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INTERPOLATE GENERALIZED RANDOM DIVERGENCE COCKROACH AGENTIC AI FOR EFFICIENT CROP RECOMMENDATION

Kanuprasad.M.K[1], Dr. N.V Balaji[2], Dr.Shameem Kappa[3]

[1]Research Scholar, Karpagam Academy of Higher Education, Coimbatore-641021, Tamil Nadu, kanucalicut@gmail.com
[2]Professor and Dean, Faculty of Arts, Science, Commerce and Management, Karpagam Academy of Higher Education, Coimbatore - 641021, nvb1977@gmail.com
[3]Associate Professor, PG and Research Department of Computer Science, Sullamusulla Science College Arecode, Ugrapuram PO, Malappuram-673639, shameemkappan@yahoo.com
Corresponding Author;- Kanuprasad.M.K

ABSTRACT
Smart agriculture is the fast developing multi-disciplinary field that encompasses the knowledge from agriculture. Crop recommendation is an essential aspect of agriculture for helping the farmers in making suitable decision for attaining the optimal yield and profitability. Many researchers used Machine Learning(ML) and Deep Learning (DL) methods for performing efficient crop recommendation. But, the accuracy level was not improved and time complexity was not reduced by the existing methods. In order to address the above mentioned issues, a new model termed an Interpolate Generalized Cockroach Agentic AI (InGCAg) model is introduced. At first, gather the agricultural data samples. To perform preprocessing, missing information is handled as well as outliers are detected. After that, the relevant features are selected by Rand Divergence Cockroach Optimization process from pre-processed database. Then, Agentic AI Data Classification is used in proposed InGCAg model to recommend and suggest the crops to the particular location with higher accuracy. Finally, the fine tuning is carried out by using stochastic adaptive moment algorithm to reduce the classification error for attaining better crop recommendation results. Experimental analysis of InGCAg model is carried out using various parameters. Outcome of proposed InGCAg model achieves higher crop recommendation accuracy with minimal time consumption than traditional schemes. The result of InGCAg model demonstrates an improvement in accuracy by 98%, precision by 97%, and F1 score by 97%, along with a 97% increase in recall. In addition, it reduces crop recommendation time by 81ms, RMSE by 0.056when compared to traditional deep learning approaches.

KEYWORDS: Smart agriculture, rand divergence cockroach optimization, Agentic AI data classification, fine tuning

1. INTRODUCTION

In agriculture, crop recommendation systems helped the farmers to select the crop depending on different characteristics like soil quality, weather and crop success. To develop farming idea, new framework termed ANFIS-SVM-PO (adaptive neuro-fuzzy inference system, support vector machine and Puma optimizer) was introduced in [1]. However, it failed to minimize time.Explainable Artificial Intelligence (XAI) -enabled CR system was designed in [2] to reduce the time with Local Interpretable Model-agnostic Explanations (LIME) algorithm. But, the crop recommendation accuracy was not improved by XAI-enabled CR system. Also, the multi-model crop recommendation was not concentrated for selecting the pertinent features. To overcome the issue, A new agricultural prescription recommendation model (AgriPR) was introduced in [3] for concentrating the multimodal crop depending on feature fusion. Features were predetermined by AgriPR. But, the time was not reduced by using vast dataset. Also, the optimal resource allocation was not considered.
Artificial Intelligence (AI) and the Internet of Things (IoT) were developed for automating processes and offering the recommendations, and observing the agricultural behavior to optimize results. The machine-learning model was introduced in [4] to perform optimal resource allocation and to recommend suitable crops for better plant growth. The machine learning model improved crop recommendation accuracy. However, selecting the right crop is essential for agricultural situation.To handle this issue, crop recommendation model was introduced in [5] through considering soil and geographical conditions. The designed model increased the profit and reduced losses faced by farmer. But, the diagnosis of crop diseases and pests are demanding issue.
Plant electronic medical records are provided to discover diagnosis and obstacle of crop diseases and pests. In [6], new cascaded multi-task crop instruction idea was introduced with maximum accuracy.However, the optimizing crop production and resource management remains challenge for farmers. ML was observed in [8] IoT device to observe soil nutrients and provide precise crop recommendations. Nevertheless, it failed to select

acceptable features with higher accuracy. For overcoming the issue, Improved Distribution-based Chicken Swarm Optimization with Weight-based Long Short-Term Memory named as IDCSO-WLSTM was introduced in [8] to recognize crop.But, the accurate soil assessments were not obtained. Crop was forecasted in [9] with Gorilla Troops Optimization by DL. However, it failed to best crop-production plans. Sandy soils were concentrated for enhancing the productivity. In [10], advanced Artificial Intelligence (AI) framework was increased for soil classification and crop recommendation. An adaptive fuzzy logic-based decision system was employed for efficient crop suggestions. But, it failed to incorporate optimization based crop prediction

1.1 Research Gap and Motivation

Crop recommendation defines to the process of offering guidance or suggestions to farmers that selection of crops is most suitable for cultivation in particular area. Crop recommendation systems were developed for precise and up-to-date agricultural information. But, high-quality data on a real-time is demanding issue. Data collection is limited by factors such as data availability, accessibility, and quality assurance. Insufficient or biased data can lead to imprecise recommendations.The deep learning algorithms or hybrid AI models were designed to examine agricultural data and create informed decisions about crop selection. But, the accuracy was reduced and time consumption was higher for considering huge data.Reinforcement learning techniques were utilized to optimize crop recommendation systems However, it unable to reduce the error by using agent and rewards.

These gaps highlight the need forscalable and novel InGCAg model based crop recommendation framework integrating diverse soil composition, climate conditions, and environmental variables. At first, **data pre-processing** dealing with noisy or environmental data and cleaning the noisy data information for mitigating the risks of biased inputs. The proposed framework integrates an **optimization-driven feature selection** for redundant data and reducing dimensionality to handle massive datasets without sacrificing accuracy or computational resources.**Agentic AI combined with correlation-based data classification** allows the AI agent to make decisions. It incorporates **fine-tuning** to minimize error metrics such as RMSE (Root Mean Squared Error).

1.2Key contribution of the model

The main contribution of proposed InGCAg model is given by,

- New model termed InGCAg model in introduced for enhancing the crop recommendation performance in agriculture sector with pre-processing, feature selection and classification and fine-tuning.
- Data preprocessing is performed in InGCAg for obtaining the preprocessing data samples. Sibson interpolation and generalized Rosner's test are employed for handling the missing data and outlier detection.
- Rand divergenced Cockroach optimization is used in InGCAg to identify the relevant features and irrelevant features. Number of features is initialized. Fitness is estimated with aid of rand similarity index. If the fitness of one feature is higher than other feature, the position of current best solution is updated for global best solution. Otherwise, the local best solution is updated. After, the dispersion and ruthless behavior are performed for selecting the global best features for improving the crop recommendation performance.The crop recommendation time is reduced.
- InGCAg model uses Agentic AI for classification via covariance correlation. This correlation is executed for estimating the training and testing data samples. Based on correlation value, precise crop recommendation is achieved with higher accuracy. A stochastic adaptive moment algorithm is employedfor hyperparameters fine-tuning with minimum error rate.
- Comprehensive experimental evaluations are carried out with different metrics that proposedInGCAg model outperforms better than conventional methods.

1.3Paper Organization

It partitioned by subsequent sections: literature of crop recommendation with their limitations are described in Section 2. Section 3 explains the proposed InGCAg model with neat architecture diagram. Experiments are described in Section 4 and result and discussionarepresented in Section 5 and 6. Conclusion is described in Section 7.

2. LITERATURE REVIEW

An artificial intelligence-driven decision support system (AI-DSS) was designed in [11] for handling the irrigation and fertilization in wheat, maize and sugar beet over successive seasons (2022–2025). A non-intrusive method was introduced in [12] for crop recommendations in different environmental conditions. The designed method was employed for AI cloud-based interface.

In [13], new methodology was introduced with multimodal data sources. The designed methodology was employed for customized recommendations. A hyperparameter optimization-based grid search algorithm was introduced in [14] for smart agriculture framework to recommend the crop with high accuracy. The designed framework improved the transparency for every crop recommended to the farmers. Artificial Neural Network (ANN) algorithm was introduced in [15] to identify optimal crop yield with minimum error for prediction. Weather yield personality was analyzed in [16] by Improved Deep Belief Networks (IDBN). In [17], innovative crop recommendation system was introduced. A robust machine learning architecture was introduced in [18] for classification and regression depending on distinct datasets. A crop recommendation dataset comprised soil pH, temperature, humidity and nutrient levels. An artificial intelligence (AI) powered smart agriculture system was designed in [19] with DL and explainable artificial intelligence (XAI) for data-driven farming. Soil humidity was determined in [20] via Intelligent Hunting Optimized Adaptive Light Gradient Boosting Ensemble DNN. In [21], tiny ML was employed.

In [22], lightweight exponential-weighted ensemble framework was designed to improve accuracy and reduce computational overhead. However, the framework did not effectively handle missing values and noisy measurements. DL architecture was developed in [23] for crop recommendation. ML models were introduced in [24] for crop selection and nutrients. Accuracy was increased in [25] through Inter-fused ML by Advanced Stacking Ensemble scheme. In [26], crop prediction was achieved with LSTM. Gradient Boosting algorithm was introduced in [27] for efficient crop recommendation based on nutrients and environmental parameters. ML architecture was developed in [28] for accurate crop recommendation through climate and soil attributes. ML based system was designed in [29] based on historical data on climatic circumstances and soil propertiesto provide personalized crop recommendations. A stacking ensemble model was introduced in [30] to enhance crop recommendation based on feature fusion. Detection framework and Large Language Model (SAMConvFormer+LLM) was employed in [31] for crop yield estimation. But, the time was higher for huge dataset. Table 1 describes the comparison analysis of state-of-the-art methods.

Table 1 Comparison analysis of state-of-the-art methods

Reference. No & Methods	**Objective**	**Dataset**	**Advantage**	**Disadvantage**
ANFIS-SVM-PO[1]	Accurate Crop recommendation	Crop recommendation dataset	Increase Accuracy of Crop recommendation	Time was not reduced
XAI-enabled CR system [2]	To offer suitable crop recommendation for optimal resource allocation	Crop recommendation dataset	Time was lesser	Crop recommendation accuracy was not improved
AgriPR [3]	Predetermine features	Agriculture dataset	Recall was enhanced	Error was not minimized
IDCSO-WLSTM [8]	Crop prediction and recommendation	Climate dataset	Precision was higher	Deep learning techniques was not employed for accurate predictions
ANN [15]	Identify optimal crop yield	Agriculture dataset	Minimum error for prediction	
Crop recommendation system [19]	Improve the crop recommendation and yield-prediction	Agriculture dataset	Increase Accuracy, precision, recall, F1score	Time was not reduced
Lightweight exponential-weighted ensemble framework [22]	Combine numerous base classifiers for CRS	Crop dataset	Enhanced accuracy and reduced computational overhead	Failed to handle missing values and noisy measurements
Long Short term Memory model [26]	Accurate Crop recommendation and forecasting system	Temporal dataset	Error was decreased	Did not focus on exploring additional parameters to improve precision
ML based system [29]	Provide personalized crop recommendations	Crop dataset	Time was reduced	Failed to improve accuracy of models' while handling large dataset
SAMConvFormer+LLM [31]	Achieve crop yield estimation	Crop recommendation dataset	Precision was enhanced	Time was higher for vast dataset

2.1 Problem statement

Agriculture is an essential role in India's economy, sustaining millions of livings. Crop recommendations play a necessary role in precision agriculture for forecasting the most suitable crops. Despite significant advancements in precision agriculture, existing crop recommendation systems struggle to balance prediction accuracy, computational efficiency, and data resilience.Based on the above conventional literature, the limitations are described such as high processing time [1, 19, and 31], lesser accuracy for huge dataset [2, 29], and failure to consider missing values, sensor noise, and environmental anomalies [22]. Also, LSTMs [8] [26] were struggle to minimize prediction errors due to a lack of hyperparameter tuning or failure to consider multi-faceted parameter interactions. Many existing models [3, 8] fail to reach optimal crop recommendation performance.

To overcome the issue, the proposed InGCAg model by integrating preprocessing, feature selection, and classification and fine-tuning. InGCAg uses **data preprocessing phase** engineered to impute missing data and systematically detect and eliminate outliers. The proposed framework introduces a dedicated **Rand Divergence Cockroach Optimization** process for feature selection. By filtering out redundant and irrelevant features early on, the model significantly reduces the dimensionality of the input data and time complexity. Also, adaptive **Agentic AI Data Classification** mechanism designed to dynamically adjust to regional soil and climatic parameters. This ensures localized, highly precise recommendations.To ensure the highest possible precision, the InGCAg model incorporates a final fine-tuning determined by **Stochastic Adaptive Moment Algorithm**. This adaptive optimization step continuously refines the model weights with minimizing the classification error rate and ensuring highly dependable and data-driven suggestions for farmers.

3. METHODOLOGY

Agriculture is an important sector in many countries to provide food for world population. Agricultural data mining is defined as the process of extracting, analyzing and interpreting the data points from the agricultural sector to find out the hidden patterns and actionable insights. Crop recommendation is an essential field in optimizing the agricultural practices. Conventional ML as well as DL examined for performing efficient crop recommendation in agricultural field. But, the accuracy level was not improved and computational cost was not reduced. In order to address these issues, an Interpolate Generalized Cockroach Agentic AI (InGCAg) model is introduced. The main objective of proposed InGCAg model is to perform efficient crop recommendation and suggestion based on the land conditions.

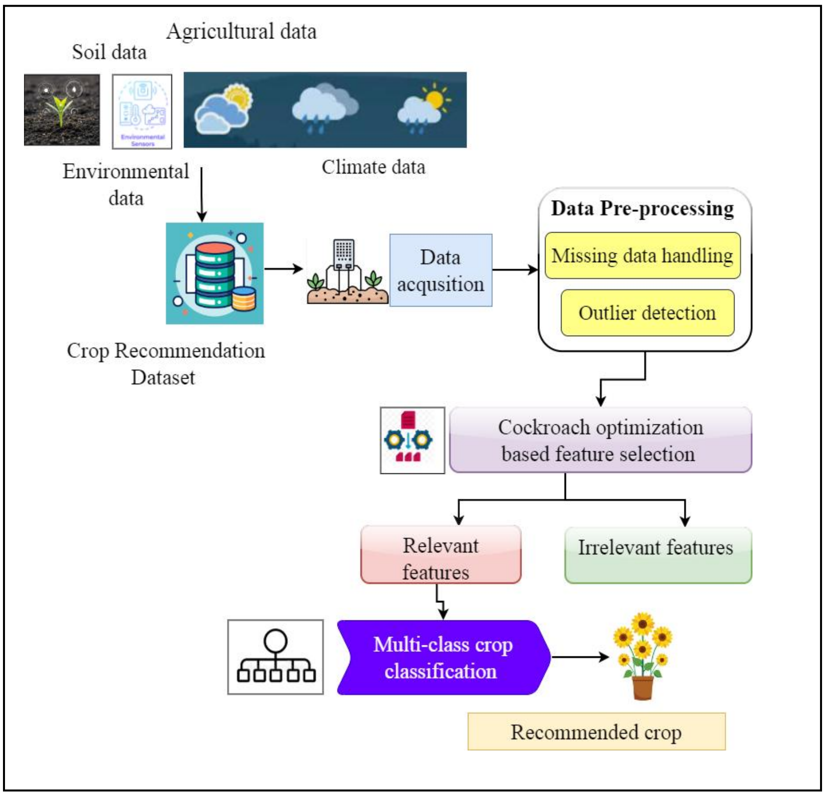

Figure 1 Architecture of proposed InGCAg Model

Diagram of InGCAg is illustrated in Figure 1 for accurate crop recommendation. The proposed model includes four processes. In InGCAg, Environmental as well as soil samples are taken as of dataset. Data pre-processing alter raw dataset into suitable form. Then, the significant feature selection process is carried out by optimization by minimal time. Finally, InGCAg model performs the crop recommendation through classification with higher accuracy and minimum error rate. Different processes of proposed InGCAg model are explained.

3.1 Data acquisition

It is initial step of proposed InGCAg. The raw data samples are collected as of crop recommendation dataset. It is extracted from https://www.kaggle.com/datasets/irakozekelly/crop-recommendation-dataset. The dataset comprised the essential information for accurate crop recommendation. It comprises 18079 records as well as 8 features. The eight features in input dataset are record ID, soil factors like pH, potassium (K), phosphorus (P), and nitrogen (N) levels, as well as climate factors like temperature, rainfall, and crop. The feature descriptions are listed in table2 and table 3.

Table 2 description of features

S. No	Features	Description
1.	ID	ID for particular record
2.	N	Nitrogen content in soil
3.	P	Soil phosphorus content
4.	K	Soil Potassium content
5.	Temperature	Average temperature (in °C) impacting crop growth cycles
6.	Ph	Soil pH level
7.	Rainfall	Average rainfall amount (in mm) influencing water availability
8.	Crop	Recommended crop type based on the given soil and weather parameters **40 Crop Type** ‘barley’, ‘sunflower’, ‘sweet potato’, ‘rice’, ‘soya bean’, ‘jowar’, ‘potato’, ‘turmeric’, ‘jute’, 'maize’, ‘moong’, ‘onion’, ‘cabbage’, ‘ragi’, ‘banana’, ‘rapeseed’, ‘wheat’, ‘horsegram’, ‘coriander’, ‘mango’, ‘tomato’, ‘cotton’, ‘brinjal’, ‘garlic’, ‘blackgram’, ‘cardamom’, ‘blackpepper’, ‘orange’, ‘bittergourd’, ‘papaya’, ‘grapes’, ‘ladyfinger’, ‘pineapple’, ‘bottlegourd’, ‘jackfruit’, ‘pumpkin’, ‘cauliflower’, ‘cucumber’, ‘drumstick’, ‘radish’

Table 3 Number of Data in Class Label

Crops	Number of data	Crops	Number of data	Crops	Number of data	Crops	Number of data
Rice	2245	cotton	613	blackpepper	119	cauliflower	23
Maize	1976	sweetpotato	576	mango	66	cucumber	20
Moong	1327	ragi	557	tomato	59	grapes	19
wheat	1287	horsegram	545	papaya	56	jackfruit	18
rapeseed	1118	turmeric	528	brinjal	55	drumstick	17
potato	1083	banana	507	cardamom	54	bottlegourd	13
jowar	1055	coriander	473	ladyfinger	41	radish	13
onion	1047	soyabean	442	orange	27	blackgram	11
sunflower	737	garlic	415	cabbage	26	bittergourd	11
barley	654	jute	211	pineapple	26	pumpkin	9
Total	12,529	**Total**	4867	**Total**	529	**Total**	154

3.2 Data Pre-processing

It is employed for making input agricultural dataset clean, consistent and suitable one for accurate crop recommendation. The raw agriculture data is gathered with noises, missing values and uneven patterns. The data inconsistency resulted in high error for accurate crop recommendation. The proposed InGCAg model performs efficient data preprocessing through arranging the raw data samples for crop recommendation. The main objective of data preprocessing is to clean the data into suitable format for accurate crop recommendation results. Data preprocessing is carried out to improve the crop recommendation. Assume agricultural dataset, features arranged in matrix format. Formulate input matrix is given by,

$$Matrix = \begin{bmatrix} F_1 & F_2 & \dots & F_{\mathrm{m}} \\ Da_{11} & Da_{12} & \dots & Da_{1n} \\ Da_{21} & Da_{22} & \dots & Da_{2n} \\ \vdots & \vdots & \dots & \vdots \\ Da_{m1} & Da_{m2} & \dots & Da_{mn} \end{bmatrix} \quad (1)$$

From (1), 'M' symbolizes the input matrix. Every row denotes agricultural data samples '$ADS = \{Da_1, Da_2, \dots, Da_n\}$'. Each column represents the number of features '$F_j = \{F_1, F_2, \dots, F_m\}$'. Missing data as well as outlier recognition was involved in preprocessing. The missing data handling process is an essential one for efficient crop recommendation. The proposed InGCAg model employs Sibson interpolation method for handling missing data points. Sibson interpolation is proposed InGCAg model whichprovides the smoother approximation to the accurate function. Therefore, Sibson interpolation function is given by,

$SI = \sum_{i=1}^{k} Da_i \, \delta_i$(2)

From (2), 'SI' symbolizes theSibson interpolation for missing data handling.'δ_i'denotes the weight allocated to neighboring data points.'k'represents the number of neighboring data points. The weights are allocated based on similarity measurement between data samples. The Braun-Blanquet similarity between the data samples is formulated as,

$BBS = \frac{|Tr_{Da} \cap Ts_{Da}|}{max(Tr_{Da}, Ts_{Da})}$(3)

From (3), 'BBS'symbolizes theBraun-Blanquet similarity coefficient between training data and testing data in the input database. '$max(Tr_D, Ts_D)$'symbolizes themaximum lengthbetween training data and testing data. It is formulated as,

$$BSS = \begin{cases} 1 & Similar \\ 0 & Dissimilar \end{cases} \quad (4)$$

From (4), the testing data and training data similarity results are obtained. The similarity output varies from 0 to 1. When similarity range has 1, then two data points are similar. Otherwise, it is not similar. Generalized Rosner's test employed for outlier identification after performing the missing data handling. It has arithmetical model for identifying outliers. It formulated as,

$RT = arg\,max\left[\sum_{i=1}^{n} \frac{Da_i - Mean}{deviation}\right]$(5)

From (5), 'RT' represent the Rosner's test outcomes. 'Da_i' symbolizes the data samples. Mean range is indicated as '$Mean$', argument of maximum role represented as '$\arg max$'. Here, samples by the highest numerical outcomes are identified as outliers. These outliers are eradicated with higher quality for performing efficient crop recommendation. The algorithmic steps of data pre-processing are given as,

//Algorithm 1: Data preprocessing
Input: Agricultural dataset 'AD',features**,** agricultural data samples **Output:** Preprocessed dataset
Begin **Step 1: Collect n**umber of data samples and featuresfrom input dataset **Step 2: For each** agriculturaldata samples **do** **Step 3:** Perform Sibson interpolation for handling missing data points **Step 4: End for** **Step 5: For each agricultural data** samples **Step 6: Compute the** generalized Rosner's test **Step 7: If** $(arg \max RT)$ **then** **Step 8:** Data sample is considered as outlier data samples **Step 9: else** **Step 10:**Data sample is consideredas normal data samples **Step 11: End if** **Step 12: End for** **Step 13: Return (preprocessed dataset)** **End**

Algorithm 1 illustrates the algorithmic steps of data preprocessing. Assume agricultural samples. Preprocessing handles missing points as well as detects outliers from input dataset. To eliminate outlier, efficient crop recommendation is performed.

3.3 Feature Selection

To diminish time, proposed InGCAg model executes feature selection for minimizing overall size of input dataset for accurate crop recommendation. It preserves more environmental or soil features for accurate crop recommendation analysis. The selected relevant feature minimized the computational performance in crop recommendation. Feature selectionprocess is carried out to minimize the crop recommendation time. Feature selection is carried out using Rand divergenced cockroach swarm optimization algorithm. The cockroach optimization process is used for choosing therelevant features for accurate crop recommendation. Cockroach swarm algorithm is a meta-heuristic cockroach swarm optimization technique. The designed optimization is inspired by cockroach behaviours foridentifying the food source. Initially, cockroach population (i.e. features) are randomly generated. Then, fitness of each feature is computed by using Rand similarity index '$RaSI$'. It is formulated as,

$fitness \Rightarrow RaSI = \left[1 - \frac{|f_i \Delta f_j|}{m}\right]$ (6)

From (6), fitness function of the features in input dataset is given as 'f_i, f_j'.The random similarity index ranges from the value 0 to 1. The current best individuals are chosen and executed three foraging behaviors. They are:

- Chase-swarming behaviour
- Dispersion behaviour and
- Ruthless behaviour

The chase-swarming behaviour is carried out where the cockroach moves to the global best solution. In chase-swarming behavior, the cockroach position gets updated and it is given by,

$P(t+1) = P(t) + M * R * 0.5|X_g - Q(t)|$ (7)

From (7), '$P(t+1)$'symbolizes the updated cockroachposition. '$P(t)$' which denotes the local feature position. 'M' symbolizes the step size.Arbitrary number [0, 1] is 'R', Global features is 'f_g', dissimilarity to compute association among global features and local feature position is '$0.5|f_g - P(t)|$'. Or else, the cockroach moves towards the local feature position. After that, the dispersion behaviour is performed to preserve the diversity behavior among the cockroach population. The cockroachmoves away from the existing results and identifies the new regions of search space. Therefore, the cockroach's dispersion behavior is illustrated as,

$P(t+1) = P(t) + RV(1, d)$ (8)

From (8), '$Q(t+1)$' symbolizes the updated solution. '$RV(1, d)$' represent the d-dimensional random vector. The ruthless behavior is executed by replacing the chosen individual to attain the better solution. It is formulated as,

$f_r = f_g$ (11) (9)

From (9),'f_r'represent the random individual. The process gets iterated until it attains the global solution. Finally, the global optimal feature is selected for crop recommendation. Algorithm 2 illustrates the rand divergence cockroach swarm optimization process.

//Algorithm 2: Rand Divergenced Cockroach Swarm Optimization
Input: Dataset 'D', features '$f_1, f_2, \dots f_{\mathrm{m}}$' **Output:** Improves the feature selection accuracy
Begin **Step 1: Collect** features '$f_1, f_2, \dots f_{\mathrm{m}}$' from the input dataset **Step 2: Initialize**the feature population **Step 3: For** each feature **Step 4:** Compute the fitness function **Step 5: While**($t < Max\_iter$) **do** **Step 6:** Update the position using **Step 7: For** each feature **Step 8:** Perform the dispersionandruthless behavior **Step 9**: **End for** **Step 10: t = t+1** **Step 11: Go to step 5** **Step 12: End while** **Step 13:** Obtain the global best features **Step 14: End for** **End**

Algorithm 2 illustrates the algorithmic steps for Rand divergenced cockroach swarm optimization for efficient crop recommendation. At search space, features are initialized. After initialization process, the fitness function is computed. To update present finest solution place, then fitness of one feature is higher than extra feature. Global best solution is obtained. Or else, local finest solution updated. For returning arbitrarily select individual by global finest, diffusion as well as ruthless actions is carried out. It gets iterated awaiting maximum runs obtained.

3.4 Classification

After performing the feature selection process, classification process is carried out in proposed InGCAg model to forecast the future events. Agentic AI is a kind of artificial intelligence concepts that aimed on autonomous systems for making the decision without human intervention. In proposed InGCAg model, Agentic AI is used to train the labeled data points with each class. The Agentic AI structure is illustrated in figure 2.

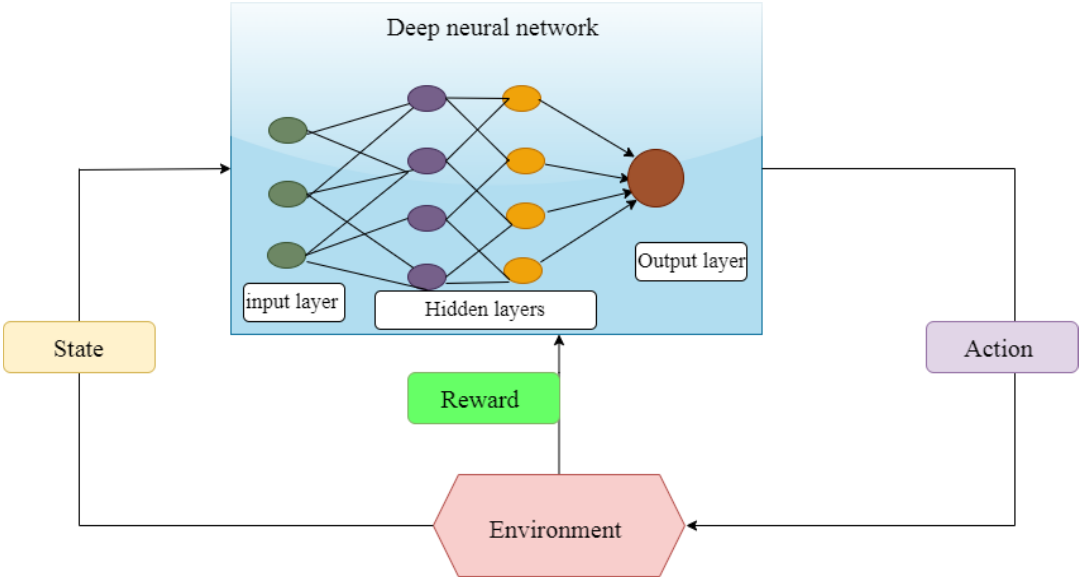

Figure 2 Block Diagram of Agentic AI

Figure 2 illustrates the Agentic AI process for accurate crop recommendation. The proposed model considered the input data points with selected features. In proposed InGCAg model, the agent uses the deep neural network for recommending and suggesting the crops. Deep Reinforcement Learning (DRL) is an Agentic AItype where multiple agents make decisions throughcommunicating with an environment. The key objective of deep reinforcement learning is to allow agent to perform the optimal actions inparticular environment through feedback in reward form. DRL comprised five elements, namely agent, the environment, actions, states as well as rewards.

Agent: It considered as judgment creator to communicate with environment and take suitable actions.

Environment: The environment obtains the reward and feedback. Environment helped the agent to enhance the prediction accuracy.

Actions: Actions are considered as the agent to make the decision. The decision influences the agent path and impacted feedback received from the environment.

States: The state denotesthe current environment situation

Rewards: The reward is the feedback provided by environment after taking the action by agents. Positive rewards are provided for attaining the accurate prediction and the negative rewards are allocated for performing the incorrect recommendation

In Agentic AI, Q-values are assigned with the fixed value for every state-action pair. It is formulated as,

$Q: (\varphi_{sta}, \varphi_{act})$(10)

From (10), Q-values are initialized with state-action pair '$\varphi_{sta}, \varphi_{act}$'. Agent picks behavior as well as collects reward from environment in every step. Agent moves for novel position after Q-value updation. The agent in proposed InGCAg model chooses the action as the crop recommendation tasks and chosen the relevant features. The proposed InGCAg model considered the training set '$\{Da_i, CO_k\}$'. 'Da_i' indicates an input data samples. 'CO_k' symbolizes the classification results.

Deep network includes several layers. Agricultural samples gathered at input layer.The hidden layers are positioned between input and output layers. The layers comprised the neurons that process input data pointsthrough weighted connections. The proposed InGCAg model allowed theneural network to identify thecomplicated patterns. Each neuron ininput layer collects the agricultural data samples and transmits data points to the hidden layer with the relevant weights and biases. In hidden layer, each neuron computes the weighted sum of inputs. It is computed as,

$In = \sum_{i=1}^{n} Da_i * W_{ih} + Bias$ (11)

From (11), 'In' represent the input layer results. 'Da_i' represent the training agricultural data samples. Weight between neuron in input as well as hidden layer denotes 'W_{ih}'. Input training DS is broadcasted to hidden layers. The training and testing data samples are examined through canonical correlation analysis. The canonical correlation ''$Cov\ (Da_{te}, Da_{tr})$' is computed depending on the covariance between testing and training agricultural data points. It is expressed as,

$$Cov\ (Da_{te}, Da_{tr}) = \frac{\sum (Da_{te} - M_{te})(W_k - M_{tr})}{m} \quad (12)$$

From (12), 'M_{te}' symbolizes the mean of testing agricultural data points. 'M_{tr}' indicates the testing agricultural data points. Correlation value obtained as 0 to 1. If high correlation range, then crops correctly recommended with high accuracy. The crop recommendation results are attained at the output layer through activation function. It is formulated as,

$Ou = A\,f[h_t * W_{ho}]$(13)

From (13), 'Ou' represent the predicted output by an agent. 'Af' symbolizes the activation function with multiple recommendation outcomes at the output layer.

3.5 Fine Tuning

In fine-tuning phase of proposed InGCAg model, the hyper-parameters are revised using the stochastic adaptive moment algorithm to minimize the classification error and increase the accuracy of crop classification. The error rate is determined with respect to squared difference between the actual and predicted outcomes. It is formulated as,

$$Err = [PO_{Ac} - CO_{ob}]^2 \quad (14)$$

From (14),'Err'symbolizes the error rate. 'PO_{Ac}'symbolizes the actual prediction output results.'CO_{ob}'represent the obtained classification results. For minimizing theclassification error and improving the classification accuracy,fine-tuning of hyper parameters are carried out using stochastic adaptive moment algorithm to minimize the error rate and increase the accuracy of crop recommendation. Thestochastic adaptive moment algorithmis used to change the weights iteratively for performing efficient convergence. It is given by,

$$W_{new} = W_t - \eta \frac{FM_t}{\sqrt{SM_t + \varepsilon}} \quad (15)$$

$$FM_t = \tau_1 FM_{t-1} + (1 - \tau_1)\left[\frac{\partial PErr}{\partial W_t}\right] \quad (16)$$

$$SM_t = \tau_2 SM_{t-1} + (1 - \tau_2)\left[\frac{\partial PErr}{\partial W_t}\right]^2 \quad (17)$$

From (15, (16), and (17), revised as well as present weights are 'W_{new}', 'W_t'.'η' symbolize learning price($\eta < 1$). Fractional derived of error regarding present weight denotes 'W_t'. 'τ'symbolizes the momentum parameter. 'FM_t' symbolizes the first moment.'SM_t'represent the second moment.'ε'symbolizes positive constant. The different weights are updated based on the computed gradients. Based on the crop recommendation results, the environment attains the reward and considered as the feedback. The feedback assists the agent to take accurate decision in crop recommendation. An exact classification collects the positive crop recommendation rewards and incorrect ones received negative crop recommendation rewards. After that, the Q-value gets updated accordingly based on the rewards observed from the environment.

$$Q^{t+1}(\varphi_{sta}, \varphi_{act}) = Q^t(\varphi_{sta}, \varphi_{act}) + \eta[R(\varphi_{sta}, \varphi_{act}) + D.max\, Q(\varphi_{sta+1}, \varphi_{act}) - Q^t(\varphi_{sta}, \varphi_{act})] \quad (18)$$

From (18),'$Q^{t+1}(\varphi_{sta}, \varphi_{act})$'symbolizes the updated Q-Value. '$Q^t(\varphi_{sta}, \varphi_{act})$'denotes the current Q value. '$R(s_t, a_t)$'represents the reward observed from environment.'D' represent the discount factor lesser than 1. Highest Q-value of next place to exact behavior is '$max\, Q(\varphi_{s_{t+1}}, \varphi_{a_t})$'. This procedure continues until utmost iterations are achieved. Final accurate prediction results are obtained by final Q-values. The process gets repeated until the error gets minimized. Agentic AI algorithm demonstrated by,

// Algorithm 3: Agentic AI based Crop Recommendation
Input: Dataset 'DS', selected features $f_1, f_2, f_3, \dots f_k$, data samples $Da_1, Da_2, Da_3, \dots Da_n$
Output: Increase crop recommendation accuracy
Begin **Step 1**: **For each** agricultural data samples 'Da_i' **Step 2** Initialize Q table with the state and action pair **Step 3**: **While** (t <= max_t) **do** **Step 4**: **For each pair** (φ_s, φ_a)**do** **Step 5:Agent** uses the deep neural network **Step 6:**Training agricultural data samples is considered as an input layer **Step 7:**Measure the weighted sum using (6) **Step 8:End for** **Step 9:For each** training and testing data samples **Step 10:**Measurecovariance correlation **Step 11**: **End for** **Step 12:** Attain crop recommendation outcomes **Step 13:** **For each** prediction output **Step 14:** Measure the error rate using (8) **Step 15:** **if** $(argminErr)$ **then** **Step 16:** Apply activation function and attain crop recommendation results **Step 17:else** **Step 18:** Update the weight **Step 19:** Go to step 14 **Step 20:** **End if** **Step 21: End for**

Step 22: Assign reward **Step 23:** Update Q table value '$Q^{t+1}(s_t, a_t)$' **Step 24:** Increment t=t+1 **Step 25:** **End while** **Step 26**: **Return** (Accurate crop recommendation results) **End**

Algorithm 2 explains the Agentic AI for accurate crop recommendation. The process initiates through Q-value initialization for state-action pairs. In action space, number of agricultural data samples with selected features is gathered from input dataset. Weights and biases are allocated as well as broadcasted toward hidden layer. Covariance correlation analysis is carried out between training and testing data samples. Depending on correlation value, accurate crop recommendation is carried out with high accuracy and minimum time complexity. After classification results, the hyperparameter fine-tuning is carried out to improve accuracy and minimize error value.

4. EXPERIMENTAL SCENARIO

To execute experiments, InGCAg model, existing ANFIS-SVM-PO [1] and existing XAI-enabled CR system [2], IDCSO-WLSTM [8] and SAMConvFormer+LLM [31]are implemented in Python with crop recommendation dataset. Feature explanation is listed in table 2 and table 3. The number of data samples ranges from 1800 to 18000 for conducting experiments.For hardware and software configuration, the entire experiment is conducted in an Intel Core i5- 6200U CPU @ 2.30GHz 4 cores with 8 Gigabytes of RAM. Cross-validation is used to compute the performance of the model ability to carry out unseen data. By using cross-validation, the dataset is divided into two sets such as training and testing. Most data samples (70%) were used for training and the remaining (20% and 10%) were taken for testing and validation. In our work, the 10-fold cross-validation is utilized for measuring the results. Hyperparameter settings are described in table 4.

Table 4 Hyperparameter description

Hyperparameter	Values
Rand divergenced cockroach swarm optimization	
Cockroach Population (Swarm Size)	40
Maximum Iterations	100
Inertial Weight (Initial)	0.7
Inertial Weight (Final)	0.4
Step Size	0.5
Divergence Factor	Randomized KL Divergence
Fitness Function Criteria	Minimizes recommendation error while selecting high relevant features to ensure the dataset
Selection Type	Binary type (0, 1)
Agentic AI	
Number of layers	One input, two hiddenand one output layer
Learning rate	0.001
Number of epochs	100
Batch size	64
Optimizer	Adam
Activation function	Softmax
Training: Testing: Validation	70:20:10

5. RESULTS

InGCAg model, conventional ANFIS-SVM-PO [1] and XAI-enabled CR system [2], IDCSO-WLSTM [8] and SAMConvFormer+LLM [31] discussed. The result analysis is carried out with different parameters.

5.1 Impact on Crop Recommendation Accuracy

Crop recommendation accuracy 'CRA' is defined as ratio of DS correctly recommended particular crop considered as an input. It computed as,

$$CRA = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) * 100 \qquad (18)$$

Where, 'TP' denotes the true positives representing the data samples correctly detected particular crop type. 'TN' symbolizes the true negatives denoting the data samples where proposed InGCAg model correctly identifies specific crop type which is not present. 'FP' represent the false positives where data samples incorrectly detect the crop type. Finally, 'FN' portays the false positives data samples where the proposed InGCAg model correctly recognizes the particular crop type which is not present.

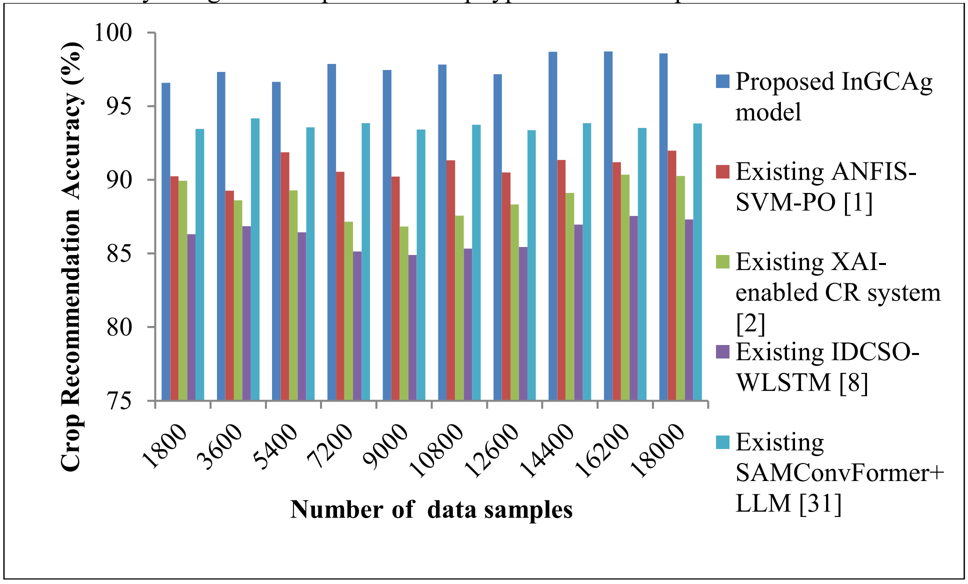

Figure 3 Graphical illustration of Crop recommendation accuracy

CRA is established in Figure 3 for five methods namely proposed InGCAg model, existing ANFIS-SVM-PO [1] and existing XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31]. Data samples are denoted as horizontal axis. Vertical axis denotes the crop recommendation accuracy. From above five methods, proposed InGCAg model attained better results. Assume 10800 data samples as an input, InGCAg, traditional [1] [2] [8] and [31] achieved an accuracy of 97.82%, 91.34%, 87.57%, 86.32% and 93.45%. The comparative analysis of crop recommendation accuracy of proposed InGCAg model is improved by 8%, 10%, 13% and 5% than [1], [2] [8] and [31]. Agentic AI Data Classification is employed to recommend and suggest crops to particular location with higher accuracy. Moreover, the fine-tuning process is carried out using stochastic adaptive moment algorithm to reduce classification error in more accurate crop recommendation.

5.2 Impact on Precision

Itis referred as percentage of data samples correctly determined as positive one. It is formulated as,

$$\boldsymbol{Precision} = \left(\frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}}\right) * \mathbf{100} \qquad (19)$$

From (19), precision level is calculated. 'TP' represent the true positive. 'FP' symbolizes the false positive. It is measured in terms of percentage (%).

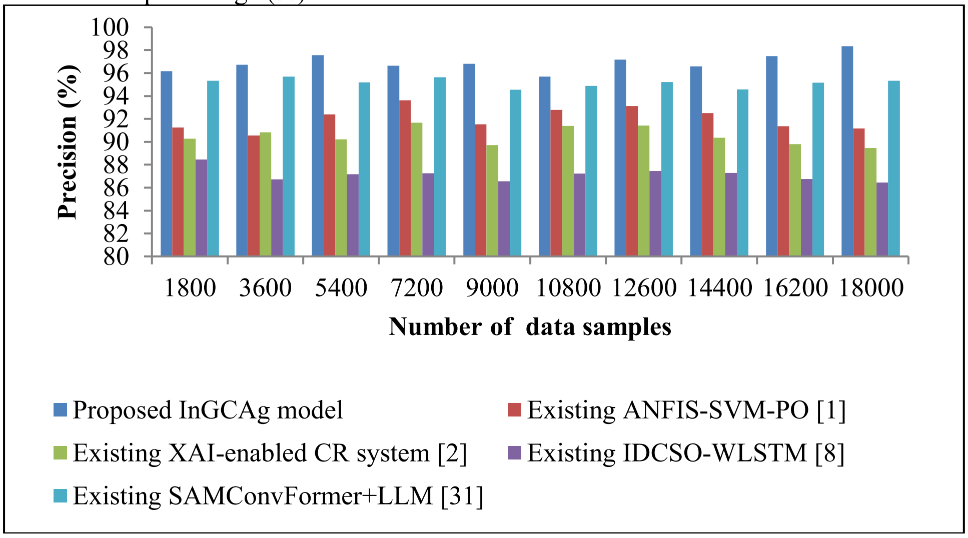

Figure 4 Graphical illustration of Precision

Figure 4 presents precision. Contrary to conventional, proposed InGCAg model attained better precision results. Assume 18000 data samples as an input, precision is found to be 98.35%, 91.18%, 89.46%, 88.45% and 95.32% for InGCAg, baseline techniques [1] [2] [8] and [31]. The comparative analysis of precision of proposed InGCAg model is improved by 5%, 7%, 11% and 2% over [1] [2] [8] and [31] respectively. This is because of using Agentic AI Data Classification for recommending and suggesting the suitable crops for particular location with higher precision.

5.3 Impact on Recall

It also called as sensitivity. Recall is defined as the ability of proposed model to correctly identify the particular crop types.

$$\boldsymbol{Recall} = \left(\frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}}\right) * \boldsymbol{100} \qquad (20)$$

From (20), 'TP' is true positive and 'FN' is false negative.

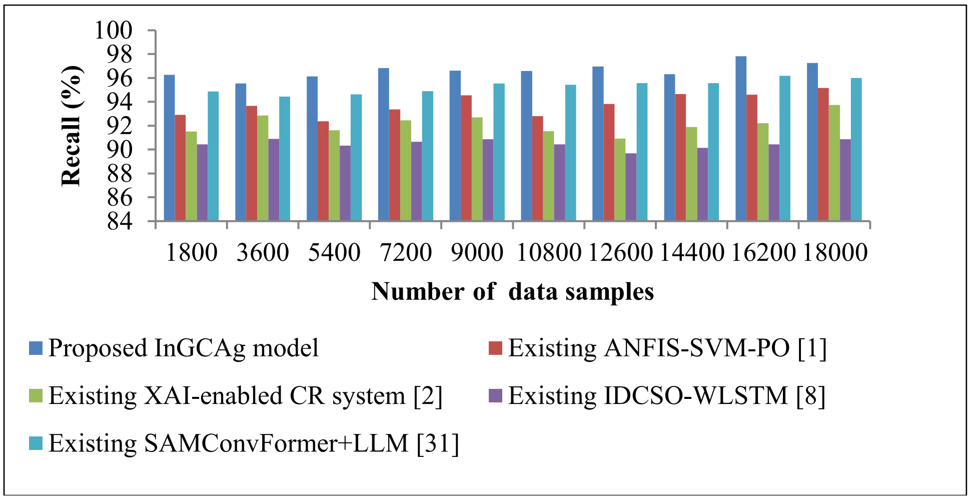

Figure 5 Graphical illustration of Recall

Figure 5 illustrate the graphical illustration of recall for five methods namely proposed InGCAg model, existing ANFIS-SVM-PO [1] and existing XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31]. From above five methods, the proposed InGCAg model attained improved recall results when compared to conventional methods. For 9000 data samples, recall was obtained as 96.62%, 94.54% and 92.69%, 90.43% and 94.87% using InGCAg, traditional [1] [2] [8] and [31]. The comparative analysis of recall of proposed InGCAg model is improved by 3%, 5%, 7% and 1% over [1] and [2] [8] and [31] respectively. This is due to the application of Agentic AI Data Classification for recommending and suggesting the suitable crops. In addition, the fine tuning process is carried for enhancing the crop recommendation performance with higher recall.

5.4 Impact on f1-score

F1-score is otherwise termed as F-measure. It measured as precision and recall range.

$$F1 - Score = 2 * \left(\frac{Precision*Recall}{Precision+Recall}\right)(21)$$

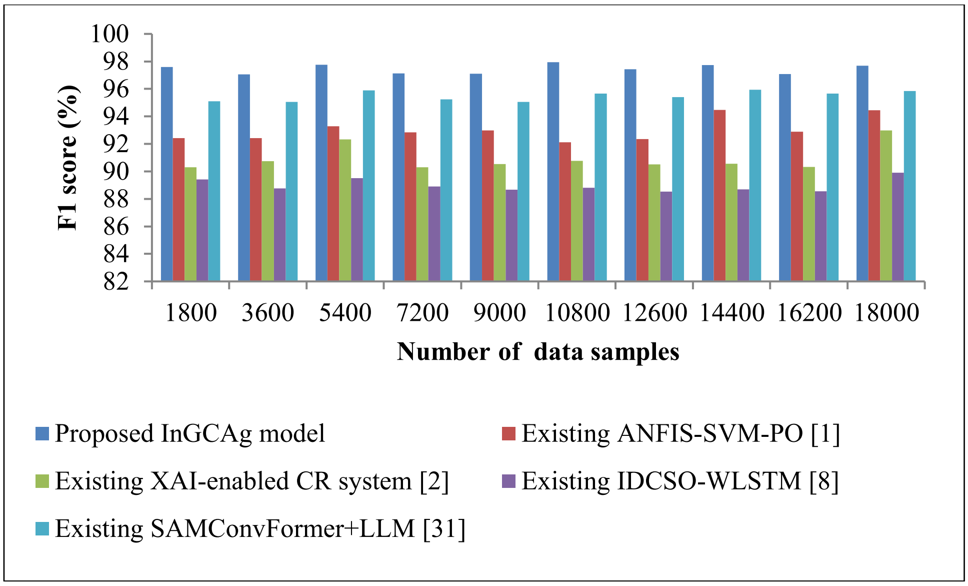

Figure 6 Graphical illustration of F1-Score

Figure 6 illustrate the performance assessment of f1-scores obtained using proposed InGCAg model, existing ANFIS-SVM-PO [1]and existing XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31].For conducting the experiments, different number of data is considered as an input 1800 to 18000. For every input data point, the f1 score is calculated for all five models.The proposed InGCAg model attained improved results than existing methods.On average of ten different runs, InGCAg model attained improvement of 5% over method [1] and 7% over method [2], 10% over method [8] and 2% over method [31].The performance is improved because of using artificial intelligence conceptsthrough optimal balance between precision and recall.

5.5 Impact onRoot Mean Square Error

It is referred as percentage of dissimilarity among actual as well as observed outcomes.

$$RMSE = \left[\sqrt{\frac{\left(Y_{actual} - Y_{prediction}\right)^2}{n}}\right] (22)$$

From (22), ‘Y_{actual}’denotes the actual prediction results. ‘$Y_{prediction}$’ represent the predicted output.

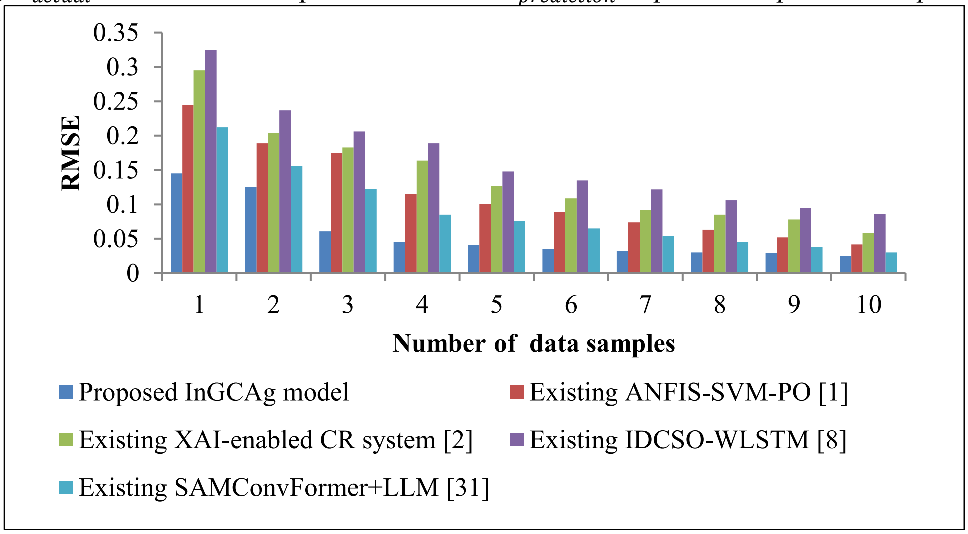

Figure 7 Graphical illustrations of RMSE

Figure 7 show performance comparison of RMSE. Proposed InGCAg model, existing ANFIS-SVM-PO [1]and existing XAI-enabled CR system [2] and existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31] were used in figure 7 for computing RMSE performance. With samples as 7200, RMSE obtained as 0.045, 0.115, 0.164, 0.325 and 0.212 for InGCAg, [1] [2] [8] and [31]. RMSE is reduced using InGCAg up to 51%, 61%, 68% and 36% over [1], [2] [8] and [31]. This enhancement is due to the application of stochastic adaptive moment algorithm for fine-tuning to minimize the error value.

5.6 Impact on Crop recommendation time

It is defined as time consumed by algorithm for main suitable crop across all agricultural data samples. It is computed as,

$$CRT = \sum_{i=1}^{n} AS_i * T\,[SCC] \quad (23)$$

From (23), 'CRT' denotes the crop recommendation time. 'AS_i' symbolizes the number of agricultural data samples. '$T[SCC]$' represents the time consumed for crop recommendation. It is measured in milliseconds (ms).

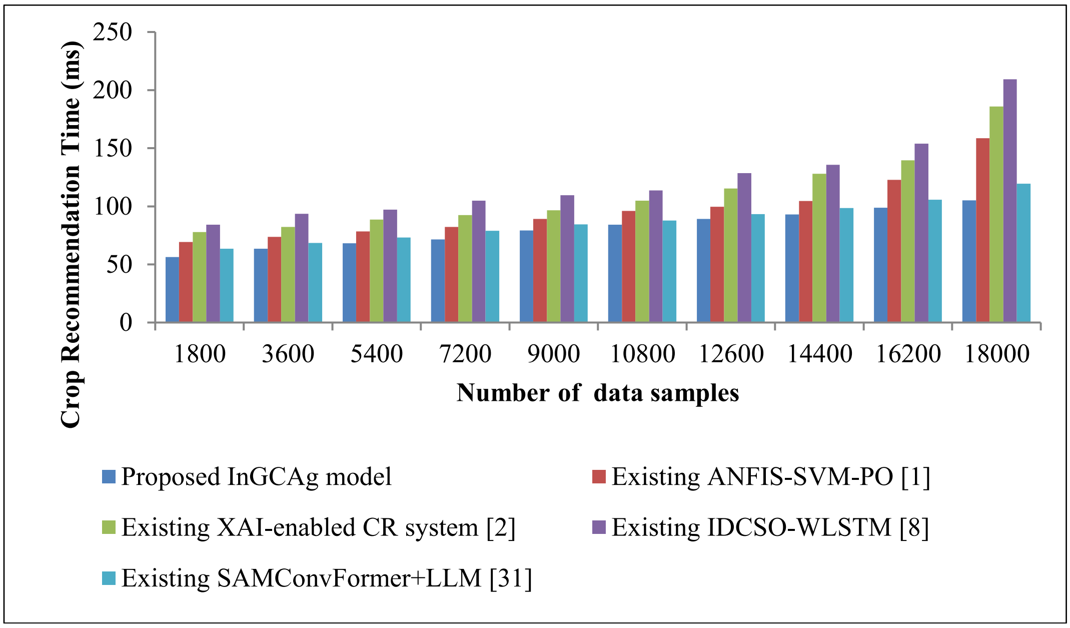

Figure 8 Graphical illustrations of crop recommendation time

Figure 8 illustrate the crop recommendation time performance using the proposed InGCAg model, existing ANFIS-SVM-PO [1]and existing XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31]. CRT is found to be $105.2ms$, $158.6ms$ and $185.9ms$, $209.34ms$ and $119.56ms$for InGCAg, [1] [2] [8] and [31]. Contrary to traditional methods, proposed InGCAg model reduces crop recommendation time by 16%, 26%, 34% and 7%. Rand Divergence Cockroach Optimization process is applied for feature selection. Then, Agentic AI Data Classification is used to recommend and suggest the crops to the particular location with minimum time complexity. Finally, the fine tuning process is carried out by using stochastic adaptive moment algorithm to reduce time complexity.

5.7 Performance analysis of ROC and AUC

Receiver Operating Characteristic (ROC) analysis is a broadly employed for evaluating the predictive performance of crop recommendation system. The ROC curve represents the variation in the True Positive Rate (TPR) or Sensitivity against the False Positive Rate (FPR) or 1-specificity under different threshold settings. The Area under the ROC Curve (AUC) serves as a summary measure of classification performance, with higher AUC values indicating better predictive accuracy and robustness.

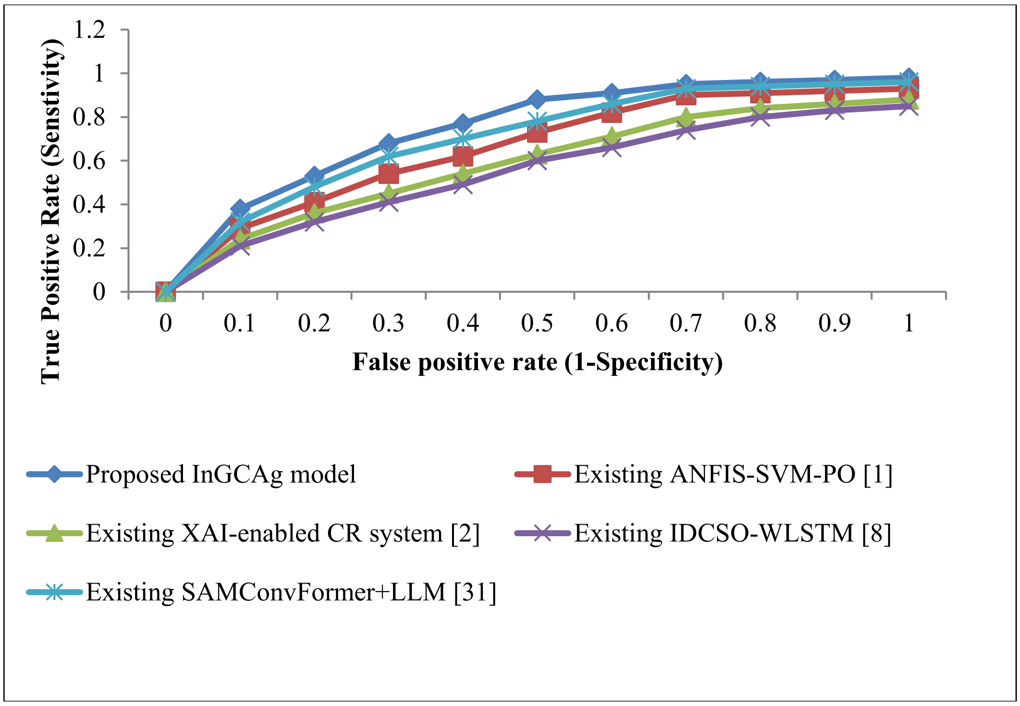

Figure 9 graphical chart of ROC Curve

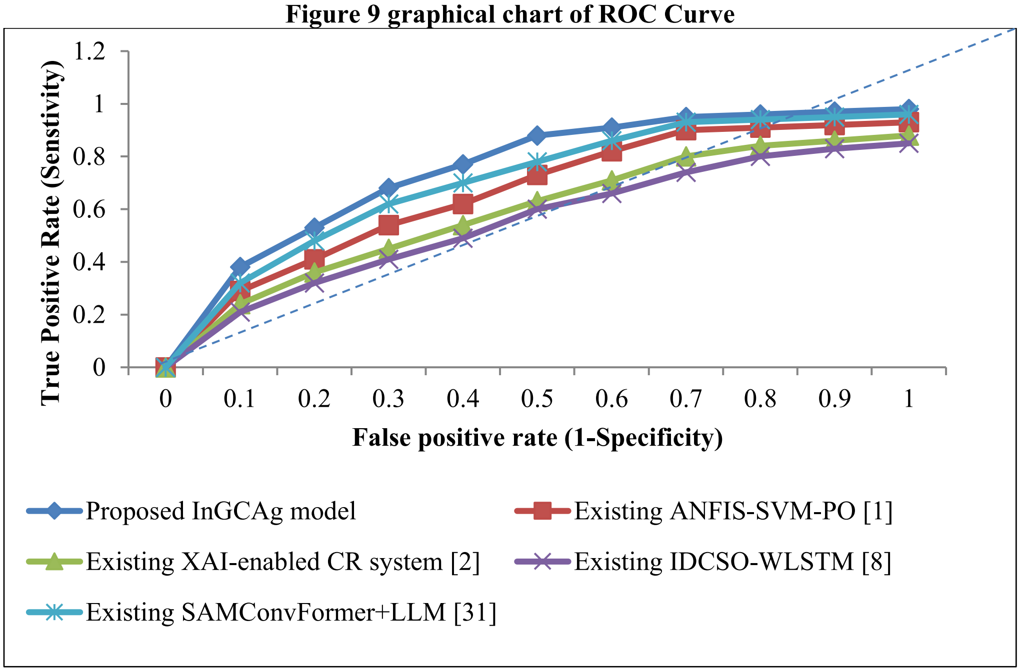

Figure 10 graphical chart of AUC Curve

Figure 9 and 10 present relative performance outcomes of ROC and AUC for five classification approaches namelyInGCAg model and existing AD-ViTNet [1], LADNET [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31]using a dataset comprising 18000 data samples. The ROC curve offers a graphical illustration of model performance by illustrating the relationship between the TPR and FPR across varying decision thresholds. As exposed in the figure, the proposed InGCAg model consistently achieves higher TPR values compared to both ANFIS-SVM-PO [1]and existing XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31]. The diagonal dashed line in the graph represents the baseline for reference. The calculated AUC values are 0.752 for the proposed InGCAg model, 0.66 for [1], and 0.587 for [2], 0.548 for [8] and 0.706for [31]. Although all five models demonstrate a reasonable level of classification ability, the proposed InGCAg model attains the highest AUC score, indicating superior discriminative performance in crop recommendation over the existing methods.

5.8Confusion matrix performance analysis

A confusion matrix is a fundamental tool for evaluating the performance of different stages of crop recommendation, particularly when assessing the proposedInGCAg model on a dataset of 18,000data samples. It organizes the model's predictions into four categories namely True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). This structured illustration provides a comprehensive outline of the model classification performance, enabling detailed analysis of its accuracy, strengths, and potential misclassifications.

Confusion matrix of proposedInGCAg

	Total images 4000	Actual value		
		Positive	Negative	
Predicted value	Positive	TP=13,720	FP=155	13,875
	Negative	FN=99	TN=4,026	4,125
		13,819	4,181	

Confusion matrix of existing ANFIS-SVM-PO [1] **for Crop Recommendation**

	Total images 4000	Actual value		
		Positive	Negative	
Predicted value	Positive	TP=12,670	FP=896	13,566
	Negative	FN=549	TN=3,885	4,434
		13,219	4,781	

Confusion matrix of existing XAI-enabled CR system [2] **for Crop Recommendation**

	Total images 4000	Actual value		
		Positive	Negative	
Predicted value	Positive	TP=12,325	FP=974	13,299
	Negative	FN=778	TN=3,923	4,701
		13,103	4,897	

Confusion matrix of existing IDCSO-WLSTM [8] for Crop Recommendation

	Total samples 500	Actual value		
		Positive	Negative	
Predicted value	Positive	TP=11895	FP=1209	13104
	Negative	FN=1073	TN=3733	4806
		12968	4942	

Confusion matrix of existing SAMConvFormer+LLM [31]for Crop Recommendation

	Total images 4000	Actual value		
		Positive	Negative	
Predicted value	Positive	TP=13000	FP=535	13535
	Negative	FN=574	TN=3891	4465
		13574	4426	

Figure 11 confusion matrix using InGCAg model and existing ANFIS-SVM-PO [1], XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31]

Figure 11 illustrates the confusion matrices for the proposed InGCAg model and existing ANFIS-SVM-PO [1], XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31]evaluated using a dataset of 18000 data samples. In the context of crop recommendation, the confusion matrix provides a comprehensive overview of classification performance by summarizing correct and incorrect predictions across all classes. The results show that the proposed InGCAg modelyields a higher proportion of correctly classified instances (TP and TN) while reducing the number of misclassifications (FP and FN). This indicates that the proposed InGCAgmodel achieves more reliable and accurate predictive performance compared with the existing methods.

5.9 Statistical test

Paired t-test is Standardized Test Statistic for efficient crop recommendation. It is also called as dependent samples t-test.Paired t-test is conducted for InGCAg modeland the existing ANFIS-SVM-PO [1], XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31] using crop recommendation datasetbased on accuracy value.

Table 5 Paired t-test result

Paired (dependent samples) t-test comparing accuracy of the proposed InGCAg model against each existing model at matching sample sizes (n=10 pairs, df = 9). 95% CI is on the mean difference.

COMPARISON	MEAN DIFFERENCE (%)	STD DEV OF DIFF (%)	T-STATSTIC	P-VALUE	95% CI OF DIFF (LOWER)	95% CI OF DIFF (HIGHER)	STATISTICAL SIGNIFICANCE
Proposed InGCAg model vs Existing ANFIS-SVM-PO [1]	6.834	0.902	23.972	1.827900e-09	6.189	7.479	Significant (p<0.05)
Proposed InGCAg model vs Existing XAI-enabled CR system [2]	8.940	1.363	20.736	6.598700e-09	7.965	9.915	Significant (p<0.05)
Proposed InGCAg model vs Existing IDCSO-WLSTM [8]	11,460	0.953	38.042	2.975000e-11	10.779	12.141	Significant (p<0.05)
Proposed InGCAg model vs Existing SAMConvFormer +LLM [31]	4,009	0.746	16.991	3.805100e-08	3.475	4.543	Significant (p<0.05)

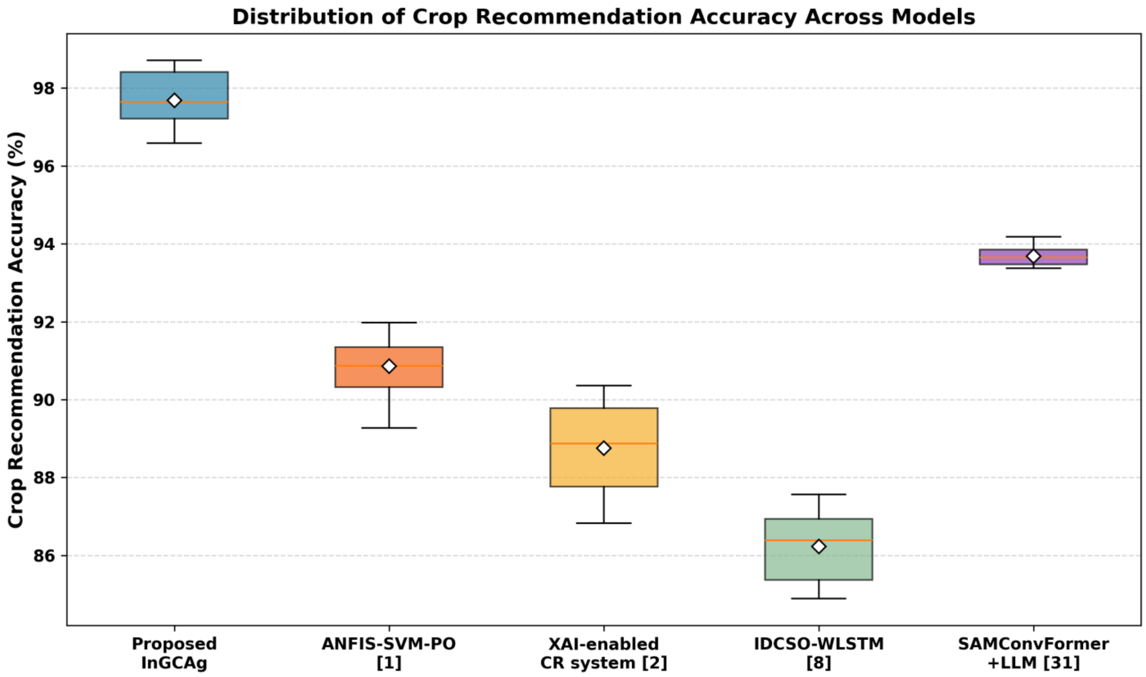

Figure 12 Paired t-tests Outcome

In Table 5 and Figure 12, paired t-tests outcome is described.InGCAg achieved statistically significant improvements over ANFIS-SVM-PO [1], XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31] with all p-values below 0.05. The highest t-statistic was observed for indicating the strongest performance difference. The paired t-test results show that InGCAg performed significantly better than all compared models.
InGCAg achieved statistically significant improvements over ANFIS-SVM-PO [1] , XAI-enabled CR system [2], existing IDCSO-WLSTM [8] and existing SAMConvFormer+LLM [31]

5.10 Ablation study
The ablation study is carried out in Artificial Intelligence (AI) to find out the contribution of preprocessing, feature selection and classification implemented to enhance overall performance. AIis carried out to perform efficient crop recommendation. AI is combined with the preprocessing (Sibson interpolation method and Braun-Blanquet similarity), feature selection (Rand Divergence Cockroach Optimization), classification (Agentic AI)and hyperparameter fine-tuning (stochastic adaptive moment algorithm) to improve the crop recommendation accuracy with minimum time consumption.

Table 6 Ablation Study

Methods/Name	**Crop recommendation dataset**					
	Accuracy (%)	**Precision (%)**	**Recall (%)**	**F-score**	**RMSE**	**Crop recommendation time (ms)**
AI	87.48	91.26	92.26	91.43	0.073	90.65
AI + Sibson interpolation method and Braun-Blanquet similarity	88.63	92.15	93.75	92.62	0.069	89.68
AI+ Rand Divergence Cockroach Optimization	90.05	92.52	94.07	93.46	0.065	86.45
Agentic AI	91.43	93.73	94.38	94.59	0.061	83.32
AI+stochastic adaptive moment algorithm	91.84	94.47	94.65	94.76	0.058	81.28
Proposed method	**92.65**	**95.38**	**95.67**	**95.85**	**0.055**	**78.64**

Table 6 shows the ablation performance for crop recommendation dataset. Agentic AI achieved accuracy of 91.43% respectively. The proposed InGCAg attained higher accuracy of 92.65%, precision of 95.38%, and recall of 95.67% and F-score of 95.85% on crop recommendation dataset. Also, the proposed InGCAg of RMSE, time is reduced by 0.055, 78.64ms. The experimental results show the efficiency of InGCAg than other methods.

6. DISCUSSION
The aim of proposed method is to attain better crop recommendation results with higher accuracy and lesser time and error. Based on the objective, the existing [1], [2], [8] and [31] are discussed and compared for proposed InGCAg model in Python with crop recommendation dataset using several metrics.Contrary to existing, proposed InGCAg designed to compute the efficiency of crop recommendation to improve the accuracy, precision, recall and accuracy and reduce the time and error. Data preprocessing is carried out through handling the missing values and detecting the outliers. For performing efficient feature selection, rand divergenced cockroach swarm optimization selects six features for performing efficient crop recommendation with maximum accuracy. Then, the crop recommendation and suggestion is carried out with Agentic AI model to recommend the different crops with minimum time. Finally, the stochastic adaptive moment algorithm based fine tuning is carried out to minimize the classification error for attaining better crop recommendation results.

From result analysis, the proposed InGCAg attains strong crop recommendation performance with high accuracy, precision, recall and minimum time and error. The classification results are used for smart agriculture in real-time application. The proposed InGCAg model helps the agriculture professionals for crop recommendation with minimum resources. InGCAg model is used in crop monitoring systems for timely efficient crop recommendation. The key issue of InGCAg model is not reduced the space complexity while collecting and storing data samples. InGCAg model is not tested for remote monitoring systems.

7. CONCLUSION

This research paper has implemented a crop recommendation system using an InGCAg model. InGCAg method is combined Sibson interpolation method and Braun-Blanquet similarity, Rand Divergence Cockroach Optimization, Agentic AI and hyperparameter fine-tuning. Thepre-processing samples were obtained and relevant features were chosen for minimizing the time consumption. The Agentic AI was used to classify the dissimilar crops. The multiclass crop recommendation results are obtained with fine-tuning to reduce the RNSE. Various metrics are employed for experimental evaluation. The outcome of InGCAg model demonstrates an improvement in accuracy by 98%, precision by 97%, and F1 score by 97%, and 97% of recall. Also, it decreases crop recommendation time by 81ms, RMSE by 0.056 when compared to traditional deep learning approaches.

The limitation of the proposed model is given by, the computational cost and scalability was not considered. The proposed method was not concentrated for larger datasets, real-time agricultural deployment, and integration with IoT-based smart farming systems. The proposed method was unable to consider the multiple dataset.

Future work will focus on integrating the framework with IoT-based smart farming networks and real-time satellite imagery through multimodal learning. Also, the real-world test will be conducted for weather changes and soil differences. In addition, proposed method will be combined with IoT sensors. IoT used to collect real-time data on the weather and soil. Additionally, proposed method will be employed to implement decentralized federated learning to scale the model efficiently across massive datasets. We will incorporate Explainable AI (XAI) techniques to provide transparent recommendations for farmers, and conduct extensive real-world field to validate the performance.

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