Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 28 No. 3s (2025)

Optimizing Crop Recommendations: A Novel IDCDMO-Enhanced ACGRU Approach for Advanced Agricultural Predictions

G.Rubia[1*] , M.Nandhini[2]

[1*]Research Scholar, Department of Computer Science, Government Arts College, Udumalpet, Tamilnadu, India

[2]Assistant Professor, Department of Computer Science, Government Arts College, Udumalpet, Tamilnadu, India.
nandumano@gmail.com[2]

[1*]Corresponding author: grubia15@gmail.com

Article History:

Received: *06-10-2024*

Revised: *29-11-2024*

Accepted: *08-12-2024*

Abstract:

Agricultural productivity is maximised to a greater extent by crop recommendation. The traditional methods of crop recommendation are often rely on limited data, simple models, heuristic rules and expert knowledge which are less dynamic and not fully address the agricultural challenges. Deep Neural Networks (DNN) play an important role in crop recommendations by providing more accurate crops that are suited to the terrain. The research proposes a novel approach utilizing Attention based Convolutional Gated Recurrent Unit (ACGRU), neural network architecture for crop recommendation. Additionally it integrates Improved Distribution based Chaotic Dwarf Mongoose Optimization (IDCDMO) algorithm for feature selection. This study compares, for crop recommendation, to see the effectiveness of proposed approach. The performance of the IDCDMO¬¬-enhanced ACGRU is compared with ACGRU without feature selection and also with the conventional neural network models such as Feed Forward Neural Network (FNN) and Long Short Term Memory (LSTM). The IDCDMO-enhanced ACGRU significantly outperforming both the ACGRU without feature selection and conventional neural network models in terms of accuracy, precision, recall and f1 score. Therefore, the integration of IDCDMO with ACGRU efficiently enhances recommendation accuracy, improves soil health and adds greater agricultural productivity.

Keywords: Crop Recommendation, DNN, Feature Selection, ACGRU, IDCDMO.

1. Introduction

Farming is one of the important sector in India, employing about 65% of workers. A common challenge faced by farmers is selecting crops that are suited to the specific land and climate. Modern agriculture depends critically on crop recommendation, which tries to maximise crop output by recommending the best crops for a particular set of soil and environmental circumstances [1]. Crop advice has always depends on manual analysis and professional knowledge where farmers making judgements based on their own experience and regional customs [2]. The accuracy, scalability and flexibility of this method to changing environmental circumstances were limited. A model changes towards using computational methods for crop recommendation has occurred with the progress in technology, especially in the domains of Machine Learning and Artificial Intelligence [3]. Through the use of enormous volumes of agricultural data such as soil attributes, climatic conditions, historic crop yield records and agronomic practices, these methods generate suggestions based on data [4]. Adopting computational techniques in crop recommendation is driven in large part by the growing need to increase agricultural production while reducing resource use and environmental effect [5]. Farmers may choose crops, schedule plantings and allocate resources more wisely by using data analytics and Machine Learning algorithms [6]. By using Machine Learning models to improve plant and crop selection practices, the recommended systems discussed contribute significantly to addressing health and global food security challenges [7-8]. Developing countries facing persistent problems in agriculture. Crop recommendation system using Artificial Intelligence techniques assist farmers to accurately estimate crop yields, leading to improved planning, efficient resource allocation and effective risk management [9]. Crop recommendation system using Machine Learning algorithms to reduce problems like crop failure and farmers hardship by taking into account factors like soil, sowing season and location [10].

This study uses DNN technique to analyze large and complex agricultural data. The agriculture dataset includes many input characteristics like soil nutrient levels, environmental variables and crop type requires an advanced method to analyze and derive actionable insights for decision making. DNN has the ability to understand patterns in the data and gives accurate recommendations. Therefore, the problem of improving crop recommendation accuracy with DNN model is addressed in this paper, with the focus on, ACGRU architecture. Comparing the performance of proposed model with existing methods in suggesting appropriate crops depending on soil and environmental variables is the core challenge.

The main objectives of this research are twofold:

1. To investigate the performance of the proposed ACGRU model with feature selection, in comparison to ACGRU without feature selection and conventional neural network models for crop recommendation.

2. To assess the impact of feature selection, particularly utilizing the Improved Distribution based Chaotic Dwarf Mongoose Optimization (IDCDMO) algorithm, on the accuracy of ACGRU for crop recommendation with feature selection.

The novelty of this study lies in its feature selection techniques with ACGRU model for crop recommendation. By leveraging the IDCDMO algorithm, this research introduces a novel approach to identify relevant input features, thereby improving the efficiency and accuracy of crop recommendation systems. Additionally, this study contributes to the broader understanding of DNN applications in agriculture, emphasizing their potential to address complex agricultural challenges.

2. Related Works

From the findings of this research [11], a method has been proposed to assist farmers in the process of crop selection. This method takes into account all of the pertinent parameters, including planting season, soil and geographical location. Precision agriculture, which places a focus on crop management that is specific to a given location, is also developing in less developed countries and is being implemented with the agricultural equipment that is now available. The study [12] presents a solution that combines deep learning and IoT to help farmers by assessing soil fertility and suggesting appropriate crops. The model evaluates soil parameters such as nitrogen, phosphorus, potassium (NPK), pH, organic carbon and moisture content to recommend the best crops and their required nutrients. With the accuracy of 87%, the deep neural network (DNN) outperformed other machine learning models, including SVM, Gaussian NB, KNN, decision tree and LDA, which recorded accuracies from 61% to 72%. This method offers a reliable and adaptable solution, enabling farmers to make better decisions about crop selection based on their soil conditions. Authors examine the current state of AI-driven precision farming and related work in the agriculture sector in [13], which examines the current state of the field. Then, they propose a novel crop recommendation platform that makes use of cloud computing and machine learning to assist farmers in selecting which crops are suitable for harvest based on a variety of variables that are already known to them. Additionally, this paper evaluates the performance of these algorithms for prediction. The purpose of this endeavour is to ascertain which of these algorithms has the highest level of performance so that they can construct their recommendation platform as a cloud service. The ultimate objective of their organisation is to make available open-source, cost-free solutions for precision farming, which will eventually result in their broad acceptance. The authors [14] introduces a machine learning-based recommendation system to assist farmers in choosing optimal crops, considering factors like soil properties, rainfall, temperature, humidity, soil type and pH. The system utilizes classifiers Support Vector Machine (SVM) and Artificial Neural Networks (ANN) to predict the most suitable crops. Data from Maharashtra's agricultural website is used, with the ANN model achieving an accuracy of 86.80%, outperforming SVM. The findings suggest that ANN provides more accurate predictions for crop selection. This system helps farmers to choose most suitable crops. Fox in red RFOERNN-CRYP, is the model design that is the primary focus of [15]. The RFOERNN-CRYP model that is given here makes use of an ensemble learning approach that integrates three different deep learning models: LSTM, BiLSTM and GRU. This is done in order to produce better prediction performance than the separate classifier models. One further way in which the study demonstrates its originality is through the utilisation of the RFO method for the purpose of selecting hyperparameters for the three DL models, which ultimately results in an enhancement of the overall performance. It is possible that the RFOERNN-CRYP approach will be helpful to farmers when they are making decisions based on a number of different agro-parameters. The key objective of the website that is presented in [16] to build a Machine Learning (ML) model that is simple to operate and has the capability to do real time analysis of environmental and soil parameters. Nitrogen (N), potassium (K), phosphorus (P), pH, temperature, humidity, soil moisture and rainfall are some of the components that are considered to be important. The model then employs a process that is based on a majority vote in order to select the best crop to cultivate, the fertiliser that should be applied based on a Fertiliser Dictionary, and the pesticides that should be applied based on an image analysis of pests using a Sequential Convolutional Neural Network (SCNN) that is derived from the Kaggle dataset. After being supplied data through a web interface, the model that is produced makes recommendations regarding the kind of crops that would flourish the most in a particular soil type. These recommendations include the types of fertilisers to use, the pests to target and the amount of pesticide to apply.

3. Proposed Methodology

This study proposes a combined approach of ACGRU for crop recommendation and IDCDMO for feature selection as given in Figure 1. ACGRU architecture is chosen for its ability to capture both spatial and temporal dependencies in the input data, making it suitable for analyzing time series data such as agricultural variables over time.

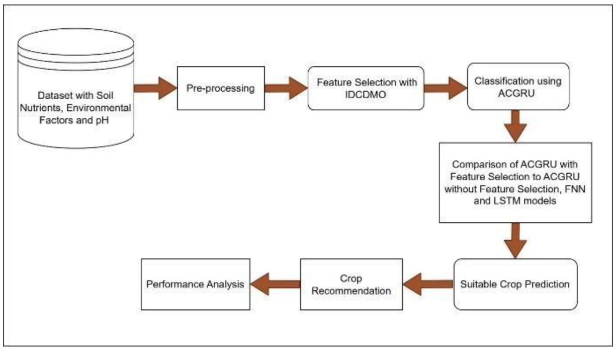


Figure 1: Proposed Workflow

The ACGRU model uses dataset collected from kaggle. A dataset containing input features such as soil nutrients (Nitrogen, Phosphorus and Potassium), environmental factors (Temperature, Humidity and Rainfall) and pH. The ACGRU model is initialized, trained using the training dataset, and then used to predict crop recommendations based on the input features. ACGRU crop recommendation process involves several steps to effectively analyze agricultural data and provide recommendations.

3.1. Data Pre-processing

Before feeding the data into the ACGRU model, pre-processing steps are carried out to ensure data quality and consistency. This may involve tasks such as data cleaning, handling the missing values and standardization to ensure that all input features are on similar scales.

3.1.1. Standardization

Standardization is the process of modifying feature values to achieve 0 as a mean and 1 as a standard deviation, typically making the features more comparable and improving the convergence of optimization algorithms. The standardization of a feature *x* is expressed as in equation 1.

$$X_{scaled} = \frac{(x-\mu)}{\sigma} \quad (1)$$

Here, x represents the original value of the feature, μ refers the mean and σ signifies the standard deviation of the feature.

Standard_Scaler

This research work using standard_scaler, a standardization technique for data pre-processing. Standard_scaler is the process to transform the features accordingly, ensuring uniformity in scale across all features. This process helps to prevent any single feature from overshadowing others during the training process. The equation 2 is the formula for scaling of a feature using standard_scaler.

$$Standardized\_value = \frac{Original\ feature\_value - Mean}{Standardization} \quad (2)$$

The original feature_value is the original data point to be standardize, mean defines the average of all data points in the given dataset and standard deviation is the distribution of data points within a dataset.

3.2. Feature Selection with IDCDMO Algorithm

Feature selection is employed to identify the most significant input features for crop recommendation, aiming to improve both the performance and efficiency of the model. The IDCDMO algorithm is utilized for feature selection, which is a metaheuristic optimization algorithm inspired by chaotic maps and dwarf mongoose behavior. IDCDMO iteratively improves solutions by applying chaotic dynamics, emulating mongoose behavior and local search. It selects a subset of input features deemed most influential for accurate crop recommendation. Selected features such as nitrogen, phosphorus, potassium, pH and rainfall, are then fed into the ACGRU model for training and prediction.

The IDCDMO consists of steps which as depicted in algorithm 1. The algorithm begins by initializing a population of potential feature subsets, with each subset (S_i), representing a unique combination of input features. These subsets are randomly generated or initialized to commence the optimization process. Following initialization, the fitness of each feature subset $f(S_i)$ is evaluated based on its contribution to model performance. Initialize a population of potential feature subsets. Next, chaotic dynamics are introduced to inject randomness and exploration into the search process. Chaotic maps perturb the selected feature subsets, aiding in escaping local optima and promoting diversity in the population. The chaotic variable x evolves according to the equation 3.

$$x_{n+1} = r.x_n.(1 - x_n) \tag{3}$$

Where:

The x_n represents the current value of the chaotic variable at iteration n. x_{n+1} , depicts the next value of the chaotic variable at iteration $n + 1$. r, a parameter controlling the chaotic behavior. Emulating the cooperative behavior observed in dwarf mongoose social interactions, the algorithm encourages information sharing among the selected feature subsets, potentially leading to collaborative improvements. Each solution's behavior $(B(S_i))$ is inspired by dwarf mongoose social interactions. The behavior of a solution S_i inspired by dwarf mongoose social interaction can be represented using equation 4 and 5.

$$X_{i+1} = X_i - CF \cdot \phi \cdot \rho \cdot (Xi - M), when\ \varphi_{i+1} > \varphi_i \tag{4}$$

$$X_{i+1} = X_i + CF \cdot \phi \cdot \rho \cdot (Xi - M),\ when\ \varphi_{i+1} \leq \varphi_i \tag{5}$$

In the given equation 4 and 5, Xi represents the current state of the solution (S_i). X_{i+1} signifies the next state of the solution S_i. CF is a control factor. *The* ϕ is a randomization factor. The ρ stands for the behavior coefficient. φ_{i+1} and φ_i, indicates randomly generated values for comparison. M is the mean of the solutions. Further improvement is achieved through the application of local search operators within each subset. The local search operators $(L(S_i))$ are applied to each selected solution S_i. Local search operators aim to improve the quality of solutions within each subset. Let's denote the application of local search operators to a solution S_iS_i as $L(S_i)$ $L(S_i)$. This operation involves iteratively exploring the solution space around S_iS_i to find a better solution. The selected feature subsets are then combined with newly generated solutions, and their fitness is evaluated to gauge the effectiveness of the improvements. Throughout the optimization process, termination criteria are monitored (C). The criteria for termination may involve getting a maximum number of iterations or attaining convergence. Upon meeting these termination criteria, the algorithm provides the optimal feature subset identified throughout the optimization process. This subset represents the best combination of input features selected by the IDCDMO algorithm, ensuring enhanced crop recommendation accuracy and efficiency.

Algorithm 1: IDCDMO (Improved Distribution based Chaotic Dwarf Mongoose Optimization)

1) Procedure ChaoticDwarfMongooseOptimization():
a) InitializePopulation()
b) EvaluatePopulationFitness()
c) While TerminationCriteriaNotMet() Do
i) SelectTopSolutions()
ii) ApplyChaoticDynamics()
iii) EmulateDwarfMongooseBehavior()
iv) ApplyLocalSearch()
v) CombineAndEvaluateSolutions()
d) Return BestSolutionFound()

// Functions

1) Procedure InitializePopulation():
a) For each solution in population Do
i) Randomly initialize solution
2) Procedure EvaluatePopulationFitness():
a) For each solution in population Do
i) Evaluate fitness of solution
3) Procedure SelectTopSolutions():
a) Sort population based on fitness
b) Select top solutions
4) Procedure ApplyChaoticDynamics():
a) For each solution in selected solutions Do
i) Apply chaotic map or equation to perturb solution
5) Procedure EmulateDwarfMongooseBehavior():
a) For each solution in selected solutions Do
i) Implement behavior inspired by dwarf mongooses
6) Procedure ApplyLocalSearch():
a) For each solution in selected solutions Do
i) Apply local search operators to improve solution
7) Procedure CombineAndEvaluateSolutions():
a) Combine selected solutions with newly generated solutions
b) Evaluate fitness of new solutions
8) Function TerminationCriteriaNotMet():
a) If termination criteria (e.g., maximum iterations, convergence) not met Then
i) Return True
b) Else

Return False

3.3. Classification using ACGRU Model

The ACGRU model consists of several steps as given in algorithm 2a and 2b. The ACGRU model is designed with a well suited architecture, including the configuration of convolutional layers, attention mechanisms and gated recurrent units as represented in Figure 2. In addition to designing an architecture, it is essential to include model hyperparameters specifically learning rate, batch size and the number of training epochs for training the ACGRU model. Then, the ACGRU model is trained using a labeled dataset comprising historical agricultural data. As the model trains, it learns to recognize the complex relationships between input features (e.g., soil nutrient levels, pH and environmental factors) and corresponding crop recommendations. Throughout the training process, the ACGRU model performance is assessed on a distinct validation dataset to evaluate its generalization ability. Based on these validation results hyperparameters are fine-tuned to enhance the performance of the model and reduce the risk of overfitting.

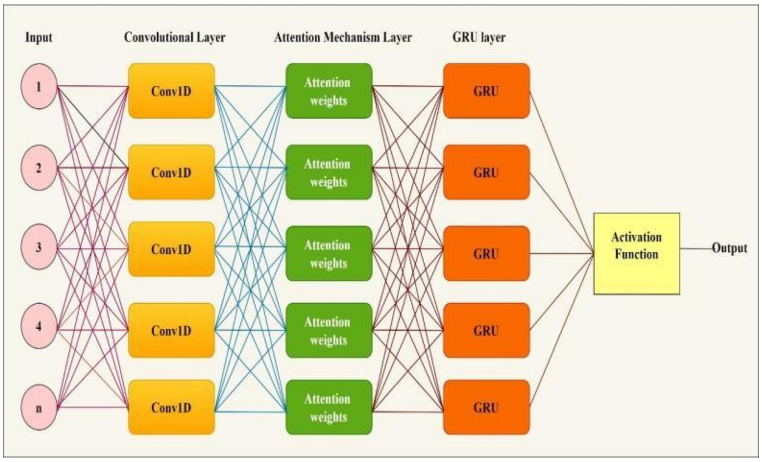


Figure 2: The ACGRU Architecture for Crop Recommendation

Once the ACGRU model is trained and validated, it is ready to make predictions on unseen or test data. The model takes input features representing current environmental and soil conditions and produces predictions or recommendations for suitable crops. Predictions may include the probability distribution over different crop classes, allowing for uncertainty estimation. The entire process may be iterated upon, with adjustments made to the model architecture, hyperparameters or training data based on evaluation results. Iterative improvement ensures that the ACGRU model continues to adapt and perform optimally in different agricultural contexts.

Algorithm 2a: Attention based Convolutional Gated Recurrent Unit with Feature Selection (ACGRU-FS):

Procedure ACGRU_FS_Classification (data, labels):
Step 1: PreprocessData(data) // Standardize the features
Step 2: FeatureSelection(data) // Apply feature selection algorithm
Step 3: Reshape(data) // Reshape the input feature
Step 4: InitializeModel() // Initialize ACGRU model with attention mechanism
Step 5: TrainModel(data, labels) // Train the model using the training data
Step 6: PredictLabels(data) // Predict labels for test data
Step 7: EvaluateModel(predictions, true_labels) // Evaluate model performance

// Functions:
1. Scale data to ensure features are on similar scales
2. Perform feature selection and return top selected features
3. Apply Reshape to change the input features required by the ACGRU model
4. Initialize ACGRU model architecture:

i. Add Conv1D layer
i. Add Attention layer
i. Add GRU layer
. Add dense layer
. Add optimizer and loss function

5. Train the ACGRU model using the provided data and labels
6. Predict the ACGRU model accuracy
7. Evaluate the trained ACGRU model on the test data

Algorithm 2b: Attention based Convolutional Gated Recurrent Unit without Feature Selection (ACGRU):

Procedure ACGRU_Classification (data, labels):
Step 1: PreprocessData(data) // Standardize the features
Step 2: Reshape(data) // Reshape the input feature
Step 3: InitializeModel() // Initialize ACGRU model with attention mechanism
Step 4: TrainModel(data, labels) // Train the model using the training data
Step 5: PredictLabels(data) // Predict labels for test data
Step 6: EvaluateModel(predictions, true_labels) // Evaluate model performance
// Functions:
1. Scale data to ensure features are on similar scales
2. Apply Reshape to change the input features required by the ACGRU model
3. Initialize ACGRU model architecture:

i. Add Conv1D layer
i. Add Attention layer
i. Add GRU layer
. Add dense layer
. Add optimizer and loss function

4. Train the ACGRU model using the provided data and labels
5. Predict the ACGRU model accuracy
6. Evaluate the trained ACGRU model on the test data

3.3.1. Convolutional Layers

Convolutional layers are fundamental components in deep learning architectures, particularly effective in processing spatial data such as images or sequences. In the context of the ACGRU model, convolutional layers are utilized to extract meaningful features from input data representing environmental and soil conditions. At each time step t, the convolutional layer processes the input x_t using a set of learnable filters represented by W_c. These filters scan across the input, extracting spatial patterns that are relevant for crop recommendation. The output of the convolutional layer denoted as h_t, represents feature maps capturing hierarchical representations of the input data are given in equation 6.

Utilizing convolutional operations allow the model to effectively find the spatial dependencies and local patterns within the input features, resulting the model to learn meaningful representations of soil nutrient levels, pH, climate conditions and other environmental factors crucial for crop recommendation. Additionally, the use of convolutional layers enables the model to automatically identify relevant features, minimizing the necessity for manual feature engineering and improves its capacity to handle unseen data. Overall, convolutional layers play a crucial role in extracting informative features from input data, facilitating the accurate prediction of suitable crops in diverse agricultural contexts.

$$h_t = Conv(x_t, W_c) \quad (6)$$

3.3.2. Attention Mechanisms

Attention mechanisms are key components in neural network architectures that allow models to focus on key elements of the input data while making predictions. In the ACGRU model, attention mechanisms play a vital role in dynamically weighting the importance of different input features across various time steps. At each time step, the model computes attention scores (e_t) using a learned weight matrix (W_a) applied to the output of the gated recurrent units are specified in equation 7. These attention scores quantify the relevance of each input feature to the current context, allowing the model to prioritize important information.

$$e_t = tanh\,(W_a . h_t) \quad (7)$$

Following this, the attention scores are normalized using a softmax function to achieve an attention weights (α_t), representing the relative importance of each input feature. The attention weights are calculated using equation 8. These weights are used to compute a context vector (C_t) stated in equation 9 which aggregates information from all time steps, emphasizing features that are most relevant for making crop recommendations.

$$\alpha_t = \frac{\sum t'\, exp(e_t)}{exp(e_t')} \quad (8)$$

$$c_t = \sum_{t=1}^{T} \alpha_t' \cdot h_t' \quad (9)$$

Where:

The e_t represents the attention scores and α_t signifies the attention weights. The C_t, is the context vector and W_a is the weight matrix for attention computation. By dynamically adjusting the attention weights, the model can effectively capture complex relationships within the input data, focusing on informative features while ignoring irrelevant ones.

3.3.3. Gated Recurrent Units

Gated recurrent units (GRUs) are specialized variants of recurrent neural networks (RNNs) designed to overcome the challenges of vanishing gradient issue and capture long range dependencies in sequential data. In the ACGRU model, gated recurrent layers play a pivotal role in processing time series input representing agricultural data over multiple time steps. At each time step, context vector (c_t), is fed into the GRU layer. Combine the context vector (c_t), which serves as a measure of relevance or importance with the current input x_t before passing into the GRU layer. This vector is obtained by applying a non-linear transformation to the current input x_t using learned weights (W_a). The resulting context vector (c_t), represents the relevance of each input feature to the current context.

$$z_t = \sigma(W_z \cdot [h_{t-1}, c_t, x_t]) \quad (10)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, c_t, x_t]) \quad (11)$$

$$h't = tanh(W_h \cdot [r_t \odot h_{t-1}, c_t, x_t]) \quad (12)$$

The final hidden state is given in equation 13.

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot h't \quad (13)$$

Where:

Z_t, is the update gate and r_t is the reset gate which are specified in equations 10 and 11. The candidate hidden state $h't$ which is computed based on the reset gate is denoted in equation 12. The weight matrices namely W_r,W_z, and W_h are assigned to reset, update, and candidate hidden state operations. The σ stands for the sigmoid activation function. The $\odot$ represents element-wise multiplication. By using attention mechanisms and gated recurrent units, the ACGRU model can effectively capture temporal dependencies and highlight crucial input features for crop recommendation. This enables the model to make informed predictions based on historical agricultural data, ensuring robustness and accuracy in diverse agricultural contexts.

4. Performance Assessment Metrics

The evaluation metrics for crop recommendation are essential as they provide a benchmark for assessing the effectiveness of the methods employed. There are the four main performance metrics namely accuracy, precision, recall and f1 score used for evaluating classification models. This study applying these four metrics for assessing the models performance.

Accuracy: Accuracy is used to measure the percentage of correctly classified predictions out of all predictions as mentioned in equation 14.

$$Accuracy = \frac{Correctly\ \ Classified\ Predictions}{All\ Predictions} \quad (14)$$

Precision: The precision metric is measured by diving the true positive values by sum of all positives values as expressed in equation 15.

$$Precision = \frac{Correctly\ Classified\ Positives}{All\ Predicted\ Positives} \quad (15)$$

Recall: It calculates how the models effectively classifies all the true positive values. It is defined in equation 16.

$$Recall = \frac{Correctly\ Classified\ Positives}{All\ Actual\ Positives} \quad (16)$$

F1 Score: It is a combined measure of both precision and recall as given in equation 17.

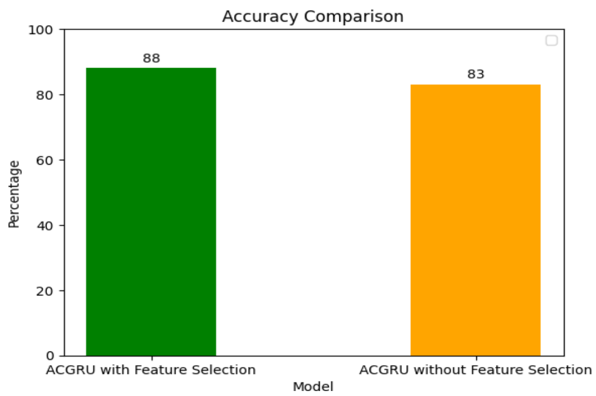
$$F1\ Score = 2 * (\frac{Precision * Recall}{Precision + Recall}) \quad (17)$$

5. Results and Discussion

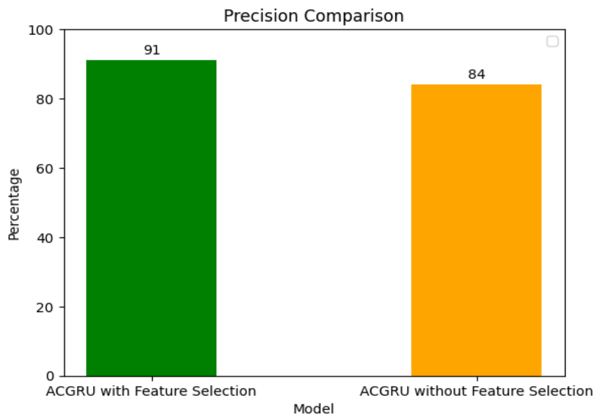
In our experimental settings, the Python programming language is employed along with popular libraries to implement the ACGRU model and the IDCDMO algorithm for feature selection. The proposed method is compared against existing approaches, including FNN and LSTM models. The results in Table 1 and Figure 3 compare the performance of the ACGRU model with feature selection to the ACGRU model without feature selection. The ACGRU model applies the neural network architecture directly to the original dataset without any feature selection process. The results indicate that without feature selection, the model achieves moderate performance across all metrics. While the accuracy, precision, recall, and f1 score are decent, there is room for improvement. The model performance might be hindered by the inclusion of irrelevant or redundant features in the input data, leading to suboptimal predictions. The ACGRU model with feature selection using the IDCDMO algorithm significantly improves performance across all metrics. By selecting the most relevant input features (such as Nitrogen, Phosphorus, Potassium, pH and Rainfall), the feature selection process enhances the model ability to capture important patterns in the data. As a result, the model achieves higher accuracy as 88%, precision as 91%, recall as 87% and f1 score as 88% compared to the ACGRU model without feature selection. This demonstrates the effectiveness of integrating feature selection techniques with DNN model, particularly in tasks like crop recommendation where input feature relevance plays a crucial role in model performance.

Table 1: Comparison of ACGRU with and without Feature Selection

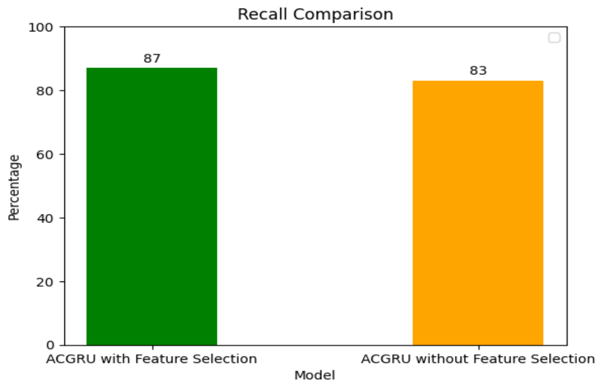
Algorithms	Accuracy	Precision	Recall	F1 Score
ACGRU with Feature Selection	88	91	87	88
ACGRU without Feature Selection	83	84	83	82



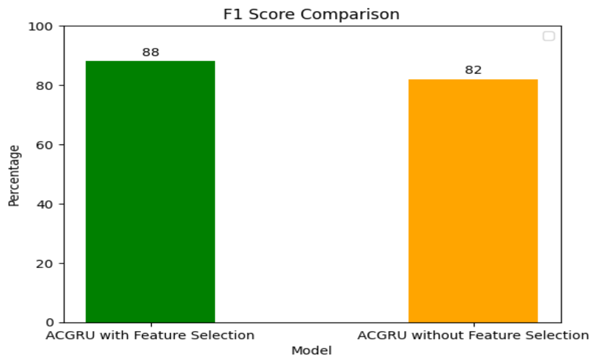
a Accuracy



b Precision



c Recall



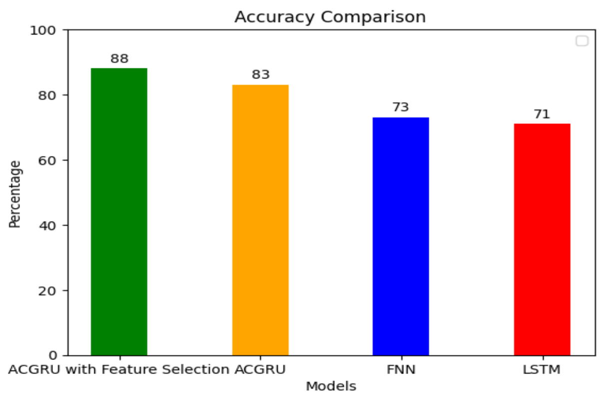
d F1 Score

Figure 3: Comparison of ACGRU with and without Feature Selection by (a) Accuracy, (b) Precision, (c) Recall and (d) F1 Score

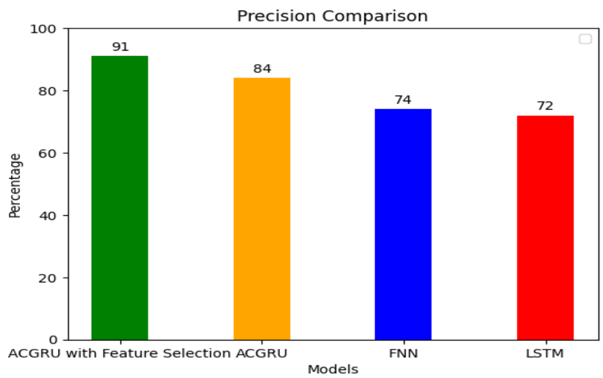
Table 2: Comparison of Algorithms

Algorithms	Accuracy	Precision	Recall	F1 Score
ACGRU with Feature Selection	88	91	87	88
ACGRU without Feature Selection	83	84	83	82
FNN	73	74	73	69
LSTM	71	72	71	67

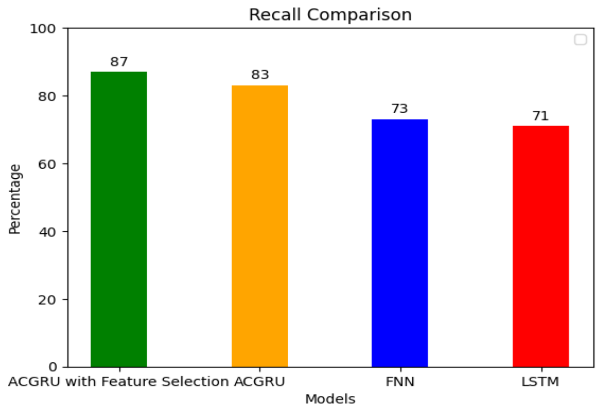
Figure 4 represents the findings presented in Table 2 by comparing the performance of four different algorithms: ACGRU without Feature Selection, ACGRU with Feature Selection, FNN and LSTM models. Without feature selection, the ACGRU model uses the neural network architecture to work directly on the original dataset.



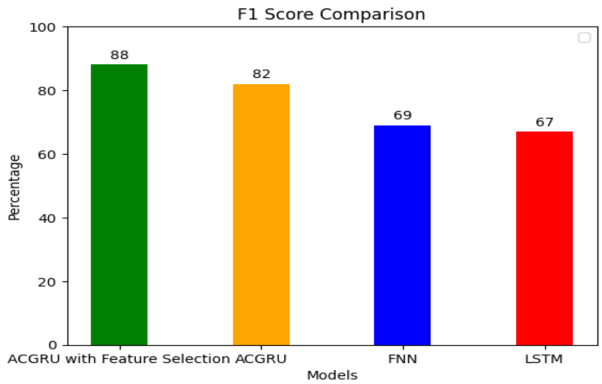
a Accuracy Comparison of Four Models



b Precision Comparison of Four Models



c Recall Comparison of Four Models



d F1 Score Comparison of Four Models

Figure 4: Comparison with Existing methods using (a) Accuracy, (b) Precision, (c) Recall and (d) F1 Score

The performance across all the metrics are moderate, implying that the model captures some patterns in the data, although the presence of irrelevant or redundant features could limit its effectiveness. By integrating feature selection using the IDCDMO algorithm, the ACGRU model significantly improves performance across all metrics compared to the ACGRU without feature selection. The selected features enhance the model ability to capture important patterns, resulting in higher accuracy, precision, recall and f1 score. The FNN model achieves lower performance compared to both ACGRU models. While FNNs are a basic neural network architecture, they may struggle with capturing temporal dependencies in sequential data like agricultural variables, leading to lower accuracy and other metrics. Similarly, the LSTM model also exhibits lower performance compared to the ACGRU models. While LSTMs are designed to handle sequential data with long-term dependencies, they may not effectively capture the complex interactions present in agricultural datasets, resulting in lower accuracy and other metrics.

6. Conclusion

This research shows the efficacy of integrating the Attention based Convolutional Gated Recurrent Unit (ACGRU) model with feature selection using the Improved Distribution based Chaotic Dwarf Mongoose Optimization (IDCDMO) algorithm for crop recommendation tasks. By selecting relevant input features and leveraging attention mechanisms, our proposed approach significantly improves prediction accuracy compared to traditional neural network models. The results highlight the importance of feature selection in enhancing the performance of the DNN model for agricultural applications. By identifying the most influential features such as nitrogen, phosphorus, potassium, pH and rainfall, the ACGRU model with feature selection achieves higher accuracy, precision, recall and f1 score in recommending suitable crops.

References

[1] Wakchaure, M., Patle, B. K., & Mahindrakar, A. K. (2023). Application of AI techniques and robotics in agriculture: A review. *Artificial Intelligence in the Life Sciences*, *3*, 100057.

[2] Senapaty, M. K., Ray, A., & Padhy, N. (2023). IoT-enabled soil nutrient analysis and crop recommendation model for precision agriculture. *Computers*, *12*(3), 61.

[3] Shams, M.Y., Gamel, S.A., & Talaat, F.M. (2024). Enhancing crop recommendation systems with explainable artificial intelligence: a study on agricultural decision-making. *Neural Computing & Applications, 36(11)*, 5695-5714.

[4] Pacal, I. (2024). Enhancing crop productivity and sustainability through disease identification in maize leaves: Exploiting a large dataset with an advanced vision transformer model. *Expert Systems with Applications*, *238*, 122099.

[5] Anguraj, K., Thiyaneswaran, B., Megashree, G., Shri, J. P., Navya, S., & Jayanthi, J. (2021). Crop Recommendation on Analyzing Soil Using Machine Learning. *Turkish Journal of Computer and Mathematics Education*, *12(6)*, 1784-1791.

[6] Gopi, P. S. S., & Karthikeyan, M. (2023). Multimodal machine learning based crop recommendation and yield prediction model. *Intell Autom Soft Comput*, *36*(1), 313-326.

[7] R. Pavithra. (2024). Medicinal Plants Analysis for Chronic Diseases using Decision Tree Based U-Net Classification. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(21s), 2409-2417.

[8] Dutta, M., Gupta, D., Juneja, S., Shah, A., Shaikh, A., Shukla, V., & Kumar, M. (2023). Boosting of fruit choices using machine learning-based pomological recommendation system. *SN Applied Sciences*, *5(9)*, 241.

[9] Sharmin, N., & Kiekintveld C. (2023) "Optimizing Crop Recommendations for Sustainable Agriculture: Leveraging Bayesian Networks in a Smart Crop Recommendation System," In *2023 20th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON)* pp. 20-26. IEEE.

[10] Priyadharshini, A., Chakraborty, S., Kumar, A., & Pooniwala, O. R. (2021, April). Intelligent crop recommendation system using machine learning. In *2021 5th international conference on computing methodologies and communication (ICCMC)* (pp. 843-848). IEEE.

[11] Pande, S. M., Ramesh, P. K., Anmol, A., Aishwarya, B. R., Rohilla, K., & SHAURYA, K. (2021, April). Crop recommender system using machine learning approach. In *2021 5th international conference on computing methodologies and communication (ICCMC)* (pp. 1066-1071). IEEE.

[12] Varshitha, D. N., & Choudhary, S. (2022). An artificial intelligence solution for crop recommendation. *Indonesian Journal of Electrical Engineering and Computer Science*, *25*(3), 1688-1695.

[13] Thilakarathne, N. N., Bakar, M. S. A., Abas, P. E., & Yassin, H. (2022). A cloud enabled crop recommendation platform for machine learning-driven precision farming. *Sensors*, *22*(16), 6299.

[14] Fegade, T. K., & Pawar, B. V. (2020). Crop prediction using artificial neural network and support vector machine. In *Data Management, Analytics and Innovation: Proceedings of ICDMAI 2019, Volume 2* (pp. 311-324). Springer Singapore.

[15] Gopi, P. S. S., & Karthikeyan, M. (2024). Red fox optimization with ensemble recurrent neural network for crop recommendation and yield prediction model. *Multimedia Tools and Applications*, *83*(5), 13159-13179.

[16] Ketheneni, K., Yenuga, P., Garnepudi, P., Paleti, L., Burla, N.R., Srinivas, O., ... Yamarthi, N.R. (2024). Crop, Fertilizer and Pesticide Recommendation using Ensemble Method and Sequential Convolutional Neural Network. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(2), 473-485.