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Artificial Bee Colony with Deep Belief Network based Crop Yield Estimation for Precision Agriculture

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Abstract

Crop yield prediction is one of the major problems encountered in precision agriculture, and several techniques were modelled and authenticated till now. This problem demands the utility of numerous data as crop yield relies upon distinct elements namely seed variety, climate, weather, use of fertilizer, and soil. Machine learning (ML) is a significant decision support tool for crop yield prediction, which includes taking decisions regarding the crop types that will be suitable for a particular growing season. Numerous ML techniques were enforced to support the study on crop yield prediction. This article introduces an Artificial Bee Colony with Deep Belief Network based Crop Yield Estimation (ABCDBN-CYE) for Precision Agriculture. The intention of the ABCDBN-CYE technique is the estimation of crop productivity in the agricultural sector. The presented ABCDBN-CYE technique operates in two stages such as yield estimation and parameter tuning. At the preliminary stage, the ABCDBN-CYE technique makes use of DBN model to estimate the crop yield. Next, in the second stage, the ABC algorithm is exploited as a hyperparameter tuning approach to improve the estimation efficiency of the DBN model. To demonstrate the improved prediction performance of the ABCDBN-CYE technique, a widespread experimental analysis is performed. The comparison study showed the enhancements of the ABCDBN-CYE technique over other ones.

Keywords: Precision agriculture; Prediction model; Crop yield; Deep learning; Metaheuristics

1. Introduction

Crop yield prediction had a major contribution to global food production. Policymakers depend on precise forecasts to do appropriate export and import choices to reinforce nationwide food safety [1]. Seed corporations have to forecast the presentations of novel crosses in several situations for breeding healthier varieties. Farmers and growers also had an advantage from harvest forecasts to make conversant organization and monetary choices [2]. Yet, crop yield prediction is very difficult because of several composite issues. For instance, genetic constitution data was generally signified by high-dimensional indicator information,

comprising numerous makers for apiece plants [3]. The belongings of the hereditary indicators should be projected, which might be focused on connections by manifold ecological situations and field administration activities [4].

Machine learning (ML) methods were utilized in numerous arenas, extending from superstores to assess the customer's behavior to the forecast buyers' telephone usage. ML was also present cast-off in farming for some years [5]. Crop yield estimation is one of the inspiring problems in agriculture, and several copies were projected and authenticated till now. This issue needs the usage of numerous datasets as crop yield rest on numerous dissimilar issues like seed variety, climate, use of fertilizer, weather, and soil [6]. This designates that crop yield prediction is not a trivial task; in its place, it contains numerous complex steps. Currently, crop yield predictive replicas can guesstimate the real yield sensibly, then an improved act in yield prediction was still necessary [7]. Many investigations are currently showing comparatively progressive possible in the usage of ML procedures than outdated statistics.

ML was a part of artificial intelligence (AI) in which mainframes are trained and deprived of convinced programming. Such methods overwhelmed agronomic constructions, which are either linear or non-linear, by guaranteeing a distinguished forecast volume [8]. The policies can be found in the learning technique in the ML agricultural scheme. Such approaches include a specific task over the training with the trained data. The classical believes that the data must be verified after positively concluding the trained stage. ML, which is a division of AI concentrating on knowledge, was applied method that can deliver improved yield estimation related to several features [9]. ML can control patterns and associations and learn information from data. The mock-ups should be skilled by means of data in which the outcomes remain signified related to past knowledge. The prognostic method was constructed with numerous features, and as such, structures of the replicas were strongminded by means of historic information throughout the training stage [10].

This article introduces an Artificial Bee Colony with Deep Belief Network based Crop Yield Estimation (ABCDBN-CYE) for Precision Agriculture. The intention of the ABCDBN-CYE technique is the estimation of crop productivity in the agricultural sector. The presented ABCDBN-CYE technique operates in two stages such as yield estimation and parameter tuning. At the preliminary stage, the ABCDBN-CYE technique makes use of the DBN model to estimate the crop yield. Next, in the second stage, the ABC algorithm is exploited as a hyperparameter tuning approach to improve the estimation efficiency of the DBN model. To demonstrate the improved prediction performance of the ABCDBN-CYE technique, a widespread experimental analysis is performed.

2. Related works

Kaab et al. [11] purposes for utilizing 2 AI techniques like ANNs and ANFIS approach, to predict lifespan environmental effects and resultant energy of sugarcane productions from planted or ratoon farms. According to the structure for graving method, life cycle assessment (LCA) was utilized for evaluating environmental effects and study environmental influence classifications of sugarcane manufacture. Kang et al. [12] examine a detailed valuation of county-level maize yield predictive from U.S. Midwest utilizing 6 statistical or ML

approaches (RF, Lasso, LSTM, SVR, CNN, and XGBoost) and a wide group of environmental variables developed in satellite surveillances, soil map, climate information, crop progress report, and land surface model outcomes.

Bhanumathi et al. [13] prepare the data with several appropriate ML techniques to make a system. This technique goes along with a method that is specific and precise in predictive crop yield and distributes the user with suitable commendations on needed fertilizer ratio dependent upon soil and atmospheric variables of lands that improve for higher the crop yield and enhance farmer profits. Khaki et al. [14] introduce a DL infrastructure utilizing CNNs and RNNs to crop yield predictive dependent upon environmental facts and management performs. The presented CNN-RNN technique, together with another famous approaches like deep fully connected neural networks (DFNN), RF, and LASSO are utilized for forecasting soybean and corn harvest beyond the whole Corn Belt. In [15], an entire development period is separated as to 3 parts. Utilizing the main barley manufacturing regions in Iran, the efficiency of the presented technique is estimated. During the primary stage, this method to integrate remote sensing data, field data, and meteorological data is arranged. The outcomes achieved illustrated that betwixt the 4 ML approaches executed, the gaussian procedure regression technique carried out optimum.

3. The Proposed Model

In this article, a new ABCDBN-CYE technique has been developed to estimate crop yield. The intention of the ABCDBN-CYE technique lies in the estimation of crop productivity in the agricultural sector. The presented ABCDBN-CYE technique operates in two stages such as DBN yield estimation and ABC based parameter tuning.

3.1. DBN based Yield Prediction

Firstly, the ABCDBN-CYE technique makes use of DBN model to estimate the crop yield. DBN is the DL algorithm which surpasses classification ability and feature extraction [16]. It is a probability generative method which comprises more than one Restricted Boltzmann Machine (RBM) stack. Also, the DBN method comprises a classification (afterward the final RBM) for accomplishing the classifier process.

The RBM is an energy based 2 stage model primarily comprised of visible and hidden layers. They are interconnected with weighting factors. The subsequent function gives joint likelihood distribution and density.

$$E(v,h) = -\sum_{j=1}^{m} a_j\, v_j - \sum_{i=1}^{n} b_i\, h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_j\, w_{ij} h_i \tag{1}$$

$$p(v_t h_t;\theta) = \frac{1}{Z(\theta)} \exp\big(-E(\mathrm{v},\mathrm{h};\theta)\big) \tag{2}$$

In Eq. (2), θ indicates the parameter of the model, 0 and 1 characterizes neuron inactivation and activation statuses, correspondingly. v and h represent the activation state of visible and hidden units, a and b denotes the corresponding deviation, and w_{ij} represents the weights among i-th visible and j-th hidden units. $Z = \sum_v \sum_h e^{-E(v,h)}$ indicates a regularization constant simulates a physical scheme.

Where $(h|v)$ refers to conditional probability distribution, then $p(v|h)$ are accomplished using Bayesian inference.

$$p(h|v) = \frac{1}{\left[1 + \exp\left[-c - \Sigma_{j=1}^{m} v_j w_{i,j}\right]\right]} \tag{3}$$

$$p(v|h) = \frac{1}{\left[1 + \exp\left[-b_j - \sum_{i=1}^{n} h_i\, w_{i,j}\right]\right]} \tag{4}$$

The core of RBM is to exploit the likelihood that the learned RBM models matching the input sampling distribution. The variable upgrading method can be implemented by means of the CD model as follows.

$$\omega_{ij}^{n} = \omega_{ij}^{n-1} + \gamma(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_k)$$

$$a_{ij}^{n} = a_{ij}^{n-1} + \gamma\left(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_k\right) \tag{5}$$

$$b_{ij}^{n} = b_{ij}^{n-1} + \gamma(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_k)$$

When $\gamma \in [0_t 1]$ indicates the learning rate that is utilized for adjusting the learning rate, n represents the number iteration of training, and k signifies the step size of the contrast divergence. Fig. 1 illustrates the infrastructure of DBN.

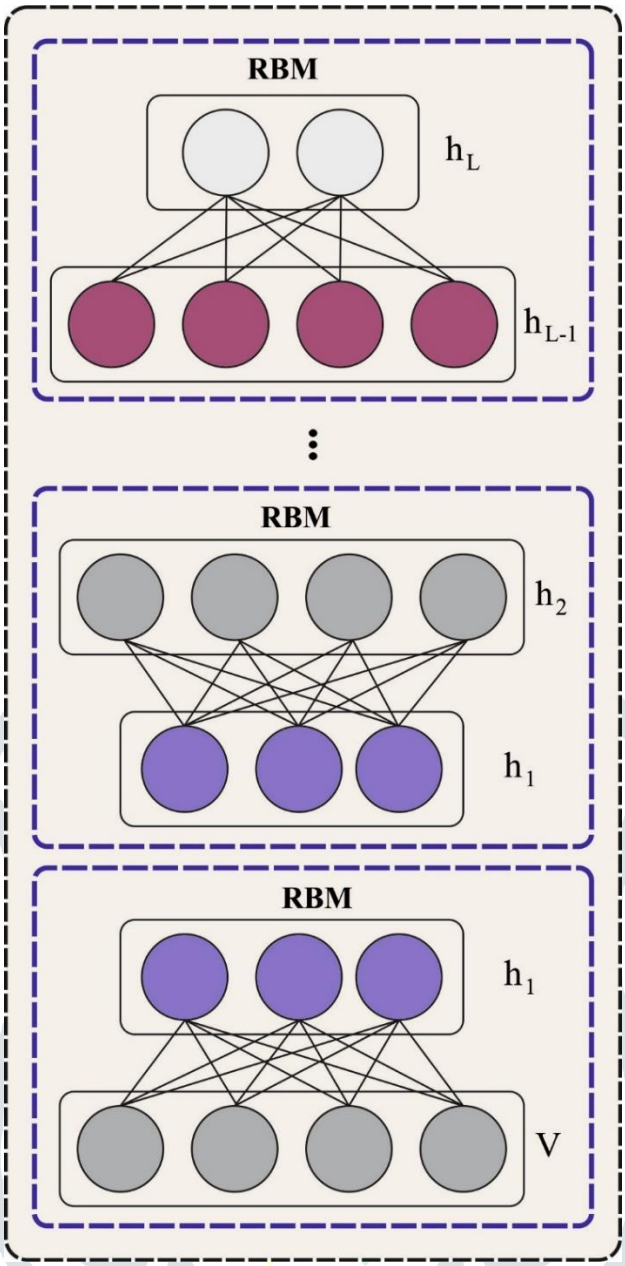

Fig. 1. Structure of DBN

3.2. ABC based Hyperparameter Tuning

In this study, the ABC algorithm is exploited as a hyperparameter tuning approach to improve the estimation efficiency of the DBN model. In 2005, Karaboga discovered the ABC approach, impacted by honey bee behaviors. A honey bee colony algorithm can able to find the rich food source [17]. Thus, the idealogy of ABC was derived from the clever foraging behaviors of honey bees to find appropriate resolutions for the optimization problem. In general, bee colonies are categorized into: scout, employed, and onlooker bees. The quality (fitness) of the likely solution to the optimization question is associated with the effectiveness of the nectar source. The existence of nectar source shows a potential solution to the optimization issue. All the nectar sources are visited by one honey bee. In another word, the number of onlookers or employed bees is proportionate to the number of nectar resources. Employed bees preserve an excellent solution, onlooker bee accelerates convergence speed, and scout bee improves the capability to preserve local optimum.

The steps for ABC Algorithm are given below:

1. Initialization: Generate N random solutions (food source) $Xi(i = 1,2,3, \dots, N)$ in a dimension search space D, whereas N signifies the number of food sources, that is half the size of colony $Xi(i = 1,2,3, \dots, D)$ refers to the D-dimension solution vector. For $i = 1,2,3, \dots, N$, the $i\text{-}th$ food resource in the original population, and the amount of optimization population parameter are indicated as D.

2. In the honey collection phase: every employed bee generates a new nectar source in the food source vicinity. Once a novel nectar source is compared to the preceding one, the higher probability would be memorized. Similar to the employed bee, they change the source position in the memory and preserve a high nectar supply. In the two stages, the subsequent equation is applied for regenerating nectar source:

$$l_{ij} = h_{ij} + \theta \cdot (h_{ij} - h_{kj}) \tag{6}$$

Whereas $(k = 1,2,3, \dots, N)$, $(j = 1,2,3, \dots, D)$, and $\theta[0,1]$ refer to arbitrary value which defines the generation range of $hij's$ neighborhood. Since the search comes closer to optimum solution, the number of neighborhoods would be decreased.

3. Food source selection. The onlooker bee compared the probability evaluated by the fitness values for selecting the food source. Nectar sources with maximum probability are selected by means of higher degree of certainty as follows:

$$P_i = \frac{Fit_i}{\Sigma_i^N Fit_i} \tag{7}$$

The fitness value of $i\text{-}th$ solutions, $Fit_i i(i = 1,2,3, \dots, N)$ is defined by the subsequent formula:

$$Fit_i = \begin{cases} \frac{1}{1 + f_i}, & if\ f_i \geq 0, \\ 1 + |f_i|, & if\ f_i \leq 0 \end{cases} \tag{8}$$

Once the quality of novel food source position is similar to or improved than preceding one, the older one is upgraded with novel one, where f_i refers to the value of main function for $i = 1,2,3, \dots, N$, that is unique to the optimized problems. Or else, the older one would be kept that similar to employed bees.

4. Population elimination. A solution is regarded to have fallen into local optimal solution if it hasn't enhanced considerably afterward a specific amount of trials, called as $''$ max iteration", and the initial location is abandoned. Consequently, the matching employed bee becomes scout bees, and a new solution, is defined as:

$$h\_ij = \theta * (h\_maxj - h\_minj) + h\_minj \tag{9}$$

In Eq. (9), h_maxj and h_minj indicates $j\text{-}th$ and $i\text{-}th$ maximum and minimum values, correspondingly.

4. Performance Evaluation

This section examines the performance of the ABCDBN-CYE model on CYP procedure. The presented ABCDBN-CYE model is validated on the CYP dataset from Kaggle repository [18]. It comprises several

attributes such as State_Name, District_Name, Crop_Year, Season, Crop Area, and Production. Table 1 and Fig. 2 offer clear CYP examination results of the ABCDBN-CYE model. The figure implied that the ABCDBN-CYE model has shown enhanced performance with MAE of 0.3129, RMSE of 0.8548, and R2 score of 0.9937.

Table 1 Result analysis of ABCDBN-CYE system

Metrics	**Values**
R2 Score	0.9937
RMSE	0.8548
MAE	0.3129

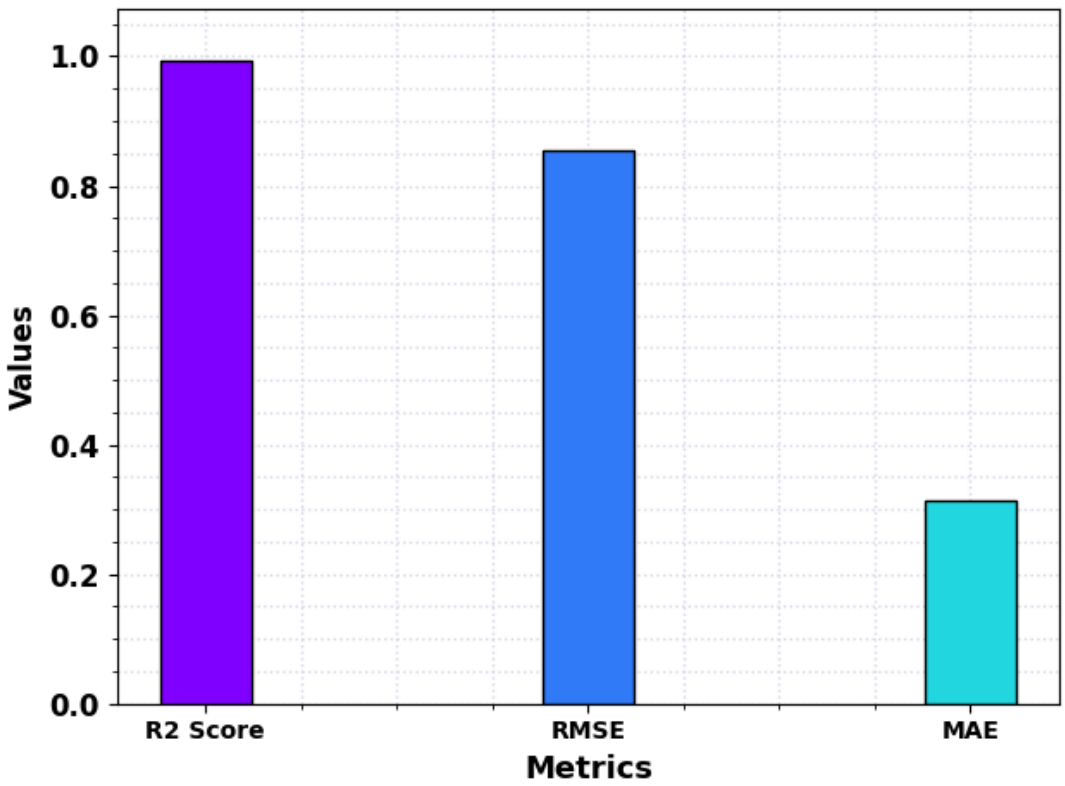

Fig. 2. Result analysis of ABCDBN-CYE system

Table 2 R2 score analysis of ABCDBN-CYE system with other existing algorithms

Methods	**R2 Score**
ABCDBN-CYE	99.37
SVR Model	91.99
KNN Model	87.05
MLR Model	89.10
ANN Model	91.97

At last, a comparative R2 score investigation of the ABCDBN-CYE model with other ML models takes place in Table 2 and Fig. 3. The attained values indicated that the KNN model has resulted to least R2 score of 87.05%. Next, the MLR model attained certainly increased R2 score of 89.10%. Meanwhile, the SVR and ANN models have obtained closer R2 score values of 91.99% and 91.97% respectively. But the ABCDBN-CYE model has shown maximum R2 score of 99.37%. Thus, the ABCDBN-CYE model surpassed the other existing models.

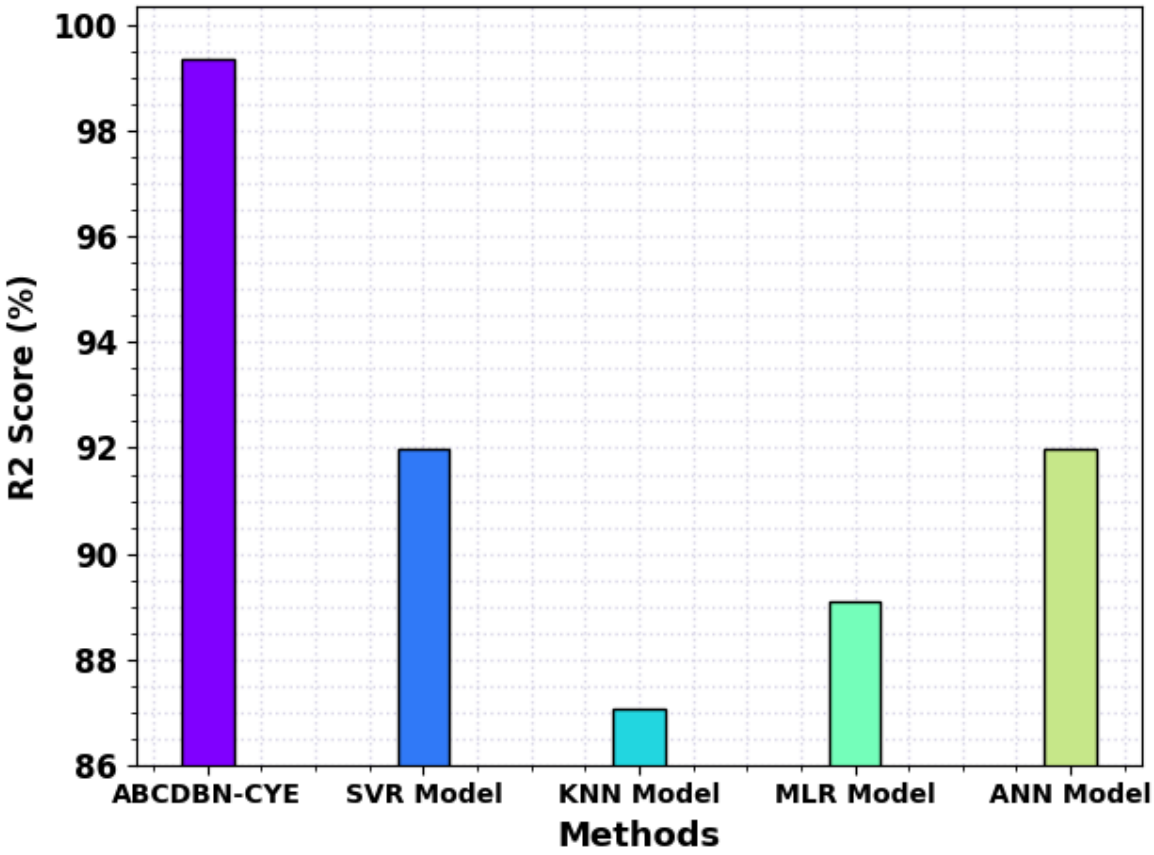

Fig. 3. R2 score analysis of ABCDBN-CYE system with other existing algorithms

5. Conclusion

In this article, a new ABCDBN-CYE technique has been developed to estimate crop yield. The intention of the ABCDBN-CYE technique lies in the estimation of crop productivity in the agricultural sector. The presented ABCDBN-CYE technique operates on two stages such as yield estimation and parameter tuning. At the preliminary stage, the ABCDBN-CYE technique makes use of DBN model to estimate the crop yield. Next, in the second stage, the ABC algorithm is exploited as a hyperparameter tuning approach to improve the estimation efficiency of the DBN model. To demonstrate the improved prediction performance of the ABCDBN-CYE technique, a widespread experimental analysis is performed. The comparison study shown the enhancements of the ABCDBN-CYE technique over other ones.

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