An EWOA-WTDCNN Model: Effective Whale Optimization Algorithm Incorporating with Weight-Tuned Deep Convolutional Neural Network for Forecasting Indian Crop Yielding Process

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Abstract: Field-level crop yield prediction (CYP) is essential for quantitative and economic analysis when developing agricultural commodity plans for import-export strategies and raising farmer incomes. Crop breeding has traditionally been a time- and money-intensive process. To predict increased agricultural output, CYP was developed. This research suggests effective dimensionality reduction (DR) and deep learning (DL) techniques for CYP for Indian regional crops. The three phases of this paper were preprocessing DR and classification. The dataset is first used to gather information about South Indian agriculture. Data cleaning and normalization are then applied as preprocessing to the gathered dataset. Squashed exponential kernel-based principal component analysis (SEKPCA) is then used to perform the DR. CYP, which forecasts the high crop yield profit, is built on a weight-tuned deep convolutional neural network (WTDCNN) with an Effective Whale Optimisation Algorithm (EWOA). According to the simulation results, the suggested strategy achieves greater performance for CYP compared to existing methods with enhanced accuracy.

Keywords: Crop Yield Prediction, Deep Learning, Effective Whale Optimization Algorithm, squared exponential kernel-based principal component analysis

1. Introduction

People in the past were skilled at predicting weather conditions, and they chose their crops and had a chance to predict the yield before the harvest season based on the weather and monsoon of that particular year[1]. The practice of agriculture and the dissemination of its knowledge have considerably decreased over time. The farmers also turned their attention to automated systems and machinery[2]. Because agriculture can only be practiced with learning and knowledge, an automated system based on AI can be put into place in this situation[3]. In AI, this is possible using the deep learning methodology, which uses the neural network concept to simulate the workings of the human brain [4]. Researchers frequently use Deep Learning techniques to estimate agricultural yields based on the aforementioned variables[5]. The structure of this paper is organized as follows.

1.1 Organogram

An overview of agricultural yield prediction and the function of deep learning in this CYP is given in Section 1. The associated research used to perform the review is presented in Section 2. Implementations of the EWOA-WTDCNN algorithm are presented in Section 3, together with descriptions of the dataset, problem formulation, and Squared Exponential Kernel-based Principal Component-based Preprocessing. The findings and discussion are presented in Section 4, and the conclusions are presented in Section 5.

1.2 Crop Yield Prediction

Environmental parameters, such as climatic conditions, temperature, rainfall, vegetative index, soil type, texture, and nutrients, have a significant effect on crop production prediction. The prediction value from deep learning algorithms will be based on environmental parameters always be helpful[6]. Increased crop yield output is a workable answer to one of the most serious problems the world faces: hunger. According to the World Health Organisation, 820 million people worldwide still lack access to enough food. By 2030, the United Nations' Sustainable Development Goals aim to end hunger, achieve food security, and support sustainable agriculture. By 2050, there will be a 9.3 billion-person global population, which would increase the need for food by 60%, according to the Food and Agriculture Organisation (FAO)[7]. Therefore, crop yield forecasting can provide essential data needed for creating a practical plan to reach the goal and end hunger [8]. Numerous factors affect crop yield, making it challenging to develop a solid prediction model using conventional techniques[9][10]. However, with improvements in computer technology, it is now possible to create and train a unique approach for predicting crop yield. Consequently, crop yield forecasts can provide essential information needed for creating a practical approach to reach the goal and end hunger[11].

1.3 Deep Learning in Yield of a Crop Prediction

Artificial intelligence (AI) is a key component that includes deep learning, which simulates the structure and function of the human brain. The neural network that serves as the foundation for deep learning is processed using hidden layers to enhance learning. The different Deep Learning architectures available include, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Boltzmann Machine (BM), long-term memory (LSTM) Networks, Generative Adversarial Networks (GAN) and Forward Deep Networks (FDN) and Deep Belief Networks (DBN). CNN and RNN are the most widely used deep learning architectures that have been used in the yield of a crop Prediction.

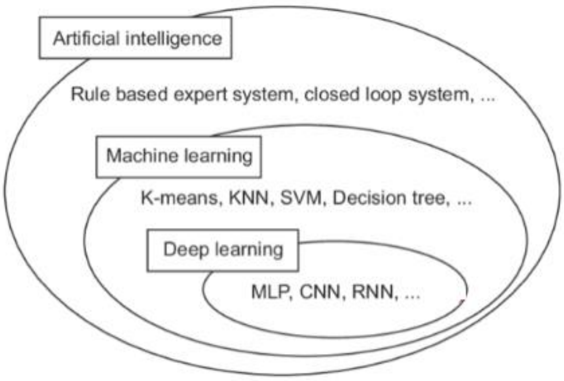

Figure 1: Artificial Intelligence Techniques

Due to its many data technologies and high-performance computers, deep learning is an important approach that is widely employed in the agricultural domain. A kind of machine learning known as "deep learning" uses numerous layers of neural networks to learn from unstructured, unlabeled data in a supervised, semi-supervised, or unsupervised fashion. Deep learning techniques emphasize learning abstract aspects of vast datasets, as pointed out by Sarker [12]. A primary understanding of the relationship between functional qualities and interacting factors is necessary to accurately forecast crop production. Deep learning can be used to create large datasets and highly effective algorithms needed to analyze such connections.

2. Related Researches

While some traditional review articles on crop yield prediction and some Systematic Literature Review papers don't specifically focus on the use of deep learning in crop yield prediction (such as conventional machine learning in crop yield prediction), there are certain traditional review papers on crop yield prediction[13]. There are some Systematic Literature Review papers that focus on the application of deep learning in agricultural yield prediction (this work must distinguish shallow learning from deep learning). This is where the current study, which paves the way for thoroughly analyzing the state-of-the-art knowledge on the development of Deep Learning-based algorithms for agricultural production prediction, represents a pioneering effort.

Table 1: AI Related Researches in Crop Yield Prediction

S.No	Study	Methodology	Description
1	Van Klompenburg et al. 2020. [14]	Crop yield prediction with Machine Learning	Analysis of Machine Learning techniques for crop yield prediction in literature. Analysis of most used features for crop yield prediction with Machine Learning. Found that CNN is the most widely used Deep Learning algorithm.
2	Koirala et al. 2019. [15]	Fruit detection for yield estimation	Overviewed the application of Deep Learning in machine vision, fruit detection, and yield estimation. Recommended using common public image sets to allow the implementation of Transfer Learning.
3	Lee et al. 2019 [16]	Crop yield prediction using Deep Learning	Usage of weather and farm status information with crop disease diagnosis to predict crop yield. Experimented with several Deep Learning algorithms on the diagnosis of crop disease and the prediction of crop yield. CNN had the best performance for crop disease diagnosis. ANN with ReLU activation function showed the best accuracy for crop yield prediction.
4	Chlingaryan et al. 2018. [17]	Crop yield prediction and nitrogen status estimation with Machine Learning	Analyzed Machine Learning techniques for crop yield prediction and nitrogen status estimation. Concluded that technological development contributes to cost-effective and comprehensive solutions.
5	Zhang et al. 2020 [18]	Employing Deep Learning for dense	Analyzed the application of Deep Learning in agricultural dense scenes.

		scenes in agriculture	Reviewed application of Deep Learning in recognition, classification, detection, counting, and yield estimation tasks. Showed that Deep Learning outperforms dense scenes in agriculture.
6	Dharani et al. 2021 [19]	Crop Prediction Using Deep Learning Techniques	Analyzed the usage of Deep Learning techniques in agriculture, with a focus on crop yield prediction. Reviewed the application of different Deep Learning algorithms for crop yield prediction with both images and tabular data. They concluded that CNN outperforms other networks when image data are used RNN, LSTM, and hybrid networks outperform other networks on tabular data.
7	Farhat Abbas et al. 2020 [20]	CYP system using ML algorithms and proximate sensing	For the purpose of forecasting agricultural yields, the gathered data were trained on ML models including elastic net (EN), linear regression (LR), support vector regression (SVR), and k-nearest neighbor (KNN). In comparison to other current techniques, the SVR produced better results for all four datasets examined while having a lower RMSE.
8	Martin Kuradusenge et al.2023 [21]	Many machine learning models for Crop Yield Forecasting	performed polynomial regression, support vector machine, and random forest analyses for CYP. Results showed that, with an RMSE of 510.8 and 129.9 on the tested datasets, the RF model outperformed the SVM and PR in forecasting the crop yields of maize and potatoes.
9	Liyun Gong et al. 2021 [22]	Recurrent neural networks and temporal convolutional networks are examples of hybrid DL methods for CYP.	The RNN was given the normalized data to process the normalized sequence data. For the collected datasets with lower RMSE, the technique produced superior results than the already used comparable schemes.
10	Dilli Paudel et al.2021 [23]	An ensemble of machine-learning models for large-scale CYP	SVM, KNN, ridge regression, and gradient-boosted decision trees were among the ML classifiers employed for CYP.

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3. Materials & Methods

3.1 Dataset Description

The public data source https://data.world/thatzprem/agriculture-india which includes State Name, District Name, Crop, Year, Season, Crop, Crop class, Area, and Production Yield, was used by the proposed system to gather the crop production statistics. Additionally, weather information is gathered from an Indian website and includes pressure, dew point, lowest temperature, maximum temperature, average temperature, precipitation, humidity, and wind speed (m/s).

3.2 Problem Formulation

Because calibration crop models execute faster, need less user expertise, and require less storage for data restrictions than simulation crop models, they are simpler to install than simulation crop models [24]. Agricultural production modeling rarely takes into account the spatial and temporal non-stationarity that is present in many geographical phenomena, despite the development of various ML models to improve prediction accuracy [25]. Since it is utilized to choose the best crop when numerous possibilities are available, DL has recently been used to build a variety of successful computations [26].

- By creating correlations between the input and response variables, this approach aims to make predictions. However, Deep Learning's reliance on hyper-parameters, which can be disregarded to increase the efficacy of the outcomes, presents a significant challenge.
- Deep Learning method experts look into issues as they hand-design previously offered architectures for predicting crop yields. Because they do not understand agriculture, they are unable to create optimal structures. Therefore, a realistic deep-learning technique with optimal hyperparameter tuning for Crop Yielding Prediction for Indian regional crops was proposed in this work.

3.3 Squared Exponential Kernel-based Principal Component-based Preprocessing

Since data are obtained from multiple sources, preprocessing or data preparation needs to be done. It is gathered in raw format, which makes analysis impossible. In order to increase the accuracy of the prediction, preprocessing is crucial before estimating crop production. The following is an explanation of the preprocessing procedures.

Figure 2: Squared Exponential Kernel-based Principal Component-based Preprocessing Flow

Where, $\underset{\rightarrow}{C}''_{Norm}$ refers to the normalized data, $\underset{\rightarrow}{C}''$ indicates the original data, $\underset{\rightarrow}{C}''_{\min}$ and $\underset{\rightarrow}{C}''_{\max}$ signifies the minimum and maximum value from the data set. The dataset values are between 0 and 1 using this min-max normalization.

$$\underset{\rightarrow}{C}''_{Norm} = \frac{\underset{\rightarrow}{C}'' - \underset{\rightarrow}{C}''_{\min}}{\underset{\rightarrow}{C}''_{\max} - \underset{\rightarrow}{C}''_{\min}} \quad \text{......................................} (1)$$

After the normalization process, it is expected that the points with similar predictor values *xi* , naturally have close response (target) values *yi*. In Gaussian processes, the covariance function expresses this similarity[27]. It specifies the covariance between the two taken hyper-parameters called $f(xi)$ and $f(xj)$, where both xi and xj are d-by-1 vectors. In other words, it determines how the response at one point xi is affected by responses at other points xj, $i \neq j$, $i = 1, 2, ..., n$. The covariance function $k(xi,xj)$ can be defined by various kernel functions. It can be parameterized in terms of the kernel parameters in vector θ. Hence, it is possible to express the covariance function as $k(xi,xj|\theta)$. For many standard kernel functions, the kernel parameters are based on the signal standard deviation σF and the characteristic length scale σl. The characteristic length scales briefly define how far apart the input values xi can be for the response values to become uncorrelated. Both σl and σf need to be greater than 0, and this can be enforced by the unconstrained parametrization vector θ, such that

$$\Theta 1 = \log \sigma l \quad , \quad \theta 2 = \log \sigma f. \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (2)$$

The built-in kernel (covariance) functions *with the same length scale for each predictor* with Squared Exponential Kernel is one of the most commonly used covariance functions and is the default option for fitrgp. The squared exponential kernel function is defined as

$$k(x_i, x_j|\theta) = \sigma_f^2 \exp\left[-\frac{1}{2}\frac{(x_i - x_j)^T(x_i - x_j)}{\sigma_l^2}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

As per (3) Squared exponential kernel-based principal component analysis (SEKPCA), which converts higher-dimension data into a lower dimension, is used to create Dimenality Reduction for the dataset. By calculating the principle components and adjusting the basis, PCA functions. In addition to greatly enhancing crop yield identification and diagnosis of high-dimensional data in the real production process, it resolves the variable's correlation. PCA is still only useful if the variables are all very dispersed. Furthermore, the PCA has trouble identifying nonlinear data models.

Algorithm 1:The SEKPCA algorithm
Input: Dataset 'DS', Features '$F = \{F_1, F_2, ..., F_m\}$', Data '$D = \{D_1, D_2, ..., D_n\}$'.
Output: dimensionality reduced crop data samples '$x \in DRCDS$'
1: **Initialize** 'm', 'n', Feature Samples 'FS', 's' 2: **Begin Cleansing** 3: **For** each Data in Dataset 'DS' with Features 'F', Data 'D', Field with Kernel Function 'K' and Crop Data Samples 'CDS' 4: Formulate sample vector matrix as given in (1) 5: Measure probability of object similarity positioned in a field as given in (2) 6: Evaluate similarity reduction of the dataset or field as given in (3) 7: **Return** Dimensionality Reduced Crop Data Samples '$DRCDS$' 8: **End for** 9: **End**

3.4 Crop Yielding Prediction with Weight-Tuned Deep Convolutional Neural Network and Effective Whale Optimization Algorithm

After DR, CYP is performed using a weight-tuned deep convolutional neural network (WTDCNN). Each layer in a DCNN consists of convolutional transforms that are computed before going on to nonlinearities and pooling1 operators. Backpropagation training in DCNN uses random weight and bias values, increasing the likelihood of suboptimal outputs and raising the prediction process' loss. To improve detection accuracy and lower network

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loss, the weights and biases in the network must be properly tuned. In order to achieve the best results, the suggested approach uses an Effective Whale Optimization Algorithm (EWOA) to calculate the network's weights and bias values. This minimizes the network's vanishing gradient saturation and prediction loss for CYP.

Initializing step: N whales are randomly generated and distributed in the search space within the predefined range [LB, UB] using Equation (1).

$$Xi,j(t)=LBj+(UBj-LBj)\times rand(0, 1) \quad \text{..................................(1)}$$

where Xij is the position of the i-th whale in the j-th dimension, LBj and UBj are the lower and upper bound of the j-th dimension, and the rand is a uniformly distributed random variable between 0 and 1, respectively. The fitness value of whale Xi in the t-th iteration is calculated by the fitness function f (Xi (t)), and the whale with better fitness is considered as X*, which is the best solution obtained.

Encircling prey using Levy motion: Whales update their position by considering the position of X* and the Levy-based pace scale PSL by Equation (2),

$$X_{i,j}(t+1) = X_j^*(t) + 0.5 \times C \times PS_{i,j}^L \quad \text{...................................(2)}$$

where *Xj*(t)* is the *j*-th dimension of the best whale, *C* is a linearly decreased coefficient from 1 to 0 over the course of iterations, and $PS_{i,j}^L$ is the j-th dimension of the i-th row of pace scale calculated by Equation(3)

$$PS_{i,j}^L = M_{i,j}^L \times (X_j{}^*(t) \times M_{i,j}^L - X_{i,j}(t)) \quad \text{..........................(3)}$$

$M^L i,j$ is a randomly generated number based on Levy movement, which is calculated by Equation (4),

$$M = \frac{u}{|v|^{1/\beta}} \times 0.05 \quad \text{..................................(4)}$$

The prey position X* is updated after the whales' new location has been established, and their fitness has been determined. Up to the predetermined number of iterations (MaxIter) is reached, the search process is iterated. Algorithm 1 displays the suggested EWO's pseudo-code.

Algorithm 2:The EWOA algorithm
Input: N, D, MaxIter
Output: The global optimum (X*)
1: Begin 2: iter = 1. 3: Randomly distribute N whales in the search space. 4: Evaluating the fitness and set X*. 5: **While** iter ≤ MaxIter

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For i = 1: N
Calculating coefficients a, A, C, and l.
For j = 1: D
If (p < 0.5)
If (|A| < 1)
Perform $PS_{i,j}^{L} = M_{i,j}^{L} \times (X_j^*(t) \times M_{i,j}^{L} - X_{i,j}(t))$
Elseif (|A| ≥ 1) and (iter < MaxIter/3)
Perform $M_{i,j}^{B} \times (X_j^*(t) - M_{i,j}^{B} \times X_{i,j}(t))$
End if
End For
Evaluating fitness and update X*.
iter = iter + 1.
End while
Return the global optimum (X*).
End

To increase the output's nonlinearity, the final feature vector is then fed into the activation layer. If the input value is positive, ReLU is used as an activation function in the activation layer to output the input immediately. Otherwise, it will output zero. The output of the convolution layer with activation is fed into the pooling layer to decrease the input data size. The output is generated by sampling the rectangular boxes from the convolution layer's smaller rectangular boxes, which are used in the polling stages. The fully connected layer receives the polling layers' output to perform CYP, which use the SoftMax activation function to carry out the classification. The output of the classifier displays the production of various crops in Indian regions.

4. Results and Discussion

The experimental results of the suggested yield prediction for local crops in India using effective DL and DR approaches are examined in this part. In terms of classification metrics, the suggested methodology is contrasted with the ones for CYP that are already in place. Here, the suggested classification model's (EWOA-WTDCNN) results are contrasted with those of the existing classification frameworks, specifically with the Deep Belief Network (DBN), Extreme Learning Machine (ELM), and Random Forest (RF) models. Precision, recall, f-measure, and accuracy of the methods are compared. Table 2 provides an analysis of this performance. The methods are also contrasted using classification error measures such as MSE, RMSE, FPR, FNR, and FRR shown in figure 3.

Accuracy = metrics.accuracy_score(original_instances, predicted_instances) = TP+TN / size of DB------------(1)

Precision=metrics.precision_score(original_instances, predicted_instances) =TP/TP+FP-------------------------(2)

Recall=metrics.recall_score(original_instances, predicted_instances) =TP/TP+FP----------------------------------(3)

F1=metrics.f1_score(original_instances, predicted_instances) =2x Precision*recall/ precision+recall------------(4)

Table 2: Performance comparisons between EWOA-WTDCNN with Other Dl Algorithms				
Techniques/Metrics (%)	**Accuracy**	**Precision**	**Recall**	**F-Measure**
Proposed WTDCNN	98.96	98.67	99.03	98.87
DCNN	96.98	96.27	97.03	96.78
DBN	94.43	94.16	94.66	94.35
ELM	90.34	90.02	90.46	90.27
RF	89.21	89.05	89.32	89.19

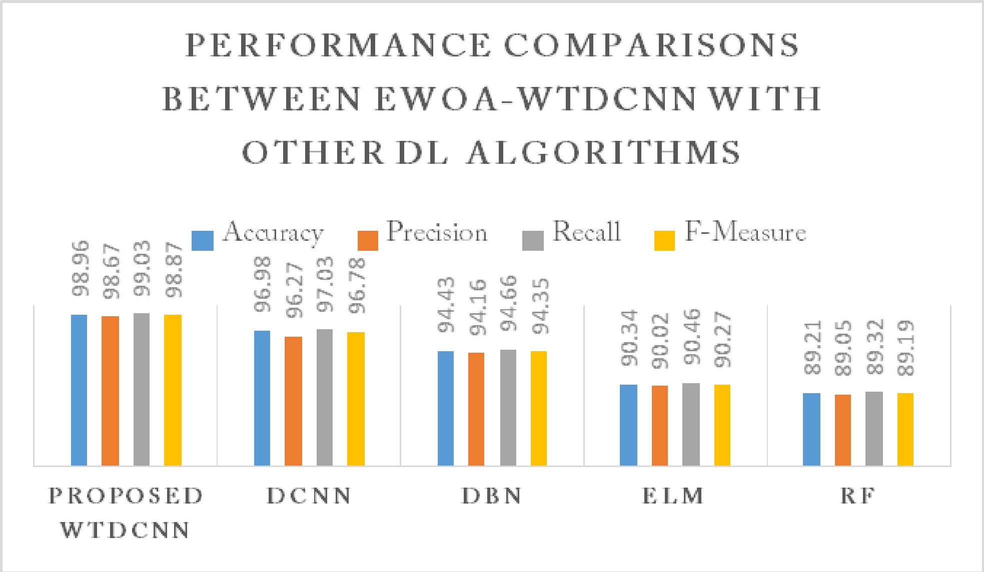

Figure 3: Performance Analysis of EWOA-WTDCNN for better Prediction of Crop Yielding

Our findings supported Table 2's assertion that DL can have a significant impact on CYP. Despite being based on crucial performance criteria, the results are contrasted with those of other cutting-edge approaches. The suggested EWOA-WTDCNN outperforms the current ones in terms of results. For instance, the current DCNN achieves 96.98% accuracy, 96.27% precision, 97.03% recall, and 96.78% f-measure, respectively. Additionally, the proposed RF achieves a maximum accuracy of 98.96% along with 98.67% precision, 99.03% recall, and 98.87% f-measure, whereas the existing RF only achieves minimal 89.21% accuracy, 89.05% precision, 89.32% recall, and 89.19% f-measure. This is similar to how the proposed strategy performs even better when compared to other existing ones (such as DBN and ELM). Thus, the results demonstrated that the suggested one

5. Conclusion

The proposed model has MSE, RMSE, FPR, FNR, and FRR of 0.034, 0.219, 0.029, 0.065, and 0.061, respectively. This shows more excellent performance than the existing methods. However, if the system has lower error levels, it is regarded as sound. Thus, it demonstrated that the suggested approach outperformed the earlier known schemes for accurate CYP. The outcomes of our superior EWOA-WTDCNN model show how the suggested work is new since it makes use of the appropriate data preprocessing techniques, architecture, and hyperparameter values. It is obvious that the suggested method effectively uses the DR method and preprocesses the dataset first before prediction. These methods are therefore more effective in making predictions.

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