84 attributes. In order to enhance the results of CNN, EPSO-CNN is proposed. The projected PSO variant is used to optimize the learning hyper-parameters of CNNs to overcome performance barriers. The empirical results have showed that the proposed EPSO CNN achieves better results in terms of precision, recall and accuracy and that too in minimum time.

keywords: Smart Farming, LUCAS, EPSOCNN, Hyper Spectral Data.

1. Introduction

Farming is one of the most vital economic activities and also plays important part in social and environmental aspects of the countries that mainly be influenced on Agriculture. Cropping patterns is determined by the nature of soil which is most significant aspect in agriculture. Different kinds of soil can be preferred for various categories of cultivation. Thus, forecasting the soil texture is the primary factor in agriculture production [1]. One of the most significant soil assets is its texture, which enables the retention level of water, the thickness of soil, nutrient proportion etc. In most of the cases, soil texture is the deciding parameter for crop selection and for its productivity plan.

The soil particle distribution denotes the feature of soil quality and it is categorized as clay, silt and sand. If the size of the particle is less than .002 mm then it is categorized as clay, where as if the size ranges from .002 to.53mm, it is slit and it is concluded to be sand if its size is from .053 to 2mm [2]. In most of the cases, the soil quality influences its capability about water storage and fertility. Soil quality and organic substance are considered to be the most preferable parameters of soil that controls the soil water retention capability.

Silt and clay which have smaller particles have a larger surface area and allow soil to hold more water. Sand which has larger particles with a small surface area will hold only less water. The available water capacity by soil texture is shown in Fig 1[3].

Available Water Capacity by Soil Texture	
Textural Class	Available Water Capacity (Inches/Foot of Depth)
Coarse sand	0.25–0.75
Fine sand	0.75–1.00
Loamy sand	1.10–1.20
Sandy loam	1.25–1.40
Fine sandy loam	1.50–2.00
Silt loam	2.00–2.50
Silty clay loam	1.80–2.00
Silty clay	1.50–1.70
Clay	1.20–1.50

Fig 1:Water capacity by soil texture[3]

The complex structural chemical and physical properties involved in the soil texture and the process of prediction are more complex. It is a challenging research topic. The solar reflectance spectra of objects which are obtained from short wave solar radiation, reflects the solid phase of the soil which is covered by organic substance and crystals. These physicochemical properties, with the incident radiation and the reflected radiation is observed by a sensor, are measured to be the chief influences on the reflectance of a soil model and are used for the soil prediction type. It is measured using hyperspectral sensors [7] which relate to particular absorption features of organic and mineral content. A much effort on pre-processing is required when mapping the reflectance spectra data to the soil texture.

1.1. Deep Neural Network for Soil Texture

A NN consists of input layers, hidden layers and output layers. When there are numerous hidden layers then it is a deep NN[6] or deep learning as shown in fig 2[4]. The hidden layers captures the non-linear relationships among the input and the corresponding output, and the number of hidden layers is based on the complication of the problem being solved[5]. There are different types of deep learning methods which are intended for different purposes.

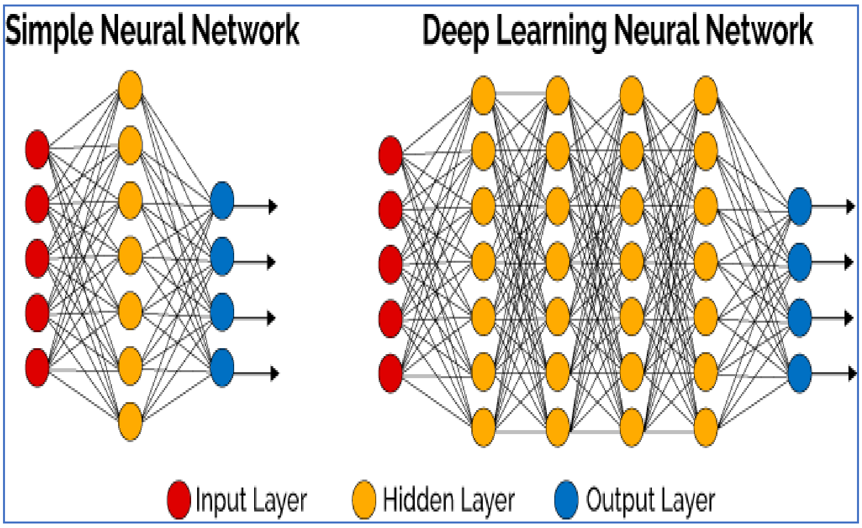

Fig 2. Simple and Deep learning Neural Network Architecture

A distinct category of NN which behaves very fine by data that is spatially associated is Convolutional Neural Networks (CNN). CNN can routinely acquire attributes with spatial relationships. Location-based relation with other information is termed as Spatial information [6,7]. Set of pixel is utilized for feature forecast instead of using distinct pixel value. The spatial and translation invariance of CNN works effectively for spatially linked data such as soil quality.

CNN[13] is utilized to extract the arrangement concealed in soil surface for hyperspectral data. Modelling complex relationship and representing nonlinearities from a very large scale data is solved by using deep learning. This research focuses on soil texture prediction using EPSO CNN. The Fig 3 shows the overall framework of the proposed architecture.

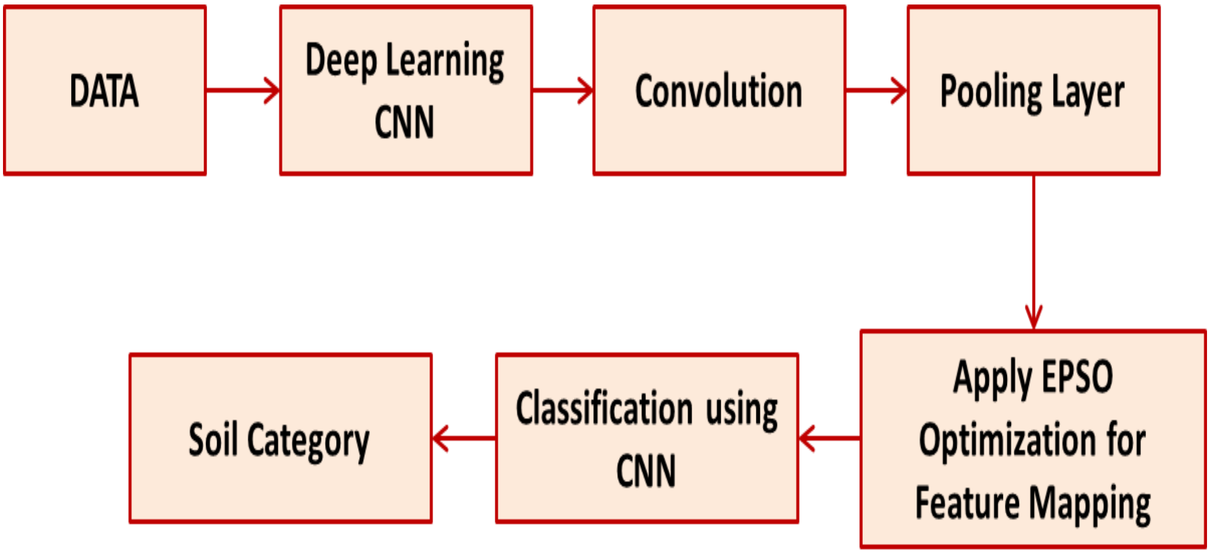

Fig 3. Overall Framework of Proposed System

Initially, the input data is divided into training and test sets respectively. Minor portion of training data is arbitrarily experimented from training set. Later this would be sent through the evolutionary step of PSO. The chief motive behind utilizing this minor subset aims to minimize the execution cost. This is because CNN always consumes less time and memory. It is not necessary to change the entire network; PSO is exploited to develop the ideal Dense Block on the minor subdivision. The proposed strategy loads the Dense Block repeatedly in order to create an established CNN architecture.

2. Related Work

In most of the environmental processes, soil consistency is treated as one of the significant factors. There are three one dimensional (1D)Convolutional Neural Network (CNN), [14] LucasCNN, and LucasResNet are proposed that consists of residual network for identification. Here the LucasCoordConv used as an extra layer for pre-processing. The CNN approach [13] with the least depth is considered as the greatest performing classifier. The LucasCoordConv achieved the first-rate performance in terms of normal accuracy.

Soil consistency is a parameter that influences the selection of crop and normalizes the water flow. [9]. The images of the soil are managed through the various phases, initially for the purpose of image enrichment, pre-processing step involved, mining the section of interest for separation and the feature vector is used for quality investigation. Actually the feature vector are derived from the following elements such as Hue, Saturation, and Value (HSV) histogram, Gabor wavelets, color auto Correlogram, color moments and discrete wavelet transform. Lastly, SVM classifier is taken to categorize the images of soil using linear kernel [10].

One of the deep learning algorithm Convolutional Neural Network (CNN) is proposed as a novel technique to foresee the features of soil from raw soil spectra[8]. To completely employ the volume of CNN model, the soil spectral data is demonstrated as a 2D spectrogram, presenting the reflectance factor as a function of wavelength and frequency. By using varied network architecture, they predicted various soil features in a certain network and trained the process using CNN. The convolutional and max pooling layers learns the structure of the spectrogram and its general representation is directed to six branches to predict six different types of soil property. With the help of an enhanced CNN structure the model can learn the features effectively by avoiding separate pre-processing.

Topsoil information captured with a smartphone camera is used as input to predict the structure and texture of the soil in [11]. The Low-level image features such as color and other texture are extracted and mapped with geolocation information with the existing land information. A NN model is used for predicting the soil texture of three types - sand, silt and clay. The prediction is also made on the soil structure with the five-point scale and other soil features such as soil density, pH value and drainage categorization of particular soil. Better spatial resolution of the soil mapping is needed in their work to further improve the performance.

Prediction of soil types based on hydrologic groups is presented by the authors[12] using machine learning algorithm. The model is trained to classify four different types of hydrologic groups by taking the features which involves the amount of sand, silt, clay and saturated hydraulic conductivity. Many machine learning representations are used for the prediction and the performance of their model is equated and analyzed using per class metrics, micro and macro averages.

The parameters that are associated to soil prediction include environmental condition and the last year production [15]. Based on these parameters, a better profitable crop can be suggested. This is highly helpful for the agriculturists to decide on a particular crop to foster. If the last year production is taken into account, the farmers can get to know about the claim of a crop in market. At the same time, an awareness about which crops could not be cultivated also is created. In the upcoming days, the devices that are associated to agriculture can be linked with IOT devices. Various sensors could be utilized to extract the parameters like weather condition, soil moisture and water content.

Justifiable growth is much needed in farming as it is considered to be the pillar of our nation's economy. The input features obtained from various sensors are controlled with the help of multi-layer perceptron[16] that consists of four hidden layers that guarantees enhanced outcomes. A well-defined recommender system with specific commands will definitely end up in good outcomes. Multiclass classification in farming would additionally fine-tune the recommendation system to monitor farmers suitably.

As agriculture is considered to be the nation's backbone; efficient crop production is highly necessary in this regard. The growth of the plant is directly influenced by Ph importance, alkalinity, and basicity. Before planting, soil preparation is the most important method. By using the techniques of color image processing, all these soil variables can be calculated. The interest of all farmers is to know the volume of yield can be predicted. In previous days, the yield expectation was calculated and identified by thinking about farmer or planter's specific domain knowledge. The harvest yield forecast is a significant problem that is not able to solve and dependent on accessible information for certain impediments. In the event that the harvest isn't yielding accurately, that implies it should have a few downsides. The proposed pH[19] esteem expectation of 40 soil pictures is done. Utilizing these kind of shading models, the pH factor of each dirt picture is determined. Various types of classifiers are applied to each and every shading space model and precision and RMSE [16] esteems are gotten. Along these lines, the framework fundamentally centers on anticipating the suitable pH of dirt so the yield will be anticipated by utilizing the pH estimations of the dirt. The dirt pictures are prepared, and the pH esteems are acquired.

Soil is a significant boundary influencing crop yield expectation[5]. Examination of soil supplements can help ranchers and soil investigators to get better return of the harvests by making earlier courses of action. Different AI methods have been executed to foresee Mustard Crop yield ahead of time from soil investigation. Information for the trial approaches has been gathered from the Agriculture Department, TalabTillo, Jammu including soil tests of various locale of Jammu area. There are Five managed AI strategies specifically K-Nearest Neighbour (KNN)[17], Multinomial Logistic Regression, Naïve Bayes Classifier, Artificial Neural Network (ANN) and Random Forest have been applied on the gathered information. To survey the exhibition of every procedure under investigation, the five boundaries specifically exactness, review, accuracy, explicitness and f-score have been assessed. The process of testing has been completed to spread the word about the most precise strategy for mustard crop yield expectation.

Subsequent to examining numerous previous frameworks on harvest forecast, this framework recommend crop dependent on soil order with ensembling classifiers framework has been made. The Artificial Neural Network (ANN), Bagged Tree, Naive Bayes, Adaboost, [18] and Support Vector Machine (SVM) calculations are joined to improve the precision of the framework which gives the rundown of suitable yield as per the dirt kind. Later on with cutting edge characterization calculations and methods, the precision of the framework can be expanded with different datasets. The framework can foresee the yield, in view of soil boundaries. Later on, the area proposal module can be added by the harvest recommendation implies as indicated by propose crop the proper area will be recommended.

AI is a significant choice help instrument for crop yield forecast, remembering supporting choices for what harvests to develop and what to do during the developing period of the harvests. A few AI calculations have been applied to help crop yield forecast research. After this perception dependent on the examination of AI based 50 papers, an extra pursuit in electronic data sets is recognized profound learning-based investigations, arrived at 30 profound learning-based papers, and extricated the applied profound learning calculations. As per this extra investigation, Convolutional Neural Networks (CNN)[20] is the most broadly utilized profound learning calculation in these examinations, and the other generally utilized profound learning calculations are Long Short Term Memory (LSTM) and Deep Neural Networks (DNN).

3. Existing System

In the existing system, the features are extracted and classified using Convolutional Neural Network (CNN).

3.1. Feature Extraction and Classification using Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) is an extra ordinary category in neural networks which works efficiently with data that is spatially associated. CNN can routinely acquire features with Spatial Relationships. In Convolutional layer, filters are used as feature detectors of the input image. The filter size used in this model is 3*3 which maps the local region of the input image and exploits the spatial relationship between the pixels. Spatial relationship refers to location based information with the neighbouring pixels.

Independent processing of each feature map is performed in pooling layer. It is used after the convolutional layer. Max pooling layer with size 3x3 is used in this model.

After many hidden layers of convolutional and pooling, six middle level branching is used to avoid separate pre-processing steps followed by convolutional layer and fully connected layer for each branching layer. The final output layer is the regression value of six soil properties.

Hyperspectral data is sent as input to the convolutional and pooling layers in the CNN model. Then the data is passed to the sequence of convolutional and pooling layers where it learns the features of input data. The overall illustration of the data is learned in the first few layers and the network is branched to learn the six soil properties OC, CEC, clay, sand, pH, N. Each branch learns the specific properties and passed to deeper convolutional layer. Finally, it is passed to the fully connected layer where it is flattened to one dimensional data and then to the output layer.

3.2. Particle Swarm Optimization(PSO)

PSO is a populace established algorithm and it can be utilized to solve the issues where the domain knowledge is insufficient. Population is attained based on the quantity of particles. Finest outcome could be obtained by updating the speed value.

$$v_d(t+1) = l*v_d(t)+r_1*a_1*(P_d-x_d(t))+r_2*a_2*(P_{gd}- x_d(t)) \tag{1}$$

$$x_d(t+1) = x_d(t) + v_d(t + 1) \tag{2}$$

Where, vd indicates the velocity of a particle in dimension d, xd denotes position of particle, Pd and Pgd are the best of local and global dth dimension, a1 and a2 are the arbitrary numbers between 0 to 1, l; r1,r2 are inertia load and the coefficients for acceleration.

4. Prediction of Soil Characteristics

Soil texture is one of the main factors in agricultural production, and its precise prediction is important for the normal use and management of water resources.

However, Soil texture involves complex structural characteristics with soil features which are difficult to make a prediction on soil type. Hyperspectral data is used as a feature for the forecast of soil features. Predicting soil features from hyperspectral data need more pre-processing for better understanding of the soil and for accurate prediction and it is a challenging research task. In the proposed methodology, a CNN model is used to train the spatial information mapped to soil texture.

Soil feature prediction is supportive in predicting and understanding the several types of hydrologic processes, such as energy, drought, moisture fluxes and the schedule of irrigation. By using spectral data, it is possible to predict different soil features. The main objective is to predict the major six soil properties are organic carbon content (OC), clay particle size fraction (%), cation exchange capacity (cmol+ kg-1), (%), pH measured in water, sand particle size fraction and total nitrogen content (N, g kg-1). The use of CNN here is, to take the data in terms of multiple arrays.

Hyperspectral data is one of the important methods for soil analysis where the classification is performed in pixel level. It consists of many spectral channels which results in higher number of dimensionalities with large spatial variability[x]. The CNN has the capability of learning the correlation that exist between the hyperspectral data and can be mapped with the soil features.

5. Proposed System

In this research work, hybrid Particle Swarm Optimization (PSO) and Convolutional Neural Network (CNN) is designed to extract the features and classification. This Enhanced PSO and CNN (EPSO_CNN) scheme is discussed below. The architecture diagram is given in Fig 4.

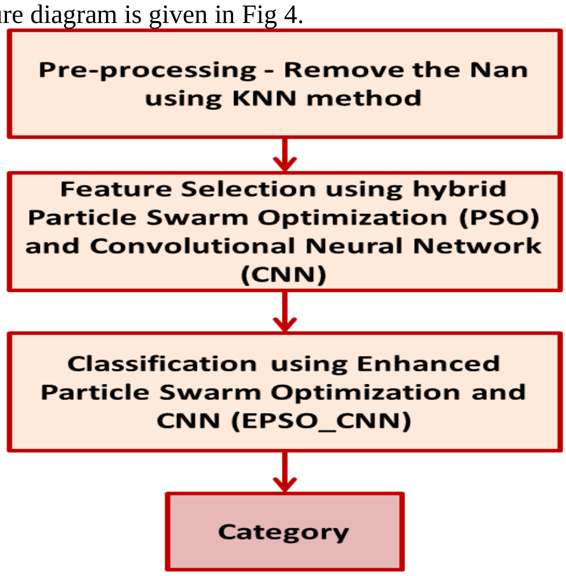

Fig 4. Overall Architecture

5.1. Classification using Enhanced Particle Swarm Optimization and CNN (EPSO_CNN)

Enhanced PSO model with optimal CNN is proposed for classification. Every distinct framework in the search space is accepted as a particle in nD (n-Dimensional) space. Here n signifies the number of individual chunks. Instead of utilizing static acceleration parameters, adaptive search factors centred on sequential and non-sequential functions are proposed. In order to generate the coefficients, nearly four innovative approaches have been used: (1) sequential parameters with an equivalent crossover in the Centre, (2) a cosine functions with an equivalent crossover in the Centre, (3) a cosine functions with the future crossover, and (4) a cosine functions with no crossover. First step is to initialize a populace of m distinct particles as arbitrary points in the search space and every element is taken from a identical distribution:

$$Y=U(p_l,p_u) \tag{3}$$

'pl' and 'pu' indicates the min and max limits of the search space, respectively. Also modify the paces of every parameter:

$$S_i=U(s_{min},s_{max})$$

Where,

$$s_{min}=s_{max}=\lambda(p_u-p_l)-s_{max} \tag{4}$$

After the initiation of a swarm, the procedure of optimization could start. Based on the approaches chosen, the weight and acceleration parameters could be updated. The below steps would be followed to handle every distinct coefficient Si. Initially, the speed rate of every coefficient is reorganized with the help of its load value and the space the particles. By utilizing this speed value, the updated place of the particle is determined. The fitness of the coefficient is estimated by this objective function. Fitness score of Si is equated with the former personal (Pi) position and global best solution, respectively.

The former position is revised as,

$$PBi=\begin{cases} S_i & \text{if } (S_i) < f(PB)_i \\ PB_i & \text{Otherwise} \end{cases} \quad (5)$$

It is highly important to get rid of unwanted parameters; it is decided to save the fitness coefficients for every evaluation for compare its score values. Instead of evaluating the fitness for every distinct particle, this could be a better strategy. This process gets repeated to certain number of iterations till it covers all the coefficients in the search space. When the iterations are complete, the final outcome aims to reduce the objective function. The fitness evaluation is given as follows

Input:
No. of layers-n,
Growing rate -g,
Training set d ; (Small subset)
1: accb; epochb; epoch; acc1 ←0, 0, 0, 0;
2: dtrain; dtest split Randomly d into 80% as training data part dtrain and 20% test data part dtest;
3: block← Construct the dense block based on n and g;
4: calculate: while acc1>= accb or epoch -epochb< 5 do
5: Use Adam optimization to train the block on dtrain for one epoch;
6: acc1 ← Evaluate block on dtest;
7: if acc1>accb then
8: accb; epochb ← epoch;acc1;
9: end if
10: epoch++;
11: end while
12: return accb
The parameters for this proposed method is given in the Table 1.

Table 1: EPSO_CNN Default Parameter

Parameter	Range
EPSCOCNN default hyper parameters	
Number of layers ά l	[6,32]
Growth rate ά g	[12,32]
PSO parameters	
Inertia weight w	0.7298
Acceleration coefficient c1	1.49618
Acceleration coefficient c2	1.49618
Batch size	20
No. of generations	20

The proposed EPSO CNN model with adaptive acceleration coefficients is given below
Function PSO(S)
f←Objective function ()
m←population
n←dimensions
pl← 0
pu← 1
Sm,n←U(pl,pu)
PB←S
G←Xargmin(f(S))
Vmax←λ(pu−pl)
Vmin← -Vmax
V←U(Vmin,Vmax)
mode←[`fixed`|`linear`|`cosine`]
for t←0,……,T do
lr←SetLearningRate (lr,t)
w,c1,c2 ←SetSearchWeights(T,t,mode)
for i←0,…..m do
Vi←wVi +c1r1(PBi-Si)+ c2r2(G-Si)
Si←Si+Vi

If f(Si) <f(PBi) then
PBi←Si
If f(PBi) <f(G) then
G←PBi

6. Results And Discussion

The LUCAS dataset used for the evaluation of the proposed method which consists of 84 attributes. Nearly, 22,000 data objects have been taken that includes the notable properties such as proportion of moisture content in soil, proportion of its chemical properties. In proposed method predict the most related parameter is Coarse, clay, Silt, clay, pH(CaCl2),pH(H2O),EC,OC,CaCO3,P,N,K addition to all these, Lucas also covers the reflectance spectra that ranges from 400 nm to 2500 nm, referred to as hyperspectral data. The spectral resolution of the practical sensor is 0.5 nm.

.Figure 5-8 shows the Accuracy, Precision, Recall and Time Period of CNN and EPSO_CNN.

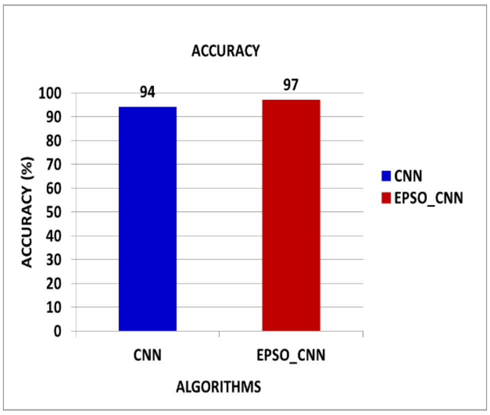

Fig 5: Accuracy

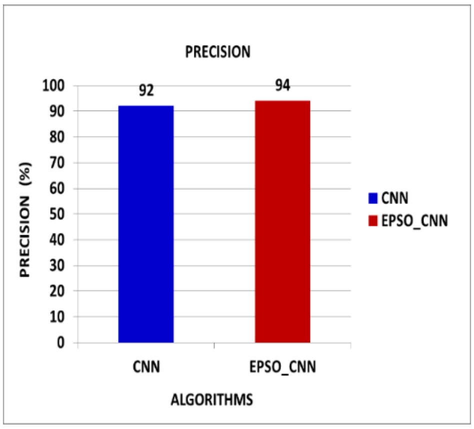

Fig 6: Precision

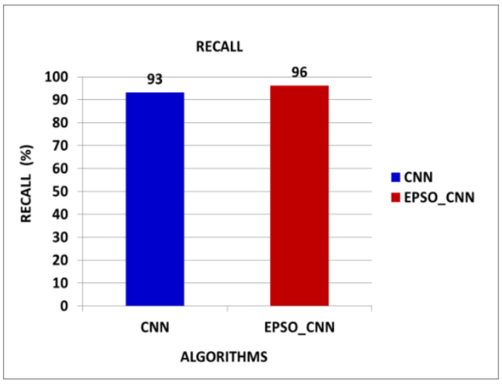

Fig 7: Recall

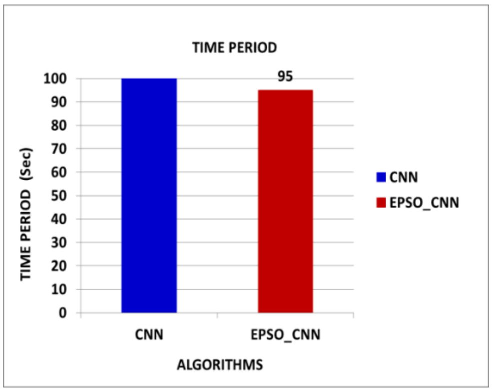

Fig 8: Time Period

7. Conclusion

Soil texture is one of the key parameters in agricultural production, and its exact forecast is significant for the normal use and management of water resources. In this work EPSO CNN is adopted to foresee the diverse soil properties from hyperspectral data. CNN is used for building the neural network model where pre-processing is done by the network and performs the regression prediction of six soil properties. The LUCAS dataset which consists of physical properties and continuous reflectance spectra, referred to as hyperspectral data are used to evaluate the model performance. The automatic feature learning by EPSO_CNN increases the prediction accuracy of the proposed methodology. As a future work this work can be extended to find the other soil properties which helps in agriculture production.

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