AoDrA-Net: an approach to recommend crop for sustainable agriculture

P. Prabharani*

Information and Communication Engineering,
Anna University,
Chennai, India
Email: p.prabharani01@gmail.com
*Corresponding author

S. Appavu Alias Balamurugan

Department of Computer Science and Engineering,
Periyar Maniammai Institute of Science and Technology,
Thanjavur, India
Email: datasciencebala@pmu.edu

S. Sasikala

Department of Artificial Intelligence and Data Science,
Velammal College of Engineering and Technology,
Madurai, India
Email: ssk@vcet.ac.in

Abstract: Agriculture is a fundamental component of India's socio-economic structure. The inability of farmers to detect the most appropriate crop for the soil through conventional and non-scientific practices is a severe problem in a nation where 58% of the approximate population is engaged in agriculture. In some cases, farmers were unable to select the appropriate crops due to different soil conditions, different sowing seasons, and different regions. This results in suicide, abandoning agriculture, and shifting to metropolitan areas for livelihood. Archimedes optimised discrete deep residual AlexNet (AoDrA-Net) builds a complete crop recommendation framework (CRS-DDRAN-AOA) which offers direction and inspiration for the mentioned deficiencies. Initially, data is taken from the dataset of crop recommendation. Then the input data is pre-processed under z-score standardisation procedure. Then, the pre-processed output data is given to DDRAN augmented with AOA that accurately recommends the crop by lessening the error and raising the recommendation accuracy.

Keywords: discrete deep residual AlexNet; crop recommendation dataset; Archimedes optimisation algorithm; z-score standardisation process; crop recommendation system.

Reference to this paper should be made as follows: Prabharani, P., Balamurugan, S.A.A. and Sasikala, S. (2024) 'AoDrA-Net: an approach to recommend crop for sustainable agriculture', *Int. J. Bio-Inspired Computation*, Vol. 24, No. 2, pp.109–121.

Biographical notes: P. Prabharani is currently working as an Assistant Professor in the Department of Information and Communication Engineering at Anna University, Chennai, Tamil Nadu, India. She received her Bachelor of Engineering in Computer Science from Madurai Kamaraj University in 1998 and Master of Engineering in Information and Communication Engineering from Anna University in 2010. Currently, she is pursuing her Doctoral study in the area of Data Analytics at Anna University, Chennai. She has published around three research articles in international journals and conferences.

S. Appavu Alias Balamurugan is currently working as a Professor in the Department of Computer Science and Engineering at Periyar Maniammai Institute of Science and Technology, Thanjavur, India. He received his PhD in Information and Communication Engineering from the Anna University, Chennai, India, in 2009. He has authored/co-authored around 210 research papers in journal and conference proceedings in the areas of data mining, big data analytics, and data science with IEEE, Elsevier, Springer, World Scientific, Royal Society-London, and Inderscience Publishers.

S. Sasikala is currently working as an Associate Professor in the Department of Artificial Intelligence and Data Science at Velammal College of Engineering and Technology Madurai, Tamil Nadu, India. She received her BE in Computer Science and Engineering from the Sethu Institute of Technology, Kariapatti affiliated to Madurai Kamaraj University, Tamil Nadu in 2001 and ME in Computer Science and Engineering from the Thiagarajar College of Engineering, Madurai affiliated to Anna University, Tamil Nadu in 2008. She received Doctorate in Faculty of Information and Communication Engineering from Anna University India in 2016.

1 Introduction

Agriculture is one of the sectors that society takes great interest in as it produces a large portion of the world's food. Due to a lack or absence of food and a growing population, many countries currently still experience hunger (Akshatha and Shastry, 2022). The best way to end famine is to increase food production. By 2030, the United Nations must achieve two important goals: increasing food security and reducing hunger. Therefore, protection of crop, land estimation, and crop yield forecasting are significant to the production of food worldwide (Sarath Kumar et al., 2023). A nation's decision-makers rely on accurate forecasts to strengthen its national food security through appropriate export and import assessments (Anupama and Lakshmi, 2021; Mishra et al., 2022). The forecast of yield helps cultivators and farmers make financial and management decisions (Prakash et al., 2023). For the purpose of determining a region's level of food security, agricultural observation, particularly crop yield, is essential (Das et al., 2021). The crop recommendation is extremely complicated owing to more difficult factors. Crop yield is primarily influenced by factors like weather, soil quality, landscapes, insect infestations, availability, water quality, genotype, and harvest activity planning (Kumar et al., 2023). Due to the integration of an extensive amount of associated parameters that are characterised and influenced using non-arbitrate runs and external aspects, the processes of crop yield vary over time and are deeply nonlinear in nature and complex (Parween et al., 2021; Veerachamy and Ramar, 2022; Amgain et al., 2021). Typically, the agricultural framework is much more complex than a simple step-by-step calculation, particularly when dealing with large, imperfect, ambiguities, and large datasets.

Precision agriculture refers to the process of determining these parameters on a site-by-site basis to identify problems (Prasad et al., 2021). While not all precision agriculture results are accurate to result, in agriculture, having accurate and precise recommendations is important because errors can result in heavy material and capital losses. A lot of work is being done to develop a more precise and effective model for predicting crops (Bian et al., 2021; Rashid et al., 2021).

Crop recommendation systems that uses deep learning algorithms examine a variety of variables, including soil and climate conditions (Shetty et al., 2021), and select the best crops in a specific region. This lead to the better resource utilisation and enhanced crop production. Early detection of plant diseases assists farmers in taking the required procedures to limit disease spread and reduce agricultural yield losses (Alikhan et al., 2023). Machine learning-based algorithms can detect plant illnesses from leaf pictures and deliver a rapid diagnosis. Pest detection devices can assist farmers in detecting pest infestations before they become severe. By detecting infestations early (Ju et al., 2021), farmers can target only the affected regions and minimise the usage of pesticides, lowering the environmental effect (Madhuri and Indiramma, 2021; Gopi and Karthikeyan, 2023; Aradea et al., 2023).

There are a limited number of crop proposed systems available, and the proposed crop planning system seems to be the most promising one. The goal is to create a recommendation mechanism that proposes the best crop based on location-specific soil features and meteorological circumstances. To the best of knowledge, no such suggestion approach ever utilising discrete deep residual Alex net (DDRAN) classifier has been reported. The major contributions are listed as follows,

- The proposed combination of improved CRS-DDRAN-AOA enhances crop recommendation. This method is simple to build, has a significant impact, is highly precise within a small margin, and effectively optimises search space for both small and large collections of characteristics.
- The optimal feature subset from the original dataset is chosen prioritising relevance over redundant and uninteresting traits.
- The DDRAN classifier using an updated method is tested or developed for accurately predicts correct crops. As a result, a special combination method ought to greatly improve detection accuracy. For accurately recommending the crop, Archimedes optimisation algorithm (AOA) Therefore, it is proposed to use AOA to optimise DDRAN classifier, which accurately recommends the crop.
- Using several indicators is important part of crop recommendation method. The results are evaluated utilising accepted clinical validation methods.

Remaining paper is organised` as follows: Section 2 presents the literature survey, Section 3 describes proposed technique, Section 4 proves the outcomes, and Section 5 gives presents conclusions.

2 Literature survey

A number of research studies were existed previously in the literatures related to Crop recommendation system. Table 1 depicts the comparison of related work. Some of the latest investigations were assessed here in table format.

3 Proposed methodology

In this section, discrete deep residual AlexNet augmented with Archimedes optimisation algorithm (AoDrA-Net) espoused crop recommendation system (CRS-DDRAN-AOA) is discussed. The block diagram of the CRS-DDRAN-AOA crop recommendation system is represented in Figure 1. It contains three stages, like crop recommendation, pre-processing, data acquisition. Thus, the complete description about each phase is provided below.

3.1 Question formalisation

In this section, some vital research queries must be addressed to deal related concerns regarding crop recommendation.

- TQ1: Which data set is applied in crop recommendation?
- TQ2: How pre-processed the input data?
- TQ3: How can DDRAN classifier are effectively utilised for crop recommendation?
- TQ4: How does the incorporation of Archimedes optimisation algorithm improve the optimisation procedure of DDRAN classifier for crop recommendation?
- TQ5: What performance metrics are typically employed in crop recommendation?

Section 3 tries to provide more detail on the technical issues mentioned.

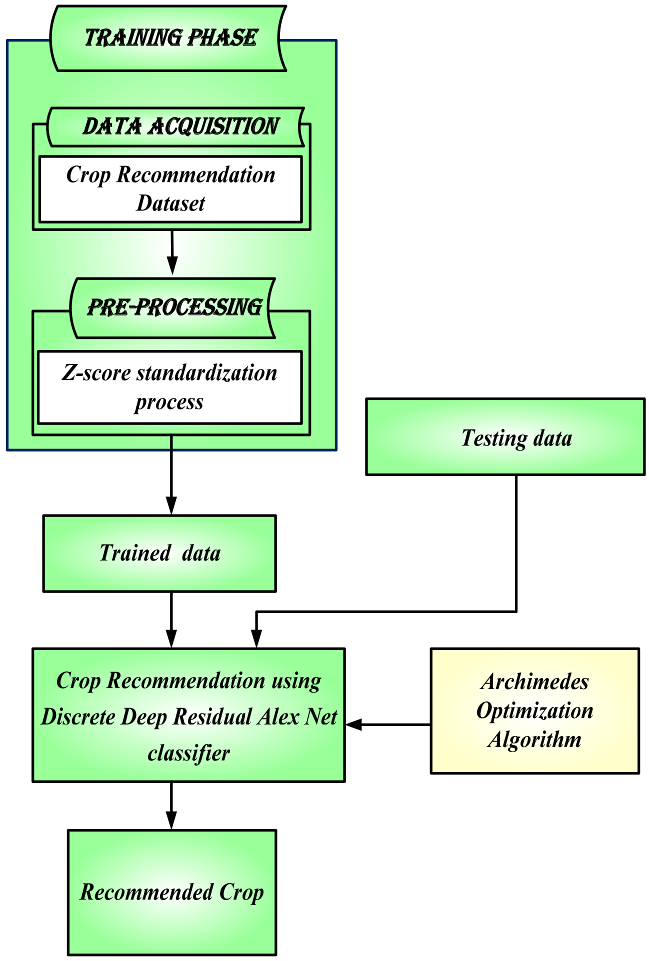
3.2 Data acquisition

This subsection goes to answer the following technical question:

TQ1 Which dataset has been used in crop recommendation?

In this work, crop recommendation dataset is taken. It contains parameters, such as Phosphorous (P), Potassium (K), Nitrogen (N), pH value of soil, Humidity, Rainfall, Temperature. The Crop Recommendation Dataset has 2201 data, which incorporates 22 diverse crops, like banana, apple, chickpea, black gram, coffee, coconut, grapes, cotton, jute, maize, lentil, moth beans, mango, muskmelon, orange, mung bean, pigeon peas, papaya, rice, watermelon, kidney beans and pomegranate (https://www.kaggle.com/datasets /atharvaingle/crop-recommendation-dataset). Then, the input parameters are fed to the pre-processing phase.

Figure 1 Proposed CRS-DDRAN-AOA crop recommendation system (see online version for colours)



3.3 Pre-processing phase

This subsection tries to answer the following technical question:

TQ2 How pre-processed the input data?

By standardising the input data, the z-score standardisation procedure is used for data pre-processing to reduce error and noise. The input data is standardised by deriving z-score value. This is computed by equation (1),

$$z-score = \left[\frac{(D-\mu)}{\sigma}\right] \tag{1}$$

Here, (μ) denotes mean value , standard deviation specifies (σ) of input data (D). The random database is expressed in equation (2),

$$(z-score)_i = \phi_0 + \phi_1 D_i + \varepsilon_i \tag{2}$$

The error value represents ε_i under standard deviation, φ_0, φ_1 indicates the factors to make data scrubbing and integration (Mondal and Goswami, 2021). Moreover, the crop recommendation data necessitate the standardisation procedure to standardise the variable movements. The standardisation (S) is revealed in equation (3),

$$(S) = \left[\frac{(D - D_{\min})}{D_{\max} - D_{\min}} \right] \tag{3}$$

here (D) implies sample input crop data, $D_{\min}$ implies minimisation of errors in the input crop data, $D_{\max}$ implies maximisation of data standardisation. Thus, the data are subjected to the standardisation process, which eliminates redundancy in all input data. The standardised data considered as an input for additional processes.

3.4 Crop recommendation using DDRAN classifier

This sub-section takes effort to answer the following technical question:

TQ3 How can DDRAN classifier are effectively utilised for crop recommendation?

In this, crop recommendation using DDRAN classifier is discussed that accurately recommend the crop. In general, DDRAN classifier is an novel form of Alexnet, VGGNet, GoogleNet, and DenseNet that is regarded as the local self-learning mode property from lesser to greater levels (Liu, 2020). DDRAN has eight primary convolutional layers, three of which are partitioned into two sub-layered. Higher layers learn more complexity from large amounts of data, and lower layers learn fundamental traits. Deformable along inflexible features are detected using affine conversion after being inserted with max-pooling guidance. The final two fully connected layers able to perceive complex co-occurrence crop features, but they lose spatial position semantics. The last classification layer receives preceding comprehensive feature extraction, such as Potassium (K), Phosphorous (P), Nitrogen (N), pH value of soil, Temperature, Rainfall and Humidity for accurate crop recommendation.

Here, the local receptive field (LRF) is a filter that accomplishes convolutional operation referred as convolutional kernel. Adopting various convolution kernel types yields numerous local aspects of crop parameters. Therefore, the convolutional kernel size is converted from 11 × 11 to 7 × 7 AlexNet initial convolutional layer for learning subtle feature extraction and reinforcing the ability to distinguish subtle crop factors (Ju et al., 2021).

Then, the 2nd, 3rd, and 5th convolutional layers of the DDRAN classifier are separated into two layers. This prevents the calculation burden from increasing over time while changing the network depth. This is used to determine crop parameters such as deep imminent without requiring additional resources at runtime. The DDRAN classifier then acts as an AlexNet by removing every local response normalisation (LRN) operations, as well as group modification in two GPU blocks. The LRN does not improve the network normalisation.

The DDRAN classifier combines the random forest classifier, soft-max classifier, support vector data description, and adaptive boosting classifier. The final label determination made by the DDRAN classifier was consistent with the 'majority' of the processed labels. The DDRAN classifier is placed in the final label choice and is determined by 'elite votes' rather than 'all votes'. Using the DDRAN classifier, certain positive votes are picked to contribute to the final accuracy, while other negative votes diminish the final accuracy eliminated. This allows for the precise identification of crop recommendations.

The DDRAN classifier runs in real time and achieves a rapid renewal speed by agreeing on newly collected information. As a result, it is desirable to speed method training while recalling higher-level performance. The accuracy and time consumption of these newly designed algorithms are assessed by reducing their depth (total number of layers) and width (filters at each layer). The number of LRFs is modified for each convolutional layer to find the best network architecture. For example, raising the depth of a DDRAN classifier from 8 to 11 layers affects the total number of LRFs, as well as the classification layer's grading style. Furthermore, certain hyperparameter in the DDRAN classifier are maximised, such as the size of the LRF.

Consider $Batch_{size}$, $chll_{in}$, hei_{in}, wei_{in} are the input parameters and $Batch_{size}$, $chll_{out}$, hei_{out}, wei_{out} are the output parameters. Here, $Batch_{size}$ specifies batch size, $chll$ specifies count of channels, hei represents the height of crop parameter in dimension and wid represents the width of crop parameter in dimension. The equations (4) and (5) explain the computation method of output after convolution.

$$hei_{out} = \frac{\begin{matrix} hei_{in} + 2 \times pdd[0] - dilat[0] \\ \times (\ker size[0] - 1) - 1 \end{matrix}}{stride[0]} + 1 \tag{4}$$

$$wid_{out} = \frac{\begin{matrix} wid_{in} + 2 \times pdd[1] - dilat[1] \\ \times (\ker size[1] - 1) - 1 \end{matrix}}{stride[1]} + 1 \tag{5}$$

where $pdd[0]$ and $pdd[1]$ signifies x and y-coordinate padding count of implicit zero-paddings on both sides for the padding count of points in every dimension, $dilat$ denotes dilation and regulates the pixel points of crop parameter spacing and the dilation of x-coordinate and y-coordinate are represented as $dilat[0]$ and $dilat[1]$. In this proposed work, 128 batch sizes are chosen for training the DDRAN classifier. $\ker size$ denotes kernel size in every convolutional layer and the LRF size of x and y-coordinate are represented as $\ker size[0]$ and $\ker size[1]$. Thus, the output size for every crop data is considered. Finally, the proposed DDRAN classifier accurately recommends the crop. Artificial intelligence basis optimisation algorithm is applied in DDRAN classifier on account of its pertinence, convenience.

AOA is used to enhance DDRAN for identifying the better parameters. Generally, manual exploration, random exploration and grid exploration are used for the purpose of constraint formation. These exploration distribute its unusual fragility depends on reiteration time then, there contains no familiar analysis about subterfuge-assembled. That's why AOA is used to overwhelm these issues.

Table 1 Comparison of related work

Author name	*Title*	*Architecture*	*Characteristics*	*Advantages*	*Disadvantages*
Mythili and Rangaraj (2021)	Crop recommendation for improved crop yield for precision agriculture utilising ant colony optimisation using deep learning approach	Ant colony optimisation	This study uses accumulated historical data of crops and climate to make recommendations	It provides better accuracy	It offers less computational time
Madhuri and Indiramma (2021)	Integrated crop recommendation system based on artificial neural networks using soil and climate parameters	Artificial neural network	To create a crop recommendation scheme based on location-specific soil and meteorological variables	It offers lesser computational time	It offers less accuracy
Choudhury et al. (2022)	Crop recommendation scheme and plant infection categorisation utilising machine learning for precision agriculture	SVM, XGBoost	To recommend the correct crop	It offers higher accuracy	It offers lower ROC
Shingade and Mudhalwadkar (2023)	A crop suggestion program based on sensor data and machine learning for Maharashtra's fertile regions	Decision tree, random forest, and support vector machine	To recommend the correct crop using sensor based information	It offers better specificity	It offers lower ROC
Ali et al. (2021)	Machine learning based crop recommendation service for local farmers in Pakistan	Linear regression algorithm	It is highly useful for farmers and other stakeholders in making educated decisions about how to boost output	It achieves lesser computation time	It achieves lesser identification accuracy
Hasan et al. (2023)	Ensemble machine learning-based recommendation scheme for effective prediction of suitable agricultural crop cultivation	Random forest and CatBoost	It suggests appropriate crops for a particular land region for cultivation at the upcoming season	It achieves better accuracy	It offers higher computational time
SSL et al. (2023)	An intelligent crop recommendation system utilising deep learning	K-nearest neighbour method	To investigate the methodologies used in collecting water bodies using satellite remote sensing	It offers higher accuracy	It offers higher computational time
Choudhury et al. (2023)	An acquisition based optimised crop recommendation system using machine learning algorithm	Moth flame optimisation, KNN and logistic regression	To increase forecast precision and consistency, a model was created utilising optimisation along ensemble techniques	It offers better specificity	It offers lesser F-score

This sub-section goes to answer the following technical question:

TQ4 How does the incorporation of archimedes optimisation algorithm upgrade the optimisation procedure of DDRAN classifier for crop recommendation?

Archimedes optimisation technique is a metaheuristic algorithm which mimics the concept of buoyant force employed mounting in object, partially or fully dipped in fluid, and it is proportionate to displaced weight of fluid. It is able to more quickly reach global optimal conditions and enable a seamless transition from exploration to exploitation. It agrees AOA to arrive in ideal fitness solution quickly. In this work, AOA is chosen because it possess own development, requires less iteration time than grid, manual, random explorations, and scales the optimal hyper parameters.

3.4.1 Stepwise procedure of AOA for optimising the DDRAN

The stepwise procedure is deliberated to get the ideal values of discrete deep residual AlexNet depending on Archimedes optimisation algorithm. First, the AOA algorithm distributes the parameter uniformly to enhance the optimal parameter values of hei_{out} and wid_{out} of DDRAN weight and biases parameters. The best solution is selected through AOA and the equivalent flowchart is depicted in Figure 2. The stepwise procedure is delimited below,

Step 1 Initialisation

Initialise the position of every object with their density, volume and acceleration from Archimedes optimisation algorithm.

Step 2 Random generation

The input parameters produced randomly after initialisation. The optimum fitness is selected depending on its clear hyper-parameter position.

Step 3 Evaluation of fitness function

The random solution is created utilising initialised values. Fitness function is assessed through parameter optimisation, hei_{out} and wid_{out} of DDRAN weight and bias parameters. Thus, it is calculated using equation (6),

$$Fitness\ Function = optimisation\left[hei_{out}\ and\ wid_{out}\right] \tag{6}$$

Step 4 Position updation for exploration and exploitation of object for optimising hei_{out} and wid_{out}.

In this section, AOA is utilised for enhancing the hei_{out} and wid_{out} of DDRAN parameters with the position updation of exploration and exploitation phase of object (Venkatanaresh and Kullayamma, 2024). Initially, the density and volume of object z from Archimedes optimisation algorithm are updated by following equations (7) to (8)

$$Dty_z(\mathrm{y}+1) = Dty_z(\mathrm{y}) + \mathrm{rdm}\left(Dty_{best} - Dty_z(\mathrm{y})\right) \tag{7}$$

$$Vlm_z(\mathrm{y}+1) = Vlm_z(\mathrm{y}) + \mathrm{rdm}\left(Vlm_{best} - Vlm_z(\mathrm{y})\right) \tag{8}$$

where Dty_{best} and Vlm_{best} specifies volume and density related to identify best object, random specifies distributed random number uniformly. Then, the transference operator O and compactness aspect C are updating by following equations (9) to (10),

$$O = \exp\left(\frac{y - y_{\max}}{y_{\max}}\right) \tag{9}$$

$$C(\mathrm{y}+1) = \exp\left(\frac{y_{\max} - y}{y_{\max}}\right) - \left(\frac{y}{y_{\max}}\right) \tag{10}$$

where y and $y_{\max}$ are iteration number and maximum iterations, respectively. If $O \leq 0.5$, the exploration phase occurs, which means there is collision occur between the object and random material and is given in equation (11)

$$Acclr_z(\mathrm{y}+1) = \frac{Dty_{RM} + Vlm_{RM} * Acclr_{RM}}{Dty_Z(\mathrm{y}+1) * Vlm_z(\mathrm{y}+1)} \tag{11}$$

where Dty_{RM}, Vlm_{RM} and $Acclr_{RM}$ specifies density, volume, acceleration of random material RM; Dty_z, Vlm_z and $Acclr_z$ specifies density, volume, and acceleration of object z. Then, the normalise acceleration are obtained with the following equation (12),

$$Acclr_{z-normalize}(\mathrm{y}+1) = p * \frac{Acclr_z(\mathrm{y}+1) - \mathrm{minimum}(Acclr)}{\mathrm{maximum}(Acclr) - \mathrm{minimum}(Acclr)} + q \tag{12}$$

where p and q specifies normalisation range and set to 0.9, 0.1. Then, the position updation of exploration phase for optimising hei_{out} is obtained with the help of the given equation (13)

$$pos_z(\mathrm{y}+1) = pos_z(\mathrm{y}) + \mathrm{Cstn}_z \times rdm \times Acclr_{z-normalize}(\mathrm{y}+1) \times DV \times \left(pos_{rdm} - pos_z(\mathrm{y})\right) \tag{13}$$

where Cstn_z is constant equals to 2 and DV specifies dimensional vector, which randomly creates number among [0, 1]. Similarly, $O > 0.5$, the exploitation phase occurs that is no collision occur between the object and random material and it is given in equation (14)

$$Acclr_z(\mathrm{y}+1) = \frac{Dty_{best} + Vlm_{best} * Acclr_{best}}{Dty_Z(\mathrm{y}+1) * Vlm_z(\mathrm{y}+1)} \tag{14}$$

where $Acclr_{best}$ specifies acceleration of best object. Then, update the normalise acceleration and update the direction flag F by using equation (15),

$$F = \begin{cases} +1; & \mathit{If}\ G \leq 0.5 \\ -1; & \mathit{If}\ G > 0.5 \end{cases} \tag{15}$$

where $\mathrm{G} = 2 \times rdm - \mathrm{Cstn}_4$. Then, the position updation of exploitation phase to optimise wid_{out} is obtained with the help of the following equation (16),

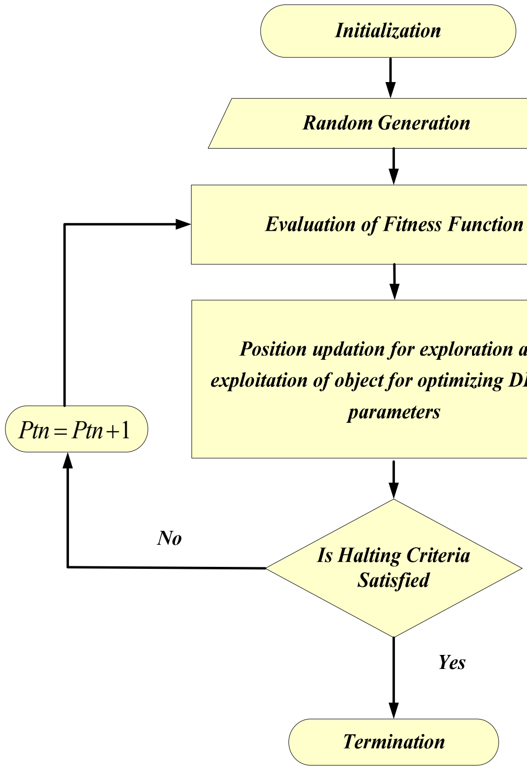
$$pos_z(\mathrm{y}+1) = pos_{best}(\mathrm{y}) + F \times \mathrm{Cstn}_2 \times rdm \times Acclr_{z-normalize}(\mathrm{y}+1) \times DV \times \left(Ptn \times pos_{best} - pos_z(\mathrm{y})\right) \tag{16}$$

where Cstn_2 specifies constant equal to 6. Ptn increases with time, which is directly proportional to the transference operator and determined using $Ptn = \mathrm{Cstn}_3 - O$. By this, it optimises the DDRAN parameters with the position updation of object exploration and exploitation phase from Archimedes optimisation algorithm.

Step 5 Termination condition

Here, the hyper-parameter hei_{out} and wid_{out} of DDRAN weight and biases parameters are enhanced using AOA Algorithm, which repeat iteratively the process till the halting criteria, $Ptn = Ptn + 1$ is met. Finally, DDRAN-AOA recommends the accurate crop with greater accurateness by diminishing the computational time with error.

Figure 2 Flowchart of AOA for optimising DDRAN parameter (see online version for colours)



4 Results and discussion

The experimental outcome of proposed discrete deep residual AlexNet augmented with Archimedes optimisation algorithm espoused crop recommendation system (CRS-DDRAN-AOA) is discussed. The simulations are done in Python using PC through Intel Core i5, 8GB RAM, Windows 7, 2.50 GHz CPU. The mentioned metrics are analysed. The obtained results of CRS-DDRAN-AOA method is compared with existing techniques, like Crop recommendation for better crop production for precision agriculture using ant colony optimisation with deep learning approach (CRS-ACO) (Mythili and Rangaraj, 2021), Artificial neural networks-based integrated crop recommendation scheme under soil and climatic conditions (CRS-ANN) (Madhuri and Indiramma, 2021), crop recommendation scheme with plant infection classification based upon machine learning for precision agriculture (CRS-SVM-XGBoost) (Choudhary et al., 2022) and sensor-based crop recommendation strategy using machine learning for the fertile parts of Maharashtra (CRS-DT-RF) (Shingade and Mudhalwadkar, 2023) methods. The snapshot of proposed CRS-DDRAN-AOA crop recommendation system page is given in Figure 3. Figure 4 shows the Assignment of test parameter to proposed CRS-DDRAN-AOA crop recommendation system. The output recommended crop result of proposed CRS-DDRAN-AOA method is given in Figure 5. The CRS-DDRAN-AOA simulation parameter is shown in Table 2.

Figure 3 Snapshot of proposed CRS-DDRAN-AOA crop recommendation system page (see online version for colours)

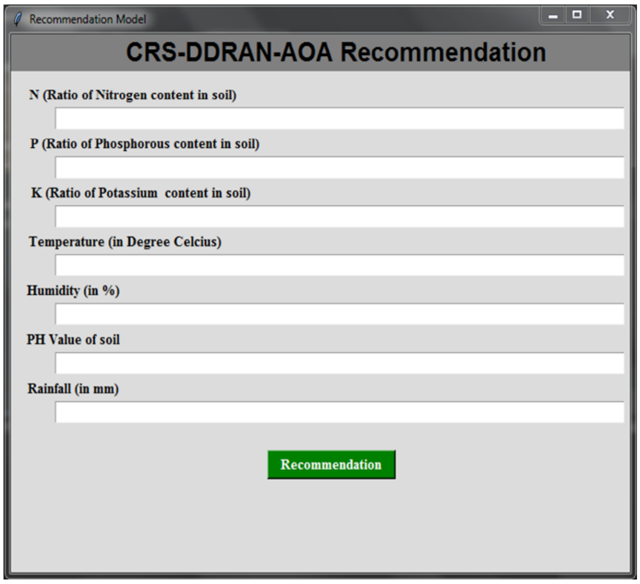


Table 2 Simulation parameter

Parameters	*Values*
Maximum iteration	200
Time	0–1
Position	30
dimensional vector *DV*	0–1
Normalisation range *p*	0.9
Normalisation range *q*	0.1
$Cstn_1$	2
$Cstn_2$	6
$Cstn_3$	2
$Cstn_4$	0.5

Experimental setup

Python's scikit-learn program created the CRS-DDRAN-AOA, which included experiments with traditional and deep learning methods. Assume that the taught deep learning algorithms are evaluated using real vs. projected curves and error metrics. To predict crop production, the supervised methods are used, wherein the data set has some features as well as target is quantity of crop production in particular area. The average outcomes of experiments are taken as 50% for training and 50% for testing phase, where each phase has 10 trials.

The hyperparameters of CRS-DDRAN-AOA is tuned to get better performance, also examined the classical and deep learning approaches. The same hyperparameters provide a superior outcome for nearly all the experiments. Z score standardisation achieves a better outcome in every case including the hyperparameters.

4.1 Dataset description

In this work, crop recommendation dataset is taken. The crop recommendation dataset has 2201 data. Among them, 50% data are chosen for the purpose of training, 50% data for testing (https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset.).

4.2 Performance measures

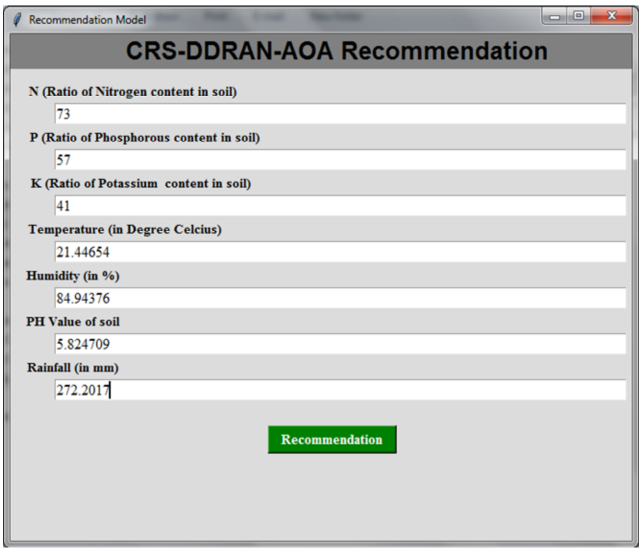
The following technical query is attempted to be addressed in this subsection:

TQ5 What performance metrics are generally used in Crop recommendation?

The performance of the proposed technique is evaluated using performance metrics, like recall (sensitivity), accuracy, precision, specificity, F1-score (dice co-efficient), Matthew's correlation coefficient, Jaccard co-efficient, error rate and computational time. The following confusion matrix is required to scale the performance metrics.

- True positive (TP): correct recommendation of crop and correct prediction.
- True negative (TN): incorrect recommendation of crop and correct prediction.
- False positive (FP): Correct recommendation of crop and incorrect prediction.
- False negative (FN): incorrect recommendation of crop and incorrect prediction.

Figure 4 Assigning test parameter to proposed CRS-DDRAN-AOA crop recommendation system (see online version for colours)



4.2.1 Accuracy

It is calculated using equation (17),

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{17}$$

4.2.2 Precision

It is calculated by equation (18),

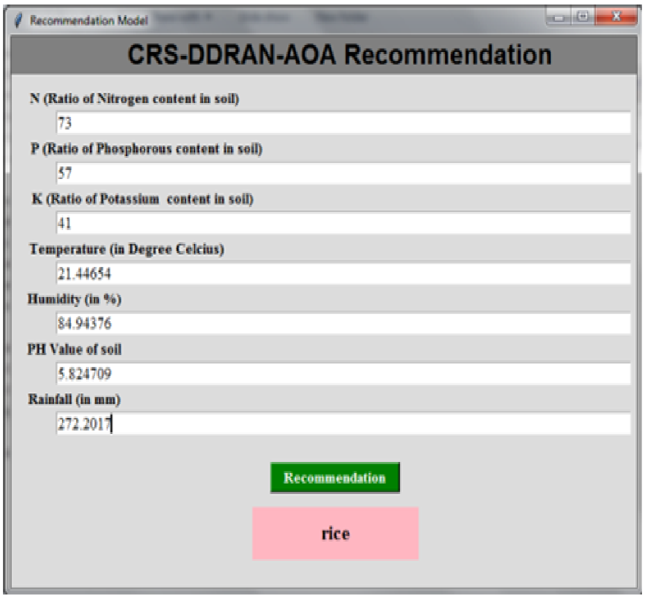
$$Precision = \frac{TP}{(TP+FP)} \tag{18}$$

4.2.3 Specificity

It is calculated by equation (19),

$$Specificity = \frac{(TN)}{(FP+TN)} \tag{19}$$

Figure 5 Output recommended crop result of proposed CRS-DDRAN-AOA method (see online version for colours)



4.2.4 Recall

This is determined by equation (20),

$$Recall = \frac{TP}{(TP+FN)} \tag{20}$$

4.2.5 F1 score

It is computed using equation (21),

$$F1Score = \frac{TP}{\left(TP+\frac{1}{2}[FP+FN]\right)} \tag{21}$$

4.2.6 AUC

AUC is computed by equation (22),

$$AUC = 0.5 \times \left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \tag{22}$$

4.2.7 Error rate

It is measured through equation (23),

$$Error\ \ Rate = 100 - Accuracy \tag{23}$$

4.2.8 Jaccard coefficient

It is determined by equation (24),

$$Jaccard\ coefficient = \left(\frac{TP}{TP + FN + FP}\right) \tag{24}$$

4.2.9 Mathew's correlation coefficient

It is scaled by equation (25),

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{\begin{pmatrix}(TP + FP) * (TP + FN) \\ *(TN + FP) * (TN + FN)\end{pmatrix}}} \tag{25}$$

4.3 Performance analysis

Figures 6 to 11 depicts the simulation results of CRS-DDRAN-AOA approach. The performance of CRS-DDRAN-AOA method is compared with existing CRS-ACO, CRS-ANN, CRS-SVM-XGBoost and CRS-DT-RF methods.

Figure 6 Analysis of accuracy and precision (see online version for colours)

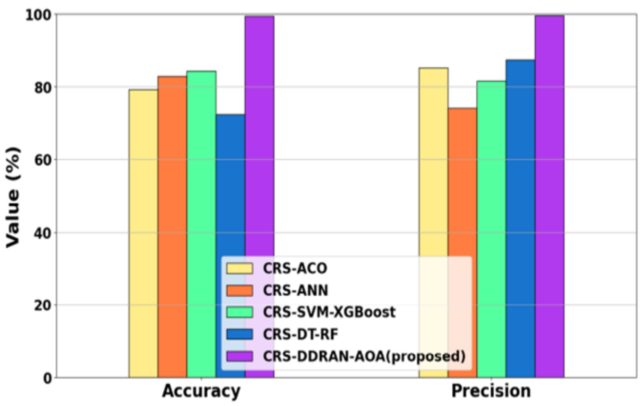


Figure 6 shows analysis of accuracy and precision. The performance of CRS-DDRAN-AOA method attains 36.08%, 25.01%, 8.54% and 10.59% higher accuracy; 38.58%, 22.61%, 6.698% and 11.62% improved precision compared with existing CRS-ACO, CRS-ANN, CRS-SVM-XGBoost and CRS-DT-RF methods.

Figure 7 shows analysis of specificity and F-score. The CRS-DDRAN-AOA provides 32.75%, 25.72%, 6.69% and 14.03% higher specificity; 29.97%, 18.35%, 7.24% and 9.88% higher F-score compared with existing CRS-ACO, CRS-ANN, CRS-SVM-XGBoost and CRS-DT-RF methods.

Figure 7 Analysis of specificity and F-score (see online version for colours)

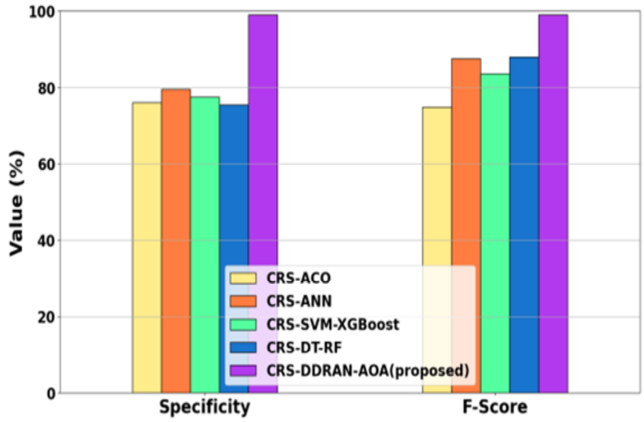


Figure 8 Analysis of recall, Matthew's correlation coefficient and Jaccard coefficient (see online version for colours)

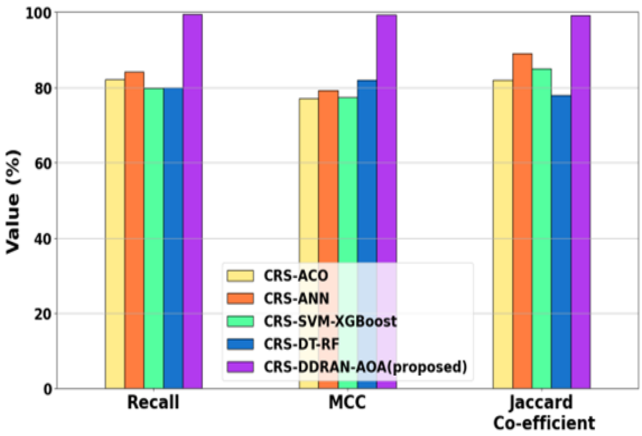


Figure 8 shows analysis of Matthew's correlation coefficient, Jaccard coefficient and recall. The CRS-DDRAN-AOA provides 41.88%, 22.53%, 10.17% and 16.97% higher recall; 35.10%, 20.07%, 7.89% and 11.15% higher Matthew's correlation coefficient, 37.71%, 24.97%, 6.58% and 12.56% higher Jaccard coefficient compared with existing CRS-ACO, CRS-ANN, CRS-SVM-XGBoost and CRS-DT-RF methods.

Figure 9 Error rate analysis (see online version for colours)

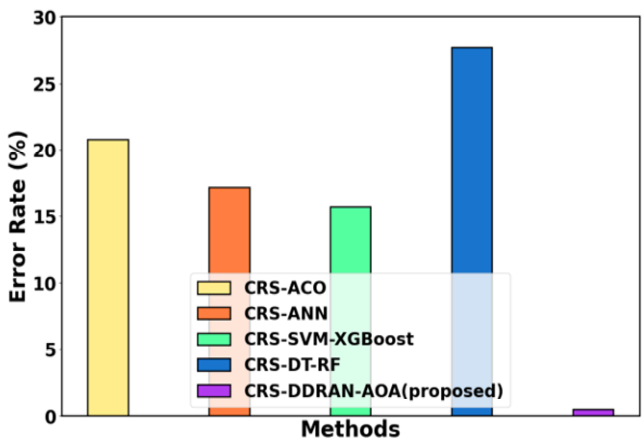


Figure 9 depicts error rate analysis. The CRS-DDRAN-AOA provides 93.49%, 91.55%, 81.02% and 83.84% lower error rate than the existing methods, such as CRS-ACO, CRS-ANN, CRS-SVM-XGBoost and CRS-DT-RF methods.

Figure 10 depicts computation time analysis. The CRS-DDRAN-AOA provides 25.83%, 16.92%, 22.91% and 15.34% lesser computation time than the existing CRS-ACO, CRS-ANN, CRS-SVM-XGBoost and CRS-DT-RF methods.

Figure 10 Computation time analysis (see online version for colours)

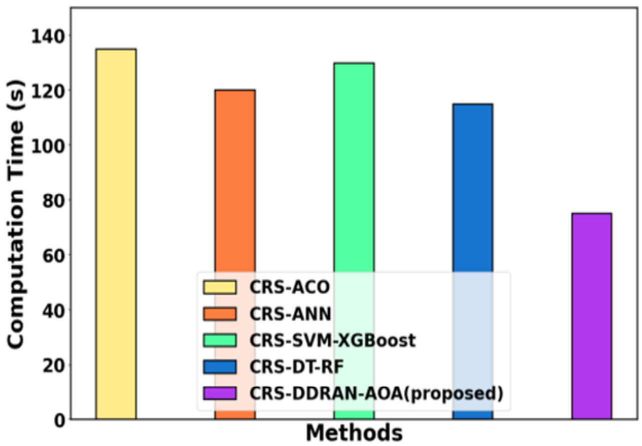


Figure 11 ROC curve (see online version for colours)

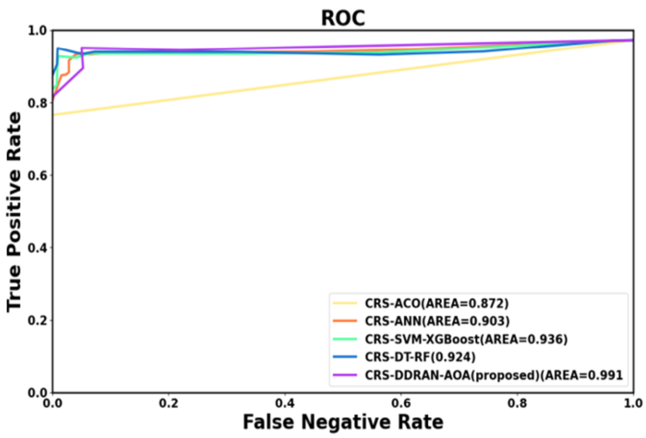


Figure 11 shows the ROC curve analysis. The CRS-DDRAN-AOA provides 5.41%, 3.54%, 0.81% and 3.33% greater AUC than the existing CRS-ACO, CRS-ANN, CRS-SVM-XGBoost and CRS-DT-RF methods.

In this manuscript, an approach called CRS-DDRAN-AOA is proposed. Apart from crop production forecasting, crop recommendation is an important part of the proposed study. The cultivation of appropriate crops on suitable soil can significantly increase the yield of any crop. Selecting the most appropriate crop for the provided soil is a laborious process. A comprehensive analysis of environmental factors and the rate of production are necessary to suggest a suitable land for production. Each area contains a distinct set of environmental parameters. Taking the standard variables as threshold values, suggest crop recommendations for any particular area. Based upon the current year's environment and area data, the technique is trained using environmental and area data to predict the predicted production for each crop. Then, the yield of each crop is compared to the crop threshold value for any given region. If the crop meets the requirements, then it will be added to the recommended crop list. The threshold value is determined using the relevant local authority and varies depending on the area, demand, policy and ecological circumstances. The model will compare the crops from the same harvest period and recommend the appropriate crops for the given location. The performance of CRS-DDRAN-AOA is compared with the existing algorithms. Simulation outcomes illustrate from Table 3 depicts that the proposed CRS-DDRAN-AOA technique offers 4.52%, 13.82%, 9.45%, 11.45%, 12.45%, 11.3% greater accuracy compared with existing Mythili, and Rangaraj (2021), Madhuri and Indiramma, (2021), Choudhury et al. (2023), Shingade and Mudhalwadkar (2023), Hasan et al. (2023), SSL et al. (2023) methods respectively; 22.33%, 28.70%, 14.56%, 19.43%, 14.79%, 13.2% greater precision compared with existing Mythili and Rangaraj (2021), Madhuri and Indiramma (2021), Choudhury et al. (2023), Shingade and Mudhalwadkar (2023), Hasan et al. (2023), SSL et al. (2023) methods respectively; 26.07%, 14.36%, 33.67%, 19.45%, 14.32%, higher Fscore compared with existing methods like Mythili and Rangaraj (2021), Madhuri and Indiramma (2021), Choudhury et al. (2023), Shingade and Mudhalwadkar (2023), Ali et al. (2021), Hasan et al. (2023) respectively; 22.33%, 28.70%, 14.56%, 19.43%, 14.79%, 13.2% greater Matthew's correlation coefficient compared with existing Mythili, and Rangaraj (2021), Madhuri and Indiramma (2021), Choudhury et al. (2023), Shingade and Mudhalwadkar (2023), Ali et al. (2021), SSL et al. (2023) methods respectively; 26.07%, 14.36%, 33.67%,19.45%, 14.32%, 12.2% greater Jaccard coefficient compared with existing Mythili and Rangaraj (2021), Madhuri and Indiramma (2021), Choudhury et al. (2023), Shingade and Mudhalwadkar (2023), SSL et al. (2023) methods respectively; 4.52%, 13.82%, 9.45%, 11.45% lesser Computational time compared with existing Mythili and Rangaraj (2021), Madhuri and Indiramma (2021), Choudhury et al. (2023), Shingade and Mudhalwadkar (2023), SSL et al. (2023) methods respectively.

Table 3 Some of benchmark table using literature support

Methods	*Performance metrics*						
	Accuracy (%)	*Precision (%)*	*F score (%)*	*Matthew's correlation coefficient (%)*	*Jaccard coefficient (%)*	*Computational time(s)*	*ROC*
Mythili and Rangaraj (2021)	65.5	56.4	54.3	56.7	65.3	124.4	0.1
Madhuri and Indiramma (2021)	65.9	67.8	65.3	65.4	54.22	112	0.2
Choudhury et al. (2023)	65.3	45.4	87.6	65.4	55.3	126	0.3
Shingade and Mudhalwadkar (2023)	71	67	81.4	63.2	76.5	127	0.5
Ali et al. (2021)	-	-	-	69.8	78.9	-	-
Hasan et al. (2023)	76.3	55.6	79.8	-	-	-	0.7
SSL et al. (2023)	65.8	78.9	-	73.2	69.2	120	-
CRS-DDRAN-AOA (proposed)	98.2	96.3	98.3	98.9	98.7	75	1

4.4 Discussion

In this paper, recommending crop for sustainable agriculture has been proposed for improving agriculture. AoDrA-Net, enable the extraction of intricate patterns and relationships from vast datasets, providing an understanding of environmental and crop parameters. It excel in capturing high-level features from raw data, offering a more comprehensive perspective on soil, water, and crop conditions. This depth of analysis is crucial for precise recommendations. Unlike traditional linear methods can handle nonlinear data relationships. This ability is essential given the inherently nonlinear nature of agricultural ecosystems. The AoDrA-Net's capacity to autonomously extract relevant features mitigates the reliance on predefined features, enhancing adaptability to diverse agricultural contexts. Accurate crop recommendations enhance resource allocation by avoiding the wasteful use of water, fertilisers, and pesticides. This encourages sustainable farming techniques while minimising environmental effect. Recommending a diverse range of crops, including resilient and locally adapted varieties, contributes to biodiversity and ecological balance, key elements of sustainable agriculture. The high accuracy rate (98.18%) demonstrated by the CRS-DDRAN-AOA framework signifies its potential for practical deployment, empowering farmers with actionable insights for sustainable crop choices.

5 Conclusions

In this manuscript, DDRAN augmented with Archimedes optimisation algorithm espoused crop recommendation system (CRS-DDRAN-AOA) is successfully implemented. The proposed CRS-DDRAN-AOA is implemented in Python and the efficiency of CRS-DDRAN-AOA is estimated by several performance metrics. Here, the performance of CRS-DDRAN-AOA attains 38.58%, 22.61%, 6.698% and 11.62% higher precision, 32.75%, 25.72%, 6.69% and 14.03% higher specificity, compared with existing CRS-ACO, CRS-ANN, CRS-SVM-XGBoost and CRS-DT-RF methods. The integration of AoDrA-Net showcases the power of network, allowing the model to autonomously extract intricate features from complex agricultural data. This method's ability to handle nonlinear relationships within the data is especially crucial in the dynamic and multifaceted agricultural landscape. Moreover, the utilisation of Archimedes optimisation algorithms enhances the precision and efficiency of the recommendation process, providing a novel perspective on optimising crop choices. In the realm of agriculture, where the livelihoods of millions are intricately woven, the importance of accurate and efficient crop recommendations cannot be overstated. The impact of these recommendations reverberates through the entire agricultural ecosystem. Farmers benefit from optimised resource utilisation, minimising costs while maximising yields. Environmental conservation is promoted through reduced use of water, fertilisers, and pesticides. Additionally, the economy benefits from increased agricultural outputs and the sustainability of farming practices. Furthermore, the emphasis on improving performance metrics in this context cannot be ignored. The agriculture sector stands to gain immensely from advancements in accuracy and efficiency. A minor enhancement in recommendation accuracy can translate into substantial gains in crop yields, directly impacting food security and the economic well-being of farming communities. In essence, the research's focus on refining these metrics is not just an academic pursuit; it's a catalyst for positive change in the lives of farmers and the agricultural outputs of nations. This work focuses on large crop predictions rather than small crop predictions owing to the lack of data in the studied area. Some factors are not taken into account, like soil properties, production costs, and the market price are challenging and time consuming to collect. In the future, further analysis of this study will be conducted, including the collection of additional data and the evaluation of deep learning techniques assist in the selection of appropriate crops for the specified land accurately. In addition, local and wholesale market analysis will be carried out to choose the crop for a particular area. To gain a more comprehensive understanding, researchers intend to incorporate both contemporary and traditional crops into future research and selection processes. By developing a scheme depends on mobile applications; farmers can easily access information from the scheme.

References

Akshatha, G.C. and Shastry, K.A. (2022) 'Crop and fertilizer recommendation system based on soil classification', *Recent Advances in Artificial Intelligence and Data Engineering*, pp.29–40, Springer, Singapore.

Ali, S.M., Das, B. and Kumar, D. (2021) 'Machine learning based crop recommendation system for local farmers of Pakistan', *Revista Geintec-Gestao Inovacao E Tecnologias*, Vol. 11, No. 4, pp.5735–5746.

Alikhan, J.S., Alageswaran, R. and Amali, S.M.J. (2023) 'Self-attention convolutional neural network optimized with season optimization algorithm espoused chronic kidney diseases diagnosis in big data system', *Biomedical Signal Processing and Control*, Vol. 85, p.105011.

Amgain, L.P., Timsina, J., Dutta, S. and Majumdar, K. (2021) 'Nutrient expert® rice-an alternative fertilizer recommendation strategy to improve productivity, profitability and nutrient use efficiency of rice in Nepal', *Journal of Plant Nutrition*, Vol. 44, No. 15, pp.2258–2273.

Anupama, C.G. and Lakshmi, C. (2021) 'A comprehensive review on the crop prediction algorithms', *Materials Today: Proceedings*.

Aradea, A., Rianto, R., Mubarok, H. and Darmawan, I. (2023) 'Deep learning-based regional plant type recommendation system for enhancing agricultural productivity', *Ingénierie des Systèmes d'Information*, Vol. 28, No. 4, pp.1–1.

Bian, Y., Guo, G., Liu, F. and Li, X. (2021) 'Residue extrapolation and group maximum residue level recommendation for four pesticides in the four kinds of vegetable crop groups', *International Journal of Environmental Analytical Chemistry*, Vol. 1, No. 1, pp.1–16.

Choudhary, M., Sartandel, R., Arun, A., Ladge, L., Hiranwal, S., and Mathur, G. (2022) 'Crop recommendation system and plant disease classification using machine learning for precision agriculture', *Artificial Intelligence and Communication Technologies, SCRS*, Vol. 1, No. 1, pp.39–49.

Choudhury, S.S., Pandharbale, P.B., Mohanty, S.N. and Jagdev, A.K. (2023) 'An acquisition based optimised crop recommendation system with machine learning algorithm', *EAI Endorsed Transactions on Scalable Information Systems*, Vol. 1, No. 1, pp.1–1.

Das, S., Sharma, R., Gourisaria, M.K., Rautaray, S.S. and Pandey, M. (2021) 'A model for probabilistic prediction of paddy crop disease using convolutional neural network', *Intelligent and Cloud Computing*, Vol. 1, no. 1, pp.1-1, pp.125–134, Springer, Singapore.

Gopi, P.S.S. and Karthikeyan, M. (2023) 'Red fox optimization with ensemble recurrent neural network for crop recommendation and yield prediction model', *Multimedia Tools and Applications*, Vol. 1, No. 1, pp.1–21.

Hasan, M., Marjan, M.A., Uddin, M.P., Afjal, M.I., Kardy, S., Ma, S. and Nam, Y. (2023) 'Ensemble machine learning-based recommendation system for effective prediction of suitable agricultural crop cultivation', *Frontiers in Plant Science*, Vol. 14, p.1234555.

Ju, S., Lim, H., Ma, J.W., Kim, S., Lee, K., Zhao, S. and Heo, J. (2021) 'Optimal county-level crop yield prediction using MODIS-based variables and weather data: a comparative study on machine learning models', *Agricultural and Forest Meteorology*, Vol. 307, pp.108530.

Kumar, P.P., Bai, V., Amala, M. and Krish, R.P. (2023) 'Krill herd optimization algorithm with deep convolutional neural network fostered breast cancer classification using mammogram images', *Concurrency and Computation-Practice & Experience*, Vol. 35, No. 7.

Liu, Z. (2020) 'Soft-shell shrimp recognition based on an improved AlexNet for quality evaluations', *Journal of Food Engineering*, Vol. 266, p.109698.

Madhuri, J. and Indiramma, M. (2021) 'Artificial neural networks based integrated crop recommendation system using soil and climatic parameters', *Indian Journal of Science and Technology*, Vol. 14, No. 19, pp.1587–1597.

Mishra, T.K., Mishra, S.K., Sai, K.J., Peddi, S. and Surusomayajula, M. (2022) 'Crop recommendation system using support vector machine considering Indian dataset', *Advances in Distributed Computing and Machine Learning*, pp.501–510, Springer, Singapore.

Mondal, A. and Goswami, R.T. (2021) 'Enhanced Honeypot cryptographic scheme and privacy preservation for an effective prediction in cloud security', *Microprocessors and Microsystems*, Vol. 81, p.103719.

Mythili, K. and Rangaraj, R. (2021) 'Crop recommendation for better crop yield for precision agriculture using ant colony optimization with deep learning method', *Annals of the Romanian Society for Cell Biology*, Vol. 1, No. 1, pp.4783–4794.

Parween, S., Pal, A., Snigdh, I. and Kumar, V. (2021) 'An IoT and machine learning-based crop prediction system for precision agriculture', in *Emerging Technologies for Smart Cities*, pp.9–16, Springer, Singapore.

Prakash, T.S., Patnayakuni, S.P. and Shibu, S. (2023) 'Municipal solid waste prediction using tree hierarchical deep convolutional neural network optimized with balancing composite motion optimization algorithm', *Journal of Experimental & Theoretical Artificial Intelligence*, pp.1–21.

Prasad, N.R., Patel, N.R. and Danodia, A. (2021) 'Crop yield prediction in cotton for regional level using random forest approach', *Spatial Information Research*, Vol. 29, No. 2, pp.195–206.

Rashid, M., Bari, B.S., Yusup, Y., Kamaruddin, M.A. and Khan, N. (2021) 'A comprehensive review of crop yield prediction using machine learning approaches with special emphasis on palm oil yield prediction', *IEEE Access*, Vol. 9, pp.63406–63439.

Sarath Kumar, R., Sampath, P. and Ramkumar, M. (2023) 'Enhanced Elman spike neural network fostered intrusion detection framework for securing wireless sensor network', *Peer-to-Peer Networking and Applications*, Vol. 18, pp.1–15.

Shetty, S.A., Padmashree, T., Sagar, B.M. and Cauvery, N.K. (2021) 'Performance analysis on machine learning algorithms with deep learning model for crop yield prediction', *Data Intelligence and Cognitive Informatics*, pp.739–750, Springer, Singapore.

Shingade, S.D. and Mudhalwadkar, R.P. (2023) 'Sensor information-based crop recommendation system using machine learning for the fertile regions of Maharashtra', *Concurrency and Computation: Practice and Experience*, p.e7774.

SSL, D.A., Praveenkumar, R. and Balaji, V. (2023) 'An intelligent crop recommendation system using deep learning', *International Journal of Intelligent Systems and Applications in Engineering*, Vol. 11, No. 10s, pp.423–428.

Veerachamy, R. and Ramar, R. (2022) 'Agricultural Irrigation Recommendation and Alert (AIRA) system using optimization and machine learning in Hadoop for sustainable agriculture', *Environmental Science and Pollution Research*, Vol. 29, No. 14, pp.19955–19974.

Venkatanaresh, M. and Kullayamma, I. (2024) 'Deep learning based concurrent excited gated recurrent unit for crop recommendation based on soil and climatic conditions', *Multimedia Tools and Applications*, pp.1–30.