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CROP YIELD PREDICTION USING DEEP LEARNING TECHNIQUES IN THE AGRICULTURE DOMAIN

Priti Prakash Jorvekar*, Sharmila Kishor Wagh, Jayashree Rajesh Prasad

Jorvekar P.P., Wagh S.K., Prasad J.R. 2024. Crop yield prediction using deep learning techniques in the agriculture domain. *Acta Biol. Univ. Daugavp., 2024(2): 223-237.*

Abstract
In agriculture, yield prediction is a critical issue as all farmers would like to know how much harvest they may expect. In past decades, yield predictions were made by considering the farmer's previous profitability with that specific crop and field. The implementation of machine learning techniques can help with the prediction of yield, which is a significant challenge that remains to be solved using the information currently available. In agriculture, many machine-learning approaches are employed and assessed to forecast crop yield. An agricultural yield prediction system is proposed and developed in this work using historical data. This is achieved by using deep learning algorithms for agriculture data, such as Independent Component Analysis (ICA) with Crow Search Optimization Algorithm (CSOA) and Deep Convolutional Neural Network (DCNN), and suggesting fertilizer optimal for each crop. The suggested study uses a DCNN classification method over the ICA-CSO approach to estimate agricultural production. The suggested approach outperforms existing models and predicts agricultural output with 97 percent accuracy while maintaining the baseline data distribution, giving an accurate perspective of forecasting crop yields using deep learning algorithms.

Keywords: Independent Component Analysis, Crow Search Optimization Algorithm.

*Corresponding author: *Priti Prakash Jorvekar. Smt. Kashibai Navale College of Engineering, SPPU University, Pune, India. E-mail: pritiprmjorvekar@gmail.com*

Sharmila Kishor Wagh. MES College of Engineering, Pune, SPPU University Pune, India

Jayashree Rajesh Prasad. School of Computing, MIT Art Design and Technology University Pune, India

INTRODUCTION

Crop harvest forecasting is becoming more important as people grow more worried about food security. Early agricultural output forecasting reduces the likelihood of scarcity by calculating the availability of food for the growing number of people worldwide (Kogan et al. 2019, Kumar et al. 2020, Rashid et al. 2021). To address one of the world's most essential concerns, raising agricultural production is one potential solution (Sajja et al. 2021). According to the World Health Organisation, there remains insufficient food sustenance on hand to feed 820 million people worldwide. The United Nations' Sustainable Development Goals aim to abolish starvation, assure food safety, and promote sustainable agriculture by 2030 (Searchinger et al. 2019). The Food and Agriculture Organisation (FAO) estimates that by 2050, food consumption will increase by 60% to feed the world's 9.3 billion people. As a result, crop production forecasts can give vital information for emerging a realistic strategy to accomplish the goal of ending hunger (Li et al. 2022). Crop harvest is unfair by many factors, making it difficult to create a valid forecast model using typical methods. However, developments in computer technology have enabled the invention and training of a novel approach for predicting agricultural yield (Nishant et al. 2020, Zsögön et al. 2022).

There have been many projects in recent decades to reduce hunger worldwide and feed the world's rapidly expanding population. Nearly 800 million people still lack enough food to consume despite the crops' output yields having increased significantly during the last 50 years (Koutika et al. 2022). As a result, the reduction of hunger and an increase in food security have been given top priority in the UN's 2030 Agenda for Sustainable Development. The ability to forecast the crop's potential yield is seen by many participants in the production and trading stage of agriculture as an important breakthrough (Batool et al. 2022). It is critical to provide farmers with production projections to assist them in managing their budgets as well as resource consumption. As a result, farmers are better equipped to make financial and managerial decisions, and early problem detection that affects production can help to start corrective actions for the entire crop (Abbas et al. 2020, Elavarasan & Vincent 2020, Zenda et al. 2021). Crop production prediction may prove to be a useful tool for helping with activity planning and execution. Because of this, predicting agricultural productivity is a difficult task that requires attention. Crop yield levels are influenced by many elements, such as soil and weather conditions, fertiliser use, and seed variety, which also affect plant phenotypes (Mohammed et al. 2023).

A variety of crop simulation and yield estimating methods have been deployed to estimate crop yields. Based on the aforementioned criteria, artificial intelligence (AI) may be utilised to provide more accurate predictions of agricultural output. Machine Learning (ML), a subset of AI, has recently become widely used for agricultural output prediction due to its capacity to unearth non-linear patterns and laws in enormous databases obtained from numerous sources (Bharadiya et al. 2023). The spectrum of ML techniques ranges from straightforward regression models to more complex Deep Learning (DL) algorithms (Khaki et al. 2020). Deep Learning is a type of machine learning that modifies raw data by applying multiple layers of analysis and reveals the dataset's important but hidden characteristics. A DL model's ability to forecast agricultural productivity can be enhanced by adding more hidden layers (Lu et al. 2022).

To maximize yield potential, stakeholders can make decisions in real-time using data from remote sensing to continuously monitor crops throughout their growing state. The yield of many crops cannot be estimated concurrently, preventing the development of a method that would enable more precise projections. Khaki et al. (2021) and Oikonomidis et al. (2022) proposed a new model Yield Net takes into account the multi-target response variable by using a fresh deep learning architecture and new loss function. The suggested strategy is competitive with other cutting-edge methods, according to numerical data, and reliably estimates production from one to four months before harvest.

Lu et al. (2022) and Khaki et al. (2021) employed images of bean pods and leaves to anticipate soybean production in the field using deep learning and a generalised regression neural network (GRNN). You Only Look Once (YOLOv3), feature pyramid networks (FPN), single shot multi box detectors (SSD), and faster region-convolutional neural networks (Faster R-CNN) were utilised to recognise bean pods. To improve the detection performance of YOLOv3, modifications were made to the partial neural network structure, the anchor frame clustering method, the IoU loss function and obtained 97.43% accuracy.

Oikonomidis et al. (2022) and Sun et al. (2019) assessed the performance of deep learning-based models using a publicly available soybean dataset. The hybrid CNN-DNN model outperformed previous models, with an RMSE of 0.266, an MSE of 0.071, and an MAE of 0.199. The model's predictions have an R2 of 0.87. When compared to the other DL-based approaches, the execution time of the second-placed XGBoost model was shorter.

Khaki et al. (2021) and Ghazaryan et al. (2020) proposed YieldNet, a novel convolutional neural network model that shares the weights of the backbone feature extractor and uses a ground-breaking deep learning framework to anticipate maize and soybean yields. A novel loss function was also proposed by the author to account for the multi-target response variable. Data from 1132 counties in the United States for maize and 1076 counties in the United States for soybeans were used in our experiment. Our proposed method is competitive with other cutting-edge methodologies, according to numerical results, and anticipates maize and soybean output with an MAE of 8.74% and 8.70% of the average yield, respectively, from one to four months before harvest.

Sun et al. (2019) and Kross et al. (2020) suggested a deep CNN-LSTM model for end-of-season and in-season soybean yield prediction at the county level in the CONUS. Crop growth characteristics and environmental variables such as weather, MODIS Land Surface Temperature (LST) data, and MODIS Surface Reflectance (SR) data were used to train the model. The experiment findings show that the suggested CNN-LSTM model outperforms the pure CNN or LSTM model in both end-of-season and in-season scenarios. In the future, the suggested technique has significant promise for enhancing the accuracy of yield prediction for other crops such as maize, wheat, and potatoes at fine scales.

Ghazaryan et al. (2020) and Kendall and Gal (2017) evaluated various algorithms and multiple remotely sensed time-series datasets for yield estimation at the county and field size in the United States. MODIS-based surface reflectance, Land Surface Temperature, and Evapotranspiration time data were employed for county-level analysis. NASA's Harmonised Landsat Sentinel-2 (HLS) product was used for field-level analysis. With a mean percentage error of 10.3% for maize and 9.6% for soybeans, the CNN-LSTM model achieved the best accuracy. When data from the middle of the growing season was utilised, all models produced accurate findings with R2 values more than 0.8. The findings demonstrate the utility of satellite data for yield estimates at various management scales.

Kross et al. (2020) and Gal and Ghahramani (2016) utilized an artificial neural network (ANN) approach to evaluate the significance of predictor variables in forecasting end-of-season yields for corn and soybeans within specific fields. Crop yield predictor factors included satellite-derived vegetation indices and elevation-derived variables, with the SR index and slope being the most influential. Corn had fewer relative mean absolute errors than soybean, with errors of less than 10% for corn and more variable for soybean. The findings are encouraging and can be utilised to improve larger-scale yield forecasts.

MATERIAL AND METHODS

Study background

In agriculture, farmers want to grow crops that produce the most. Selecting the optimum crop among the many varieties available is essential for increasing the profitability of agriculture.

So, choosing the right crop is the largest issue for farmers. They typically expand the product offerings from last year at an attractive price (Suganya 2020). But a variety of things affect crop productivity. It is possibly better to select the best hybrid seeds or crops for a crop mix that is better suited to the needs of the farm with the help of data mining technology in agriculture. The likelihood of crops achieving their full yield potential in each environment can be estimated using a range of advanced algorithms. However, there are drawbacks to each proposed algorithm. Thus, the problems with crop selection are resolved using a sophisticated computerised crop forecasting method as shown in figure 1. Therefore, choosing a crop requires an efficient decision-making process.

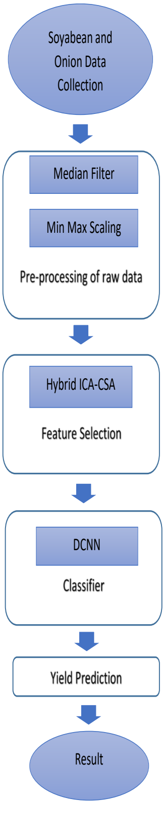

Figure 1. Flow chart of proposed prediction model.

Pre-processing

Before using the data collected image for further processing, pre-processing is performed to clean up any noise or irregularities. The Median filter is used for noise reduction, a standard pre-processing technique. To get better results later, the median filter, a non-linear filter, is employed to lower noise and enhance image quality. In some circumstances, this method minimises noise by conserving the image's edges. The techniques used to improve an image must minimise the image's noise while preserving the image's intrinsic information. To evaluate if a pixel is a part of the background, the median filter looks at the nearest pixels in the image. The median filter calculates the median values and substitutes the values rather than merely obtaining the mean value. The median value is calculated, the 3x3 dimension (9 elements) is used, and the values are swapped in our proposed method so that the feature quality is not diminished. By mathematically organising the surrounding numbers and substituting the center value for the other values, the median value may be calculated. Because the median value is one of the values in the set of data and does not create any false new data, the median filter is better than the mean filter.

A widely used approach for pre-processing data in agricultural production prediction is the Min-Max algorithm. It involves scaling the input features of the dataset to a specific range, typically between 0 and 1.

This determines the minimum and maximum values for each feature in the dataset. These values are computed based on the entire dataset or specific subsets, depending on the requirements. For each feature, calculate the scaled value using the Min-Max formula:

$$\textit{Scaled value} = (\textit{original value - minimum value}) / (\textit{maximum value - minimum value}) \quad (1)$$

To scale all features in the dataset to the range [0, 1] using Min-Max scaling. The Min-Max algorithm offers several advantages for pre-processing data in crop yield prediction, by scaling the features to a specific range, the Min-Max algorithm ensures that the features have a consistent scale and are comparable. This prevents any single feature from dominating the analysis due to differences in magnitudes. The Min-Max algorithm preserves the relative relationships and patterns among the features. It does not alter the distribution or shape of the data, maintaining the information contained in the original dataset. Scaling the features using Min-Max can improve the performance and convergence of machine learning models used for crop yield prediction. It can help prevent issues like gradient explosion or vanishing gradients that can arise from unnormalized data. The scaled values obtained using the Min-Max algorithm are easily interpretable, as they lie within the range of 0 to 1. This allows for a straightforward understanding of the relative magnitudes and comparisons between different features.

Feature extraction

The method used Crow Search Optimization (CSO) combined with Independent Component Analysis (ICA) following pre-processing to select specific attributes effectively. A group of mixed signals can be dissected into their underlying independent components using the statistical signal processing technique known as ICA. The intention is to estimate the original sources or signals, and it is assumed that the observed signals are a linear mixture of these separate components. ICA is commonly used in various fields, including image processing, speech recognition, and bioinformatics. In the context of data analysis, ICA can be employed as a feature extraction method to identify meaningful and independent features from a dataset. The ICA considers n-dimensional set of data vectors represented as, where the vectors (directions) along which statistics of data projections are independent of one another. Formally, if A transforms the provided reference frame to the reference frame of the independent component, then

$$x = As \quad (2)$$

such that

$$p(s) = \Pi p\_a\ (s\_i) \quad (3)$$

Where the marginal distribution is represented as (·) and is the joint distribution over the n-dimensional vector as . Many different algorithms are suggested for carrying out independent component analysis, such as maximisation of conditional entropy in the output (the information content in the output that, generally, increases if the output components become independent), minimization of the divergence measure between the joint density and the product of marginal using natural gradient and relative gradient, using nonlinear principal component analysis.

The method for doing independent component analysis (ICA) is typically described as the method for determining one specific W,

$$y = Wx \quad (4)$$

Such that each yi becomes independent of the others. If one such W can be found, the resultant marginal densities become a scaled permutation of the original density functions if the individual marginal distributions are non-Gaussian. The natural gradient descent of the Kullback-Leibler divergence between the joint density and the sum of the marginal densities is one generic learning method for determining one W.

$$\Delta W = \eta(I - \varphi(y)y^T)W \quad (5)$$

where is a nonlinear function of the output vector y. Similar to Independent component analysis (ICA), feature analysis may also be utilised when each data vector is the outcome of the fusion of many independent sources.

CSO is a nature-inspired optimization algorithm based on the behavior of crows, particularly their foraging behavior. It simulates the search process of crows for locating food sources and applies this concept to solving optimization problems. CSO utilizes a population of "crows" that iteratively search for the best solution in a multidimensional search space. By mimicking the social learning and information sharing behaviors of crows, CSO can effectively leverage the search space and explore it to discover ideal or almost ideal answers. The approach entails many stages to iteratively search in a multidimensional search space for an optimum or nearly ideal solution. The basic steps involved in CSO are as follows:

Step 1: Initialization
- Determine the problem's search space and the number of crows (population size).
- Generate an initial population of crows randomly within the search space.
- Assign fitness values to the crows based on their objective function evaluations.

Step 2: Foraging Behavior
- Divide the search space into different regions, called nests, representing potential solutions.
- Each crow searches for food in its assigned nest and shares information with other crows.

Step 3: Evaluate Fitness
Calculate the fitness value for each crow based on its position in the search space and the objective function.

Step 4: Communication and Information Sharing
Crows exchange information about their food sources, which corresponds to sharing the best solutions found so far.

Step 5: Update the Positions
Update the position of each crow based on its current position, the information from other crows, and the exploration-exploitation balance. This is done by employing update strategies, of global search.

Step 6: Check Termination Criteria
- Evaluate if the termination criteria are met, such as reaching a maximum number of iterations or achieving a desired fitness value.
- If the termination criteria are not met, go back to step 3.

Step 7: Output
The CSO algorithm outputs the best solution found during the optimization process, along with its corresponding fitness value.
By leveraging the advantages of ICA and CSO, crop yield prediction models for soybean and onion can benefit from feature extraction, dimensionality reduction, global optimization, versatility, robustness, and convergence. These techniques can enhance the accuracy, efficiency, and interpretability of the models, enabling better understanding and prediction of crop yields for informed decision-making in agriculture.

Classifier

Since Deep Convolutional Neural Network (DCNN) comprises several hidden layers and may acquire hierarchical presentations from the input pictures, it has a strong learning capacity. The learned characteristics grow more abstract as the convolutional neural network's depth rises, which helps with the following classification challenge.

Proposed Algorithm
Input: Input data
Output: Classified data
Step1:
Data normalization,
Error removal $\mathbf{Eo_c}$
Maximum length of the data
Normalized data $= \mathbf{z}' = \frac{(z-z)}{(z_{max}-z_{min})}$
Step 2:
Feature extraction with ICA-CSO
Create feature subset

Step 3:
Relative closeness features estimation
for optimized fitness features
Selected features
Step 4:

Classification
for $\mathbf{ED = objED = -20 * q\left(-2 * \sqrt{\sum S_v}\right)/2 - exp\ (\sum cos\ (2\pi * S_v)/db) + 20exp}$
Hybrid $\mathbf{DCNN - ICA - CSO}$
Class merge
flag
end

Convolutional and pooling layers are frequently arranged in sections, with a few completely coupled layers appearing last. To create deep architecture, multiple components are stacked. The network receives the dataset directly, uses a large number of convolution and pooling components, and then feeds the learned representations into fully connected layers. Finally, the output layer neurons that are directly associated with the neurons in the preceding layer offer a suggested label for classification. CNN presents the notion of a local receptive field as an alternative to fully connected neural networks. This implies that the whole input picture can be divided into numerous localised portions, each of which is connected with a distinct hidden unit, rather than attaching each hidden neuron to the complete input image. The number of parameters is greatly reduced through local connection, which also reduces the model's overall training difficulty.

Furthermore, while the biases and weights of each convolution kernel used to scan the whole image are identical, there are differences between the biases and weights of different convolution kernels. So a specific convolution kernel detects the same feature at different input locations to ensure translation invariance. What matters is the trait itself, not where it is. The learned features from a single convolution kernel make form a feature map. To acquire relevant and sufficient features from the input, the classification task is accomplished by employing a number of convolution kernel types to build a range of feature maps. Due to shared weights and biases, the number of network parameters is greatly reduced, accelerating training. Doing a pooling operation after a convolution operation is another way to reduce the spatial resolution of the learned features to enhance spatial invariance. Rectified Linear Unit (ReLU) is used as the activation function in CNN architecture to avoid saturation in traditional sigmoid and tanh functions.

Many convolution kernels are used in a convolutional layer to extract information from the input. A set of trainable weights connects a tiny portion of the input to one neuron in a convolutional layer, and different portions are linked to various neurons. The whole network of neurons creates a feature map, and each neuron has a linked region known as a receptive field. The trainable weights linking neurons and their receptive fields remain constant inside a single feature map, which is referred to as one convolution kernel. The convolution kernel acts as a feature extractor as a result, performing convolution on the input's related areas before applying a nonlinear activation function and swiping over the whole input. Different convolution kernels are used to create many feature maps within one convolution layer to learn different features. Each convolution kernel learns one kind of feature from the input. Formally, the feature value of the kth feature map before nonlinear transformation is denoted byand can be determined as follows:

$$Z_k = W_k \otimes x + b_k \quad (6)$$

Where represents the input image; denotes the convolution kernel related to the k-th feature map and is bias term; ⊗

To minimise the spatial dimension of the convolved feature maps, a pooling layer is often added after the convolutional layer. By downsampling the feature maps produced by the preceding layer, input pictures are divided into numerous tiny areas, and a pooling function is used for each region to derive a new value, resulting in spatial invariance. High-level reasoning is carried out using fully-connected layers, where each unit is linked to every unit from the preceding layer until there are enough stacked groups of convolutional and pooling layers. The output layer uses the softmax operation to forecast the classification that each image belongs to for classification tasks.

To train the created model to identify the right set of parameters so that the intended output may be attained, learning methods are used. Cross entropy loss is determined during training to assess the discrepancies between the built-in model's anticipated outputs and true labels. There are numerous techniques to optimise deep neural networks, and in this research, the adaptive moment estimation (Adam) optimisation algorithm is used. It is a substitute for the traditional stochastic gradient descent method and computes adaptive learning rates for various parameters while taking into account both the first and second moments of the gradients. It performs remarkably well when training a large number of parameters and reaches rapid convergence, increasing computation efficiency.

RESULTS AND DISCUSSION

Python was used to design the entire system. Numerous statistics, including those for crops, crop yield, location, soil and crop nutrients, and fertiliser, are acquired from various sources such as agricultural publications and websites. The dataset aims to predict the yield of soybean and onion crops by analyzing environmental, soil, and agricultural factors. An innovative crop yield prediction model, employing a DCNN + CSO approach, was executed on a computing system featuring an AMD Ryzen 5 3600 6-Core Processor with a clock speed of 3.60 GHz and 16 GB RAM. AICRP on Integrated Farming System, Mahatma Phule Krishi Vidyapeeth (MPKV), Rahuri, Maharashtra, India provided the dataset. This experiment they carried out for the Development of an Organic Farming Package for soybean, a newly introduced high valued, cropping system of the year 2006-2007 to 2012-13 (7 years), This is an authorized dataset prepared at Mahatma Phule Krishi Vidyapeeth(MPKV) Rahuri with Latitude 190 22.091' , Longitude (0E) 740 38.660' and Altitude(m, amsl) 539 Geographical Coordinates with Plot size (m) Gross: 8.90 x 4.50 Net 8.10 x 3.60 and Spacing Soybean- 45 cm x 10 cm.

A dataset is prepared for Soybean crop yield with 65 different features majorly depending upon metrological parameters and soil parameters, In the dataset, we are considering various metrological parameters like relative humidity at 8:00 IST (RH I) and relative humidity at 15:30 IST (RH II), maximum temperature (Tmax), minimum temperature (Tmin), Wind speed, Evaporation and Soil parameters like Soil electrical conductivity (EC), Soil Organic Carbon, Available Nitrogen, Available Phosphorus, Available Potassium, Uptake Nitrogen, Uptake Phosphorus, Uptake Potassium with 8 different soil treatment data (T1, T2, T3, T4, T5, T6, T7, T8) that is all soil parameters present in dataset 8 time for 8 different treatment example: T1 Available Nitrogen, T1 Available Phosphorus, T1 Available Potassium, T1 Uptake Nitrogen, T1 Uptake Phosphorus, T1 Uptake Potassium. And dataset consists of output feature; yield by considering all 8 soil treatments. Using 80% of the available data, the model was trained, and the remaining 20% was used for evaluation.

Table 1. Performance metrics of the proposed method.

Parameters	Soyabean	Onion
Accuracy	97%	98.5%
Precision	99.3%	99.5%
Recall	99.56%	99%
F1 Score	97%	98%

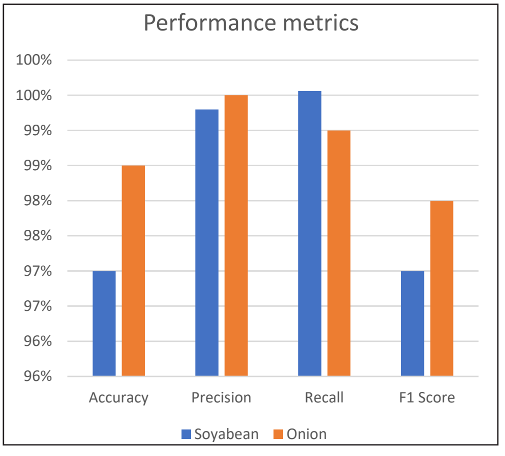

Figure 2. Performance metrics attained for soyabean and onion yield prediction.

The success indicators of the suggested approach for forecasting crop production in onion and soybean crops are shown in Table 1 and Figure 2. The method's excellent accuracy—98.5% for onions and 97% for soybeans—demonstrates the dependability of the predictions. 99.3% precision for soybeans and 99.5% precision for onions demonstrate how well the model reduces false positives. Its capacity to accurately identify true positives is demonstrated by recall rates of 99% for onions and 99.56% for soybeans. The robustness of the method is demonstrated by the F1 scores, which balance precision and recall, which are 97% and 98% for soybean and onion, respectively. Combining these strategies allowed the suggested method to estimate yield with high accuracy, as seen by its robust findings (97% accuracy for soybeans and 98.5% for onions) and other metrics including precision, recall and F1 scores. The method offers practical insights, such as the best fertilizer recommendations, to increase agricultural output in addition to making accurate crop yield predictions.

The graph depicts the relationship between fitness and the number of iterations for the ICA-CSO algorithm used for feature selection in accurate crop yield prediction (Fig. 3).

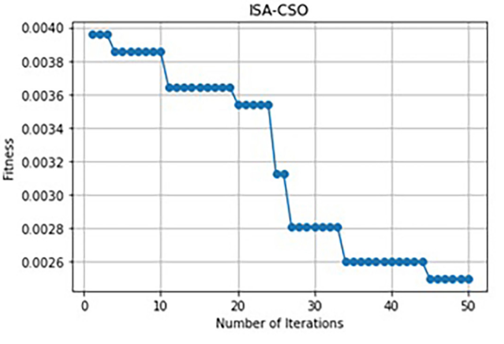

Figure 3. Fitness value attained for proposed ICA-CSO.

The fitness value indicates the quality or performance of the selected features, with a lower value generally indicating better performance. According to the graph, at the 0th iteration, the fitness value is 0.0040. As the iterations progress, the fitness value increases and eventually drops to 0.0025 at the 50th iteration. This implies that during the initial iterations, the algorithm may not have found the optimal set of features, resulting in a higher fitness value. However, as the iterations continue, the algorithm likely refines the feature selection process and identifies a subset of features that contributes to better accuracy in crop yield prediction. This leads to a decrease in the fitness value, indicating an improvement in the predictive performance.

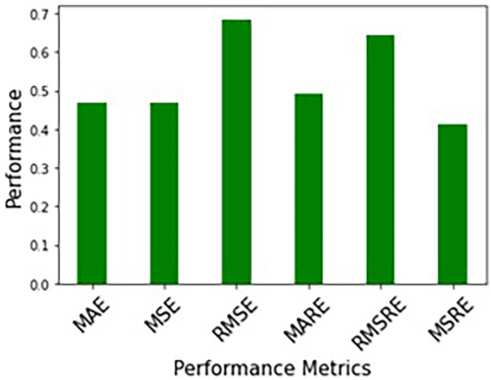

Figure 4. Error attained for proposed DCNN-ICA-CSO.

Based on the evaluation of the proposed DCNN (Deep Convolutional Neural Network) model with ICA-CSO (Independent Component Analysis-Crow Search Optimization) feature extraction, multiple performance metrics have been used to assess the accuracy of the crop yield prediction for soybean and onion (Fig. 4). The metrics include MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), MARE (Mean Absolute Relative Error), RMSRE (Root Mean Squared Relative Error), and MSRE (Mean Squared Relative Error). The plot illustrates that the MSRE achieved the lowest error of 0.45%, indicating that the predictions made by the DCNN model with ICA-CSO feature extraction have a small average deviation from the actual values. On the other hand, the RMSE exhibited the maximum error at 0.67%, representing the average magnitude of the deviations between predicted and actual values are still low. Furthermore, the other performance metrics like MAE resulted in an error of 0.48%, indicating the average absolute difference between the predicted and actual values. The MSE was found to be 0.47%, representing the average squared difference between predictions and actual values. The MARE resulted in an error of 0.5%, reflecting the average relative deviation between the predicted and actual values. Lastly, the RMSRE yielded an error of 0.64%, representing the average squared relative difference between predictions and actual values. Overall, the obtained results indicate the optimum performance of the proposed DCNN model with ICA-CSO feature extraction for soybean and onion crop yield prediction. These metrics demonstrate the accuracy of the predictions made by the model, with small errors and deviations between predicted and actual values.
A comparative analysis was conducted between the proposed DCNN+ICA-CSO model and several other variations, namely DCNN+MFO (Modified Firefly Optimization), DCNN+PSO (Particle Swarm Optimization), DCNN+GWO (Grey Wolf Optimization), and DCNN+WOA (Whale Optimization Algorithm). The evaluation was based on the MSRE (Mean Squared Relative Error) values obtained from the predictions (Fig. 5).

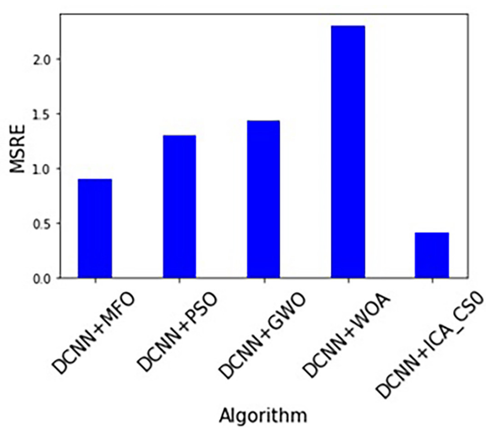

Figure 5. Comparative analysis based on MSRE of DCNN-ICA-CSO.

The results reveal that the proposed DCNN+ICA-CSO model achieved the lowest MSRE value of 0.45%, indicating its superior performance in terms of the average relative deviation between the predicted and actual values. In comparison, the MSRE values of the other models were found to be higher, with DCNN+MFO at 0.97%, DCNN+PSO at 1.34%, DCNN+GWO at 1.47%, and DCNN+WOA at 2.34%.

The comparison demonstrates that the proposed DCNN+ICA-CSO model outperforms the other models in terms of accuracy and predictive power, as evidenced by its significantly lower MSRE value. This suggests that the integration of Independent Component Analysis (ICA) and Crow Search Optimization (CSO) in the feature extraction process provides a more effective representation of the data for crop yield prediction.

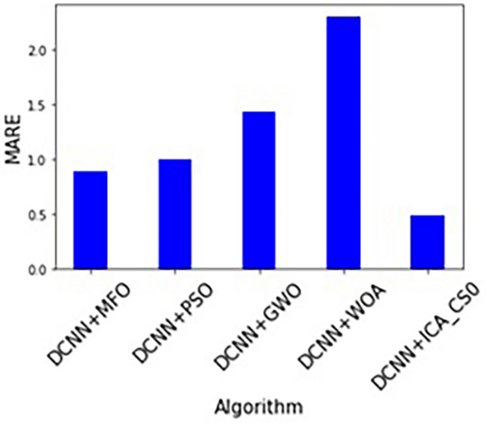

Figure 6. Comparative analysis based on MARE of DCNN-ICA-CSO.

The lower MSRE value indicates reduced deviations and improved precision in the predictions made by the proposed model.

The graph presented illustrates a comparative analysis of the proposed DCNN+ICA-CSO model with other variations, including DCNN+MFO (Modified Firefly Optimization), DCNN+PSO (Particle Swarm Optimization), DCNN+GWO (Grey Wolf Optimization), and DCNN+WOA (Whale Optimization Algorithm). The evaluation was based on the MARE (Mean Absolute Relative Error) values obtained from the predictions.

According to the graph, the proposed DCNN+ICA-CSO model achieved a minimal MARE value of 0.5%, indicating its superior performance in terms of the average relative deviation between the predicted and actual values (Fig. 6). On the other hand, the MARE values for the other models were higher, with DCNN+MFO at 0.93%, DCNN+PSO at 1.02%, DCNN+GWO at 1.48%, and DCNN+WOA at 2.4%. The results highlight the potential of the proposed DCNN+ICA-CSO model as a promising approach for crop yield prediction, showcasing its ability to achieve more accurate and reliable results compared to the other optimization algorithms considered in the analysis.

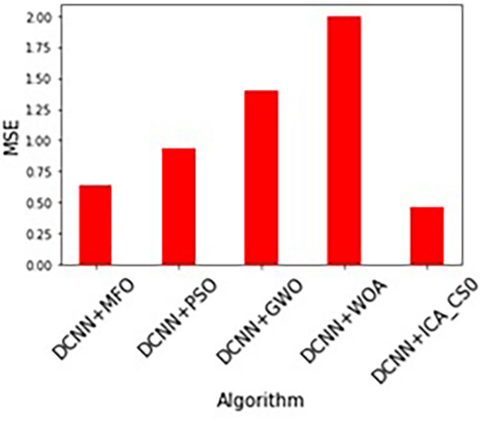

Figure 7. Comparative analysis based on MSE of DCNN-ICA-CSO.

The graph depicting the Comparative Analysis of the proposed DCNN+ICA-CSO model with other variations, including DCNN+MFO (Modified Firefly Optimization), DCNN+PSO (Particle Swarm Optimization), DCNN+GWO (Grey Wolf Optimization), and DCNN+WOA (Whale Optimization Algorithm), focuses on the evaluation of Mean Squared Error (MSE) values (Fig. 7).

According to the graph, the proposed DCNN+ICA-CSO model achieved a minimal MSE value of 0.47%, indicating its superior performance in terms of the average squared difference between the predicted and actual values. On the other hand, the MSE values for the other models were higher, with DCNN+MFO at 0.68%, DCNN+PSO at 0.97%, DCNN+GWO at 1.38%, and DCNN+WOA at 1.97%. This analysis demonstrates that the proposed DCNN+ICA-CSO model outperforms the other models in terms of accuracy and precision, as evidenced by its significantly lower MSE value.

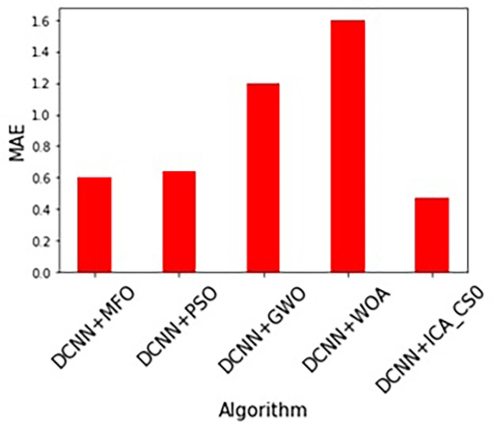

Figure 8. Comparative analysis based on MAE of DCNN-ICA-CSO.

The integration of Independent Component Analysis (ICA) and Crow Search Optimization (CSO) in the feature extraction process appears to provide a more effective representation of the data for accurate crop yield prediction.
The graph comparing the DCNN+ICA-CSO model with other variations, such as DCNN+MFO, DCNN+PSO, DCNN+GWO, and DCNN+WOA, evaluates Mean Absolute Error (MAE) values (Fig. 8). The DCNN+ICA-CSO model achieved a minimal MAE value of 0.48%, indicating superior performance in terms of average absolute difference between predicted and actual values. The other models had higher MAE values, with DCNN+MFO at 0.6%, DCNN+PSO at 0.62%, DCNN+GWO at 1.08%, and DCNN+WOA at 1.6%. The proposed DCNN+ICA-CSO model outperforms other models in terms of accuracy and precision, with a significantly lower MAE value. The integration of Independent Component Analysis (ICA) and Crow Search Optimization (CSO) in feature extraction provides a more effective representation of data for accurate crop yield prediction. The results highlight the potential of the DCNN+ICA-CSO model as a promising approach for crop yield prediction, achieving more accurate and reliable results compared to other optimization algorithms.

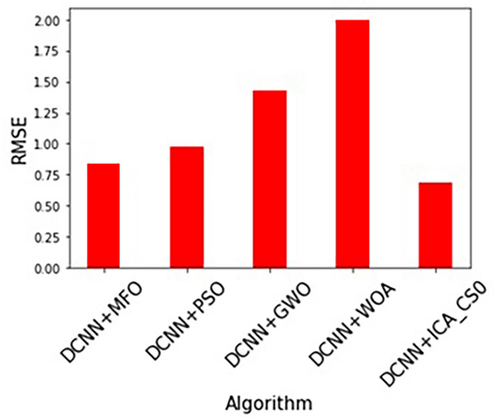

Figure 9. Comparative analysis based on RMSE of DCNN-ICA-CSO.

According to the graph depicting the Comparative Analysis of the proposed DCNN+ICA-CSO model with other variations (DCNN+MFO, DCNN+PSO, DCNN+GWO, DCNN+WOA), the proposed model achieved a minimal RMSE (Root Mean Squared Error) value of 0.68%. In comparison, the RMSE values for the other models are as follows: DCNN+MFO at 0.78%, DCNN+PSO at 0.93%, DCNN+GWO at 1.36%, and DCNN+WOA at 1.95% (Fig. 9). The lower RMSE value for the proposed DCNN+ICA-CSO model suggests that it outperforms the other models in terms of accuracy and precision. The reduced RMSE indicates smaller deviations between the predicted and actual values, showcasing the superior performance of the proposed model for crop yield prediction. These results highlight the potential and effectiveness of the DCNN+ICA-CSO model as a promising approach for accurate crop yield prediction. It demonstrates its ability to achieve more accurate and reliable predictions compared to the other optimization algorithms considered in the analysis.

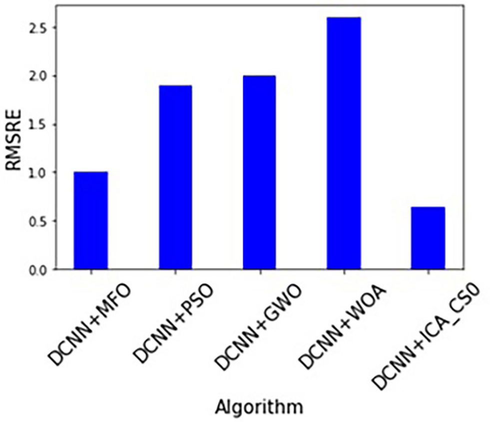

Figure 10. Comparative analysis based on RMSRE of DCNN-ICA-CSO.

The suggested model produced a minimal RMSRE (Root Mean Squared Relative Error) value of 0.64%, as shown in the graph comparing it to other versions (DCNN+MFO, DCNN+PSO, DCNN+GWO, and DCNN+WOA). In contrast, the RMSRE values for the other models are as follows: 0.99% for DCNN+MFO, 1.97% for DCNN+PSO, 2.38% for DCNN+GWO, and 2.67% for DCNN+WOA (Fig. 10). The suggested DCNN+ICA-CSO model performs better than the other models in terms of accuracy and precision in predicting crop production, as evidenced by its lower RMSRE value. The decreased RMSRE highlights the greater performance of the suggested model by denoting fewer relative deviations between the anticipated and actual values.

CONCLUSIONS

Higher agricultural yields may be produced, as evidenced by the location-based crop yield forecast and effective algorithm implementation. From the foregoing research, the authors conclude that DCNN with ICA-CSO is superior to DCNN+MFO, DCNN+PSO, DCNN+GWO, and DCNN+WOA for soil classification, with an accuracy rate of 97.35%. Using DCNN in conjunction with ICA and CSO to forecast agricultural yields has benefits including enhanced feature extraction, dimensionality reduction, parameter optimization, accuracy, robustness, generalization, and automated feature learning. These methods can help predict crop yields with more accuracy and dependability, assisting in agricultural decision-making and improving farming methods. However, the work may be further expanded to include the following features with the creation of a mobile application to assist farmers by uploading images of their fields. Crop diseases may be found using image processing, and users can order pesticides based on disease photos. Smart irrigation systems can also be used by farmers to increase productivity.

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