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Research Article

Enhancing crop recommendation with deep residual networks optimized by chronological sparrow search algorithm

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Abstract
In India, agriculture plays a crucial role in feeding the population and boosting the country's gross domestic product. Farmers often face challenges in choosing the right crop based on soil conditions, which can greatly influence the success of their cultivation. By selecting the most suitable crop, farmers can maximise yield potential, leading to increased economic profitability. Precision agriculture (PA) utilizes machine learning (ML) techniques to address challenges in agriculture. The concept of PA enables using advanced technologies and data-driven approaches to effectively enhance agricultural production. A model for crop recommendation was developed using a deep residual network (DRN) optimized by the chronological sparrow search algorithm (CSSA). Initially, the input dataset undergoes data preprocessing, including mean imputation to handle missing values and Z-score normalization to standardize feature values. This process enhances model performance by accounting for various factors such as , content in the soil, as well as temperature and rainfall. Subsequently, the deep maxout network (DMN) with Canberra similarity performs feature fusion to reduce the dimensionality of data. The DRN is train the model using the CSSA, which optimizes hyperparameters to improve the model's performance. The CSSA–DRN model was observed to outperform other models. The proposed model achieved a precision of 85.4%, a recall of 87.5%, an F-measure of 81.3%, and an accuracy of 92.7%. The CSSA-DRN enhances crop recommendations, maximizing yield and boosting profitability.

Keywords
Crop recommendation, Precision agriculture, Chronological sparrow search algorithm, Deep residual network, Machine learning.

1.Introduction
Agriculture has been part of human survival and evolution for decades [1]. The collaboration of farmers with artificial intelligence (AI) transformed conventional agriculture into a novel format that provides more benefits for the survival of humans. In recent times, the gross domestic product (GDP) of many nations heavily depends on agriculture and the production of agricultural goods, highlighting its importance as a key industry. Due to the involvement of machinery and technologies, the majority of the labour in agriculture is substituted to a huge extent, hence improving quality and efficacy and encouraging several people to contribute to agriculture for its livelihood [2].

India is recognized as one of the leading producers of agricultural products globally. Agriculture provides livelihoods for 58% of the population and contributes approximately 19% to the GDP [3].

The yield of a crop is based on different parameters like conditions of soil, accessible sunshine, rainfall, fertilizer application, irrigation, and preparation of land. The main complication that the majority of Indian farmers endure is that they choose crops based on inherited experience and which are cultivated around, not based on soil properties and weather conditions [1–3].

Precision agriculture (PA) is regarded as a promising field in India, with the potential to revolutionize farming practices. PA refers to the use of advanced technologies to achieve 'site-specific' farming. It

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offers effective solutions and improved decision-making in farming. Even though PA has distributed improved enhancements, still it faces specific problems. It is essential to encourage agriculture to meet the emerging requirements. Few methods have been adopted to reduce crop loss by using precision farming. The harvest relies on topographical parameters like temperature, soil synthesis, and stickiness [4]. These aspects played an imperative role in elevating the production of crops. As a result, the accuracy of crop selection remains low, often leading to high costs.

Crop recommendation is one of the main areas of PA. The goal of PA is to identify site-specific attributes to address challenges in crop selection [5]. The properties of soil are unswervingly based on weather conditions of land and hence are imperative aspect for taking into deliberation. The technical assessment of micronutrients, macronutrients, and soil pH is used for determining soil fertility. Machine learning (ML) techniques are extensively utilized for solving this miscellaneous group of agriculture issues [6–8]. Deep learning (DL) indicates the sub-region of ML that is trained with huge data and utilizes deep neural networks (DNN) for making effective decisions. In the progression of the harvesting and yield process, the DL techniques are adapted to such tasks for improving productivity. DNN has the ability to address several contemporary issues and generate precise outcomes [9,10].

Creating a precise crop recommendation model based on soil and climatic factors presents several challenges. These include effectively training artificial neural network (ANN) models [11] on limited datasets, which restricts generalizability, and applying deep neural network (DNN) models [12] to constrained datasets, which may lack diversity. The use of particle swarm optimization–modified deep neural networks (PSO-MDNN) [13] suffers from computational inefficiency, despite having considerable potential for improvement. Similarly, methodologies such as ant colony optimization-based deep convolutional neural networks (DCNN) and long short-term memory (LSTM) [14] are complex for farmers to use in selecting suitable crops. Addressing these challenges is essential to improve the precision, scalability, and practical applicability of crop recommendation systems.

Crop profitability can be significantly increased by using advanced technologies such as PA to improve crop recommendations [15,16], thus enhancing the economic status of farmers. By tapping into these technological advancements, farming practices can become more sustainable as they encourage the efficient use of resources. So, precise crop recommendation techniques contribute to better performance, user-friendly, and environmentally sustainable agricultural sector. This motivates the design of a novel crop recommendation system.

The objectives of this paper are as under:

1. To design an efficient and accurate crop recommendation model using DL techniques by leveraging a deep residual network (DRN) optimized with the chronological sparrow search algorithm (CSSA), ensuring superior performance over conventional and hybrid models.
2. To enhance the practical usability of the model by integrating it with a user-friendly web interface, enabling farmers to make informed decisions based on soil and climatic data while achieving scalability and ease of access.

This research introduces a crop recommendation model that leverages a DRN optimized with the CSSA to deliver precise recommendations based on soil and climatic data. The proposed model incorporates advanced data preprocessing, feature extraction, and fusion techniques using the deep maxout network (DMN) and Canberra similarity, ensuring enhanced accuracy and efficiency.

The remaining sections of the paper are organized as follows: Section 2 reviews previously developed crop recommendation methods. Section 3 illustrates the proposed and designed model for recommending suitable crops. Section 4 discusses the results and analysis, and Section 5 concludes the proposed research work.

2.Literature review

Crop recommendation systems have gained significant attention for improving agricultural productivity by utilizing ML and DL techniques. These models aim to provide data-driven solutions for selecting optimal crops based on soil, climatic, and environmental factors, addressing the challenges faced by farmers in making informed decisions.

A crop recommendation model [11] based on climatic criteria and location-specific soil data utilized ANN to suggest appropriate crops. The crops were recommended using soil properties, crop features, and climatic attributes. However, this model considered only four crops and was ineffective in adapting to economic, geographical, and environmental factors to enhance efficiency. A method [12] was developed to assist farmers in selecting suitable crops by providing input data, which many farmers were unaware of. While this method helped prevent monetary losses and provided good accuracy, it did not account for all relevant soil parameters.

A DL-based system [13] employed PSO-MDNN to recommend suitable crops by predicting yield through DL models. This system used appropriate attributes to aid farmers in making effective decisions and improving crop yields. However, the process was complex, making it less practical. Another hybrid model [14] utilized ant colony optimization (ACO) to optimize deep convolutional neural networks DCNN and LSTM networks, incorporating historical crop and climate data for crop prediction. Despite its relevance, this method was computationally intensive and unsuitable for reducing complexity.

A two-fold approach combining data balancing and ML was proposed for crop recommendation [15]. Using Kaggle data, 14 ML models were evaluated, with boosting (CBoost) achieving top accuracy (99.15%), F-measure (0.9916), and precision (0.9918). Gaussian Naive Bayes excelled in receiver operating characteristic curve and Matthew's correlation coefficient (0.9569). However, most classifiers only considered basic parameters like nitrogen, phosphorus, and potassium. Similarly, a crop recommendation system [16] for Maharashtra combined ML and DL models like random forest (RF) with 92% accuracy and LSTM for weather forecasting, but it supported only a limited number of crops.

A DL model [17] predicted suitable crops by analyzing soil attributes like N, P, and K, leveraging DNN and Internet of Things (IoT) features. While the model identified crops suitable for specific soils, it struggled to achieve higher accuracy. A k-nearest neighbor RF ridge regression (KRR) ensemble model [18] successfully predicted major crop yields in Bangladesh, achieving 99% accuracy for rice, wheat, and potatoes, outperforming other algorithms. However, it was limited to basic ML models for a few crops.

A gated recurrent units (GRU)-based crop prediction model [19] used historical data with soil parameters like nitrogen, phosphorus, and potassium for crop recommendation. While effective, it lacked support for additional crops and a graphical user interface (GUI) for farmers. A comparative study [20] evaluated various ML algorithms (decision tree, RF, XGBoost, etc.) for crop recommendations, with XGBoost emerging as the most accurate for crops like rice, cotton, and jowar. However, the dataset used in the study was small, limiting its generalizability.

IoT-enabled systems have also been explored for crop recommendations. A system [21] using parameters like soil moisture, pH, humidity, and temperature, combined with a GUI, suffered from computational complexities. Another framework [22] provided crop recommendations based on temperature, reducing monetary losses for farmers, but it failed to include critical soil parameters like nitrogen, phosphorus, and potassium, or advanced techniques like DNN and fuzzy logic.

Several user-friendly applications have also been developed. A GUI-based mobile app [23] recommended crops based on meteorological and soil data while considering cultivation expenses and irrigation sources. An ML prediction model [24] achieved high accuracy (99.59%) by integrating IoT data and online resources. Another crop recommendation system [25] used ML algorithms to predict yields and suggest optimal management practices, while a separate study [26] applied linear regression and neural networks for crop price prediction. However, these models struggled to optimize accuracy and scalability effectively.

A mobile application integrated with ML [27] helped farmers determine optimal planting and harvesting conditions. Another regression-based system [28] used Naive Bayes classifiers for fertilizer recommendations and crop yield predictions in Mysore, achieving high accuracy for wheat, ragi, and paddy. However, these systems lacked broader usability for farmers. A model [29] utilized Arduino microcontrollers to collect environmental data and ML algorithms like naive Bayes and neural networks, achieving 98.8% accuracy but with limited features for broader crop recommendations.

From the literature, it is evident that various ML, DL, and hybrid models have been proposed for crop recommendation. While ANN-based systems focused on soil and climatic variables, they were restricted in scalability. Hybrid models like PSO-MDNN and ant colony optimization-based DCNN approach improved yield prediction but were computationally intensive. IoT-enabled frameworks and GUI-based systems improved accessibility but often lacked advanced analytics. Despite these advancements, challenges remain in integrating diverse datasets, soil parameters, and user-friendly tools to improve agricultural outcomes. Addressing these gaps is crucial for developing efficient and scalable crop recommendation models that assist farmers in making data-driven decisions.

3.Methods

PA indicates a contemporary farming model that utilizes research data on soil features and weather criteria to advise the farmers for right crop based on site-specific attributes. This reduces incorrect crop choice and elevates productivity. A novel model proposed based on DL is devised to recommend crop. Initially, the dataset is subjected to data pre-processing methods including removing duplicates, imputation for missing values, and Z-score normalization [30]. Next, the dataset is prepared with various features, including nitrogen, phosphorus, potassium, and other soil components, along with weather attributes such as temperature and rainfall. Feature extraction is applied to identify relevant features from the original data. Later, feature fusion is performed using the DMN [31] with Canberra similarity [32] to minimize data dimensionality. Further, crop recommendation is carried out using the DRN [33], which is trained using the CSSA [34] for better performance of the model, which recommends the most suitable crop. *Figure 1* illustrates the overall framework of the crop recommendation model utilizing CSSA-DRN.

The model's development and experiments were conducted using hardware components, including an Intel Core i5-13500H processor, 16 GB RAM, and a 500 GB SSD. The software components utilized were Python 3.9 and its associated libraries, along with the PyCharm Community Edition, all of which are open-source.

3.1Accumulation of data

The crop data was collected from the Rayalaseema region (Ananthapur, Chittoor, Kadapa, Kurnool) and Sri Potti Sriramulu Nellore districts of Andhra Pradesh state. This dataset was sourced from a government website. It comprises 473,0145 data records for 7 crops, organized into 15 columns and 315,343 rows. The dataset includes features related to soil nutrients, such as nitrogen (N), phosphorus (P), potassium (K), electrical conductivity (EC), pH, organic carbon (OC), boron (B), iron (Fe), zinc (Zn), copper (Cu), manganese (Mn), and sulphur (S), as well as weather data like rainfall and temperature. Soil nutrient data was obtained through laboratory soil testing conducted every 2–3 years. Weather data represents average values for the entire crop season and was retrieved from the government website (http://www.apsdps.ap.gov.in/). The dataset was analyzed and verified by an agricultural field expert to ensure its accuracy and reliability.

After collecting the data, missing values are handled by mean imputation, where missing data is replaced with a measure of the central tendency mean of that particular column. Removing duplicates is essential to prevent biased results. Data type conversion adjusts data formats to ensure compatibility with analysis models.

Assume a database $'D'$ with the crop data specified in Equation 1.

$$D = \{\hbar_1, \hbar_2, \cdots, \hbar_o, \cdots, \hbar_u\} \tag{1}$$

where, u indicated the total number of crops and $\hbar_o$ specifies o^{th} particular crop.

3.2Pre-process the data using Z-score normalization

Data values of each feature in the dataset are in different scale. So, all values need to scale down to the same range. Here, the Z-score normalization [23] is applied for pre-processing the input data. Pre-processing of data is an important step that involves converting raw data into a format that can be used to train a model. It contributes significantly to improving data interpretation and model performance. Generally, these methods are utilized for adjusting the variability of each variable and its relations to comply with improved data analysis. It is also considered a useful measure as it computes the probability of a score occurring in a normal distribution and facilitates comparison between two scores that belong to different distributions. Moreover, the unstructured data are normalized using the z-score calculated using Equation 2.

$$t(c,d) = \frac{f(c,d) - \mu}{\eta} \tag{2}$$

where $f(c,d)$ depicts old values, $t(c,d)$ indicate new value, μ states the mean of the column considering input value and η denote the standard deviation of the column considering input value, c states index of row and d depicts the index of the column. For example, Nitrogen's old value is '131', the mean is '168.95', the standard deviation is '62.46' then the Nitrogen's new value is '-0.60'. Hence, the pre-processed outcome is denoted as α.

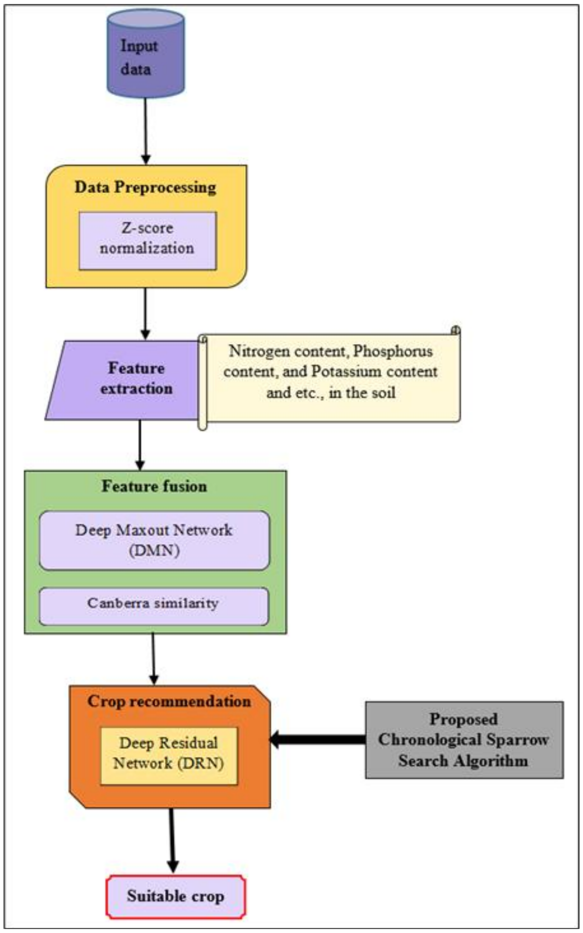

Figure 1 Flow of the crop recommendation model using the proposed CSSA-DRN

3.3Acquire a set of features

Here, the pre-processed outcome α is provided for this phase. The yield of crop depends on the existence of these imperative parameters in soil. However, the discrepancy in nutrients of soil can huge loss impact on crop cultivation and efficiency. Hence, the efficient analysis and observation of soil nutrient status are imperative for identifying priority regions for executing proper nutrient administration. Some of the important features utilized for improved processing are elaborated below. Soil nutrients are in two categories, macronutrients and micronutrients. Macronutrients are N, P, K, EC, pH, OC, B, Fe, Zn, Cu, Mn, and S.

3.3.1Soil parameters

Nitrogen content (N) arises in soil considering both inorganic and organic formats and seasonal alterations are featured using assorted distribution in the soil. The nitrogen occurs using fixation relationships either with symbiotic microorganisms or through diazotrophs which are imperative for plant growth. This feature is specified as Q_1. Phosphorus content (P) availability is most reactive phosphate obtained through phosphates of calcium, aluminium, and iron which are equal in soil solution and hence reflect crop uptake. It is essential for the photosynthesis process. This feature is specified by Q_2. Potassium content (K) is imperative to plant processing tasks such as absorbing water, nutrients and carbohydrate movement. It is obtainable in various formats and freely accessible in soil for plant uptake. The rate of potassium varies amidst various soils and eventually, the uptake of potassium affects the growth and plant yield. This feature is specified by Q_3. Soil pH (pH) is an imperative feature that affects the growth of plants in various manners. The optimum pH range of soil relies on 4.5-8.0. This feature is specified as Q_4. EC has been employed to infer the relative concentration, extent, and movement of animal waste within soil. Given its capacity to detect soluble salts, EC acts as a valuable tool for assessing the contamination of surface and groundwater, making it an effective indicator. This feature is specified as Q_5.

OC is a substantial part of soil organic matter and is acknowledged for its essential contribution to various soil functions and ecological characteristics. The amount of OC present in soil is affected by factors like local geology, climate, land utilization, and management approaches. It is specified as Q_6. Boron (B) plays a vital role in regulating plant hormone levels and supporting optimal growth. It enhances the production and retention of flowers, promotes the elongation and germination of pollen tubes, and contributes to the development of seeds and fruits. This feature is considered as Q_7. Zinc (Zn) is an important element found in many enzymes that are needed for growth hormones and other metabolic activities in all plant species. It also plays an important function in protein synthesis and chlorophyll synthesis. Maintaining proper zinc levels is critical for promoting healthy plant growth since low levels can stifle growth, limit reproductive ability, and result in lower yields by impeding root and tissue development. This is taken as Q_8. Iron (Fe) is a micronutrient that is required by practically all living creatures because it is involved in metabolic activities such as synthesis, and respiration. Iron also activates several metabolic processes and is a prosthetic group constituent of many enzymes. The basic causes of iron chlorosis are an imbalance between the solubility of iron in soil and the plant's need for iron. It is considered as Q_9. Manganese (Mn) is a vital mineral nutrient for plants, playing a crucial role in various physiological processes, including photosynthesis. The deficiency of manganese is a common concern, primarily observed in sandy soils, organic soils with pH levels above 6, and extensively weathered tropical soils. Factors such as cool and damp weather tend to exacerbate the issue. This is taken as Q_{10}. Copper (Cu) activates several enzymes involved in lignin formation in plants and is required by various enzyme systems. It is also required for photosynthesis, is necessary for plant respiration, and aids in glucose and protein metabolism in plants. Copper also enhances the flavour and colour of vegetables and flowers. Copper is taken as Q_{11}.

Sulphur (S) is found in soils as an element, as well as sulphides, sulphates, and in organic combinations with carbon and nitrogen. It is required for the plant energy production process. The majority of S sources in soil are in organic matter and so concentrated in the topsoil layer. Elemental S, as well as other forms found in soil organic matter and some fertilizers, are inaccessible to crops. Sulphur is considered as Q_{12}.

3.3.2Weather parameters

Rainfall is a critical factor for any crop, as it supports growth and development by providing essential water and nutrients, ultimately contributing to increased crop yield. Rainfall is considered as Q_{13}.

Temperature is another important factor affecting the rate of plant development. It is mainly involved in photosynthesis to produce good yields. Temperature is considered as Q_{14}.

All parameters(features) are taken vectors in Q in Equation 3 to process the data.

$$Q = \{Q_1, Q_2, \cdots, Q_{14}\} \quad (3)$$

All parameters of soil and weather have individual nature of characteristics. *Table 1* gives in detailed description of each parameter.

Table 1 Characteristics of soil and weather parameters

	Parameter	Abbreviation	Characteristic
Soil data	Nitrogen	N	It is an essential element for plant growth
	Phosphorus	P	It helps transfer energy from sunlight to plants
	Potassium	K	It increases the resistance power of plants to disease
	Sulphur	S	It plays a role in the energy production processes within plants.
	Iron	Fe	It helps the growth of a plant as part of respiration.
	Zinc	Zn	It helps in the production of plant hormones.
	Manganese	Mn	It helps with photosynthesis.
	Copper	Cu	It is an essential constituent of enzymes.
	Boron	B	It helps with the formation of the cell walls of plants.
	pH	pH	It is important for plant growth
	Electrical Conductivity	EC	It improves nutrient management
	Organic Carbon	OC	It regulates terrestrial ecosystem functioning and provides diverse energy
Weather data	Rainfall	N/A	It provides water and nutrients to plant
	Temperature	N/A	It is a critical factor that affects plant growth

3.4Feature fusion process

Here, the feature vector Q established is supplied to the feature fusion phase. Feature fusing aims to combine multiple sets of features to improve the performance of a model. These features may come from different sources, layers, or modalities and can capture various aspects of the data.

Feature fusion is a two-step process, that calculates Canberra similarity between features, which are taken to DMN as input. Canberra similarity is considered to calculate the distance between a pair of points in a space. The features are arranged based on Canberra similarity and it is notified by Equation 4.

$$\partial(x, y) = \sum_{e=1}^{k} \frac{|x_e - y_e|}{|x_e| + |y_e|} \quad (4)$$

Thus, k symbolize total features, computed probability density functions are signified by $|x_e|$ and $|y_e|$of candidate features and targets are offered by x_e and y_e.

The task of feature fusion is attained as shown in Equations 5 and 6.

$$B^{new} = \sum_{a=1}^{b} \frac{\kappa}{\vartheta} B_a; 1 \leq \vartheta \leq b \quad (5)$$

$$a = a + \frac{E}{m} \quad (6)$$

where, E states count of features and b are selected features and thus $m = \frac{b}{E}$.

Ground truth C value is generated by computing Canberra similarity between data record B_m and average of B_m denoted as ϖ_m that fit into a class and it is stated as in Equation 7.

$$C = C_d(B_m, \varpi_m) \tag{7}$$

Hence C_d is Canberra distance. The features are provided as DMN input.

DMN comprises unit named as Maxout that contains leaky functions and ReLU generalization. It expresses a piecewise linear function that evaluates the highest of inputs designed to be used by combining dropout. In addition, the network contains the ability to control the complex convex functions. Consider input $M \in Q^{v}$ in which v depicts a state vector provided through a hidden layer using hidden unit activation and it is stated by Equations 8 to 12,

$$r_{1,n}^{1} = \boldsymbol{max}_{\in[1,z_1]}^{v^T} \lambda_{v,w} + \upsilon_{v,w} \tag{8}$$

$$r_{2,n}^{2} = \boldsymbol{max}_{w\in[1,z_2]}^{{\tau_{i,z}^{1}}^T} \lambda_{v,w} + \upsilon_{v,w} \tag{9}$$

$$r_{i,n}^{l} = \boldsymbol{max}_{w\in[1,z_m]}^{{v_{v,w}^{h-1}}^T} \lambda_{v,w} + \upsilon_{v,w} \tag{10}$$

$$r_{v,w}^{\psi} = \boldsymbol{max}_{w\in[1,z_n]}^{{v_{v,w}^{\psi-1}}^T} \lambda_{v,w} + \upsilon_{v,w} \tag{11}$$

$$v_{\psi} = \boldsymbol{max}_{w\in[1,z_n]}^{v_{v,w}^{\psi}} \tag{12}$$

Thus, ψ states total DMN layers, and $\lambda_{v,w}$ stands for weights and υ signify bias. Hence, the obtained feature produced is signified as F.

3.5Crop recommendation with CSSA-DRN

The DRN efficiently predicts suitable crops using hierarchical convolutional layers and residual connections. The CSSA dynamically optimizes weights and hyperparameters, ensuring robust training and faster convergence. The fused feature F obtained through preprocessing and feature fusion is passed to the next step of the crop recommendation process. To enhance crop productivity, a crop recommendation model has been designed using a DL approach, where the CSSA-based DRN is applied for precise and efficient crop recommendations. Compared to other DL methods, such as conventional CNNs, the DRN offers faster training speeds and effectively addresses the vanishing gradient problem through residual connections that skip layers. These residual connections facilitate the training of deeper models and improve generalization, particularly for analyzing complex datasets involving crop features, soil characteristics, and climatic conditions. The DRN is leveraged for its ability to extract hierarchical features from high-dimensional and complex data while learning long-term dependencies, making it a robust solution for crop recommendation tasks.

The process of the DRN involves ResNet layers, where each ResNet layer comprises a Convolutional layer, Batch Normalization, a Pooling layer, and an Activation function. The operation of each layer is detailed below:

Input layer: Input data is actually in the form of vectors [N, P, K, … Rainfall] =[50, 30, 40, … 300]. It is reshaped into 32×32×3.

Convolutional layer: The convolutional layers are responsible for making several calculations. These layers are responsible for the extraction of spatial features, which are used to capture patterns in environmental and soil data. It needs fewer components that include input data, a feature map, and a filter. It acquires the group of weights and multiples it with the inputs of a network. Here, the filter passes through the data several times and is adapted from right to left and top to bottom. The process involved in the conv layer is stated in Equation 13,

$$Conv2d(j) = \sum_{l=0}^{h-1} \sum_{g=0}^{h-1} N_{l,g} * j_{(v+l,i+g)} \tag{13}$$

Where (v, i) depicts input co-ordinates, N signified kernel having dimension $h \times h$, j denote the outcome of the former layer, l, g delineate the position of an index, and $*$ states convolutional operator.

Pooling layer: The pool layer minimizes the data size keeping the imperative information. For instance, for each set of 4 pixels, the pixel with the maximal or the average value is retained. It helps to manage the overfitting by lessening the count of computations and attributes of the network. The pool layer functionality is depicted by Equations 14 and 15.

$$l_{out} = \frac{l_{in} - \varepsilon_g}{\alpha} + 1 \tag{14}$$

$$g_{out} = \frac{g_{in} - \varepsilon_l}{\alpha} + 1 \tag{15}$$

Thus l_{in} and l_{out} refers to input width and output matrices, and its heights are stated as g_{in} and g_{out}. Moreover, the height and width of the kernel is delineated by ε_g and ε_l.

Activation function: The activation function aids to describe output of a node provided an input. The outcome of the network in a certain range helps in making effectual predictions. The activation function is given by Equation 16.

$$\text{Relu}(j) = \begin{cases} 0, j < 0 \\ j, j \geq 0 \end{cases} \quad (16)$$

Batch Normalization: It is a technique utilized for making the training faster and more stable using layer normalization by adapting re-scaling and recentring techniques. It helps to normalize each input in terms of batches amidst all features. It optimizes network training and prevents additional computations.

Residual blocks: It permits the memory to flow from the initial to the last layers despite the deficiency of gates in its skip connections. Its operation is provided by Equations 17 and 18.

$$\omega = \gamma(j) + j \quad (17)$$

$$\omega = \gamma(j) + \varphi_j j \quad (18)$$

Thus, j and ω offers input and output, γ depicts function to map, and φ_j signify matching factor dimension.

Equation 17, considered as a residual block, adds the input of a block to its output, ensuring the direct flow of gradients during backpropagation. This bypassing of a few layers allows the model to focus on critical features without losing information from earlier stages.

Linear classifier: The feature produced by the conv layer is utilized for categorization in a linear classifier which contains a SoftMax function and a fully connected layer. The SoftMax function is applied for multi-class classification. The outcome accomplished by DRN is signified by ϑ_{out} like higher probability crop of all crops, which are given by SoftMax function.

The conventional backpropagation technique requires a longer duration to reach convergence for DL models to update weights and biases. To address these challenges associated with DL models, particularly the DRN, an optimisation technique is necessary.

For example, assume the input tensor 'X' represents soil and climate data.

$X=\begin{bmatrix} 50 & 30 & 40 \\ 25 & 300 & 0 \end{bmatrix}$

The tensor is passed through a residual block with: Convolution kernel $W=\begin{bmatrix} 0.1 & 0.2 \\ 0.3 & 0.4 \end{bmatrix}$, Bias b=1, ReLU activation, Batch Normalization. Then,

$Y_{conv} = X*W + b$ is calculated as $Y_{conv}[1,1]$ = (50*0.1+30*0.2)+(25*0.3+300*0.4)+1= 139.5

$Y_{bn} = ([Y_{conv} - \mu]/\sigma)$ with μ=100, σ=20.

$Y_{bn}[1,1]$ =1.975

$Y_{relu} = max\ (0, Y_{bn})$

$Y_{relu}[1,1] = max(0,1.975)$=1.975

$Y_{out} = Y_{relu} + X$ =1.975+50=51.975.

$Y_{out} = \begin{bmatrix} 51.9 & \dots \\ \dots & \dots \end{bmatrix}$

The Y_{out} data is passed to further subsequent layers for multi-class classification.

To achieve better performance with the DRN in terms of accuracy, convergence rate, stability, and avoidance of local minima, the CSSA proves to be more effective. CSSA excels in real-world search domains, offering a robust balance between exploration and exploitation.

The steps of CSSA are incorporated below:

Step 1: Initialize process: The first task is to initiate the sparrow location, and it can be notified by Equation 19.

$$B = \begin{bmatrix} s_{1,1} & s_{1,2} & \dots & \dots & s_{1,p} \\ s_{2,1} & s_{2,2} & \dots & \dots & s_{2,p} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{q,1} & s_{q,2} & \dots & \dots & s_{q,p} \end{bmatrix} \quad (19)$$

Hence, p signify dimension of variable, q indicate a count of sparrows, and $s_{q,p}$ specifies location of q^{th} sparrow in p^{th} dimension.

Step 2: Estimate Fitness: After the initiation of the sparrow's position, the fitness function of each position is evaluated. Here, the fitness is a mean square error (MSE) and it is notated by Equation 20.

$$Fit_1 = \frac{1}{A}\sum_{j=1}^{A}\left(N_j^* - N_j\right)^2 \quad (20)$$

Hence, N_j and N_j^* signify original and predicted output of DRN and A represent samples utilized to train DRN.

Step 3: Update the position of producer: The sparrows having improved fitness are adapted as producers and it search for food and direct the colony. As per sparrow search algorithm (SSA) [23], the location of the producer is stated in Equation 21.

$$B_{W,X}^{S+1} = \begin{cases} B_{W,X}^{S} \cdot exp\left(\frac{-W}{\gamma \cdot \tau_{max}}(\quad)\right) & if\ \Re_2 < \Im \\ B_{W,X}^{S} + G \cdot V & otherwise \end{cases} \quad (21)$$

Hence, $B_{W,X}^{S}$ signify position of W^{th} sparrow in X^{th} dimension, W depicts current iteration, $\gamma \in (0,1)$ signify random number, τ_{max} refers to elevated iteration count, $\Re_2 \in (0,1)$ depicts the rate of alarm, G specifies normally distributed arbitrary number, $\Im \in (0.5,1)$ signify safety threshold, and V depicts unit matrix of size $1 \times `c$.

Step 4: Update position of scrounger: The producers are regularly observed by scroungers and whenever producers are monitored to discover improved food, the scroungers progress to new position deserting its definite location. The location of scroungers is given as in Equation 22.

$$B_{W,X}^{S+1} = \begin{cases} G \cdot exp\left(\frac{B_Y^S - B_{W,X}^S}{\beta \cdot l_{max}}(\quad)\right) & if\ W > \ell/2 \\ B_o^{S+1} + \left|B_{W,X}^S - B_o^{S+1}\right| \cdot U^+ \cdot V & else \end{cases} \quad (22)$$

Hence, B_Y symbolize the worst global location, B_o depicts the best position of the producer, U denote the matrix of size $1 \times c$ and parameters pose a value -1 or 1and $U^+ = U^T(UU^T)^{-1}$. If $W > \ell/2$ then W^{th} scroungers with the highest fitness are likely to starve.

Step 5: Prevaricate Danger: On danger discovery, the sparrows at the flock's edge move to a safe place and randomly walk to neighbouring sparrows. This process is provided in Equation 23.

$$B_{W,X}^{S+1} = \begin{cases} B_{best}^S + \delta.\left|B_{W,X}^S - B_{best}^S\right|, & if\ \aleph_1^W > \aleph_1^{cb}(a) \\ B_{W,X}^{S+1} + \mathrm{T} \cdot \left(\frac{\left|B_{W,X}^S - B_Y^S\right|}{\left(\aleph_1^W - \aleph_1^{cw}\right) + \nabla}\right), & if\ \aleph_1^W = \aleph_1^{cb}(b) \end{cases} \quad (23)$$

Hence, B_{best} symbolize the current global best location, $\aleph_1^{cb}$ and $\aleph_1^{cw}$ signify fitness values of present best and worst sparrows, δ is step size, $\mathrm{T} \in [-1,1]$ indicate the random number and minimal constant utilized to avoid zero-division error and is signified by ∇.

If $\aleph_1^W > \aleph_1^{cb}$, then the edge of the sparrow group updated by Equations 24 to 26.

$$B_{W,X}^{S+1} = B_{best}^S + \delta\left|B_{W,X}^S - B_{best}^S\right| \quad (24)$$

Assume $B_{W,X}^{S+1} > B_{best}^S$, $B_{W,X}^{S+1} = B_{W,X}(S+1)$,$B_{W,X}^S = B_{W,X}(S)$, and $B_{best}^S = B_{best}(S)$ then,

$$B_{W,X}(S+1) = B_{best}(S) + \delta\left(B_{W,X}(S) - B_{best}(S)\right) \quad (25)$$

$$B_{W,X}(S+1) = B_{best}(S)(1-\delta) + \delta B_{W,X}(S) \quad (26)$$

From chronological idea, the update is provided as in Equation 27.

$$B_{W,X}(S+1) = \frac{B_{W,X}(S+1) + B_{W,X}(S+1)}{2} \quad (27)$$

At iteration S,

$$B_{W,X}(S) = B_{best}(S-1)(1-\delta) + \delta B_{W,X}(S-1) \quad (28)$$

Substitute Equation 28 to Equation 26,

$$B_{W,X}(S+1) = B_{best}(S)(1-\delta) + \delta\left[B_{best}(S-1)(1-\delta) + \delta B_{W,X}(S-1)\right] \quad (29)$$

$$B_{W,X}(S+1) = B_{best}(S)(1-\delta) + \delta B_{best}(S-1)(1-\delta) + \delta^2 B_{W,X}(S-1) \quad (30)$$

$$B_{W,X}(S+1) = (1-\delta)[B_{best}(S) + \delta B_{best}(S-1)] + \delta^2 B_{W,X}(S-1) \quad (31)$$

Substitute Equation 26 and Equation 31 in Equation 27,

$$B_{W,X}(S+1) = \frac{B_{best}(S)(1-\delta) + \delta B_{W,X}(S) + (1-\delta)[B_{best}(S) + \delta B_{best}(S-1)] + \delta^2 B_{W,X}(S-1)}{2} \quad (32)$$

$$B_{W,X}(S+1) = \frac{B_{best}(S)(1-\delta) + \delta B_{W,X}(S) + (1-\delta)B_{best}(S) + (1-\delta)\delta B_{best}(S-1) + \delta^2 B_{W,X}(S-1)}{2} \quad (33)$$

The final equation of the CSSA is represented in Equation 34.

$$B_{W,X}(S+1) = \frac{2B_{best}(S)(1-\delta) + \delta B_{W,X}(S) + (1-\delta)\delta B_{best}(S-1) + \delta^2 B_{W,X}(S-1)}{2} \quad (34)$$

Step 6: Re-calculate fitness: The best solution is discovered by evaluating the fitness of the newly produced position with expression () and the location with the least objective is noted as the best solution.

Step 7: Termination: The steps are continued till the value S attains S_{max} to accomplish better hyperparameters.

Weight updating by CSSA, for example, $P = \{W_1, W_2, W_3\}$,

$W_1 = \begin{bmatrix} 0.1 & 0.2 \\ 0.3 & 0.4 \end{bmatrix}$, $W_2 = \begin{bmatrix} 0.2 & 0.3 \\ 0.4 & 0.5 \end{bmatrix}$, $W_3 = \begin{bmatrix} 0.3 & 0.4 \\ 0.5 & 0.6 \end{bmatrix}$

$f(W_1)=0.15$,$f(W_2)=0.12$,$f(W_3)=0.10$

$W_1^{t+1}=W_1^{t+1}+ \alpha * rand(0,1).$ $\alpha=0.05$, $rand(0,1)=0.2$

$W_3^{t+1}=\begin{bmatrix} 0.3 & 0.4 \\ 0.5 & 0.6 \end{bmatrix} + 0.05 * 0 \cdot 0.2$

$W_3^{t+1}=\begin{bmatrix} 0.31 & 0.41 \\ 0.51 & 0.61 \end{bmatrix}$

$W_2^{t+1}=W_3^t+\beta * |W_3^t - W_2^t|$ with $\beta=0.1$

$W_2^{t+1}=\begin{bmatrix} 0.31 & 0.41 \\ 0.51 & 0.61 \end{bmatrix}$

Final optimized weights: $W^*=\begin{bmatrix} 0.31 & 0.41 \\ 0.51 & 0.61 \end{bmatrix}$

The pseudocode of CSSA is shown below:

Pseudo code of CSSA

Input: Producer count ρ_c, Scrounger count S_c, highest iteration S_{max}, total sparrows l, alarm value $\Re_2$

Output: $\aleph_1^{cb}$,B_{best}

Initiate sparrow location with Equation 21

While $(S < S_{max}(\ \ ))$
Discover fitness using Equation 20, rank, and discover the worst and optimum sparrow.
$\Re_2 = rand(1)$
For $W = 1{:}\,\rho_c$
Alter sparrow location with Equation 22
End for
For $W = \rho_c + 1{:}\,l$
Alter sparrow location with Equation 34
End for
For $W = 1{:}\,S_c$
Alter sparrow location with Equation 23a or 23b
End for
Compute fitness
$S = S + 1$
End while
Return $\aleph_1^{cb}$,B_{best}

The DRN is trained using CSSA, which combines the concepts of the SSA with a chronological approach. SSA, inspired by the behaviour of sparrows, demonstrates strong optimization potential and effectively handles both multimodal and unimodal test functions. It achieves a robust balance between exploitation and exploration, enabling it to identify promising regions in the search space and avoid local optima, thus performing well in large and complex search spaces. The CSSA-integrated DRN has delivered optimal performance using the following parameters and hyperparameters:

- **Model Parameters:** Input Shape: (32, 32, 3), Kernel Size: 3 (for ResNet layers), Number of Filters: 16, Pooling: Average pooling with a pool size of 8, Activation Function: ReLU.
- **Hyperparameters:** Batch Size: 128, Epochs: 10, Learning Rate (LR): 0.25, Regularization: L2 regularization.

The DRN processes agricultural data through convolutional layers that extract spatial relationships between soil and climatic parameters. Its residual connections ensure effective gradient flow, enabling the model to learn deeper patterns and achieve improved generalization.

4.Results and discussion

The efficiency analysis of the CSSA-DRN model is detailed based on various performance criteria, including Precision, Recall, F-measure, and Accuracy. The analysis is conducted by varying the learning data values along the x-axis to observe the model's behavior. Each methodology is evaluated using a crop dataset, which aims to enhance agricultural yield by recommending the most suitable crops. The dataset includes key features such as nitrogen, phosphorus, potassium, and other soil components, as well as weather parameters like temperature and rainfall.

4.1Performance criterions

Efficiency computation graphs for the CSSA-DRN model, along with former methodologies, are generated using various performance metrics, which are described below:
Precision: It evaluates the proportion of positive class predictions that correctly belong to the positive class, as defined by Equation 35.

$$\partial = \frac{\rho_\mu}{\rho_\mu + \kappa_\mu} \tag{35}$$

Hence, ρ_μ depicts true positive, κ_μ depicts false positive.

Recall: It evaluates the ratio of positive class predictions made out of all actual positive samples in a database, as defined by Equation 36.

$$\zeta = \frac{\rho_\mu}{\rho_\mu + \kappa_\eta} \tag{36}$$

Hence, κ_η states false negative.
F-measure: The F-measure provides a single score that balances both recall and precision, combining them into a single metric. It is defined by Equation 37.

$$\psi = 2 * \frac{\partial * \zeta}{\partial + \zeta} \tag{37}$$

Thus, ∂ and ζ depicts precision and recall.
Accuracy: It describes how close an obtainable set of observations is to its true value and is defined by Equation 38.

$$\text{Acccuracy} = \frac{\rho_\eta + \rho_\mu}{\rho_\mu + \rho_\eta + \kappa_\eta + \kappa_\mu} \tag{38}$$

Hence, ρ_μ signify true positive, ρ_η depict true negative, κ_μ states false positive, and κ_η denote false negative.

4.2Comparative analysis

The results considered models such as ANN [11], PSO-MDNN [12], DNN [13], ant colony optimization-based deep convolutional neural networks and LSTM [14], and the proposed CSSA-DRN. The analysis of these models was conducted by varying the learning data size and evaluating their performance using metrics such as precision, recall, F-measure, and accuracy. In *Figure 2*, the proposed CSSA-DRN model demonstrates consistently high precision across all dataset test sizes. Its hybrid approach ensures superior and stable performance. While models like [14] also perform well, their precision declines with larger datasets. Traditional models such as ANN and PSO-MDNN exhibit limited effectiveness compared to the newer and more advanced approaches.

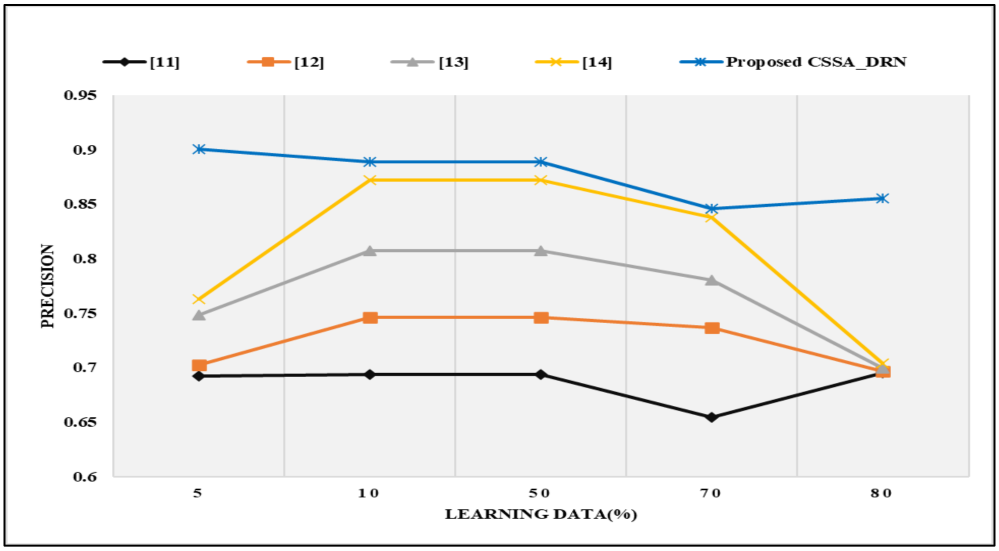

Figure 2 Technique efficacy calculation graphs with learning data using precision

The proposed CSSA-DRN model is the most reliable model when compared to those remaining models and it maintains a high and stable recall across various levels of learning data, as indicated in *Figure 3*. The ant colony optimization-based deep convolutional neural networks and LSTM also performs well, but it experiences a minor decrease as data is increased. The performance of recall is lower scored by traditional models such as ANN and PSO-MDNN. In general, the CSSA-DRN model that has been proposed is the most robust in terms of recall, particularly as data availability changes.

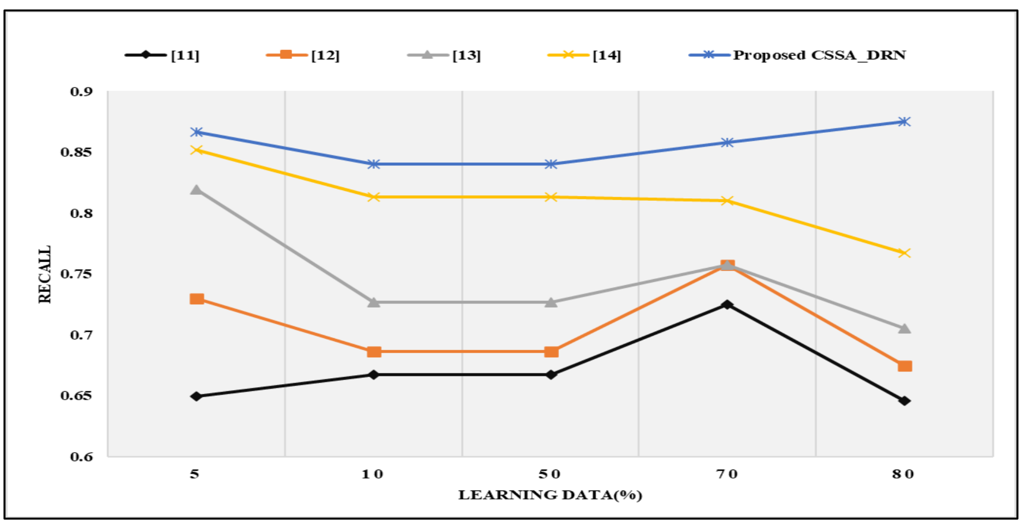

Figure 3 Technique efficacy calculation graphs with learning data using recall

Figure 4 illustrates that the proposed CSSA-DRN model is the most efficient and well-balanced, consistently maintaining a high F-measure across different learning data percentages. While it also exhibits a similar declining trend as data accumulates, the ant colony optimization-based deep convolutional neural networks and LSTM model perform admirably. In contrast, conventional models such as ANN and PSO-MDNN show significant lag, leading to a reduced F-measure. This indicates that more advanced hybrid models, such as CSSA-DRN, are better suited for achieving balanced performance in terms of the F-measure. Overall, the graph highlights the superior performance of the proposed CSSA-DRN model, particularly in maintaining a high F-measure for lower to moderate volumes of learning data.

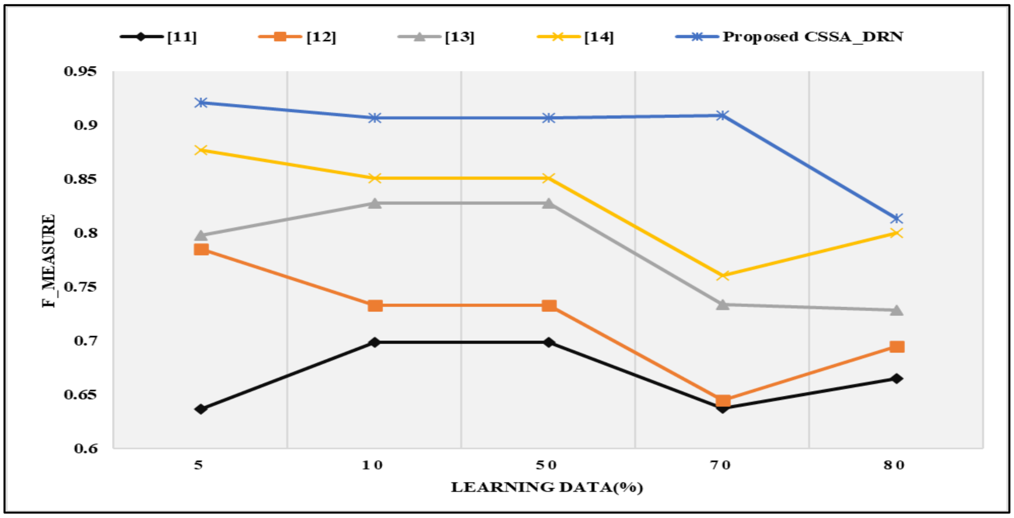

Figure 4 Technique efficacy calculation graphs with learning data using F-measure

Figure 5 shows that the proposed CSSA-DRN model performs better than other considered models in terms of accuracy, even when dealing with different sizes of learning data. Even with more comprehensive data, the ant colony optimization-based deep convolutional neural networks and LSTM model works well similar to the model. Conversely, conventional models such as ANN and PSO-MDNN demonstrate notably reduced accuracy, highlighting their shortcomings compared to more sophisticated models. The proposed CSSA-DRN model's consistently high accuracy demonstrates its efficacy and resilience in producing accurate predictions across a variety of data circumstances.

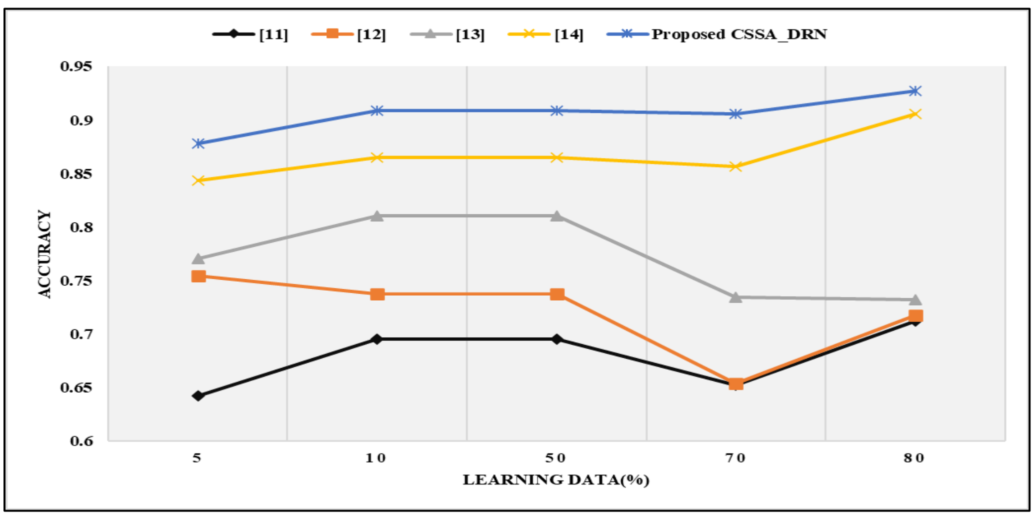

Figure 5 Technique efficacy calculation graphs with learning data using accuracy

The efficiency of all models is evaluated and analyzed in *Table 2*. The performance of each previous technique is compared with CSSA-DRN using various performance metrics. When using a learning data value of 80 for evaluation, CSSA-DRN achieves the highest performance, with a precision of 85.4%, recall of 87.5%, F-measure of 81.3%, and accuracy of 92.7%.

The model's performance metrics—precision (85.49%), recall (87.52%), F-measure (81.36%), and accuracy (92.75%)—demonstrated its superior ability to recommend suitable crops accurately. These results establish that the model outperforms competing approaches, including ANN, PSO-MDNN, DNN, and ant colony optimization-based deep convolutional neural networks and LSTM model in crop recommendation systems. The CSSA-DRN demonstrates improved performance even on the Kaggle dataset, as it maintains diversity, showing its applicability to broader datasets with varying crop conditions.

Table 2 DL models evaluation

Metrics in %	**ANN**	**PSO-MDNN**	**DNN**	**[14]**	**CSSA-DRN**
Precision	69.52	69.66	69.94	70.35	85.49
Recall	64.60	67.46	70.56	76.71	87.52
F-Measure	66.52	69.48	72.85	80.02	81.36
Accuracy	71.22	71.78	73.17	90.55	92.75

4.3Results of CSSA-DRN on Kaggle crop dataset

The proposed CSSA-DRN model is also applied to the Kaggle crop dataset along with ANN, PSO-MDNN, DNN, and ant colony optimization-based deep convolutional neural networks and LSTM model models. *Figure 6* compares the DL model's performance with respective accuracy. It is observed that the proposed model outperformed other models, achieving an accuracy of 92.13%. In comparison, ANN, PSO-MDNN, DNN, and the ant colony optimization-based deep convolutional neural networks with the LSTM model attained accuracies of 69.88%, 77.47%, 82.3%, and 91.06%, respectively, when using an 80-20 training-testing split on the dataset.

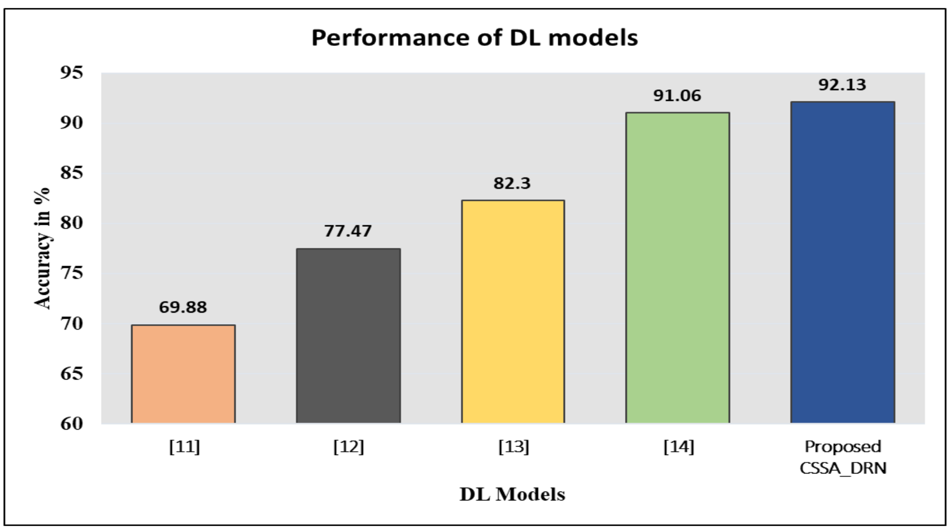

Figure 6 Performance of DL models on the Kaggle crop dataset

The proposed CSSA-DRN model demonstrates significant advancements in crop recommendation systems by effectively handling large datasets, which was challenging for the ANN model. The integration of the CSSA and DRN framework enhances the computational efficiency of the model by dynamically optimizing hyperparameters. This results in faster convergence during training while maintaining high prediction accuracy compared to PSO-MDNN. This eliminates local optima, which is a common hurdle in complex datasets.

4.4Web interface for crop recommendation

The proposed model needs to integrate with a web interface used by farmers in simple steps. The model is converted into a pickle file to deploy on the web by using the Flask library. This web framework is built using a hypertext markup language (HTML) and

Python, utilizing libraries such as NumPy, Pandas, Flask, and Pickle. The model is saved as a pickle file, which is then deployed within the web framework using Flask. The setup is flexible and can be customized to include features like input validation, error handling, or scaling for broader deployment, such as predicting crop yields based on input data.

The web interface offers two ways to give input data. Farmers(users) can either manually enter all fields on the web form or use the autofill feature by selecting a district, if the farmer unable to produce data values. For instance, in *Figure 7*, selecting "Chittor" will automatically populate fields like nitrogen, phosphorus, potassium and other inputs with the average values for that district. It can recommend suitable crop without storing input parameters.

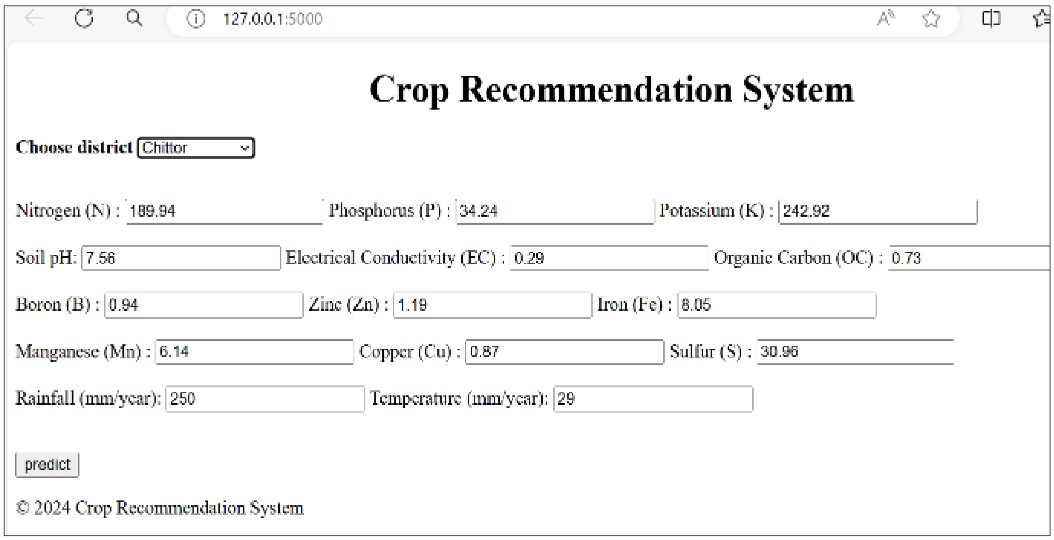

Figure 7 Web interface for crop recommendation

The CSSA-DRN integrates deployment with a user-friendly web-based interface to give input values that ensure accessibility and ease of use to farmers. This research conclusively showcases the efficacy of modern ML approaches, notably CSSA-DRN, in enhancing agricultural yields by providing accurate crop recommendations. These results are valuable in the broader agricultural technology field, helping to improve crop selection through data-driven insights. The CSSA-DRN improves crop recommendation to create a standard framework for sustainable and profitable agricultural advances.

4.5Limitation

This study required substantial computational resources, including a considerably higher resource consumption in terms of process computation and memory. The integration of DRN with CSSA can lead to a complicated and time-consuming process. DRN is susceptible to overfitting, especially when dealing with limited data. This study does not consider soil type, soil colour and weather factor humidity in crop recommendation. A complete list of abbreviations is listed in *Appendix I*.

5.Conclusion and future work

The novel CSSA-DRN model evidences a transformative approach to crop recommendation by leveraging advanced DL and optimization techniques. In the preprocessing stage, utilizing Z-score normalization, ensures data uniformity, enabling robust feature extraction of essential soil and environmental parameters such as nitrogen, phosphorus, potassium, temperature, pH, and rainfall. Through a sophisticated feature fusion process using the DMN and Canberra similarity, the model effectively reduces data dimensionality while preserving critical relationships between features. The integration of the DRN, optimized by the use of CSSA, enhances predictive accuracy and computational efficiency. Achieving a precision of 85.4%, recall of 87.5%, F-measure of 81.3%, and accuracy of 92.7%, the CSSA-DRN significantly outperforms existing methodologies, demonstrating its ability to address complex agricultural challenges. This research predicts crop suitability with high accuracy and supports sustainable farming practices by optimizing soil fertility and resource allocation. By resolving key issues in PA, such as handling large datasets, improving accuracy, and managing diverse data, the CSSA-DRN contributes to improving food security, enhancing resource efficiency, and boosting the economic viability of farming. Its ability to empower data-driven agricultural decisions paves the way for scalable solutions to global food production challenges, marking a major leap forward in agricultural technology and sustainability.

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None.

Conflicts of interest
The authors have no conflicts of interest to declare.

Data availability
Dataset 1 was obtained upon request for research experiments from the government website https://soilhealth.dac.gov.in. Dataset 2 is the crop dataset, which is publicly accessible at https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset.

Author's contribution statement
All authors contributed equally to the following stages of this study: model conception and design, data collection, analysis, implementation, interpretation of results, and manuscript preparation.

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Appendix I

S. No.	Abbreviation	Description
1	ACO	Ant Colony Optimization
2	AI	Artificial Intelligence
3	ANN	Artificial Neural Network
4	CSSA	Chronological Sparrow Search Algorithm
5	DCNN	Deep Convolution Neural Networks
6	DL	Deep Learning
7	DMN	Deep Maxout Network
8	DNN	Deep Neural Networks
9	DRN	Deep Residual Network
10	EC	Electrical Conductivity
11	ELM	Extreme Learning Machine
12	GDP	Gross Domestic Product
13	GRU	Gated Recurrent Units
14	GUI	Graphical User Interface
15	HTML	Hypertext Markup Language
16	IoT	Internet of Things
17	KRR	k-Nearest Neighbor Random Forest Ridge Regression
18	LSTM	Long Short-Term Memory
19	ML	Machine Learning
20	MSE	Mean Square Error
21	OC	Organic Carbon
22	PA	Precision Agriculture
23	PSO-MDNN	Particle Swarm Optimization–Modified Deep Neural Networks
24	RF	Random Forest
25	SSA	Sparrow Search Algorithm