Effectiveness of Crop Recommendation and Yield Prediction using Hybrid Moth Flame Optimization with Machine Learning

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ABSTRACT

Agriculture is the main source of income, food, employment, and livelihood for most rural people in India. Several crops can be destroyed yearly due to a lack of technical skills and changing weather patterns such as rainfall, temperature, and other atmospheric parameters that play an enormous role in determining crop yield and profit. Therefore, selecting a suitable crop to increase crop yield is an essential aspect of improving real-life farming scenarios. Anticipating crop yield is one of the major concerns in agriculture and plays a critical role in global, regional, and field decision-making. Crop yield forecasting is based on crop parameters and meteorological, atmospheric, and soil conditions. This paper introduces a crop recommendation and yield prediction system using a Hybrid Moth Flame Optimization with Machine Learning (HMFO-ML) model. The presented HMFO-ML method effectively recommends crops and forecasts crop yield accurately and promptly. The proposed model used a Probabilistic Neural Network (PNN) for crop recommendation and the Extreme Learning Machine (ELM) method for the crop yield forecasting process. The HMFO algorithm was used to improve the forecasting rate of the ELM approach. A wide-ranging simulation analysis was carried out to evaluate the HMFO-ML model, showing its advantages over other models, as it exhibited a maximum R^2 score of 98.82% and an accuracy of 99.67%.

Keywords-agriculture; crop yield prediction; crop recommendation; machine learning; moth flame optimizer

I. INTRODUCTION

The estimation of crop production has attracted a lot of research interest recently. The most outstanding aspect of crop yield is climatic situations [1]. If the climate-established forecast is accurate, farmers can be notified and mitigate damage, which can help economic progress [2]. Proper anticipation can serve as an aiding factor for farmers in substituting crop selection or abandoning a crop in its initial phase in severe circumstances [3]. In addition, crop yield forecasts could provide farmers with a good idea of harvesting seasonal crops and their preparation [4]. Achieving an ultimate crop harvest rate by employing inadequate field capacity is a target of agronomic scheduling in an agro-based nation. Crop pickers can reduce their financial damage during adverse situations or expand the degree of crop harvest when there is the possibility of encouraging conditions [5]. Therefore, it is necessary to predict crop yields before harvest to achieve efficient crop administration and predicted results [6]. As there is a non-sequential link between crop yield and the factors persuading crops, ML might be efficient for yield prediction.

ML is a subdivision of AI that focuses on education and is a real-world method that can offer good harvest forecasts [7]. ML can also regulate outlines and associations from data that represent results from previous practice. The analytical approach is constructed by adopting many procedures, and the parameters are decided using previous records during the training stage [8]. The testing stage uses a fragment of the record that was not used for training. ML can be definitive or predictive [9]. Descriptive methods are used to describe what has happened, while predictive methods are used to forecast the future. ML incorporates various risks when trying to construct a high-performance predictive method [10]. It is significant to pick the appropriate process/algorithm to resolve the given issue, along with the algorithms and basic platforms required to manage data capacity.

This paper introduces an intelligent crop recommendation and yield prediction system using the Hybrid Moth Flame Optimization with Machine Learning (HMFO-ML). The presented HMFO-ML model effectively recommends crops and forecasts crop yield promptly and accurately. The HMFO-ML model uses a Probabilistic Neural Network (PNN) for crop recommendation and the Extreme Learning Machine (ELM) method for the crop yield forecasting process. The HMFO algorithm was used to improve the prediction rate of the ELM approach. A wide-ranging simulation analysis was carried out to demonstrate and evaluate the results of the HMFO-ML method.

II. RELATED WORKS

In [11], a crop recommendation method was presented that used CNN and RF techniques to predict better crop yield, exploring several parameters, such as harvest, area, selling price, soil variety, etc. In [12], a hybrid DL-based crop yield forecasting method was proposed using FNN and DBN techniques to overcome the problems of nonlinearity and gradient diffusion. DBN incorporates statistics and probability with NNs. This method primarily executed an effectual pre-trained system by DBN to improve model progress and feature vector generation. In [13], a system was proposed to predict crop yield in earlier data using ML approaches, such as Random Forest and SVM in agriculture data, and to recommend appropriate fertilizers for specific crops. This study emphasized the design of a predictive method that could be used for future crop prediction. In [14], a DL algorithm was presented for crop production, using previous information on crops and climate. This method was a hybrid mechanism that used Ant Colony Optimization (ACO) to optimize Deep Convolution Neural Network (DCNN) and LSTM network inputs for crop prediction. Based on the number of layers used in processing, DCNN achieved a higher level of accuracy but had a higher computational complexity.

In [15], a DL method based on Gray Wolf Optimization (GWO) was proposed that could suggest the best crop depending on the chemical and climatic situations. This study considered many chemical features, namely nitrogen, pH, potassium, and phosphorus, and different climate factors, namely humidity, rainfall, and temperature, to recommend crops to farmers. The method was established in diverse folds: a CNN was initially used to extract and categorize the main characteristics, and then the GWO was used to optimize the features to recommend an improved crop based on various factors. In [16], a fusion intellectual model for soil was established and examined with different baseline methods on the South Australian Soil dataset to assess forecasting. Semantic similarity can be evaluated using the SemantoSim measure, Jaccard, and Cosine similarity in the Squirrel search process to ensure that the related results and set entity generated from a set of recommendations are improved.

III. THE PROPOSED MODEL

This study presents the HMFO-ML method for robust crop recommendation and yield forecasting. The proposed HMFO-ML method effectively recommends crops and forecasts crop yield accurately and promptly, encompassing PNN-based crop recommendation, ELM-based yield forecasting, and an HMFO-based tuning process. Figure 1 shows the workflow of the HMFO-ML approach.

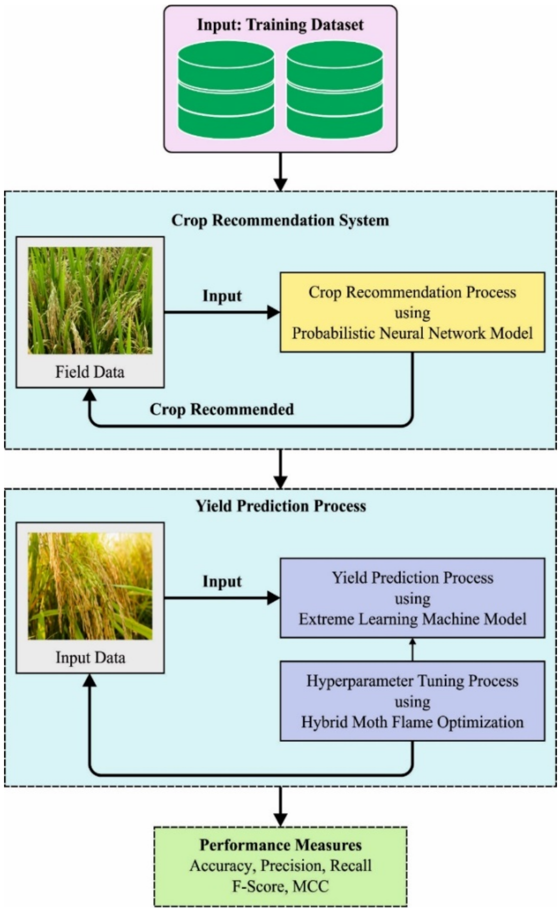

Fig. 1. Workflow of HMFO-ML approach.

A. *Crop Recommendation using PNN*

The proposed HMFO-ML method uses a PNN model for crop recommendation. An ANN can characterize any nonlinear relation between input and output via proper training and a flexible model [17]. ANN is used for real-time prediction and classification problems. The PNN is a kind of ANN that depends on Bayesian classification and has similarities to the backpropagation method in the way they progress. However, the model has variations in the learning process. The structure of the model includes the summation, input, output, and pattern layers. The summation layer is similar to the competitive network and has similar neurons to the targeted class, but the pattern layer is similar to RBN and has several neurons identical to the input sample number. The input layer neuron takes input from an input vector:

$$X = (f_w^{\overline{m_1}}, s^{m_i}, K^{m_i}), \in R^n, \quad n = 9$$

where $m_i = (R, G, B)$ signifies a color map for i = 1, 2, 3. This input is sent to the patterning layer where the neuron is split into an amount of classes C.

The resultant of the j-th pattern neurons c-th class evaluated by the Gaussian kernel:

$$F_{ci}(X) = \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}} \exp\left(-\frac{\|X - X_{c,j}\|^2}{2\sigma^2}\right) \quad (1)$$

where $X_{C,j} \epsilon R^n$ denotes the center of the kernel, and σ indicates spread (smoothing) parameters, defining the magnitude of the corresponding kernel area. The summary layer calculates the conditional class probability estimation function with a fusion of the formerly calculated density:

$$G_c(X) = \sum_{j=1}^{N_c} F_{c,j}(X), c \in \{1,2, \dots C\} \quad (2)$$

where w_{cj} indicates positive coefficient satisfying, N_c denotes the pattern neurons number of class c and $\sum_{j=1}^{N_c} w_{cj} = 1$. The patterning vector X is categorized in class respectively to the unit of summary with the maximal result:

$$0(X) = \arg\max_{1 \le c \le C}(G_C) \quad (3)$$

This is the diagrammatic representation of the presented method. The images are chosen sequentially, and their features will be extracted. The feature was used for training the PNN network for classification.

B. ELM-based Crop Yield Forecasting

The ELM model was applied to the crop yield forecasting process [18]. Consider a learning issue of evaluating an arbitrary targeting function with an unknown relation amongst input $X \subset R^n$ and output $T \subset R^m$. The objective of the learning is to find an appropriate non-linear mapping $\tilde{f}(x) \approx t(x \in X, t \in T)$ with the presented dataset $\{(x_i, t_i)\}_{i=1}^{N} \subset R^n \times R^m$ with N identically distributed and independent samples. ELM integrates a three-layer framework, was initially developed for SLFN, and expanded to widespread SLFN where the Hidden Layer (HL) should not be the same. Unlike other traditional methods to train SLFN, its HL variables (a_i, b_i) are produced randomly. Therefore, the learning problem is reduced to evaluate the optimum output weight β. T and β are the ELM output and target weight matrix, respectively. In general, ELM is processed as a linear integration of the L activation function:

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta \quad (4)$$

where L indicates the HL number of ELM, and $h_i(\mathrm{x}) = g(x, a_i, b_i)$. The abovementioned formula is expressed as follows:

$$H\beta = T \quad (5)$$

where H denotes the HL output matrix:

$$H = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{bmatrix} = \begin{bmatrix} h_1(x_1) & \dots & h_L(x_1) \\ \vdots & \ddots & \vdots \\ h_1(x_N) & \dots & h_L(x_N) \end{bmatrix} \quad (6)$$

$$T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix} \; and \; \beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix} \quad (7)$$

Unlike other traditional ML methods, ELM aims to obtain the smallest norm of the output weight and the most minor training error. The objective function can be formulated as:

$$min : L_{ELM} = \frac{1}{2}|\beta||^2 + \frac{1}{2} C \sum_{i=1}^{N} \xi_i^2 \quad (8)$$

$$s.t. \, h(x_i)\beta = t_i - \xi_i, \;\; i = 1, \dots, N$$

where $\xi_i = [\xi_{1,m}, \dots, \xi_{i,m}]$ represents the m output node's training error vector regarding the training instance x_i, and C shows the regularization factor to improve the overall performance. Based on the Karush-Kuhn-Tucker (KKT) formula:

$$\beta = \begin{cases} H^T(\frac{1}{C} + HH^T)^{-1}T, & N < L \\ (\frac{1}{C} + H^T H)^{-1}H^T T, & N > L' \end{cases} \quad (9)$$

where I indicates the unity matrix.

C. Parameter Tuning using the HMFO Algorithm

The HMFO method was used to improve the forecasting rate of the ELM method. MFO uses the moth transverse orientation navigation algorithm [19]. A moth flies a long distance during night-time by keeping a stable angle toward the sky. In this problem, the solution candidate is a moth and the problem variable is its spatial placement. Moths might fly in a hyper-dimensional space of 1D, 2D, or 3-D by adjusting their location vectors. The MFO algorithm is robust and computationally efficient and can be scientifically represented in the following:

$$M = \begin{bmatrix} CO_{1,1} & CO_{1,2} & \dots & \dots & CO_{1,h} \\ CO_{2,1} & CO_{2,2} & \dots & \dots & CO_{2,h} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ CO_{a,1} & CO_{a,2} & \dots & \dots & CO_{n,h} \end{bmatrix} \quad (10)$$

where h denotes the dimension numbers, and a denotes the moths' numbers.

$$S = \begin{bmatrix} S_{1,1} & S_{1,2} & \dots & \dots & S_{1,h} \\ S_{2,1} & S_{2,2} & \dots & \dots & S_{2,h} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ S_{a,1} & S_{a,2} & \dots & \dots & S_{n,h} \end{bmatrix} \quad (11)$$

MFO is a three-stage process for universal optimization:

$$MFO = (I, F, T) \quad (12)$$

where I denotes the function, F represents the moth flight in the search space, and T represents the termination condition criteria.

$$X_i = t(C_i, S_j) \quad (13)$$

where C_i specifies the count of the i-th moth, S_j denotes the count of the j-th flames, and r represents the twisting function.

$$S(C_i, S_j) = Z_i . e^{bt} . \cos(2\pi t) + S_j \quad (14)$$

where Z_i denotes the distance between the moth and flame, b indicates constant values, and t shows a random number within [−1, 1].

$$Zi = |S_j - X_i| \quad (15)$$

Particles in PSO with a specific random solution follow the present optimal particles to search for global optimization. With N particles in a search space of D-dimension at the t-th iteration, q_i^t and xr_i^t denote the velocity and location, respectively. Correspondingly, at the i-th iteration, $pbest_i^t$

indicates the personal solution attained for the i-th particle, and $gbest_i^t$ shows the optimum solution attained. The following equations were used to calculate the upgraded value for the i-th particle's velocity and position:

$$q_i^{t+1} = wq_i^t + c_1 r_1 + (pbest_i^t - x_i^t) + c_2 r_2 + (gbest_i^t - x_i^t) \quad (16)$$

$$x_i^{t+1} = x_i^t + q_i^{t+1} \quad (17)$$

where r_1 and r_2 denote the random number [0, 1], c_1 and c_2 indicate constant terms, and w represents the inertia weight. The early convergence problem is addressed by integrating the idea of local attractors from PSO, including the location-adjusting method of a moth around the flame from MFO. It is shown that the PSO method was ensured to converge if every particle converged towards the local attractor Q_i^t:

$$Q_i^t = \phi pbest_i^t + (1 - \phi) gbest_i^t \quad (18)$$

where ϕ denotes a vector.

$$S(C_i, Q_i^t) = Z_i . e^{bt} . \cos(2\pi t) + Q_i^t \quad (19)$$

$$Zi = |Q_i^t - C_i| \quad (20)$$

Fitness selection is a crucial factor in the HMFO algorithm. The encoded solution was used to develop aptitude or candidate goodness outcomes. At present, the accuracy value is an essential situation exploited for scheming a fitness function.

$$Fitness = \max(P) \quad (21)$$

$$P = \frac{TP}{TP+FP} \quad (22)$$

where TP and FP signify the True Positive and False Positive values, respectively.

IV. RESULTS ANALYSIS

This study used the Crop Recommendation Dataset [20] to evaluate the performance of the HMFO-ML method. This dataset was constructed by improving databases of weather, rain, and manure information for India [21]. The dataset was split into 70:30 subsets for training and testing. The modes presented were simulated using Python 3.6.5 on an i5-8600k, GeForce 1050Ti 4GB, 16 GB RAM, 250 GB SSD, and 1TB HDD PC. The parameter setups were: rate of learning: 0.01, epochs count: 50, size of the batch: 5, rate of dropout: 0.5, and activation: ReLU. Figure 2 shows the classifier outputs of the HMFO-ML method under the test data. Figure 2(a)-(b) show the confusion matrices presented by HMFO-ML. The HMFO-ML method recognized distinct instances under 21 class labels. Figure 2(c) shows the PR investigation of the HMFO-ML method. The figures show that the HMFO-ML approach achieved maximal PR under total classes. Figure 2(d) shows the ROC investigation of the HMFO-ML model, showing its effectiveness with maximum ROC values under discrete class labeling. Figure 3 shows the comprehensive outputs of the HMFO-ML method on training. The results indicate that the HMFO-ML method recognized all 20 classes. It is also noticed that the HMFO-ML model accomplished an average $accu_y$ of 99.67%, $prec_n$ of 96.43%, $recall$ of 96.39%, F_{score} of 96.40%, and MCC of 96.23%.

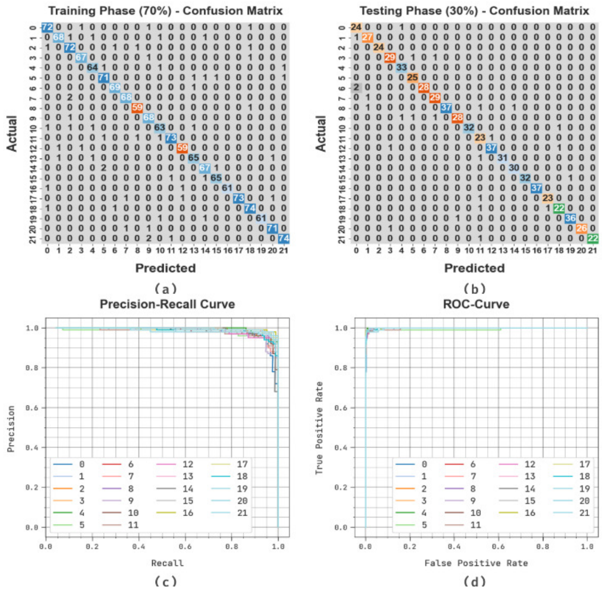

Fig. 2. (a), (b) Classifiers for 70:30 training/testing of the dataset, (c): PR curve, and (d): ROC curve.

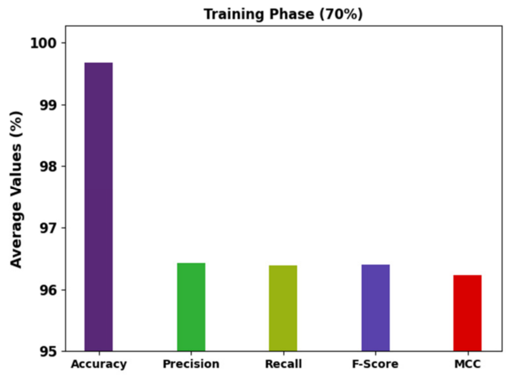

Fig. 3. Average results of the HMFO-ML method in training.

Figure 4 shows the overall outputs of the HMFO-ML method on testing. The outputs indicate that the HMFO-ML method recognized all 20 classes and accomplished an average $accu_y$ of 99.66%, $prec_n$ of 96.07%, $recall$ of 96.23%, F_{score} of 96.08%, and MCC of 95.94%.

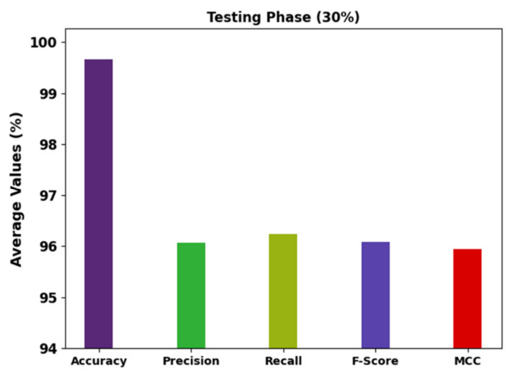

Fig. 4. Average results of HMFO-ML approach under 30% of testing.

Table III shows a brief comparative study of the HMFO-ML method with others [22-24]. Based on $accu_y$, the HMFO-ML method achieved a higher $accu_y$ of 99.67% while the SVM, SVM-Kernel, SSAE and PCA CNN, NC-SAE, and DT methods obtain lesser $accu_y$ of 94.64%, 91.73%, 90.85%, 89.49%, 88.62%, and 85.07%, respectively.

TABLE I. COMPARATIVE RESULT OF HMFO-ML WITH OTHER METHODS

Methods	$accu_y$	$prec_n$	*recall*	F_{score}
HMFO-ML	99.67	96.43	96.39	96.40
NC-SAE	94.64	94.06	94.78	95.49
SVM-Kernel	91.73	91.13	92.42	93.80
SVM	89.49	88.17	88.70	88.46
SSAE-CNN	90.85	93.86	90.60	92.94
PCA-CNN	88.62	89.27	87.75	89.08
DT	85.07	84.73	85.91	85.39

Table IV shows the results of the HMFO-ML approach in terms of R^2. The HMFO-ML method reached a higher R^2 of 98.82%, while the SVM, KNN, MLR, and ANN methods obtained a lower than 91.99% R^2, respectively, 87.05%, 89.10%, and 91.97%. These results demonstrate the improved efficiency of the HMFO-ML model.

TABLE II. R^2 OF THE HMFO-ML WITH OTHER METHODS

Methods	R^2
HMFO-ML	98.82
SVR	91.99
KNN	87.05
MLR	89.10
ANN	91.97

V. CONCLUSION

This study proposes an HMFO-ML model for robust crop recommendation and yield forecasting. The introduced HMFO-ML method effectivelly recommended the crops and forecasted crop yield accurately and promptly. The HMFO-ML method exploited a PNN model for crop recommendation purposes and an ELM model for the crop yield forecasting process. The HMFO algorithm was used to improve the forecasting rate of the ELM method. The results of the proposed method were evaluated and compared with other methods, showing its superiority. In the future, the HMFO-ML method can also embed ensemble ML methods.

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