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An Acquisition Based Optimised Crop Recommendation System with Machine Learning Algorithm

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Abstract

The agricultural sector makes a significant economic impact in India. It contributes 19.9% to the national GDP. The prosperity of the country's economy greatly affects the country's progress and the quality of life for Indian citizens. The vast majority of farms still use antiquated methods rather than adopting a data-driven strategy to increase output and earnings. It is considered a cornerstone of India's financial structure. Since achieving independence, increasing output through the implementation of cutting-edge technologies has been a top priority. Such cutting-edge technology is the application of machine learning algorithms to forecast agricultural outcomes such as harvest size, fertilizer requirements, and the effectiveness of specific farming implements. In this research, a model was built using an optimization and an ensemble of methods to improve the precision and consistency of prediction. Classifiers based on Support Vector Machines (SVM), K Nearest Neighbors (KNN), Decision Trees (DT), and Logistic Regression (LR) were competed against those based on voting and stacking in the ensemble technique. With an accuracy of 99.32%, the Moth Flame Optimization (MFO) algorithm was utilized to recommend the best crop to be harvested.

Keywords: MFO, SVM, DT, KNN and Logistic Regression, Voting and Stacking Classifier

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1. Introduction

In India, farmers are the backbone of the economy. The economic well-being of farmers and the economy as a whole are both negatively impacted by low crop yields or crop loss. Most farmers in the subcontinent still use time-honored techniques to provide food for their families. Both are the result of natural enemies like erratic weather patterns and sudden or recurring floods. Farmers have trouble in anticipating climate changes, air temperature shifts, and the possibility of flood because they lack of necessary information and expertise. Crop yields are affected by a wide variety of environmental and anthropogenic variables, but not limited to mineral content, soil pH, topography, improper application of manures and fertilizers, and weather conditions including precipitation, temperature, humidity, and sunshine.

Integrating contemporary technologies onto existing farming practices is necessary to meet gross requirements while enhancing agricultural production. It has been determined that employing state-of-the-art machine learning techniques is essential to creating a practical crop recommendation model. Artificial intelligence and machine learning allow authorities to select appropriate seeds, fertilizers, and crops based on expected crop yields. In this research, we apply a machine learning ensemble approach to boost the precision of yield predictions in agriculture. Many ingenious methods are used to increase productivity in this context, all with the goal of satisfying people's basic requirements. Recommendations for high-quality seeds, fertilizers, and instruments are necessary for increased agricultural output. Planting the incorrect crops in the incorrect method might have detrimental effects, so it's important for farmers to select the suitable raw material and rectify any nutritional deficiencies in the field.

2. Literature Review

(Jaiswal, Sapna, Kharade, & et al., 2020) proposed a framework that combines collaborative filtering with model-based approaches like KNN algorithm, Support Vector Machine, and Brute algorithm. KNN outperformed over KNN and SVM algorithm as when compared. For better prediction, (Rajak, Kumar, and Pawar et al., 2017), (Waikar, Sheetal and et al., 2020) & (Reddy, Dadore and et al., 2019) focussed on Ensembled approach with Majority Voting. The ensemble models included SVM, bagged trees, AdaBoost, Naive Bayes, and ANN. The majority voting method is utilized to propose the best crop, utilizing Naive Bayes and KNN. These were employed as basic learners and obtain high accuracy values. Implementation of IoT was to obtain real-time values of soil conditions and the related essential actions for greater yield. Using RF, KNN, and SVM, (Mariappan, Madhumitha, and et al., 2020) presented Crop Suitability and Fertilizers Recommendation with accuracy rates 89% and 80% respectively. Support Vector Machine (SVM), Naive Bayes (NB), Multi-Layer Perceptron (MLP), and Random Forest (RF) were used in combination to boost the accuracy of the model. After the model has been trained and can predict its own class, the class predicted by the majority of learners is chosen as the sample's class level. (Patil & Mohmmad, 2019) suggested a modified approach for crop and fertilizer recommendation that employs NB classification and the results were beneficial to farmers depending on their crop fields. RF and NB were employed by (Raj, Angu, and Balashanmugam et al., 2021) to create prediction models. The Gradient Descent technique is used to train the model, which minimizes the loss function by increasing forecast accuracy. For the soil analysis, classifiers such as SVM, NB, MLP (artificial neural network), J48(C4.5), and JRip were employed. This establishes a system for data mining climate expectations, which produces excellent results. In contrast to traditional metrological approaches, machine learning approach raised the possibility of a higher yield. (Parikh, Jain and et al., 2021) used the Tkinter graphical interface to compare LR, SVM, and RF classifiers. Following the research, KNN outperformed over Decision Tree, RF etc. for agricultural datasets in terms of efficiency and precision. Phosphorus, nitrogen, potassium, and pH are input factors used by the KNN algorithm and are highly helpful in predicting crops for appropriate soil. The system provides a list of acceptable crops depending on the soil parameter, but it is up to the farmers to choose which crop to plant. (Suruliandi, Mariammal, and et al., 2021) discussed the feature selection and fragmentation of the key elements of machine learning algorithms. This research was used to choose the best plants depending on the soil and other environmental factors. Feature selection method improves prediction accuracy, reduces the number of features without losing any essential information, and eliminates unnecessary data. Selection processes such as Recursive Feature Elimination (RFE), Sequential Forward Feature Selection (SFFS), and Boruta were used to determine which features to use. Availability of SFFS is effective for a small dataset, despite it selects one element at a time and the loop continues with each attribute got selected. Better predicted accuracy is made possible by RFE, which chooses the most correct features based on the conventional approach. Separation plays a significant role in crop prediction as well since it is frequently used to forecast the best harvest in a certain location. (Potnuru, Pinapa Sai, and et al., 2020) suggested the CRY algorithm, a prediction model of agricultural-related data for crop harvesting employing beekeeping methods. Crop production depended on sensitivity, humidity, soil type, and plant kind along with different machine learning techniques, including Linear Regression (LR), ANN, and KNN approach, their analysis largely focused on categorizing crops in India, including paddy, rice, and sugarcane. It employed a neuro-fuzzy system and multiple linear regression to forecast crop output while taking into account soil and environmental factors.

A recommender method was put out by (Doshi, Nadkarni, Agarwal, & Shah, 2018) to determine the type of crop to be cultivated based on a variety of variables, including the type of fertilizers used, the forecasted weather, and the availability of irrigation systems. They found out that the optimal crop type may be determined or anticipated on total quantity of rainfall and the current training model. (Mythili and Rangaraj, 2021), provided a novel deep learning-based method for agricultural production prediction. The suggested method of PSO-Modified DNN advocated an appropriate crop recommender model to arrive at a suitable crop harvesting choice, and its accuracy exceeded several machine learning approaches. The suggested model suggested cultivating crops and estimated yields under unproven conditions. The model tunes the MDNN hyper-parameters using PSO and weight matrices with L2 regularisation. Using a network topology with PSO-optimized weights, prediction accuracy is increased. The ensemble model with a majority voting approach is covered in (Rajak, Pawar, & Pendle, 2017). For a suggestion of an effective and extremely precise crop yield, SVM with ANN as a learner is combined with Random Tree and NB-classifier. Based on the region and preferred methods of farming, (Kuanr, Rath & Mohanty, 2018) suggest seeds, insecticides, and equipment. Using fuzzy logic and cosine similarity, it is possible to estimate the crop output during the Kharif growing season. Using data on historical yields and predicted weather conditions, farmers may get an early sense of crop production. A different body of research (Pudumalar, Ramanujam, Rajashree & et al. 2017) discussed the precision agriculture approach, which utilizes crop yield and soil attributes to help farmers choose the best crop. In order to achieve high accuracy, the authors suggested an ensemble model that combines Naive Bayes, CHAID, KNN, and Random tree technique. Focused on the creation of a suggestion system for agricultural growth monitoring, (Lakshmi, Priya, Sahana & Manjunath, 2018) considered geographical features such soil texture, hue, drainage, depth, Ph value, water retention capacity, erosion, porosity, and climate condition. The crop type is efficiently and precisely recommended by map-reduce using KNN. According to the information (factors impacting the yield of a crop) supplied, (Akshatha & Shreedhara, 2018) suggested a precision agriculture ensemble model that used a number of machine learning algorithms to choose a crop that was best suited for the farmer. A fuzzy expert multi-layer system was developed by (Aarthi & Sivakumar, 2020) for crop recommendation. Twelve variables from the Mamdani fuzzy inference were prioritized and divided into six fuzzy subsystems. (Banerjee, Sarkar & Ghosh, 2021) concentrated on the key elements, such as geographic, soil texture, and meteorological data, which have an impact on continuous crop production. Their suggested approach includes a parallel fuzzy rule base system and addressed the main crops farmed in West Bengal. The type of crop is suggested by (Rekha, Siva, Sai, & Bharathi, Siva, & et al., 2021) using the KNN algorithm focused on the criteria for assessing the effectiveness of the algorithm. (Majumdar, Naraseeyappa & Ankalaki, 2017) used PAM, CLARA, DBSCAN, and Multiple Linear Regression to mine agriculture data in order to identify the ideal crop production enhancement factors. The clusters are formed by using the Batchelor Wilkins method to calculate the value of "k". Optimizing the production of several current crops while considering soil and climatic data, analysis of novel and non-experimental data makes agriculture more receptive to climate change. (Pravin, Muthuvel, Ramprabhu and et al., 2022) employed ANN and Kmean with the Lightweight GBM technique to increase seasonal agricultural yield. Farmers have received appropriate advice and proposals for crops depending on several characteristics to generate a large quantity of merchandise. Cold start problem was major drawback in a recommended system. This problem was well handled by (Choudhury S.S, Mohanty S.N. & Jagdev A.,2020). They proposed movie recommendation using user's trust with similarity measure in association with ANN, SVM and Deep Neural Network (DNN).

3. Outline of Dataset

The dataset collection includes information on 22 different types of crops, soil nutrient levels, and environmental elements that are beneficial to a crop's growth and production. Better yields are seen across a variety of weather and soil consistency characteristics using 100 data points for each distinct crop. This dataset, which includes characteristics like N, P, K, temperature, humidity, pH, rainfall, and crop type, was compiled from Kaggle for agricultural-production-optimizing-engine. The dataset will only comprise a subset of the crops, which may not lead to an accurate prediction. To distribute the sequential type of crop throughout the database, the full set of data was shuffled. Variations of various crops will be spread out between the train and test sets to achieve equal distribution of all features. The data distribution in the data base shown in the figure(1).

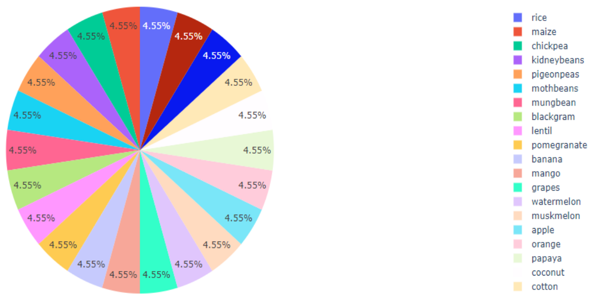

Fig 1: Data distribution in the data set

3.1 Data Processing and Acquisition

Any machine learning system's accuracy is determined by the number of data points and the precise division of training and testing data. Rice, maize, chickpeas, kidney beans, blackgram, pigeonpeas, mothbeans, mungbeans, lentils, pomegranates, bananas, mangoes, watermelons, grapes, muskmelons, oranges, apples, papayas, coconuts, cotton, jute, and coffee are just a few of the crops covered in this collection. The specifications for soil composition and weather are given in Table1.

Table 1: Variations of the attribute value

Attribute	Min Value	Max Value
N	0	140
P	5	145
K	5	205
Temperature	8.82	43.67
Humidity	14.25	99.98
Ph	3.50	9.93
Rainfall	20.21	298.56

The Correlation between the above-mentioned parameters is shown in Figure-2. From the figure we can find out the high correlation between potassium and phosphorus.

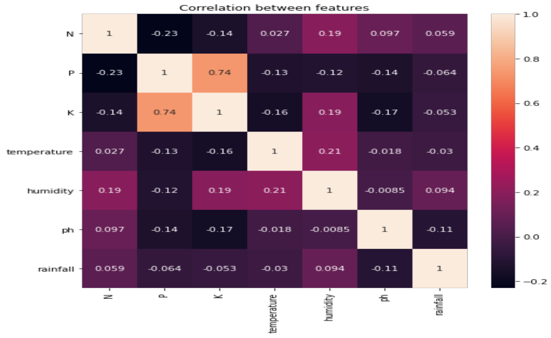

Fig 2: Feature correlation matrix

4. Proposed Method

Figure (3) depicts the propose model for crop recommendation system. The suggested approach attempts to decrease crop seed waste brought on by selecting an inappropriate crop, to boost yield, and to provide the user with potential profitability. The soil and climatic conditions act as the model's input. The climatic parameters include factors like humidity, temperature, and rainfall, whilst the soil conditions include the pH levels and nutrient content of the soil. The appropriate crop has been predicted and recommended using four machine learning techniques, including LR, SVM, KNN, and DT. These methods were chosen due to their reasonably simple implementation and relatively high accuracy when compared to other algorithms employed on the same datasets.

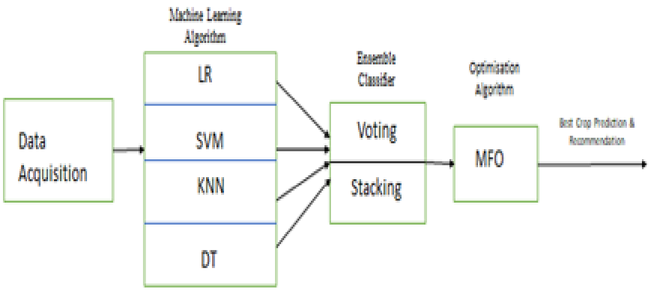

Fig 3: Proposed Model for Crop Recommendation

The ensemble model was a prediction model that combines decisions from other models to enhance overall performance. To enhance model performance, four different algorithms—SVM, LR, DT and KNN were integrated. In order to create the best predictive model, predictions from various algorithms were combined to form an ensemble model. To create the most accurate crop predictions, voting and stacking classifier algorithms were applied. The voting classifier (VC) was an ensemble learning classifier that manages various models separately and produced each model's output depending on the class with the highest likelihood of being chosen, which was referred to as "vote". The label with the majority of votes was predicted after the projections for each label have been added together. This method was employed to enhance the single model's performance inside the ensemble. SVM, Logistic Regression, Decision Trees, and KNN classification models were merged. The class that received the most votes became the output of the model.

The stacking classifier was an ensemble learning technique in which the meta classifier was trained using new features derived from the predictions of other classifiers. The predictions from two or more baseline machine learning algorithms were combined using a meta classifier learning algorithm. Common Python implementation of the stacking ensemble available in scikit-learn library. The training dataset for the meta-model was built using k-fold cross-validation which based on the out-of-fold predictions.

4.1 Moth Flame Optimisation (MFO)

The proposed model is subjected to an optimization paradigm inspired by nature using the MFO algorithm. The main source of inspiration for the proposed algorithm was transverse orientation travel technique of moths in nature. Moths have learned to use moonlight to fly at night, and they achieve this by performing a transverse orientation. A moth used this technique by keeping a steady inclination toward the moon (light source). This method was considered to be one of the most effective ways to travel long distances in a straight line. This method assures straight-line flight due to how far the moon is from the moth. Human-made artificial light causes moths to seek to keep a comparable angle in order to fly straight. But due to the proximity of the moon to the light source, maintaining a same angle to the moon causes moths to fly in a useless or hazardous spiral. It is seen that the moth advances toward the light gradually in artificial lighting. The algorithm's primary elements are moths and flames(solutions). The variables in the situation are the spatial locations of the moths, which could be potential solutions. As a result, moths may fly with altering position vectors in 1-D, 2-D, 3-D, and even hyper-dimensional space (of dimension d). Since the MFO method uses a population-based approach, a group of n moths is utilised as a search agent in the domain of interest. So far, moth positions found in flames have been the best. Moths position will be updated with respect to flames is given by equation (1).

$$M_i = S(M_i, F_j) \qquad (1)$$

Where M_i represents i^{th} Moth from the population size, S denotes the spiral function and F_j indicates the j^{th} Flame. Therefore, each moth checks the vicinity of a flag (flame) and adjusts itself, if a better choice is found. Consequently, flames were d-dimensional data points as well. Using a logarithmic spiral as a starting point, a particular moth updates its location in relation to a given flame as in equation (2).

$S(M_i, F_j) = D_i \cdot (e) ^\wedge b * t \cdot \cos(2\pi t) + F_j$ (2)

where D_i means the Euclidian distance of the i^{th} moth for the j^{th} flame, b is a constant for defining the shape of the logarithmic spiral flame and t is a random number in [−1, 1]. The next location of a moth in relation to a flame was established. How near to the flame the moth should be in its next position was determined by the t parameter in the spiral equation. Since the flame was surrounded by a hyper-ellipse in all directions, it is sense to assume that the moth was there. We assume that t was a random number in the interval [r, 1], where r is the convergence constant and falls linearly from 1 to 2 iterations. This assumption is made to emphasize exploitation even more. Moths tend to use this tactic more precisely while utilizing their separate flames, depending on the number of repeats. The possibility of convergence to a global solution was increased if a particular moth updated its position used just one of the flames. The flames were arranged according to their fitness levels at the end of each iteration and upgrading of the list of flames. After that, the moths arrange themselves differently in relation to the appropriate flames. The quantity of flames to be followed reduced as the number of iterations raised, as in equation (3).

N flames = round $(N - l * (N - 1) / T)$ (3)

where l is the current iteration number, N is the maximum number of flames, and T indicates the maximum number of iterations.

4.2 Pseudocode of MFO

1. Initialize all parameters.
2. Initialize Moths position randomly in the search place.
3. Update Flame number.
4. Calculate fitness values for each individual/ Moths.
5. If (iteration = =1) then
   F = sort (M)
   OF = sort (OM)
   Else
   F = sort (M_{t-1}, M_t)
   OF = sort (M_{t-1}, M_t)
   Endif.
6. For i = 1 to n
   For j = 1 to d
   Update r and t.
   Calculate distance for corresponding moths.
   Update Moths position.
   End.
   End.
7. Display best solution obtained.

As it eliminates the most closely related qualities to reduce computational complexity, MFO offers the optimised attributes. The spatial locations of the moths are their database properties, which may hold the key to finding a solution. In the crop dataset, a group of moths was used as a search agent, and uncorrelated qualities end up being the best solutions. At each iteration, the targeted traits were updated and placed according to their fitness levels. The best classifier for recommending the farmer on the best crop to plant in order to increase yield was ensemble stacking classifier because it provides better accuracy.

5. Results & Discussion

With the suggested model's optimised features, we were able to achieve an accuracy of 99.32% with high precision and recall value. Stacking classifier was chosen as the MFO's objective function because it offers higher accuracy than the other techniques. The optimised features were N, P, K, Humidity, and Rainfall. To reach high accuracy the hyper parameters have been tuned in line with each model to find the optimal parameters and ensemble into a single model to make effective predictions. Recall, accuracy, and precision are among the performance metrics, along with various error metrics for various algorithms are shown in the table (2).

Table: 2 Performance measure of different algorithm

Algorithm	Recall (%)	Accuracy (%)	Precision (%)
LR	94.58	94.69	95.25
SVM	96.53	96.51	97.23
KNN	97.54	97.57	97.99
DT	98.22	98.03	98.24
VOTING	98.24	98.03	98.25
STACKING	98.46	98.33	98.51
MFO	98.66	99.32	98.78

Different types of error have been calculated such as MSE (Mean squared error), MAE (Mean absolute error), RMSE (Root mean squared error) and RMSLE (Root mean squared logical error). It is found that RMSLE is very close to other algorithm but accuracy of MFO is increased by 1%. Different error with respect to each algorithm is given in figure (4).

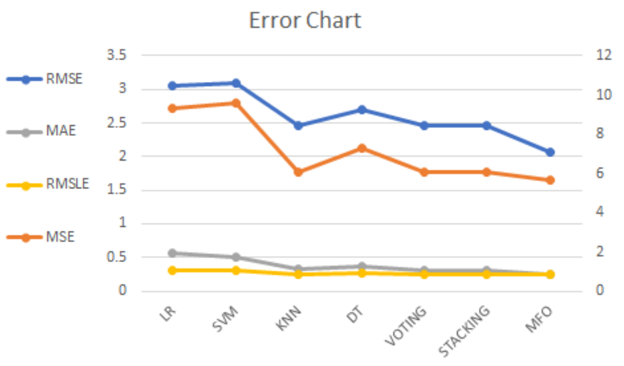

Fig 4: Different error comparison for the respective algorithm.

The table (2) indicates that MFO provides better accuracy with reduced error measure as compared the machine learning algorithm. Convergence graph (Fig 5) indicates that after 2nd iteration the objective function's value is constant. The convergence graph of MFO is shown in figure-5.

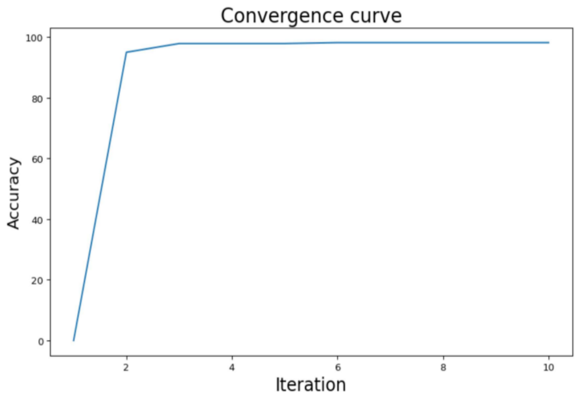

Fig 5: Convergence curve of MFO

6. Conclusion and Future Scope

According to the literature review, the main focus of the research and development on this issue has been crop prediction utilising machine learning with optimisation technique. Specific accuracy levels were attained in this work. Farmers in India now have access to a technology that makes intelligent agricultural recommendations. The suggested model attempts to deliver the optimum crop recommendation as per the geographical conditions put forward by the user with an accuracy of 99.32%. This would aid farmers in decision-making with regard to optimal crop selection for greater yield, forgiving geographical circumstances. Because the suggested method provides accurate findings, there is a good possibility that farmers will be able to maximise production by relying on the circumstances indicated by the soil test and the local meteorological conditions. A hierarchical method is used since each component's findings build on the results of the others. The suggested architecture uses data-based forecasts to assist the agricultural industry in making decisions. The authors' approach is all-encompassing and extensive, extending the scope of the current work to incorporate cost estimation and fertiliser prediction as crucial elements in crop planning.

The MFO approach can be seen as an alternative optimizer to the previously well-known methods for completing the crop recommendation process because it was able to outperform other algorithms on the majority of test scenarios in this study. For prospective works, a number of different study directions can be offered. It's crucial to consider different twists impact how well the MFO functions. The modular implementation of the MFO algorithm may be used for other intriguing future tasks including recommending fertilizers, insecticides, pesticides, and disease detection leveraging IoT. In order to resolve multi-objective computations for crop recommendation, it is required to propose specialized algorithms.

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