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Crop Recommendation for Better Crop Yield for Precision Agriculture Using Ant Colony Optimization with Deep Learning Method

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Abstract: PAG (Precision Agriculture) is managing farms with the use of IT (Information Technology). PAG can monitor and administer required health to crops and soil thus helping productivity. Agriculturists use traditional recommender systems for farming. This research work proposes a DLT (Deep Learning Technique) recommender system for crops. This study uses gathered historical data of crops and climate for its recommendations. This work's proposed scheme is a hybrid scheme that uses ACOs (Ant Colony Optimizations) for optimizing DCNN (Deep convolution Neural Networks) and LSTM (Long Short Term Memory) network inputs called (ACO-IDCNN-LSTM) for crop predictions. DCNNs generally achieve high levels of accuracy but involve computational complexities based on the count of layer used in processing. DCNNs adding of weights in its nodes are a major part of complexity increments and hence this work adjusts these weights in training to reduce complex processing. ACOs optimize hyper parameters in training to help reduce complexity in weights and for DCNN predictions on crops. The recommender system produced satisfactory results.

Keywords: Crop Recommendation, Deep learning, Deep Convolutional neural network, Long short-term memory, Crop Yield and Precision Agriculture

1.Introduction

India has been practising natural agriculture for centuries which has been evolving where modern techniques are applied due to globalization. This has also induced ill-health of crops in India [1]. Many systems have proposed farming methods and use of fertilizers based on the land used for farming. Thus, new techniques and technologies like PAG have been proposed for overcoming ill-health of crops. PAG is a "site-specific" farming technology and a recommender system. It has several advantages in terms of farming outputs and crop decisions, but challenges also exist in PAG [2]. PAG recommendations for crops are based on many parameters. PAG aims to identify site-specific parameters in an attempt to resolve issues in crop selections.

Though site-specific methods have enhanced productivity, yet their results need to be supervised as not all PAGs provide accurate results. Agricultural outputs need to be precise as imprecision lead to financial and material losses. Studies have been attempting to improve the efficiency and accuracy of crop predictions [3].Thus this work aims to assess crop yields based on datasets encompassing important parameters including historical data about temperature, humidity, rainfall, and prior crop yields. This work's contribution is detailed below:

- Initially, the mass of historical crop production data and climate data is gathered and is made to data pre-processing work.

- Then the prediction model using Improved Deep Convolutional Neural Network with ACO is utilized for crop recommendation and named as ACO-IDCNN. ACO is adopted to determine the optimal architecture of IDCNN sub-models for each group of datasets.

The remainder of this paper is organized as follows. Section 2 describes related work on crop recommendation for crop yield. Section 3 provides a detailed description of the proposed hybrid deep learning model for yield prediction. Section 4 presents the results of the proposed model and compared with existing model. Finally, conclude the paper in section 5 with future work.

2.Related Work

The study in [4] used CNNs (Convolution Neural Networks) for image classifications and built a crop yield prediction model using UAV's RGB and NDVI data. A multi-level DLT using RNNs (Recurrent Neural Networks) and CNNs was proposed in [5]. The study extracted spatial and temporal features from inputs which included sensed time-series data and properties of soils for modelling their yield outputs. Experimental results of the study proved its effectiveness over other methods. The model was found useful to predicting soybean and winter wheat yields with its decisions.

MLPs (Multi-Layer Perceptrons) were used in [6] for forecasting wheat crop yields and data mining was used to predict district level outcomes. The study used a modified activation function in MLPs neural network. The study used multiple weather parameter datasets with random weights and bias values for its crop yield judgments. CNNs were also used in [7] where related spatial parameters of different features were studied and combined to model nutrient seed management for better yields. Corn field experimental results were used to form the dataset for CNN training and predictions.

The study in [8] proposed a DRQN (Deep Recurrent Q-Network) model with Q-Learning for crop yield forecasts. RNNs in the study used sequentially stacked layers where the Q- learning network constructed crop yield predictions based on given inputs. A linear layer was used to map RNN outputs to Q-values. The study's reinforcement learning incorporated a threshold value on a combination of parametric features which were then output to predict crop yields.

DCNNs predicted rice yields in [9]. The scheme estimated ripening stage of rice where CNNs learnt significant spatial crop yield features from high intensity rice crop RGB images. The study in [10] used DLTs to estimate crop yields using field images as inputs. The images captured in half hour time slots by agricultural camera stations were utilized by DLTs for approximation on crop yields.

RF (Random Forest) and MLPs were used in [11]. The scheme trained on data collected from Karnataka's four major crops. The inputs included Weather and prior yield data of 30 districts and encompassing minimum/maximum/average pressure, temperature and moisture values. The study [12] predicted rice yields end-to-end using their scheme called BBI which combined two BPNNs (Back-Propagation Neural Networks) with an IndRNN (Independent RNNs). The study aiming to overcome existing challenges, pre-processed meteorological data and fed into the BPNN/IndRNN framework for extracting intricate spatial and temporal features. BPNNs then combine the two types of features to assess relationships between features and thus predict rice yields in summer and winter seasons.
Thus, it is evident from literature that DLTs are can be used for efficient yield estimation of crops.

3.Proposed Methodology

NNs (Neural Networks) identify primary predictors while CNNs can adapt themselves to crop feature extractions using their hierarchical representative architecture. Using CNNs however, needs experience and prior knowledge posing limitations in its generalization capabilities. Hence, CNNs using ACO has been proposed as a solution to examine crop yield predictions. This scheme gathers historical crop and climate data which is pre-processed and used by the proposed scheme to recommend decisions on crops. ACO's part in the scheme is determining optimal architecture for IDNN-LSTM sub-models created for datasets. The hyper-parameters of IDCNN-LSTM is optimized for refining their cellular structure. The proposed methodology of ACO-IDCNN-LSTM is depicted in Figure 1.

Fig.1. ACO-IDCNN-LSTM based crop recommendation

Dataset collection

The study's data was obtained from two main sources. Climate data was obtained from the Indian water portal. Org (https://www.timeanddate.com/weather/india/new-delhi/historic) while crop yields data was collected from faostat3.fao.org (https://data.world/thatzprem/agriculture-india). The collected climate information had details on recorded rainfall of specific regions while crop yields historical (Monthly/Yearly) data was in a CSV (Comma Separated Values) format. Historical data of six years was taken for this study.

Data pre-processing

Pre-processing is an important step in this study as less important data is a part of climate dataset features. Unimportant information is ignored as a part of pre-processing and only important information is considered. Multiple types of historical data are thus pre-processed and combined. Climate data features included every month's Wind Pressure, Maximum/Minimum/Average Temperatures, Dew, Humidity and Wind Pressure. Average Temperature is the generic temperature found in an area for a month, while Maximum temperature depicts the highest recorded temperature in an area and Minimum temperature is the least temperature value in the area. The dataset was split into a sixty-forty combinations where 60% was used in training while testing was done with 40% of data.

Proposed Classification method for crop yield prediction and recommendation

This section describes segments of the proposed study of crop yield recommendations. .

DCNN-LSTM model: DLTs compute feature representations while training from datasets where CNNs capture features from consecutive datasets, while LSTM assesses temporal their information. These feature vectors processed by the LSTM layer is then fed into Softmax classifier layer depicted as a probabilistic function [13] is depicted in the following Equation:

$$T(y^l = n|x^i; W) = \frac{1}{\sum_{j=1}^{n} e^{W_t^j x^i}} \begin{bmatrix} e^{W_1^j x^i} \\ e^{W_2^j x^i} \\ \vdots \\ e^{W_n^j x^i} \end{bmatrix}$$

Where, T - i^{th} training sample in training samples (m) and j^{th} class in classes (n), $W_t^j x^i$ – input weights of Softmax layers. The implementation steps of the model is detailed below:

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Stage 1: The pre-processed dataset with only required information forms the input of IDCNN. The convolution layers calculate outputs connected to a corresponding local region in each dataset using a dot product of weights and these regions. This results in an n-dimensional fully connected feature vector layer.

Stage 2: The n-dimensional feature vectors produced in stage 1 are fed into LSTM at stage 2, which then trains for extracting sequential temporal features. This results in LSTM's sequential feature generations.

Stage 3: Stage two's temporal dataset is processed by the Softmax classifier to generate probabilities for predictions. This processing on time series data helps in representing crop yields that can be recommended. Figure 2 depicts the overall flow of the proposed recommender system for crop yield predictions.

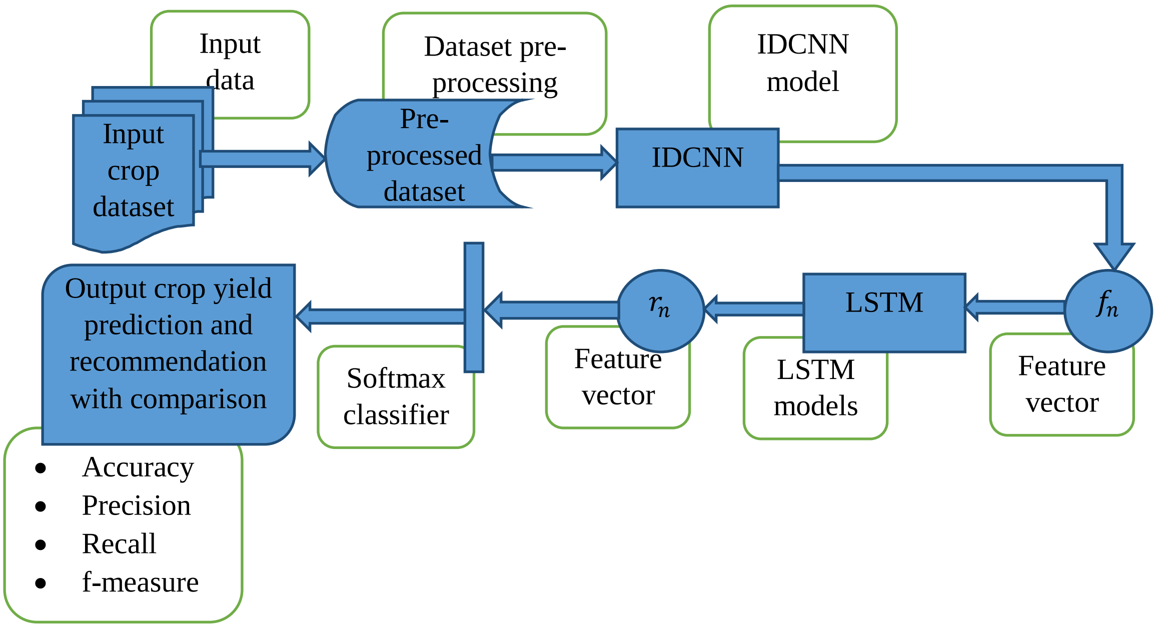

Fig. 2. Method of IDCNN-LSTM models-based crop yield prediction and recommendation

IDCNN: Two DCNN parameters are adjusted while training. The first parameter is weights of the fully connected layer while the second is the filter coefficients of convolution layers. The modifications of parameters are executed for enhancing efficiency and improving accuracy of predictions. This works trains on the data using SGDA (Stochastic Gradient Descent Algorithm). Moreover, this work adjusts convolution layer's parameters only and this is done to estimate weights without recursions. The proposed steps of IDCNN are detailed in the following steps:

Phase 1: The convolution operation of random initialization for filter coefficients on inputs are computed using the following Equation:

$$y(m,n) = \sum_{i,j=1,2,\ldots,k} x(i,j) * w(i,j)$$

Where, y – resultant matrix, x - input matrix, and dw - weight. A value for 4 is used for k, m - input data row size/ weight of row, n - input data column size/ Column weight. This process is reiterated for all 3 convolution layers where ReLu activation function is executed after each convolution.

Phase 2: Max pool layer down samples convolution layer outputs in this phase.

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Phase 3: Multi-column outputs get converted into single column data and fed into the fully connected layer of the network in phase 3.

Phase 4: Conventional DCNNs assume convergence when value higher than 0 is achieved. Phase 4 fixes the convergence value of this study as 0.01.

Phase 5: Phase 5 computes the cross entropy values using the following Equation:

$$CE = -\frac{1}{N}\sum_{n=1}^{N}[t_n \log(y_n)]$$

Where, t- fully connected network's target, $y = \frac{1}{1+e^{-out_{tot}}}$, $tot_{out} = \sum XW$ - output layer's total, W- hidden layer's weight matrix and X - inputs

Phase 6: Phase 6 estimatesoutput layer's value y.

Phase 7: This phaseadjust weights output and hidden layers using assuming ΔW_{jk} is the difference in weights and using following Equations:.

$$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk}$$

$$\Delta W_{jk} = \partial\delta_k tot_{out}, \forall\partial = 0.6 \rightarrow learning\ rate$$

$$\delta_k = (t_k - y_k)f(tot_{hid})$$

Difference between any two weight must be a minimum for convergence as it cannot be 0, the ideal condition. The estimated output value hid_{tot} is used to estimated the NET value of output layer and its weights are estimated using Equation (5).

Phase 8: The hidden layer's total value is estimated using the following Equation

$$\mathbb{W}_{ij}(new) = \mathbb{W}_{ij}(old) + \Delta\mathbb{W}_{ij}$$

Where, $\mathbb{W}$ – matrix of weights between input and hidden layers

$$\Delta\mathbb{W}_{ij} = \partial\delta_j tot_{hid}, \forall\partial = 0.6$$

$$\delta_j = \delta_j f(tot_{hid})$$

$$tot_{hid} = \sum X\mathbb{W}$$

This phase signifies training steps deviates from the output layer.

Phase 9: This phase estimates weights as input and total value are known.

Phase 10: This phase **a**lters the weights of three convolution layers as per phase 7 and 8 directions. Chain rule differentiation is method is adopted while training. Thus, weight estimations are done without iterations. The phase's mathematical estimation helps achieve desired objectives in a single iteration, greatly reducing computational complexity and eliminating adjustments of convolution layer filter coefficients values. This also results in avoiding back propagation and re-trains in this IDCNN-LSTM model.

LSTM model: LSTMs can process sequential input data attribute sequences $\{x_1, x_2, \ldots, x_N\}$ where N is the count of attributes. RNNs learn complex temporal information by mapping input sequences to

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hidden and its output sequernces, but have issues in gradients and vanishing of data in long sequences [45]. LSTMs use memory units which helps up-date hidden states with new information. This helps LSTMs while learning long-range dependencies and control information flow levels from a cell. LSTM models use three gates namely inputs, forget and outputs to control the afore said flow of information also shown in Figure 2. Each memory cell has a sigmoid neural net layer and a multiplication operator. sigmoid layer outputs range in the interval [0,1] specifying the progress of each cell. For any time step t, a cell's state is updated using the following Equations:

$$\begin{cases} i_t = A(W_{xi}x_t + \mathbb{W}_{hi}h_{t-1} + b_t) \\ f_t = A\left(W_{xf}x_t + \mathbb{W}_{hf}h_{t-1} + b_f\right) \\ o_t = A(W_{xo}x_t + \mathbb{W}_{ho}h_{t-1} + b_o) \\ g_t = tanh(W_{xc}x_t + \mathbb{W}_{hc}h_{t-1} + b_c) \\ c_t = f_t \otimes c_{t-1} + i_t \otimes g_t \\ h_t = o_t \tanh \otimes (c_t) \end{cases}$$

Where, A – sigmoid activate function defined as $A(x) = \left(1 + e^{(-x)}\right)^{-1}, i_t$,- Input gate, f_t – forget gate, o_t - output gate ,c_t - cell at time t. h_t,b_t,b_f,b_o andb_c - offset vectors, W_{xi},W_{xf},W_{xo},W_{xc},$\mathbb{W}_{hi}$,$\mathbb{W}_{hf}$,$\mathbb{W}_{ho}$ and$\mathbb{W}_{hc}$ - coefficient matrix. This study's proposed hybrid model as shown in Figure 1 is a 2 layer LSTM networks for learning from crop dataset features generated by final pooling layer. As per Figure 1, if $\{f_1, f_2, \dots, f_n\}$ represent n features for$n$attributes in dataset then LSTM layers output the sequence $\{r_1, r_2, \dots, r_n\}$ which is averaged for the total time period to result in Feature vectors, FV, depicted by the following equation:

$$FV = \frac{r_1, r_2, \dots, r_n}{n}$$

FV becomes the input of Softmax layer to identify unwanted features in the input dataset. F stands for mean pooling feature vector using weights $\{w_1, w_2, \dots, w_n\}$learned by LSTM layers and W represents the parameter vector of the final logistic regression layer.

Hybrid ACO-IDCNN-LSTM: This proposed hybrid technique aims at developing an automatic optimizer based technique that is efficient for classifying tasks.

DCNN Hyper-parameters: The hyper-parameters considered include initial weights, learning rates, activation functions, epochs and iterations. In addition, the convolution layer's counts, count of kernels and their sizes are also considered as hyper-parameters in this study.

LSTM Hyper-parameters: LSTM hyper-parameters include count of nodes in the hidden layer and count of batches as hidden layer nodes in LSTM directly influence learning results by their non-linear mapping ability and similar to FFNNs (Feed Forward Neural Networks). Selected batch sizes influence computational costs and learning accuracy gradients in data updates.

ACO: This algorithm, modelled on Ant's behaviour is an excellent optimization algorithm. Ants constantly search for food in a random manner. On finding food they distinctly mark their search paths with pheromone [14]. This amount of pheromone is based on the quality and quantity of the food that is found. Higher concentration of pheromones implies abundance of high-quality food paths. Other ants find this food based on pheromone concentrations and bring back food to their nests. Thus, pheromone concentrations define shortest/ optimal paths. This concentration also defines the population needed for bringing food. Ants exercise a global search state and if it is the final state, the ants deposit pheromone in the place signalling other ants to follow. Thus, on finding a final state, their activities aim dispersion of pheromones.

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ACO-IDCNN-LSTM: As explained before accuracy of the proposed IDCNN-LSTM model is based on hyper-parameters. The ACO algorithm optimizes hyper-parameters and hence called ACO-IDCNN-LSTM model. The proposed model is applied for estimations of crop yield and thus is a recommender system for crop yields. The hyper-parameters of IDCNN-LSTM are altered by ACO's global to reach optimality and enhanced performance. The fitness for ant's positions in this study has been evaluated using f-measure as the objective function. Figure 4 depicts the search and optimization processes of this study which recommends crop yields with its accurate predictions.

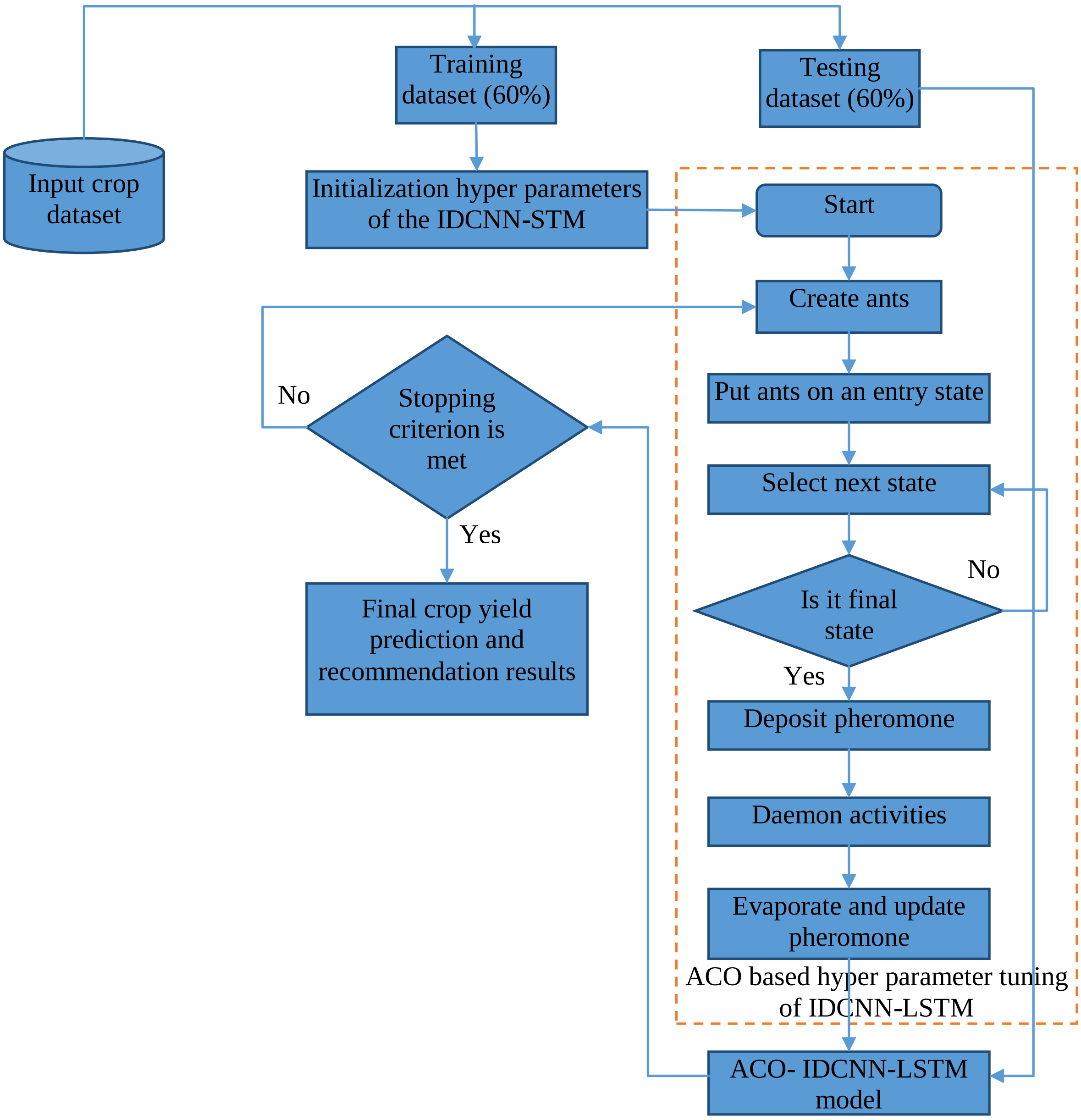

Fig. 4. Flowchart of the ant colony and optimization of IDCNN-LSTM

4.Experimental Results and Discussion

This section provides the performance evaluation of proposed research methodology, here the proposed research method ACO-IDCNN-LSTM for crop recommendation system is compared with existing research techniques namely DTs (Decision Trees), KNNs (K-Nearest Neighbours), RF (Random Forest), Neu-Net and PSO-MDNN using the metrics of accuracy, precision, recall and f-measure. The proposed study classifies a sample as positive when correctly classified TP (True

Positive) and FN (false Negative) if classified as negative. TN (True Negative) stands for negative sample classified as negative while the vice versa is FP (False Positive).

Precision: Represents correctly classified positive crops to the total positives in the dataset, given by the following Equation:

$$Precision = \frac{TP}{FP + TP}$$

Recall: Represents correctly classified crops to total count of positive samples given by the following Equation:

$$Recall = \frac{TP}{TP + FN}$$

F-measure: Also known as F_1-score is the harmonic mean of precision and recall given by:

$$F - measure = \frac{2 * (Recall\ *\ Precision)}{(Recall\ +\ Precision)}$$

Accuracy: Is defined as the ratio between correctly classified crop samples to total crop samples and given as :follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Table: 1. Performance comparison results

Metrics	Dec-Tree	KNN	R-Forest	Neu-Net	PSO-MDNN	Proposed ACO-IDCNN-LSTM
Accuracy	90.5743	88.1404	91.7180	92.9512	94.9842	95.1833
Precision	86.2837	80.7650	85.0594	80.1179	90.3240	90.8804
Recall	90.0606	88.4942	91.7944	91.4750	95.2698	95.6390
F-measure	88.1317	84.4531	88.2986	85.4206	92.7310	93.1990
Error rate	9.4257	11.8596	8.2820	7.0488	5.0158	4.8167

4.1. Precision Rate comparison

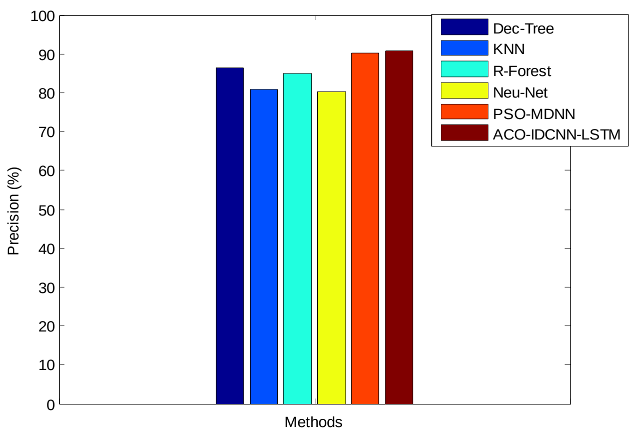

Fig.5 Result of Precision Rate

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Figure 5 depicts comparative performances of the benchmarked methods namely DT, KNN, RF, NN and PSO-MDNN with the proposed ACO-IDCNN-LSTM in terms of precision, the graph explains that the precision comparison for the number of datasets in specified datasets. Precision values increased when the datasets increased. Results show that the proposed ACO-IDCNN-LSTM has higher precision values of 95.1833 % when compared to Dec-Tree, KNN, R-Forest, Neu-Net and PSO-MDNN which scored 86.2837%, 80.7650%, 85.0594%, 80.1179% and 90.3240% respectively. ACO-IDCNN-LSTM method overcomes limitations of traditional models for producing enhanced crop yield accuracies as traditional model's assumptions result in wide deviations in actual production and hypothetical values.

4.2. Recall Rate comparison

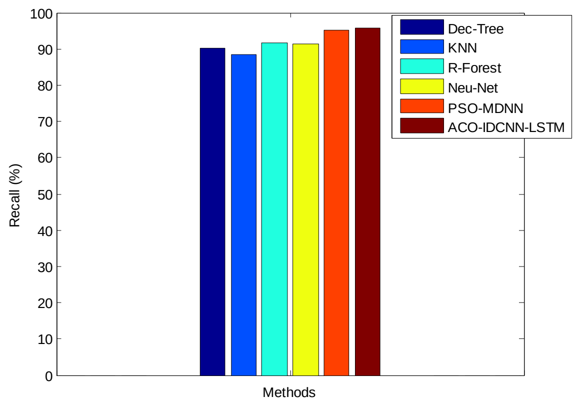

Fig.6. Result of Recall Rate

Figure 6 depicts comparative performances of the benchmarked methods namely DT, KNN, RF, NN and PSO-MDNN with the proposed ACO-IDCNN-LSTM in terms of Recall, the graph explains that the Recall comparison for the number of datasets in specified datasets. Recall values increased when the datasets increased. Results show that the proposed ACO-IDCNN-LSTM has higher Recall values of 95.1833 % when compared to Dec-Tree, KNN, R-Forest, Neu-Net and PSO-MDNN which scored 90.0606%, 88.4942%, 91.7944%, 91.4750% and 95.2698% respectively. ACO-IDCNN-LSTM method overcomes limitations of traditional models for producing enhanced crop yield accuracies as traditional model's assumptions result in wide deviations in actual production and hypothetical values. The proposed IDCNN-LSTM is beneficial for neuro evolution as it is scalable and parallizable. It can be used for training any NNs and thus improves its recall values.

4.3. F-measure Rate comparison

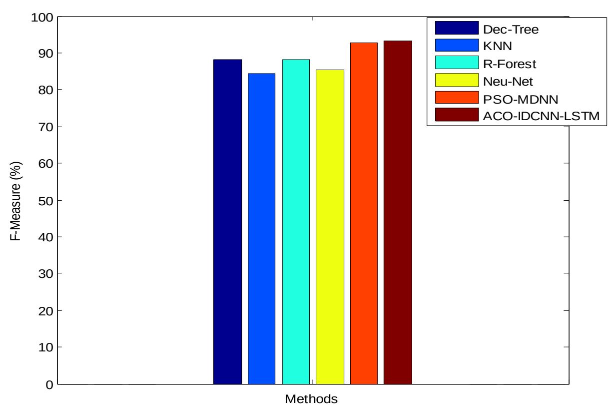

Fig.7. Result of F-measure Rate

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Figure 7 depicts comparative performances of the benchmarked methods namely DT, KNN, RF, NN and PSO-MDNN with the proposed ACO-IDCNN-LSTM in terms of f-measure, the graph explains that the f-measure comparison for the number of datasets in specified datasets. f-measure values increased when the datasets increased. Results show that the proposed ACO-IDCNN-LSTM has higher f-measure values of 93.1990% when compared to Dec-Tree, KNN, R-Forest, Neu-Net and PSO-MDNN which scored 88.1317%, 84.4531%, 88.2986%, 85.4206% and 92.7310% respectively. ACO-IDCNN-LSTM method overcomes limitations of traditional models for producing enhanced crop yield accuracies as traditional model's assumptions result in wide deviations in actual production and hypothetical values.

4.4. Accuracy comparison

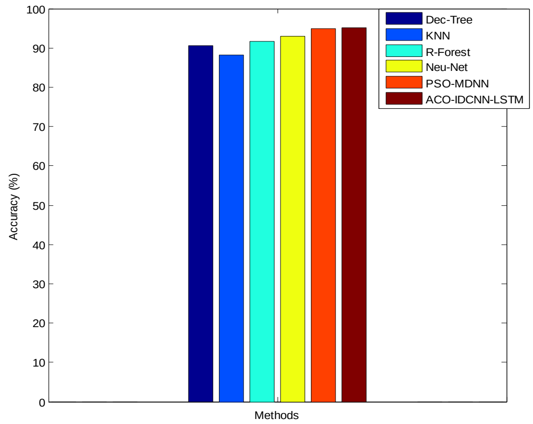

Figure.8. Result of Accuracy

Figure 8 depicts comparative performances of the benchmarked methods namely DT, KNN, RF, NN and PSO-MDNN with the proposed ACO-IDCNN-LSTM in terms of accuracy, the graph explains that the accuracy comparison for the number of datasets in specified datasets. Accuracy values increased when the datasets increased. Results show that the proposed ACO-IDCNN-LSTM has higher accuracy values of 95.1833% when compared to Dec-Tree, KNN, R-Forest, Neu-Net and PSO-MDNN which scored 90.5743%, 88.1404%, 91.7180%, 92.9512% and 94.9842% respectively. ACO-IDCNN-LSTM combining the advantages of IDCNN which extracts features and LSTM which finds interdependence of data and its relevancy automatically thus improving accuracy of crop yield predictions.

Error rate

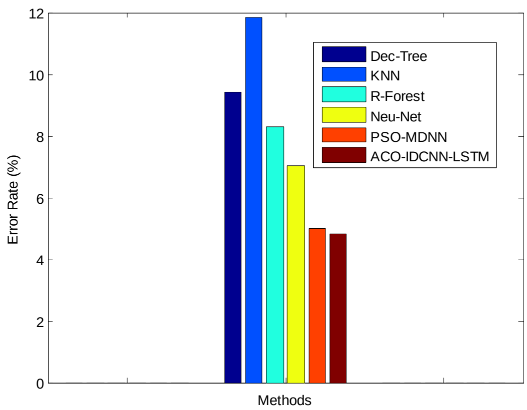

Figure.9. Result of Error rate

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Figure 9 depicts comparative performances of the benchmarked methods namely DT, KNN, RF, NN and PSO-MDNN with the proposed ACO-IDCNN-LSTM in terms of error rates, the graph explains that the error rate comparison for the number of datasets in specified datasets. error rates values decrease when the datasets increased. Results show that the proposed ACO-IDCNN-LSTM has lower error rate values of 4.8167% when compared to Dec-Tree, KNN, R-Forest, Neu-Net and PSO-MDNN which scored 9.4257%, 11.8596%, 8.2820%, 7.0488% and 5.0158% respectively. ACO-IDCNN-LSTM method overcomes limitations of traditional models for producing enhanced crop yield accuracies as traditional model's assumptions result in wide deviations in actual production and hypothetical values.

5.Conclusion and future work

In this work, a novel ACO-IDCNN-LSTM scheme combining IDCNN and LSTM with ACO was proposed for the prediction of crop yield and recommendation. Also, a series of hyperparametersof IDCNN-LSTM were selected and optimized using ACO. Experiments were conducted to evaluate the proposed scheme with traditional methods such as Dec-Tree, KNN, R-Forest, Neu-Net PSO-MDNN being baseline models. The hyper parameters of all the methods were optimized to obtain the best results. Due to the capability of extracting features on dataset and different time steps, better efficiency and accuracy were obtained by ACO-IDCNN-LSTM than baseline models. This study provides a potential direction of deep learning methods by integrating different architectures for individual advantages such that reduces the computational complexity to high extent that would be a beneficial contribution to the accurate and stable prediction of crop recommendation. The proposed ACO-IDCNN-LSTM recommender model is found to be effective in recommending a suitable crop. Future work will focus on auto encoder based deep learning mechanism to obtain better results and explore the application of the proposed scheme on crop dataset.

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