NATURALISTA CAMPANO
ISSN: 1827-7160
Volume 28 Issue 1, 2024

Enhanced Convolutional Neural Network for Accurate Crop Recommendation System on Climate Data

S. Kiruthika[1*], Dr. D. Karthika[2]
[1*]Research Scholar, Department of Computer Science, P.K.R Arts College for Women, Gobichettipalayam, Tamilnadu.
Email: kirthi.deepak@gmail.com
[2]Associate Professor & Head, School of Computer Science, VET Institute of Arts and Science (Co-education) College, Erode, Tamil Nadu, India.
E-mail: karthikad@vetias.ac.in

Abstract: A major factor in the nation's economic development and progress is agriculture. The primary cause of the significant decline in crop productivity is farmers' poor crop selection. However, the current approach struggles to estimate crop growth appropriateness only on a single characteristic, like soil or weather. Because of this, for the greatest and most reliable prediction, each of these aspects must be taken into account simultaneously. To enhance the overall system performance, this work proposes the Fusion of Lion Swarm Optimisation with Simulated Annealing (FLSOSA) and Enhanced Convolutional Neural Network (ECNN) algorithm. To boost crop productivity, a crop suggestion method based on the FLSOSA-ECNN algorithm is to be developed. This study's primary stages include crop forecast that is appropriate, FS (Feature selection), and pre-processing. The K-Nearest Neighbour (KNN) technique is employed for pre-processing, filling the values that are missing in the provided dataset.

Then the pre-processed data is taken into attribute selection which is performed using FLSOSA algorithm. Utilizing an objective function, it is utilized to choose more relevant soil and meteorological parameters. Finally, these selected attributes are given into classification phase. In order to create a system that integrates the predictions of the FLSOSA-ECNN model and recommends the best crop based on the soil-specific type and attributes with a high degree of accuracy, the ECNN algorithm is utilised in this study for optimal crop prediction. According to the study findings, the suggested FLSOSA-ECNN methodology outperforms the current methods in terms of recall, accuracy, precision, and duration of execution.

Keywords: CRS (Crop Recommendation System), Fusion of Lion Swarm Optimization with Simulated Annealing (FLSOSA) and Enhanced Convolutional Neural Network (ECNN).

1. Introduction

Agriculture is an important area for human existence as well as the Indian economy. It is among the primary occupations required to sustain human existence. It also has a big impact on the way individuals spend our routine life [1]. Most often, farmers commit themselves as a result of a decrease in productivity because they are unable to repay the bank loans they took out for their businesses. India is one of the countries that produces the most agricultural goods, yet its farm productivity is still quite low. It's possible for farmers to use less labour and make greater profits in a similar piece of land, production must be increased. The solution is provided by smart farming. As the name suggests, precision farming is providing exact and appropriate amounts of input, such as manure, fertilizer, soil, etc. to the crop at the right time to increase production and yields. Not all precise agricultural techniques provide the greatest outcomes. However, it is crucial that the advice offered in agriculture be correct and precise since mistakes might result in equipment damage and financial loss. Numerous investigations are being carried out in order to create an accurate and useful approach to crop projections [2].
For a considerable amount of time, agriculture was widely regarded as India's main cultural activity. Their needs were successfully satisfied because ancient individuals farmed their own crops. People have concentrated on producing artificial and hybrid goods, that worsen their standard of life, as a result of the numerous inventions that have hindered the growth of novel cutting-edge technology and practices in agriculture [3]. The significance of growing crops at the right time and place is lost on people today. Food insecurity is an outcome of seasonal

climate conditions shifting due to these cultivation practices, which in turn deplete essential resources including land, water, and air.

Recently, agricultural yield prediction has incorporated DL (Deep Learning) models [4]. In [5], CNNs and RNNs (Recurrent NNs) two DL techniques are used to estimate soybean production in the United States with a set of remotely detected photographs taken prior to the harvesting process. Their model has a 15% lower MAPE (Mean Absolute Percentage Error) than conventional remote-sensing based techniques (MAPE). Convolutional neural networks were used in [6] to forecast agricultural production based on satellite photos. Their model exceeded previous machine learning techniques and employed three-dimensional convolution to add spatiotemporal information.

Crop output affected a wide range of features, containing soil characteristics, rainfall, sunlight availability, irrigation, fertilizer application, insect control, and site preparation. Indian farmers often get into trouble since they don't choose their crops depends on the local climate and capacity of the soil. Given that soil and climatic characteristics directly affect crop harvest, it is essential to develop crop management techniques based on soil and site appropriateness in order to maximize output. The relationship between weather and agriculture is significant, and it is essential to use the changing climatic patterns efficiently. Strategies for climate-smart agriculture are crucial for increasing productivity and yield quality. The results of earlier studies describe how harsh weather conditions affect crops.

The important goal of this research is the robust crop recommendation system. Numerous studies and approaches have been developed, however the efficiency of the crop selection mechanism has not been greatly improved. The detection of various weed species and end outcomes are problems with the current methods. In order to solve the above described issues and improve system efficiency, the Enhanced Convolutional Neural Network (ECNN) technique and the Fusion of Lion Swarm Optimisation with Simulated Annealing (FLSOSA) methodology are presented in this dissertation. The main contributions of this research include pre-processing, crop prediction using ECNN, and attribute selection using the FLSOSA approach. The recommended method makes use of effective algorithms to produce accurate outcomes for the given climate dataset.

This essay's remaining sections are organised in the following order: Section 2 describes the CRS's literature review. In Section 3, the suggested FLSOSA+ECNN method for crop prediction and RS is detailed. Section 4 presents the outcomes of the experiment. Section 5 concludes the work.

2. Related work

Kulkarni et al. (2018) build a system in [8] that combines the predictions of numerous ML (Machine Learning) models to precisely recommend the optimal crop based on the kind and characteristics of the soil. For independent base learning (SVM), the ensemble model makes utilises Random Forest (RF), Naive Bayes (NB), and Linear SVM. With a reasonable degree of precision, each classifier provides a distinct set of class labels. The integration of distinct base learners' class labels is done by the maximum voting approach. The crop selection algorithm separates the input soil data into two groups, Kharif and Rabi. The data contains physical and chemical characteristics unique to soil, in addition to environmental variables such as average rainfall as well as surface temperature samples.

In [9], Modi et al (2021) the CRS for formers depends on the SVM algorithm is shown. Analyzing the crop's profit in this task is crucial since doing so will prevent farmers from losing money and boost production. To categories the many soil factors and forecast the best crop, the SVM algorithm is employed for classification. Analyzing the soil properties and suggesting a appropriate crop is modeled by the algorithm in Anaconda Navigator. Consideration is given to the SVM method for classification. Reliability and ambiguity matrices are calculated to evaluate the efficacy of the technique.

ML was introduced by Pant et al. (2021) in [10], and it is used to predict four yields that are extensively grown in India. Fertiliser applications can vary depending on the expected crop and soil requirements after the crop yield estimate for a particular region has been determined. In this study, we employ ML approaches to develop a model that detects trends in the information and is then applied to crop prediction. In this study, the crop yields of India's 4 most popular crops are predicted using ML. These crops consist of corn, wheat, potatoes, and paddy rice.

Crop selection was established in [11], Mishra et al. (2021) by using ML techniques like K-Nearest Neighbour (KNN) and RF algorithms. The Indian Data Set has been subjected to extensive simulations of both models, and an analysis report has been produced. This model will help farmers determine the type of crop they are planting on agricultural land so they may make informed decisions.

In [12], Yazdani et al (2016) presented the Lion Optimization Algorithm, a revolutionary optimization technique (LOA). It is built using a simulation of the lions' cooperative and solitary habits, including hunting, mating, marking territory, defending, and other actions. We evaluated the newly proposed method against a number of common benchmark functions in order to assess its efficiency. The results achieved by LOA are often superior to those of other metaheuristics in terms of quick converging and achieving worldwide optimum.
Thenmozhi, K., and U. Srinivasulu Reddy (2019) reported an effective DCNN (Deep CNN) model in [13] for the intention of classifying three public databases of bugs. The first insect dataset (NBAIR) contains images of field crop insects in 40 classes, while the second and third datasets (Xie1, Xie2) contain photos of insects in 24 and 40 classes, respectively. For the purpose of classifying insects, the suggested approach was evaluated against AlexNet, ResNet, GoogLeNet, and VGGNet. Pre-trained models were refined by TL (Transfer Learning). In order to prevent overfitting, reflection, scaling, rotation, and translation are applied. The suggested model's analysis of hyperparameters increased accuracy. The insect datasets from Xie1 (24 classes), Xie2 (40 classes), and NBAIR (40 classes) are most accurately classified by the CNN model. According to the research, CNN can recognise insects in field crops more accurately than pre-trained models, which could have applications in crop security.

3. Methodology

In this research work, Fusion of Lion Swarm Optimization with Simulated Annealing (FLSOSA) and ECNN algorithm is designed for suitable crop prediction and CR. The main contribution of this work is such as pre-processing, FS and appropriate crop prediction. Fig 1 shows the overall framework of the proposed FLSOSA-ECNN algorithm

a. Dataset
https://www.kaggle.com/siddharthss/crop-recommendation-dataset is the link for determining the CR dataset. The research takes into account the amount of crop output occurring, and the CR database has several parameters that influence the amount of rain that falls in a certain place. Phosphorus (P), nitrogen (N), potassium (K), temperature, humidity, ph, rainfall, and label are all included in the CR dataset.

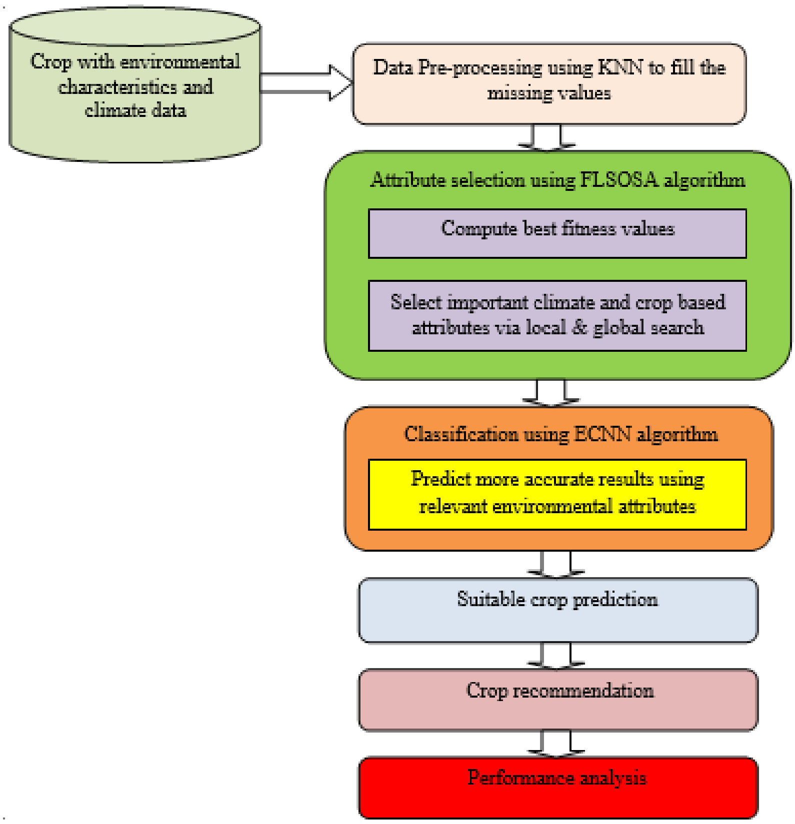

Fig 1 Overall framework of the proposed FLSOSA-ECNN algorithm

b. Pre-Processing using K-Nearest Neighbor (KNN) algorithm

The pre-processing in this study uses the KNN approach to improve the efficiency of categorization. The closest neighbour approach is based on comparing given test tuples with similar training tuples in order to learn from them. KNN is regarded as a SL (Supervised Learning) technique in which training sets are used to help classify points for a specific category. Let I = 1, 2,…. n represent the data points (Xi, Ci). Xi denotes feature values, while Ci denotes the labels associated with each i in Xi. The training tuples are characterised by n attributes. Every tuple in an n-dimensional space corresponds to a point [14]. When presented an unknown tuple, a KNN classifier finds the k training tuples that are most similar to the unknown tuple. These k training tuples are the k "NNs" of the unknown tuples. A distance measurement metric, such the Euclidean distance, is described as,

$$(X1, X2) = sqrt\ (sum\ ((xj - xij)\ \text{^}2) \quad (1)$$

where, x - new point
xi – existing point through each input features j.

Algorithm 1: KNN

Input: Original crop recommendation dataset with climate parameters
Output: Pre-processed dataset
Start
{
For all input features ∈ crop recommendation dataset do
Compute the Euclidean distance using (1)
End for
Determine the K training instance which are closest the unknown class instance
Fill the error and missing values then replace it by KNN values
The instances are sorted to the closest neighbor based on distance
Choose the most commonly occurring K instance values
}
End

c. Attribute selection through Fusion of Lion Swarm Optimization with Simulated Annealing (FLSOSA) algorithm

The FLSOSA technique is utilized in this research to pick attributes, increasing the amount of relevant data and reducing the amount of duplicated features. LOA is a stochastic optimization technique that uses a metaheuristic algorithm. Each iteration of a metaheuristic algorithm might provide a distinct solution to the issue. The lion is the greatest animal in the world because of its distinctive social behaviour. Lions live in a group called a prides, where both resident males and females help in childbirth. Territory is the name given to the region where pride resides. The nomadic lion needs lions and cubs to protect it against attacks from other prides [15]. If the territorial lion is defeated by the nomadic lion, the territorial lion will kill the territorial lion or drive it away, and in order to prove its territoriality, it will also kill the lost lion's pups before compelling the female lion to go into estrus and mate in order to produce progeny. When the territory cub reaches sexually mature, if it is stronger than the territorial lion, it may kill it to seize control of the pride. The new, stronger lion kills the territorial sluggish lion's young and gets ready to have its own cubs.

Lions may transition between their two social organization kinds, from residents to nomads and vice versa. Lions have two different social behaviour patterns: residences and nomadic. Based on the actions of two lions, LOA searches for the best solutions.

- Males on mobility and resident lions and cubs defend their territories. This behaviour is used by the method to assess the territorial lion, the current solution, with the nomadic lion, the most recent solution. If the new solution proves to be better than the old ones, the old solutions are eliminated.
- There is a territorial takeover between the former territorial male and the new territory male. This means that the system will keep the better solutions and delete the undesired ones. It will do this by only storing the best male and female replies over new answers and removing any other solutions from the pride.

Fig 2 shows the nature of LSO (Lion Swarm Optimization) algorithm

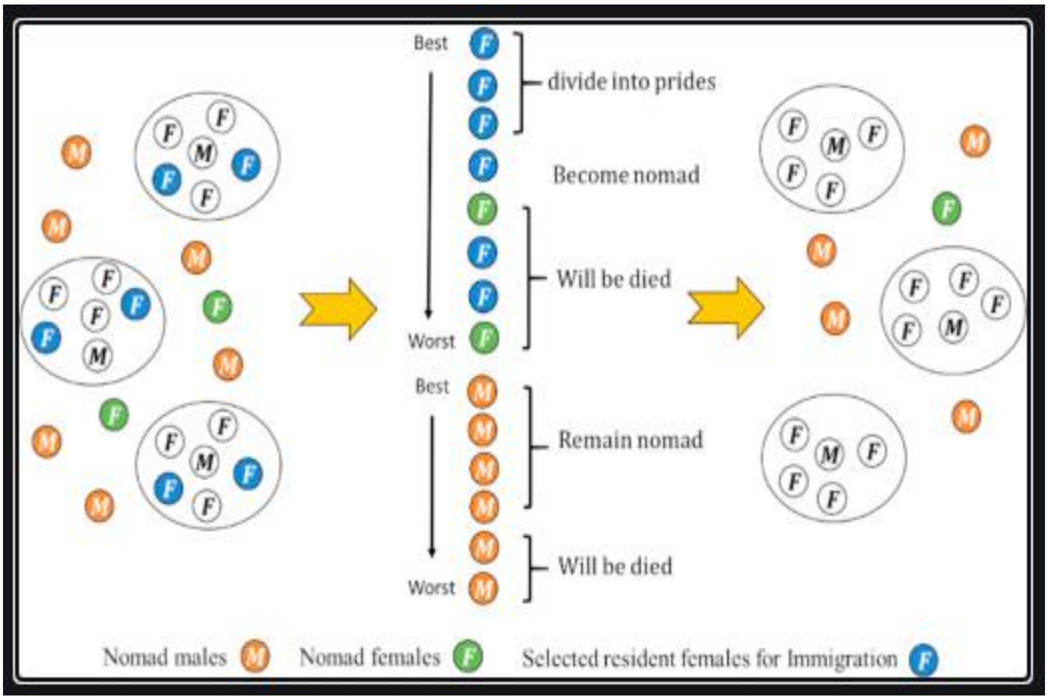

Fig 2 Nature of Lion Swarm Optimization algorithm

Initialization: The location of the lions is kept in a matrix, and the population is produced at random throughout the solution space. The populations over the solution space is randomly generated as the initial stage in LOA. Every solution in LOA is referred to as a lion, which is symbolized by:

$$Lion = [x_1, x_2, \ldots\ldots x_{N_{var}}] \quad (2)$$

Where $x_{N_{var}}$overall selection of attributes in this work and The remainder of the population is made up of resident lions, and the percentage of nomad lions is is%N arbitrarily produced. Here, the input solution is taken into account while determining the optimum attribute selection number.
LOA is used to improve attribute selection by looking for and identifying people' unspoken connections with one another in given crop based dataset.

Fitness calculation process
Each lion's performance index is determined by analyzing the optimal solution before being categorized and recorded in a matrix.

$$f(Lion) = f(x_1, x_2, \ldots\ldots x_{N_{var}}) \quad (3)$$

The precision of the classification is a factor in this efficiency computation. The process of updating the answer will be completed after the efficiency calculation. The main updating processes in the lion algorithm are defence, roving, mating, and hunting. In the pride's region, few female lions hunt for prey, and some will settle in the same area. Each region has its own top qualities, which will aid in determining the finest on every repetition. Based on efficiency, the best characteristics from the first solution are chosen in this study. Additionally, we must pick the top features from the revised solutions.

Hunting
The hunters are divided into 3 groups at random. The two surviving hunters are the left and right arms, with the hunter with the finest physical condition chosen as the center. At the moment the fake prey is attacked, one hunter is randomly selected. If the hunter becomes more fit and the new location is updated, the prey flees.

$$hunter = \begin{cases} rand\ (hunter, prey), hunter < prey \\ rand(prey, hunter), hunter > prey \end{cases} \quad (4)$$

PREY is the prey's present location, and HUNTER is the hunter's present location in random generation

Moving toward safe place
Few female lions in each pride specialize in hunting. The remaining ladies relocated to a portion of the land that was safe. Each pride's personal best position is computed and kept. A large number of wins indicate that the

lions' combination is still far from being at its best. Additionally, a lack of successes indicates that the lions are circling the optimal configuration deprived of important growth. As a result, the accomplishment esteems are used to evaluate the contest's measurement.

Roaming

One of the challenging and constrained search methods used by LOA to scour the search area and improve the answer is traveling. The lion moves by n units in the direction of its favourite region, where n is a uniformly distributed randomly integer.

$$n \sim U(0{,}2 * d) \quad (5)$$

where d is the range among the location of the male lion and the chosen region. Also, the nomadic lion roams aimlessly throughout the search area.

Mating

The crucial process that ensures the lions' survival is mating. It involves producing 2 novel children from the parents. The right male and female lions are chosen, and then the cubs are born. Crossing and evolution are two processes that provide people the chance to create new, better solutions from those already available. Killing sick or weak cubs guarantees that the solutions that result are the best.

Defense

One of the main crucial behaviours in a lion's everyday existence is defense. The fully grown male lions become aggressive, destructive, and engaged in combat with other lions in that pride. Male lions that have lost are expelled from the pride or became nomads. A migratory lion will turn into a residential lion in that pride and drive the resident lion out of that pride if it feels physically fit and attempts to battle the other lions in the pride and loses. It takes the operator two steps.

- Protection from adult newly inhabitant males
- protection versus male nomads

The most formidable lion in the group is identified by this operation.

Migration

Some female lions are selected at random for this migration procedure and become nomads. The placement of the fresh and old nomads is determined by their highest performance values. To fill the role of moved or migratory female lions, the female lions in the pride with the greatest endurance level are changed.

Lions' population equilibrium

An equilibrium point is kept on the populations of lions at the end of each cycle. Every lion's gender is limited to a certain number in the nomadic group. The number of lions that are not in good physical condition is reduced. When closer to the base station, it reduces the group number, and as the group head gets further away from the base station, the size grows.

Termination criteria

The procedure is stopped by this algorithm if a large amount of repetitions is completed with the highest level of fitness. In this case, the division with the greatest efficiency is chosen as the one where the communication should be broadcast first. Between the old and new aggressive males, territory takeover occurs. By acting in this manner, the algorithm will only store the best male and female solutions over new solutions and erase any old solutions in the pride, or preserve the better solutions and eliminate the undesirable options. (selection operation). In some cases, it has problem with local and global optimal values. To overcome these problems, Simulated Annealing (SA) is introduced.

SA is one of the first and still most predominant metaheuristic algorithms, that is a trajectory-based, arbitrary search approach for global optimization [16]. It imitates annealing procedure used during the material processing once a metal cools down and freezes into crystalline state with a minimal energy and bigger crystal sizes such that limitations are reduced in metallic structures. The annealing technique, sometimes referred to as the annealing schedule, involves precise temperature control and cooling rate. SA is successfully used in a variety of sectors. The approach starts with the main result, obtains a near answer for that result, and if the goal function does not improve, it is applied with probability p. ΔE stands for the difference between the neighbor's reaction and the current response's objective function, and T stands for temperature. Multiple rounds are performed at each temperature before the temperature is progressively lowered. Temperature is kept quite high in the beginning to increase the likelihood of receiving negative reactions. The procedure converges to the optimal answer as a result of the gradual temperature decline in the last phases that reduces the likelihood of receiving worse responses. With this technique, one is not constrained to a locally advantageous site. This finally makes model to go toward a reduced energy. Rather, in this method, at every level of solution x having fitness function f(x), a neighbour x' in neighbourhood of x, N(x), is chosen. In every stage difference among objective functions is given by:

$$\Delta = \mathrm{f(x)} - \mathrm{f(x')} \tag{6}$$

X' the following equation may be used to calculate it:

$$\mathrm{P_s} = \exp\left(-\frac{\Delta}{\mathrm{T}}\right) \tag{7}$$

Next, the likelihood of accepting a random number r(0,1) is compared, and x' is accepted if P>r. T is the temperature that the cooling strategy regulates. However, additional elements like the main temperature are included in the simulated annealing approach, a process for varying temperature, and a cooling plan till it ceases.

Fitness computation using FLSOSA

$$Fitness = \frac{\sum_{x_{i,j}}^{N} (F_{higher\ classifier\ accuracy}^{i,j})}{2} \tag{8}$$

Algorithm 2: FLSOSA
Input: Pre-processed dataset
Output: Optimal features with higher classifier accuracy
Begin
Initialization: the no. of lions N, maximum no. of iterations T and the adult lions
Initialization: simulated annealing method factors including total repetitions, primary temperature (T) and reduction factor c
Initialize the random position of lion (crop features)
t=1
while t<T do
Creation of N lion (primary solution)
For every pair of lion (solutions) utilizes subsequent steps:
For $i \in [1, N] do$
{
If fitness of lion $L_i > L_j$
L_i *travels towards* L_j *using (8)*
End if
End for
}
Modify the position P_i *based on the distance* D.
While termination criteria is not satisfied do
For new best solution (best crop features)
Select new solution $x_0 + \Delta x$
If $f(x_0 + \Delta x) > f(x_0)$ *then*
$f_{new} = f(x_0 + \Delta x);\quad x_0 = x_0 + \Delta x$
Else

$$\Delta f = f(x_0 + \Delta x) - f(x_0)$$

End if

$$f = f_{new}$$

Decrease the temperature periodically $T = c \times T$
Repeat until the termination gets end
End for
End while
Evaluate the fitness of each crop based feature using soil and weather parameters
Select the best features which has higher classifier accuracy
Memorize the best crop features

End

This method explains the stages taken from the lion optimization algorithm. 1. Lions are the world's strongest mammals because of their distinctive social behaviour. Lions have two distinct social behaviour patterns: residents and nomads. Residential may transition to nomadic behaviour, and vice versa. The pride groups that the residents live in are where the resident men and women give birth. Nomads, the second organisational behaviour, are sporadic travellers who may travel alone or in pairs. Among related males who have been cut out of their mothers' pride, pairs are more common.

d. Crop prediction using Enhanced Convolutional Neural Network (ECNN) algorithm

In this work, based on the selected features, Enhanced Convolutional Neural Network (ECNN) recommends suitable crop production. The selected features are taken as an input for ECNN training and testing phases. The Convolutional Neural Network (CNN), which may have numerous hidden layers doing computation and sub sample in order to remove low to high levels of features from the input data, is one of the most potent deep networks. Convolution layers, pooling layers or sub sampling, and FC (fully connected) layers are the basic building blocks of this kind of network. The network receives a chosen feature as input. The network includes three layers: an input layer that accepts input in the form of features, an output layer from which the system receives trained output, and intermediate levels known as hidden layers, as illustrated in Fig. 3. The weight values of the features are tuned in this suggested ECNN to provide reliable outcomes. Since a certain soil type may be suited for growing a particular crop, the yield will decline if the region's climatic factors are unsuitable for that crop type. Hence, it is used to recommend all types of crop using both soil and weather parameters via ECNN algorithm

Convolution layer

This layer combines an input picture of size RC with a kernel (filter) of size aa. Each block of the input matrix is convolved independently with the kernels to generate a pixel in the output. The convolutional output of the input information and parameter is used to create N output features [17]. The kernel of a convolutional matrix is commonly called a filter, and the features generated by correlating the kernels with the input information are described by dimension ii FMs (Feature Maps).

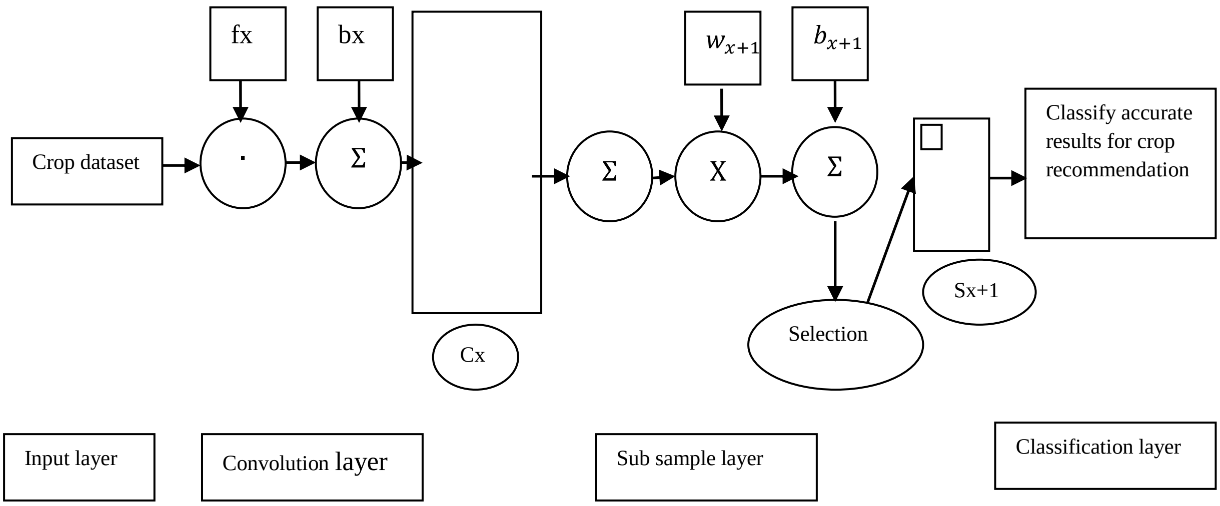

Fig 3 Architecture Diagram of ECNN

Convolutional layers may be used in a CNN in multiples, with feature vectors serving as their inputs and outputs in subsequent levels. In each convolution layer, there are n filters in total. The depth of the generated FMs (n) is equal to the number of filters used throughout the convolution method because these filters are convolutional with the input. Recall that every filter map appears as a unique feature at a specific location inside the input image.

The l-th convolutional layer's outputs is represented by $C_j^{(l)}$, includes featured maps. It's calculated as

$$C_i^{(l)} = B_i^{(l)} + \sum_{j=1}^{a_i^{(l-1)}} K_{i,j}^{(l-1)} * C_j^{(l)} \tag{9}$$

Where, $B_i^{(l)}$ is the bias matrix and $K_{i,j}^{(l-1)}$ the jth FM in layer (l 1) and the ith FM in the similar layer are connected by a convolutional filtering or kernels of size. The output $C_i^{(l)}$ maps of features make up the layer. the top layer of convoluted $C_i^{(l-1)}$ is input space, that is, $C_i^{(0)} = X_i$

Feature maps are produced by the kernels. After the convolution layer, the outputs of the convolutional layer may be nonlinearly transformed using the activating feature:

$$Y_i^{(l)} = Y(C_i^{(l)}) \tag{10}$$

Where, $Y_i^{(l)}$ reflects what the activating functional produces, and $C_i^{(l)}$ is the input that it receives.

Sigmoid, tanh, and rectification linear units are the most often employed activation functions (ReLUs). ReLUs, which is referred to in this work as $Y_i^{(l)} = \max(0, Y_i^{(l)})$ when utilized. Due to its assistance in decreasing the interactions and nonlinearities, this function is often utilized in DL methods. ReLU yields the same input value if it gets a positive input, else it changes the output to zero. The benefit of this activating functional over other functional is quicker training since the error derivatives shrinks dramatically in the saturation area, which causes the weight updates to nearly completely disappear. The vanishing gradient issue is what this is known as.

Sub sampling Layer

This layer has a basic goal is to geographically lower the dimensions of the FMs that were obtained from the preceding convolution layer. In order to achieve this, a mask with a size of bb is chosen, and the feature maps are subsampled using the mask. Keep in mind that a sub sampling layer aids the convolutional layer's ability to accept rotations and translations between the input pictures. In this proposed research work, optimal weights are updated depends on the mean of the weights of features.

Weighted mean $w_H = \frac{N}{\sum_{i=1}^{N} w x_i}$ (11)

Where,
N − Number of features
w- Weight value of the feature
x_i- Features

Full Connection

Soft max activating function is employed through the output layer:

$$Y_i^{(l)} = f(z_i^{(l)}), \text{ where } z_i^{(l)} = \sum_{i=1}^{m_i^{(l-1)}} w_H y_i^{(l-1)} \tag{12}$$

where w_H are the weighted Harmonic mean of the features f is the transfer function, which defines the non - linearity, and must be tweaked by the whole FC layer to produce the representations of all class. The suggested technique divides the input picture into three categories, including weed, crop, and backdrop.

To finish the categorization choice process, a classifier is utilized to link the completely integrated layer and output layer. Fig 4 shows the ECNN algorithm

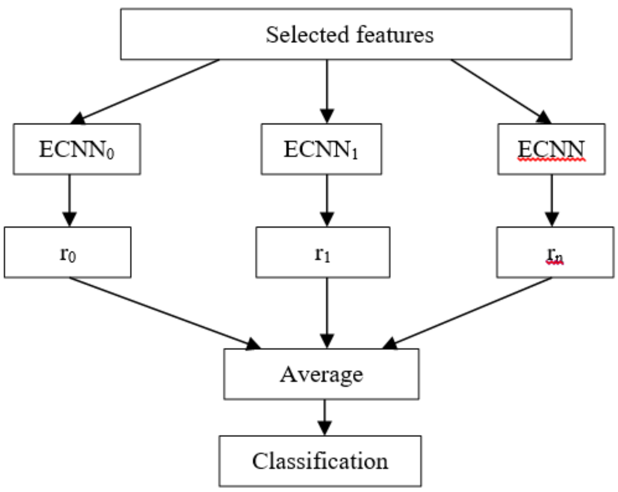

Fig 4 ECNN algorithm

Before classifying an input, the outcome probability of each ECNN are combined. The averaged output S_i for output I is determined as follows:

$$S_i = \frac{1}{n}\sum_{j=1}^{n} r_j(i) \quad (13)$$

Thus, for a certain input data, network j's output is indicated by the symbol rj I.

The strategy involves of giving each network a unique weight. Networks with a greater categorization efficiency in the evaluation set will be given more weight when merging the findings. The output probability from every ECNN are compounded by a weight after being given an input pattern before the prognostication:

$$S_i = \sum_{j=1}^{n} \alpha_j r_j(i) \quad (14)$$

In the suggested research project, the weight is determined by computing the weighted mean. The following is how the weight calculation is done:

$$\alpha_k = \frac{A_k}{\sum_{i=1}^{n} A_i} \quad (15)$$

Where I traverse the n, Ak is correctness in the network k's verification set, and Based on the ECNN network's typical output, inputs are classified for suitable crop recommendation. The novelty of the ECNN is to classify the crop using average best classifier values. ECNN supports and identifies which crop kind and which climatic circumstances may be best suited to each soil type are suitable for that crop type. Finally, it provides better yield for various weed species

Algorithm 3: ECNN

1. Procedure crop recommendation dataset
2. For all input feature, describe crop recommendation feature ∈ crop recommendation dataset do
3. Convert the input into sub layers
4. Detect crop recommendation features
5. Extract more informative and relevant features based on temperature, humidity and pH level
6. Perform training and testing process for given crop recommendation dataset
7. Copy predefined feature label for each feature as per the input dataset
8. Classify more accurate crop recommendation results

4. Experimental Result

In this work, crop recommendation dataset is obtained from https://www.kaggle.com/siddharthss/crop-recommendation-dataset. This work, utilize the MATLAB to assess existing ANN and IDCSO-WLSTM classification performance. In terms of recollection, specificity, reliability, and processing time, the proposed FLSOSA-ECNN is compared to the current ANN and IDCSO-WLSTM categorization for crop recommending system. Table 1 displays the data used to compare the current and planned systems.

Table 1 Comparison values for existing and proposed system

METHODS/METRICS	ANN (%)	IDCSO-WLSTM (%)	FLSOSA-ECNN (%)
Accuracy	87.71	92.68	95.36
Precision	82.06	90.88	94.41
Recall	84.78	91.98	95.36
Execution time (sec)	250.47	241.0484	129.01

Accuracy

Utilising all the real categorization variables $(T_p + T_n)$ and dividing the outcome by the sum of all the categorization criteria $(T_p + T_n + F_p + F_n)$, one may determine the overall consistency of the framework, which is determined by accuracy. This formula is used for determining the accuracy:

$$\text{Accuracy} = \frac{T_p + T_n}{(T_p + T_n + F_p + F_n)} \quad (16)$$

Where T_p is True positive, T_n is true negative, F_p is false positive and F_n is false negative

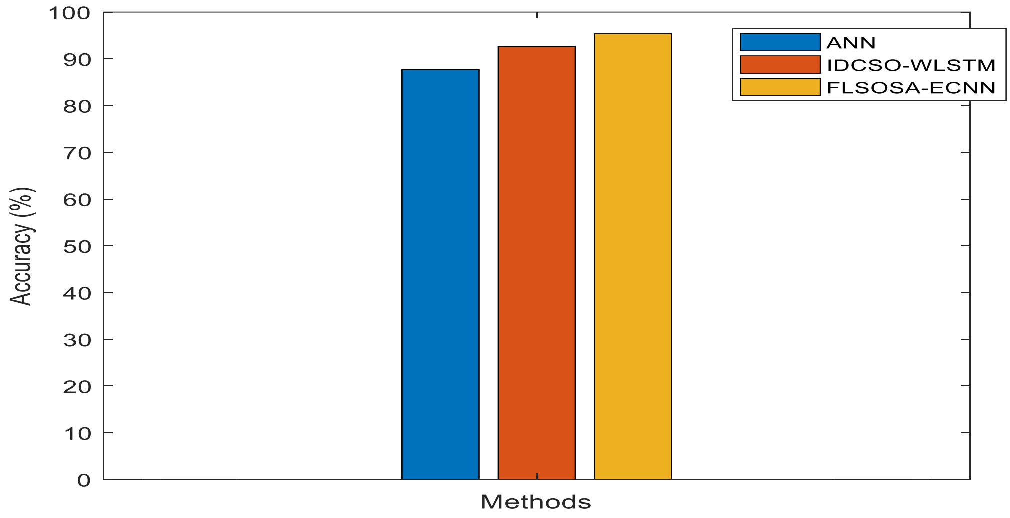

Fig 5 Accuracy

The accuracy of the comparison metric is evaluated with both the suggested and current approaches, as Fig. 5 illustrates. The methods used are plotted on the x-axis, while the y-axis displays the accuracy value. For the suggested crop recommendations dataset, suggested FLSOSA-ECNN algorithm offers improved efficiency compared to current methods like ANN and IDCSO-WLSTM algorithms. Through the KNN algorithm, pre-processing is utilized to improve detection accuracy. The proposed FLSOSA based feature selection improves the important soil and temperature features for the better crop production. As an outcome, the suggested FLSOSA-ECNN increases crop forecast accuracy by carefully choosing climatic parameters, according to the results.

Precision

This formula is used to calculate the precision:

$$\text{Precision} = \frac{T_p}{T_p + F_p} \quad (17)$$

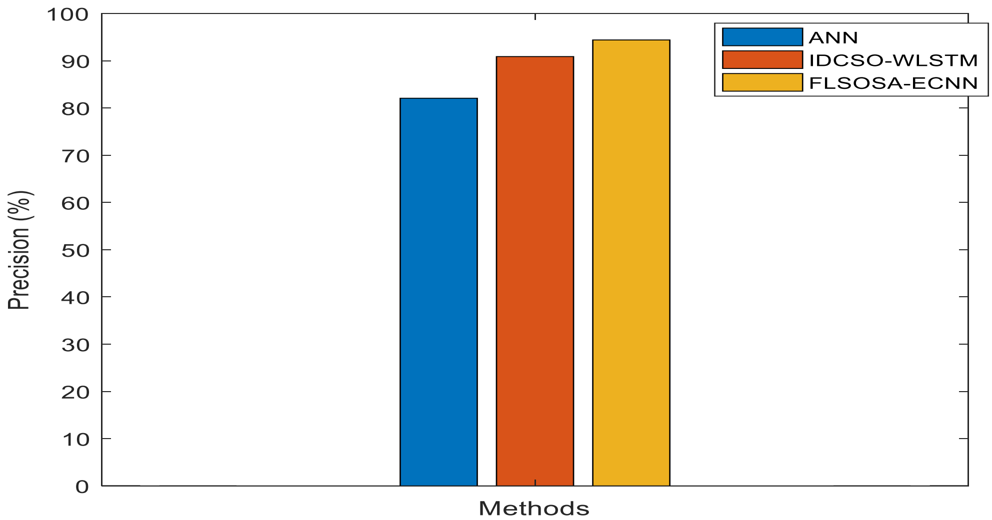

Fig 6 Precision

The accuracy of the comparison metric is evaluated with the methods that are currently in usage, as seen in Fig. 6 above. The y-axis displays the accuracy amount, while the x-axis displays the techniques. The proposed FLSOSA-ECNN algorithm provides higher precision whereas existing ANN and IDCSO-WLSTM methods provide lower precision. The system under consideration aims to select the more relevant information from multi features of the same crop production. By this FLSOSA-ECNN algorithm, best soil and weather parameter is identified at the early stage of cultivation. So that the final yield will be more productive and the outcome suggests that the suggested FLSOSA-ECNN approach increases the informative features accurately for crop recommendation process

Recall

The memory factor is determined in the manner described below:

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive+False negative}} \quad (18)$$

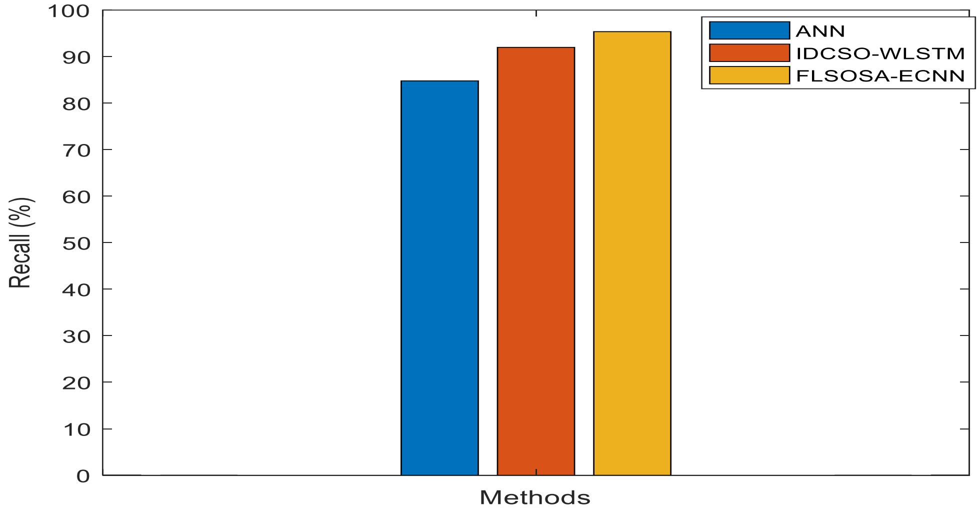

Fig 7 Recall

The comparison measure is evaluated on the basis of recall utilising the methods that are currently in usage, as illustrated in Fig. 7. The y-axis displays the memory level, and the x-axis displays approaches. The proposed FLSOSA-ECNN algorithm provides higher recall whereas existing ANN and IDCSO-WLSTM methods provide lower recall. The proposed system is focused to select the more relevant information from multi features of the same crop production. The proposed FLSOSA-ECNN model helps to improve the productivity of agriculture in better way using both soil and weather parameters. Thus, the outcome indicates that the suggested FLSOSA-ECNN approach increases the informative features accurately for crop recommendation process

Execution time

The system operates well when the recommended approach operates more quickly.

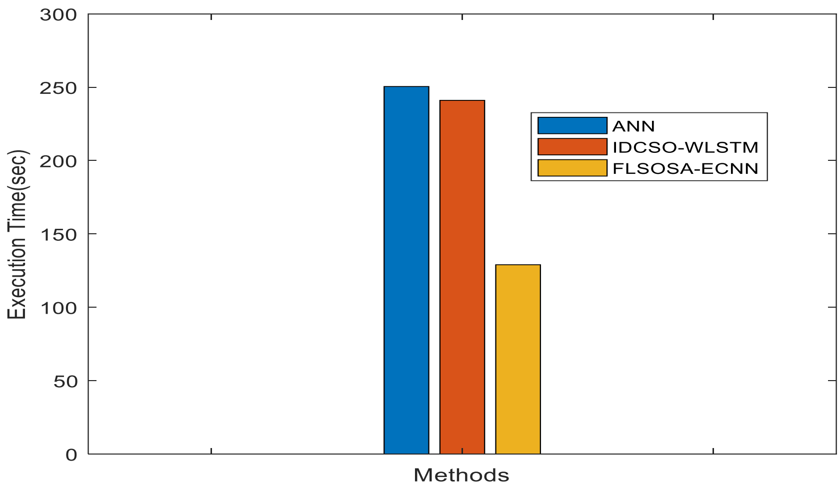

Fig 8 Execution time

The comparison measure is evaluated in terms of time required for implementation utilising both the recommended and current approaches, as seen in Fig. 8 above. The implementation time value is shown on the y-axis, while the methods that have been selected are plotted on the x-axis. The proposed FLSOSA-ECNN algorithm has a shorter execution time than the current techniques, including ANN and IDCSO-WLSTM, for the given CR dataset. Consequently, the findings show that by carefully selecting climatic parameters, the proposed FLSOSA-ECNN boosts crop forecast accuracy.

5. Conclusion

This paper proposes the FLSOSA-ECNN method to improve the effectiveness of the CRS for the specified dataset. 3 primary parts, including pre-processing, attribute selection, and classification, make up this study. The goal of pre-processing is to increase the dataset's integrity by handling the missing values. The attribute selection is done by using FLSOSA algorithm which selects optimal climate, soil and weather features efficiently. Then the FLSOSA algorithm provides the useful and relevant feature which is used for real time applications. Finally, the classification is done by using ECNN algorithm which provides more accurate prediction performance. The proposed FLSOSA-ECNN model helps to improve the productivity of agriculture in better way. The suggested FLSOSA-ECNN algorithm outperforms the current techniques in terms of accuracy, precision, recall, and time complexity, according to the test outcomes. By using ML techniques, it will be possible to prescribe fertilisers for the land and insecticides for the chosen crop in future research.

6. References

1. Pudumalar, S., et al. "Crop recommendation system for precision agriculture." 2016 Eighth International Conference on Advanced Computing (ICoAC). IEEE, 2017.
2. Teja, M. Sai, et al. "Crop Recommendation and Yield Production using SVM Algorithm." 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, 2022.
3. Madhuri, J., and M. Indiramma. "Artificial Neural Networks Based Integrated Crop Recommendation System Using Soil and Climatic Parameters." Indian J. Sci. Technol. 14.19 (2021): 1587-1597.
4. Shingade, Sachin Dattatraya, and Rohini Prashant Mudhalwadkar. "Hybrid deep-Q Elman neural network for crop prediction and recommendation based on environmental changes." Concurrency and Computation: Practice and Experience (2022): e6991.
5. You, Jiaxuan, et al. "Deep gaussian process for crop yield prediction based on remote sensing data." Thirty-First AAAI conference on artificial intelligence. 2017.
6. Nevavuori, Petteri, Nathaniel Narra, and Tarmo Lipping. "Crop yield prediction with deep convolutional neural networks." Computers and electronics in agriculture 163 (2019): 104859.
7. Dahikar, Snehal S., and Sandeep V. Rode. "Agricultural crop yield prediction using artificial neural network approach." International journal of innovative research in electrical, electronics, instrumentation and control engineering 2.1 (2014): 683-686.
8. Kulkarni, Nidhi H., et al. "Improving crop productivity through a crop recommendation system using ensembling technique." 2018 3rd International Conference on Computational Systems and Information Technology for Sustainable Solutions (CSITSS). IEEE, 2018.
9. Modi, Daneshwari, et al. "Crop Recommendation Using Machine Learning Algorithm." 2021 5th International Conference on Information Systems and Computer Networks (ISCON). IEEE, 2021.
10. Pant, Janmejay, et al. "Analysis of agricultural crop yield prediction using statistical techniques of machine learning." Materials Today: Proceedings (2021).
11. Mishra, Tapas Kumar, et al. "Crop Recommendation System using KNN and Random Forest considering Indian Data set." 2021 19th OITS International Conference on Information Technology (OCIT). IEEE, 2021.
12. Yazdani, Maziar, and Fariborz Jolai. "Lion optimization algorithm (LOA): a nature-inspired metaheuristic algorithm." Journal of computational design and engineering 3.1 (2016): 24-36.
13. Thenmozhi, K., and U. Srinivasulu Reddy. "Crop pest classification based on deep convolutional neural network and transfer learning." Computers and Electronics in Agriculture 164 (2019): 104906.
14. Kuhkan, Maryam. "A method to improve the accuracy of k-nearest neighbor algorithm." International Journal of Computer Engineering and Information Technology 8.6 (2016): 90.
15. Yu, Haiyan, et al. "Fuzzy Clustering Algorithm Based on Improved Lion Swarm Optimization Algorithm." International Conference on Swarm Intelligence. Springer, Cham, 2021.

16. Mafarja, Majdi M., and Seyedali Mirjalili. "Hybrid whale optimization algorithm with simulated annealing for feature selection." Neurocomputing 260 (2017): 302-312.
17. Barbosa, Alexandre, et al. "Modeling yield response to crop management using convolutional neural networks." Computers and Electronics in Agriculture 170 (2020): 105197.