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Optimized Deep Learning Methods for Crop Yield Prediction

K. Vignesh[1,*], A. Askarunisa[2] and A. M. Abirami[3]

[1]KLN College of Information Technology, Pottapalaiyam, 630612, India
[2]Sethu Institute of Technology, Kariyapatti, 626115, India
[3]Thiagarajar College of Engineering, Madurai, 625015, India
*Corresponding Author: K. Vignesh Email: vignesh.vkv2@gmail.com
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Abstract: Crop yield has been predicted using environmental, land, water, and crop characteristics in a prospective research design. When it comes to predicting crop production, there are a number of factors to consider, including weather conditions, soil qualities, water levels and the location of the farm. A broad variety of algorithms based on deep learning are used to extract useful crops for forecasting. The combination of data mining and deep learning creates a whole crop yield prediction system that is able to connect raw data to predicted crop yields. The suggested study uses a Discrete Deep belief network with Visual Geometry Group (VGG) Net classification method over the tweak chick swarm optimization approach to estimate agricultural production. The Network's successively stacked layers were fed the data parameters. Based on the input parameters, a crop production prediction environment is constructed using the network architecture. Using the tweak chick swarm optimization technique, the best characteristics of input data are preprocessed, and the optimal output is used as input for the classification process. Discrete Deep belief network with the Visual Geometry Group Net classifier is used to classify the data and forecast agricultural production. The suggested model correctly predicts crop output with 97 percent accuracy, exceeding existing models by maintaining the baseline data distribution.

Keywords: Data mining; deep learning; crop production; tweak chick swarm optimization algorithm; discrete deep belief network with VGG Net classifier

1 Introduction

Crop production is influenced by a number of factors, including crop genotype, environmental conditions, and management practices. Over the years, seed companies have made significant strides forward in the field of crop genotyping. Changing climatic conditions, both in spatial and temporal, may result in a broad variety of agricultural yields from one year to the next. Highly precise yield forecasting is extremely helpful in these situations for global food production. Accurate projections can inform import and export decisions. Consequently, farmers may utilize the anticipated yield to make better management and financial decisions. Hybrids may be expected to operate well in new and untested environments. Predicting crop yields with any degree of accuracy is almost impossible due to the sheer number of variables that must be considered. Because of interactions between genotype and environmental factors, crop yields may be more difficult to estimate. Predicting the complex nonlinear effects of external elements like weather, for example, is impossible with any precision. Random forests, multivariate regressions, association rule mining and artificial neural networks have previously been attempted. In a machine learning model, an advanced nonlinear connection between input parameters, such as weather and soil conditions, and output, crop yield, is feasible. It's referred to as a "non-linear" link. Wheat, maize, and potato yields were forecasted using random forest and multiple linear regressions in the United States. – Multi-linear regression was beaten handily by random forest for estimating agricultural output. Jeong et al. [1]. Fukuda et al. [2] For mango fruit production estimates, random forest was shown to be beneficial in the response to water availability under different irrigation regimes. Adisa et al. [3] Artificial neural networks were used to mimic a nonlinear connection between maize productivity and environmental parameters such as weather and soil. By analyzing soil and meteorological data, a research was carried out. Ransom et al. [4] A machine learning strategy was tested for corn nitrogen recommendation tools. Artificial neural networks and stepwise multiple linear regression were used by the researchers at the Nosratabadi et al. [5]. Random forest and linear regression approaches were utilized in another work Shahhosseini et al. [6], Awad [7] Corn production and nitrate loss may be forecasted using this method. In order to estimate potato yields, a mathematical optimization model using the model's biomass computations was constructed. Instead of multiple linear regression based on data from remote sensing and climate data, an artificial neural network model forecasted winter wheat yields better Khan et al. [8]. Romero et al. [9] maize and soybean yields were predicted using remote sensing data and other surface features, including a breakpoint. For categorizing the yield components of durum wheat across all research sites, association rule mining was shown to be the most successful machine learning technique. Crop yield estimations may be forecasted utilizing the most advanced modeling and solution approaches in this study that use environmental data and management strategies. Nonlinear modules are used in the representation teaching techniques class, which includes deep learning methods, to alter representations from multiple levels of abstraction. Any function may be represented by a deep neural network using this design. There is no requirement for deep learning algorithms to be constructed in order to improve their accuracy. Instead, they use data to identify the traits.

Applying decision-making approach for crop selection is the primary goal of this article. The Hybrid Deep belief network -VGG Net classifier may be used for this purpose. The remainder of the article is arranged as follows: Section 1 provides an overview of the decision-making and crop selection processes. Section 2 presented the relevant current techniques. Section 3 presented the problem's definition. Section 4 explains the method used to choose crops, while Section 5 explains the study's findings and results. Ultimately, Section 6 sums up the paper.

2 Related Works

Ma et al. [10] Using these data sources, a Bayesian Neural Network (BNN) is utilized to predict future climate. Late-season forecasting in the US Corn Belt using a BNN model has an R2 of 0.77, above the average coefficient of determination (R2) in testing years 2010 to 2019. Under both normal and exceptional weather circumstances, the suggested BNN model accurately predicted the production of maize. An R2 of 0.75 was achieved two months before to harvest in the middle of August, confirming the accuracy of the forecast. Kross et al. [11] As a means of determining which of a number of predictor elements are most important, an artificial neural network (ANN) approach was used. A least optimum variable dataset was used to test ANN models for their capacity to anticipate maize and soybean yields over a long period of time at the within-field level. Agricultural production was predicted using Normalized Difference Vegetation Index (NDVI) collected from satellite data, as well as red edge NDVI (simple ratio) and elevation-related factors (flow accumulation, aspect). Kaneko et al. [12] Six African countries' grain yields were estimated using satellite pictures and deep learning . Jiang et al. [13] Recurrent neural networks(RNN) with long short-term memory (LSTM) might be used to forecast maize yields. Data on county-level maize production and hourly meteorological factors make the sample space big enough for deep learning systems. A good fit for this application is LSTM's ability to anticipate time series with complicated internal linkages. Layona et al. [14] Swarm Optimization (SSO) based on Particle Swarm Optimization (PSO) and Cat Swarm Optimization is described in this study in order to anticipate industrial production. Saranya et al. [15] A neural network and an incremental learning approach are used to forecast and improve the system's performance . Peng et al. [16] Researchers looked at three satellite products for maize and soybean production projections in the Midwest: gap-filled Smooth Inverse Frequency (SIF) from the Orbiting Carbon Observatory-2 (OCO-2), new SIF data from TROPOspheric Monitoring Instrument (TROPOMI) , and coarse-resolution SIF data from Global Ozone Monitoring Experiment-2 (GOME-2). For the purpose of estimating SIF yields, VIs derived from land surface temperature were put up against satellite-based vegetation indices like Normalized Difference Vegetation Index, Enhanced Vegetation Index, Near Infrared Index (NDVI, EVI, and NIR). A total of five machine learning algorithms were used to create remote sensing-only and climate-remote sensing forecasts. Higher resolution SIF data from OCO-2 and TROPOMI allowed for more accurate crop production predictions than coarse-resolution SIF data from GOME2. Corn and soybean yields were accurately forecasted by high-resolution SIF products utilizing satellite-based high-resolution SIF data. The SIF's high-resolution outputs did not outperform alternative satellite-based remote sensing variables in any of the analyzed instances. Zhong et al. [17] Deep learning-based time series classification is the goal of this study. Commercial crops prevail in irrigation systems in Yolo County. Landsat Enhanced Vegetation Index (EVI) time-series data was utilized to identify summer crops because of the large diversity of crops that may be identified. We also looked into XGBoost, Random Forest, and Support Vector Machine (SVM).

3 Problem Statement

In agriculture the farmers are looking for cultivate the crop which yield maximum. Among the many variants in crops, choosing the best crop should be vital in making the agriculture with more profitable. So the biggest problem with farmers is the crop selection. They generally grow that product which was marketed at a great price last year. But the crop yield is based on many factors .The use of data mining technologies in agriculture could help determine the best crop choice or the best hybrid seed choices for a crop mix adapted to various objectives, conditions and better suited for farm's needs. Many algorithms can be developed to help determine which crops have the probability of achieving maximum yield potential in every environment. But each algorithm proposed having some disadvantages. Hence an advanced computerized crop forecasting approach solves the crop selection issues consequently, an effective decision-making methodology is needed for crop selection.

4 Proposed Methodology

There are several factors that affect the pace at which crops may be harvested in a given region. It is possible to employ a variety of machine learning approaches in order to estimate agricultural yields. Among these prediction methods, the deep learning strategy is the only one that has yet to be used. Fig. 1 demonstrates the methodology proposed to increase the crop yield based on decision-making using optimization. Here in which initially the dataset can gets collected and then the preprocessing can be done to normalize the Z-score will gradually remove the unwanted errors. Then from the pre-processed data adaptive shearlet approach was implemented for the purpose of extracting the features. The Tweak Chick Swarm Optimization (TCSO) based feature selection method was used for pointing out the specialized features. Finally by implementing the discrete hybrid Deep belief network with VGG NET classifier for efficiently ranking and classify the crops based on the yield.

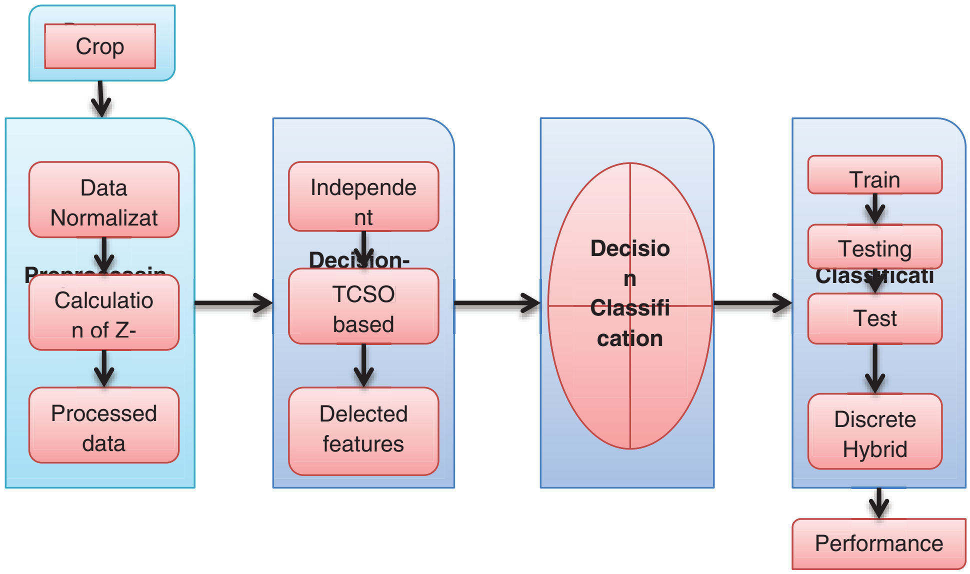

Figure 1: Visual depiction of the suggested approach

4.1 Preprocessing

The values must be standardized before they can be used in data processing. Some methods of normalization merely need a rescaling procedure in order to get the values that are connected to another variable. When we know the crop population characteristics, we need to make some easy changes to correct the mistakes. After correcting the inaccuracies, the population values may be normalized rather than randomly distributed. The Z-score is obtained as the initial stage in the normalizing procedure. Eq. (1) shows how the Z-score is calculated.

$$\mathrm{X} = [(\mathrm{Z} - \mu)/\sigma] \tag{1}$$

Calculating the population standard deviation is a simple process. Eq. (2) may be used to represent the sample mean and standard deviation if the population mean and standard deviation are unknown.

$$X = \frac{Z - \bar{Z}}{S} \tag{2}$$

$\bar{Z}$ is the calculated value of mean, and S is the standard deviation value. It is necessary to alter the mistakes in order to achieve the same values as the input values during the normalization process, hence the regression analysis approach is used. There is a basic linear regression model Y shown in Eq. (3) that may be used for this purpose.

$$Y = \alpha_0 + \alpha_1 X + \in \tag{3}$$

The random sample is in the form of,

$$Y_i = \alpha_0 + \alpha_1 X_i + \in_i \tag{4}$$

where $\in_i$ is the deviating errors and it is dependent on the σ^2

The residuals are pseudo errors that can be created. $\sum_{i=1}^{n} \hat{\in}_i$ are the residuals.

$$\sum_{i=1}^{n} \hat{\in}_i = 0 \tag{5}$$

$$\sum_{i=1}^{n} \hat{\in}_i z_i = 0 \tag{6}$$

When this Eq. (7) is used, the Hat matrix (H) may be determined,

$$\mathrm{H} = Z * \left(z^T z\right)^{-1z^T} \tag{7}$$

The variance for the Hat matrix is represented in Eq. (8)

$$Var(\hat{\in}_i) = \sigma^2(1 - h_{ii}) \tag{8}$$

$$Var(\hat{\in}_i) = \sigma^2(1 - \frac{1}{n} - [\left(z_i - \bar{z}^2\right) / \sum_{j=1}^{i} \left(z_j - \bar{z}^2\right)]) \tag{9}$$

Following that, we must normalize the variable's movement using the standard deviation. The following formula may be used to determine the moment scale deviation,

$$\mathrm{K} = \frac{\mu^k}{o^k} \tag{10}$$

In Eq. (11), k denotes the moment scale

$$\mu^k = E(z - \mu)^\wedge K \tag{11}$$

where z is a random variable and E is the expected value

$$o^k = (\sqrt{E(z - \mu)^\wedge K})^\wedge 2 \tag{12}$$

For normalizing the distribution of the variable using the mean μ particularly for the normal orderly distribution

$$C_v = \frac{S}{\bar{z}} \tag{13}$$

where C_v is the coefficient of the variance represented in the Eq. (13). The normalized data will be in the form of X'

$$z' = \frac{(z - z)}{(Z_{max} - Z_{min})} \tag{14}$$

It is possible to standardize and equalize range and variability in the data set after the normalization of the data. Data redundancy should be reduced or eliminated in the majority of cases. Afterwards, the normalized data may be used as an input for the next processes.

4.2 Feature Extraction

It then used an independent shearlet approach (ISA) to choose certain characteristics after pre-processing. To remove second-order mathematical texture properties, use this method. For instance, it has been used in a number of applications where higher-order features are involved in the interaction of three or more data attributes. This is a math problem that is often efficient at removing unnecessary information. When it comes to cutting down on dimensions, the most popular method is ISA. Variables and components associated with each other are transformed into a set of linearly uncorrelated variables using the ISA technique Initial variables linear combinations are often used as components of a linear combination. As a result, these first few components are able to minimize dimension and categorize data more successfully by maintaining maximum data variance. Shearlet may be used to indicate the frequency of data characteristics in a certain differential feature. It is possible to arrange the shearlet procedure as follows::

$$g(v,w) \approx \sum_{i,j} \left[I(i,j) + vI_x + wI_y - I(i,j)\right]^2 \tag{15}$$

It's not uncommon for a certain component of G to have a frequency of 0 or 1, (v,w) is the component of (i, j) and I is the standardized constant. The ISA uses N-dimensional vectors to express the location of each component in the feature space. Once the connection is established, the attributes may then be selected. Consider each function's predictive power and redundancy while evaluating the subset of functions (or similarity). The correlation between the characteristics may be established using the following equation.

$$K\left(\frac{o}{\partial},\mu\right) = \left[\frac{\varphi(\partial+\mu)}{\varphi(\partial)\varphi(\mu)}\right]o^{\wedge}(\partial+\mu)^{\wedge}(\mu-1) \tag{16}$$

Finally, some of the most essential crop characteristics that are available may be illustrated in the following illustration.

$$Minimalcapital = \frac{1}{l} - 1\sum_{l-1}^{l-1} a(j+1) - y_i(\mathrm{j}) \tag{17}$$

$$\text{High yield} = \sum\nolimits_{i,j=0}^{n-1} F(i,j)\left[\frac{(i-\mu i)(j-\mu j)}{\sqrt{(\sigma i^2)}\sqrt{(\sigma j^2)}}\right] \tag{18}$$

$$\text{Flexible marketing} = \sum_{i,j=0}^{n-1} \frac{F(i,j)}{F} - (F+2) \tag{19}$$

With this technique, data can be processed and crop characteristics may be extracted from the data in an efficient way. Fig. 2 depicts the desired characteristics for crop prediction in the following way:

4.3 Feature Selection

Feature selection for categorization presents a variety of issues and considerations. Due to the need for large numbers of samples for feature selection algorithms, this is a major issue. Feature selection in classification is the focus of this research study. Supervised learning is required for the vast majority of classification tasks, which aids prediction models. The running time of a learning algorithm is impacted by the number of duplicate features in a large dataset, and minimizing those redundant features yields a better classifier. The optimum feasible combination of feature subsets may be found using optimization methods, which reduces the computational cost. The number of features in a feature vector should be kept to a minimum in order to increase classification accuracy. The experimental field will be planted with a variety of agricultural crops based on the results of a decision model. There were 100 input variables that were grouped into 25 fundamental variables, such as land and water and the seasons. A decision-making model was developed to assist farmers in making crop selection decisions at various agricultural areas using data collected *via* the extraction of features. This data included 100 input variables. A Tweak Chick Swarm Optimization technique is used to pick 25 of the 100 input variables. In our technique, we employ optimization to assign relative weight to features based on their relative information and reduce training error, as indicated by the optimization. These algorithms cannot detect the connection of features according hierarchy of features but the tweak chick swarm optimization can, but it does so by using semantic similarity rather than geometrical similarity, which is used in other optimizations like PSO and ACO. Because chick swarm optimization offers an efficient connection between features and information from features, it reduces the number of features used in Discrete Hybrid deep belief network with VGG NET, which reduces the training error of classifier. Classification error is reduced, but accuracy, precision, and recall are all improved. The recommended optimization technique populates the layout based on a user's subjective preferences. In order to improve the algorithm that detects this perfect solution quickly, solution creation is essential. Look at the [–1, 1] binary output class's F1 and F2 characteristics, which are equally distributed on [–1, 1]. Accordingly, the final feature set is shown in the following way:

S. No	Features	S. No	Features	S. No	Features	S. No	Features
1	Minimum Capital	26	cloud, haze and rain	51	Disease susceptibility	76	Transpiration
2	Short Duration (Yield)	27	light interception	52	Length	77	growth and reproduction
3	Minimum Irrigation	28	dry matter production	53	gross assimilation	78	morphology
4	CO_2 assimilation	29	leaf age and condition	54	Mass	79	pest lifecycles
5	Low Manpower	30	degree of stomata control	55	net daily growth rate	80	Intercropping
6	light saturation	31	soil surface wetness	56	Root longevity	81	Vitamin supplements
7	Easy Cultivation	32	soil water evaporation coeff	57	Potential grain growth rate	82	pest and weed pressure
8	Gross assimilation	33	irrigation system design	58	Root hair length	83	range of traits
9	Minimum Fertilizer	34	organic matter content	59	Salt resistance	84	tolerance traits
10	leaf area index	35	unsaturated soil matrix	60	Soil type	85	physiological and
11	Low risk	36	water infiltration and redist	61	normalized difference	86	pattern and configuration
12	Easy Harvesting	37	breeding	62	Climate (season)	87	food and water transport
13	leaf nitrogen content	38	field capacity	63	biomass	88	Seed-Producing Capability
14	Marketing Facilities	39	wilting point	64	Orders/supply	89	Vascular System
15	Water deficiency	40	Crop Circle	65	Marketing strategies	90	hormone production
16	High profit	41	Photosynthesis	66	Water /nutrient requirebility	91	conversion of light into
17	radiation tolerance	42	Crop response	67	Finance support	92	Flower visibility or
18	Plant cell size	43	pest infestation	68	Labor	93	stability
19	Drought tolerance	44	Stomatal conductance	69	water stress	94	structural qualities
20	Width of the cortex	45	Greenness	70	Leaves structure	95	Gas exchange
21	Leaf chlorophyll content	46	layers of vegetation	71	Canopy structure	96	water loss
22	Root diameter	47	agronomic performance	72	Leaf pigments	97	haploid and diploid
23	Pest susceptibility	48	consumer-preferred traits	73	vegetation heterogeneity	98	Alternation of Generations
24	Growth rate	49	seasonal	74	vegetation indices	99	reduced tillage
25	Angle	50	doses of fertilizer	75	sun illumination	100	Crop rotation

Figure 2: Selected features

$$\mathrm{O} = \begin{cases} 0 \; if \;\; F1 + F2 \; < 0 \\ 1 \; if \;\; F1 + F2 \; \geq 0 \end{cases} \tag{20}$$

In this situation, the data points are located in the depths. F1 and F2 may be selected with ease since the issue is linearly separable. For each cycle that has been recorded, the following fitness function may be calculated:

$$\mathrm{N}\left(R_{i\,,}\, P_{j\,,}\,\right) = \; N_{i\,,} \;\; e^{bt}.\ \mathrm{F\ Cos}\ (2\pi t) + P_{j\,,} \tag{21}$$

Rooster index P is chosen at random from the roosters' group, and rooster P's fitness value R_i is its fitness value as represented by a normal distribution N_i. According to the following scenario, the chick's pursuing behaviour is typically impacted by its own movements:

$$\sigma_{km} = G_{km}/G_{km(\max 1)} = \frac{\sqrt{(G_{kz} - G_{mz})}\hat{}2 + (G_{ky} - G_{my})\hat{}2}{|G_k| * |G_m|} \tag{22}$$

where σ_{km} the movement of the hens. It is possible to get a better understanding of data by selecting optimum characteristics for the ranking process, which is made possible *via* the use of optimization. Each iteration and after making adjustments to the crop list, the best crops are categorized based on their physiological values.

$$Best = \ min_{i=1}^{M} OV_{*}^{i} \tag{23}$$

when the i th iteration number is reached, OV is the best choice for crop production. 100 features may now be prioritized using the TCSO algorithm. Fig. 3 shows the 25 options for pointed characteristics that may be chosen. This suggests that the characteristics were supplied to the classification model after the best fitness with ideal features was attained. In terms of memory and runtime, the proposed optimization approach is a good fit for the task. Also adept at discovering the smallest possible feature set.

S.No	Features	Rice	Wheat	Maize	Millets	Pulses	Cotton	Sugarcan	Coconu
1	Minimum Capital	7	5	8	6	8	8	8	3
2	Short Duration (Yield)	6	3	7	4	7	7	5	2
3	Minimum Irrigation	5	2	5	4	4	3	3	3
4	Low Manpower	6	4	3	5	4	5	4	4
5	Easy Cultivation	5	3	5	4	5	3	3	2
6	Minimum Fertilizer	5	4	3	5	6	6	4	5
7	Low risk	6	3	5	3	5	4	3	4
8	Easy Harvesting	7	4	4	5	6	3	4	6
9	Marketing Facilities	8	6	7	7	8	5	7	8
10	High profit	9	7	7	8	8	7	8	9
11	Plant cell size	5	6	4	7	2	4	8	9
12	Width of the cortex	3	2	4	5	2	6	8	8
13	Root diameter	3	2	5	7	7	8	8	8
14	Growth rate	7	6	5	8	8	7	5	5
15	Angle	5	6	7	5	6	7	7	5
16	Length	6	2	4	2	3	4	9	9
17	Mass	7	5	6	2	5	3	6	7
18	Root longevity	6	7	8	9	6	6	7	8
19	Root hair length	5	5	6	8	9	8	6	7
20	Soil type	8	8	9	7	8	8	7	6
21	Climate (season)	9	5	9	8	8	7	9	9
22	Orders/supply	4	6	7	8	6	6	7	7
23	Water /nutrient	8	7	9	6	5	4	5	7
24	Finance support	9	5	6	7	8	7	5	6
25	Labor	8	8	7	5	7	3	5	4

Figure 3: Extracted features

4.4 Discrete Hybrid Deep Belief Network with VGG NET Classification

Deep belief networks include multiple non-linear hidden layers, which may be pre-trained in the network trainer to act as a non-linear decrease of input dimensionality. There are several similarities between neural networks and VGG's KNN version. In order to better identify anomalies, a deep belief neural network may be combined with VGG to create a hybrid. Because of this, the crop must be differentiated, and whether it can be used in a certain location depends on the traits that can be removed and improved. The input data are classified according to their unique properties in order for the extraction and recovery procedure to be improved. The vegetation data are analyzed using a Discrete Hybrid Deep Belief Network with VGG Classification for improved or specific functionality. Deep belief networks with VGG classification techniques both exhibit improved accuracy and efficiency and consistency in fundus pictures. Featured were utilized to help identify the specific crop. It is the features obtained that are used to classify things in this manner. Deep belief networks using VGG are able to estimate probability and carry out a step of classification. There's a general dispersion to be found. Classifiers first analyze and resize the data, and then the classification procedure by measuring the class probability is performed. Crop may be forecasted using the provided classifier, which takes into account the numerous input factors. As a result, the model forecast three harvests, based on their respective ranks. It's therefore possible to rank data S, based on how far apart they are from each other.

$$obj_{ED} = -20 * \mathrm{q}\left(-2 * \sqrt{\sum \mathrm{S}_v}\right)/2 - \exp\left(\frac{\sum \cos(2\pi * \mathrm{S}_v)}{d_b}\right) + 20\exp \tag{24}$$

where ED signifies the Euclidean distance, q denotes the query data and s is the score value of the image .

$$\text{classify F}(obj_{ED}) = \mathrm{a}_j^l \mathrm{b}_j^l \tag{25}$$

The classification concluded as

$$\mathrm{F} = \mathrm{a}_j^l \mathrm{b}_j^l - \mathrm{n}\left(\mathrm{a}_j^l \mathrm{b}_j^l\right)^2 \tag{26}$$

where F denotes the feature, n is the highlighted feature, and $\mathrm{a}_j^l \mathrm{b}_j^l$ denote the categorized features, respectively. Finally by implementing the novel classifier the crops can be ranked as per the yield expectation. The suggested methodology can also be tested in some other datasets like soil dataset, and rainfall dataset. The prediction of crop is dependent on soil parameters and rainfall such as PH, electrical conductivity, nitrogen, phosphorus, potassium, soil type, rainfall event (E), intensity (I), and duration (D) to predict crop accurately. By using the National soils database (https://data.gov.ie/dataset/national-soils-database) and data. World (https://data.World/datasets/rainfall) dataset the suggested methodology can gets analyzed to test the multi scalability of the implemented model. Here for training the suggested classifier

- Make two separate training sets.
- Run half of the dataset for training and half of the dataset for testing.

The training and testing mainly depends on the length or size of the input. Finally depend upon the trained features the test data can gets classified.

Algorithm 1 (*Discrete* Hybrid Deep belief network with *VGG NET)*

Input: Input data

Output: Classified data

Step1: *Data normalization*,

Error removal Eo_c

Data n_e

Data_id s_{id}

speed s_p

maximum_length of the data

Normalized data = $z' = \frac{(z-z)}{(Z_{max}-Z_{min})}$

Step 2: Feature extraction

Decision matrix dm_{mat} *= [];*

*for:size (*1*)*

feature subset

end

Else

end

end

end

step 3: Relative closeness features estimation

for optimized fitness features

tweak chicks

selected features

end

step 4: Classification

for $ED = obj_{ED} = -20 * \ q \ \left(-2 * \sqrt{\sum S_v}\right)/2 - exp \ \left(\sum cos(2\pi * S_v)/d_b\right) + 20exp$

*Hybrid DBN*VGG*

Class merge

flag

end

end

end

Classified_val = F = $\mathrm{a}_j^l \mathrm{b}_j^l - \mathrm{n}\left(\mathrm{a}_j^l \mathrm{b}_j^l\right)^2$

end

end

end

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5 Result and Discussion

This section focuses on the findings of the model's experiments. Since the new decision-making model has been put into place, it is now possible to run simulations under MATLAB. Consistent results would be achieved by increasing the number of tests. As a result, the overall performance of this section's recommended method will be evaluated.

5.1 Dataset and Study Area Description

Data for crop predictions was collected from India's state agriculture webpage. Cultivating crops with a wide range of cultivars and soil types is essential to cultivating crops with a high level of crop competence. In addition to district-level segmentation and yearly monsoon precipitation data, this dataset includes high and low temperature rates and other weather-related metrics. The Dataset and its attributes are described in Tabs. 1 and 2.

Table 1: Dataset description [17]

Dataset	Total number of attributes	Number of instances
Agriculture crop dataset	7	13,457

Table 2: Description of the attributes

No of Attributes	Description of the attributes
Season	Data from 1997 to 2015 is included.
Name of the states	India's state names are included.
Name of the districts	In Tamil nadu, there are 32 district names in this list.
Name of the crops	There are 124 different sorts of crops in this area.
Area	A variety of farmed areas are present.
Production range	Limit the number of crops that may be grown.

The preprocessing of the input data as a first step is recommended. Once the data is preprocessed, the adaptive shearlet technique may be used to extract features. A combinatorial optimization approach known as global combinatorial optimization is used here to minimize the amount of features, eliminate unnecessary, noisy and redundant data, and achieve standard classification accuracy. As a result, TCSO was recommended for use in the feature selection process. The optimizer may pick 25 characteristics that can be used as an input for the process of categorization. In this case, crops may be sorted and categorized using the Discrete Hybrid deep belief network with VGG NET classifier. The suggested solution's results and feasibility are calculated and compared to the calculation's parameters.

A decision optimization model and a Discrete Hybrid deep belief network with VGG Classification were used to identify the optimal crop as shown in Tab. 3. Higher yields may be expected from millets, rice, and wheat than from other crops.

Table 3: Calculating the best crop related to its rank

Crops	Minimum capital (f1)	Flexible marketing (f2)	Rank (f1)	Rank (f2)	R(f1)-R (f2)	$(R(f1)\text{-}R(f2))^2$
Millet	7	8	2	1	1	1
Rice	5	6	4	3	1	1
Maize	8	7	1	2	–1	1
Pulses	6	7	3	2	1	1
Sugarcane	8	8	1	1	0	0
Cotton	8	5	1	4	–3	9
Coconut	8	7	1	2	–1	1
Wheat	3	8	5	1	4	16
Total $\sum(R(f1) - R(f2))^{2}$						30

5.2 Performance Analysis

Dice Score:

The characters o and p stand for the properties of the underlying truth data and the data characteristics that were discovered. As a result, the Dice coefficient can be computed,

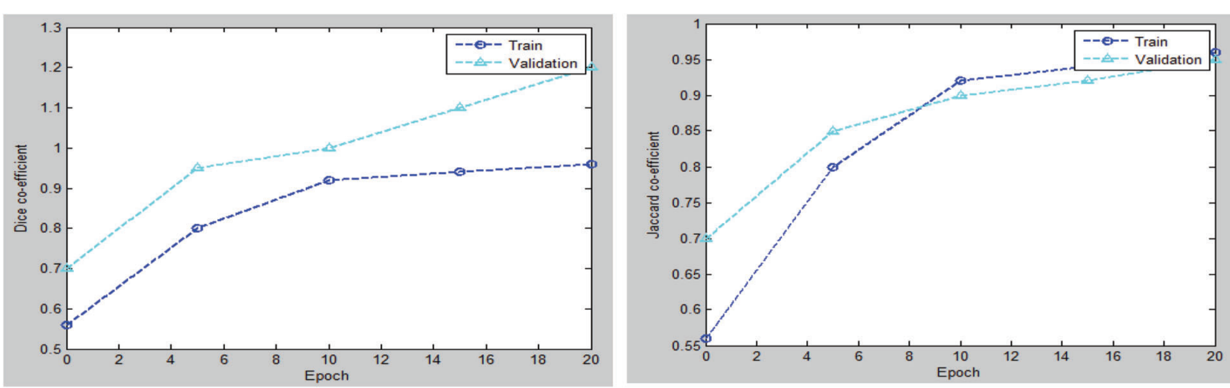
$$D(o, p) = (2o \cap p/o + p) = 2\text{True Positive}/2\ \text{True Positive} + \text{False Negative} + \text{False Positive} \quad (27)$$

Jaccard Score:

It is possible to determine the degree of similarity between the two groups.

$$\begin{aligned} J(o, p) &= (o \cap p/o\mathbf{U}p) \\ &= (o \cap p)/o + p - (o \cap p) \quad (28) \\ &= (\text{ True Positive } / \text{ True Positive } + \text{ False Negative } + \text{ False Positive}) \end{aligned}$$

Figs. 4a and 4b provide a dice and Jaccard rating for the solution. The results demonstrate that the suggested technique accurately displays high Jaccard values and the dice coefficient.



(a) (b)

Figure 4: (a), (b) Comparative analysis of proposed dice and Jaccard

Comparative Analysis:

Existing research [14] and [17] use a variety of novel methodologies, which are briefly discussed in this section.

Accuracy

It's a slew of well-planned mistakes. It is the fraction of real results that determines the quality of the data (both positive and negative).

$$\text{Accuracy} = \text{Recall} = [a/(a+d)] \times 100 \tag{29}$$

Precision

Algebraic variability is measured by precision, which depicts random mistakes.

$$\text{Precision} = [a/(a+d)] \tag{30}$$

Recall

The genuine optimistic rate, warning, or likelihood of identification are all terms used to describe the percentage of positive information that can be recognized accurately.

$$\text{Recall} = [a/(a+d)] \times 100\text{Specificity} \tag{31}$$

Here a represents true positive, d represents true negative.

Mean Square Error

Measurement of the average squared difference between estimated and actual values is done using this technique.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \widehat{x_i})^\wedge 2 \tag{32}$$

Based on substantial performance measures, the notion is compared with existing algorithms and approaches for identification. For the crop selection technique, the Discrete Hybrid deep belief network with VGG was employed. Data set result values of the proposed decision-making model output are shown in Figs. 4–8. The best results may be attained if the proposed classification model is used. The results indicate that the recommended strategy will perform better. Total accuracy and precision of 97 percent, with 94 percent recall.

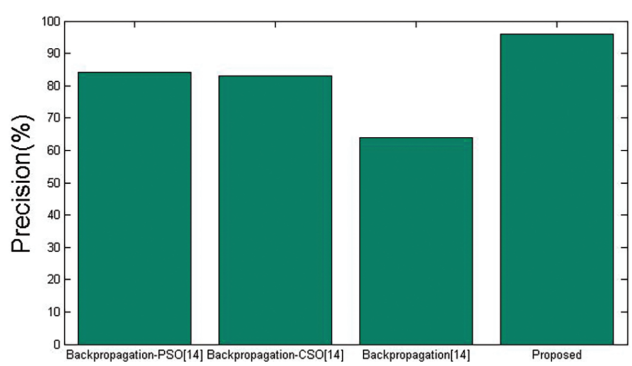


Figure 5: Output of precision

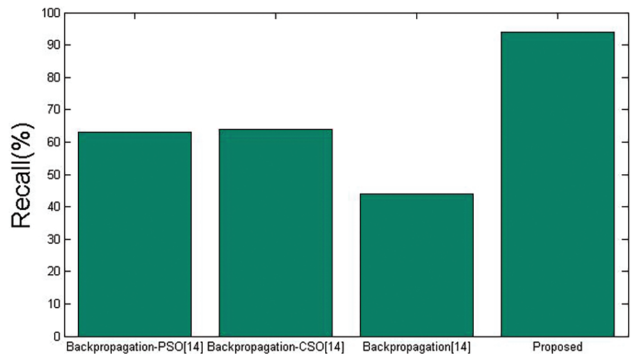


Figure 6: Output of recall

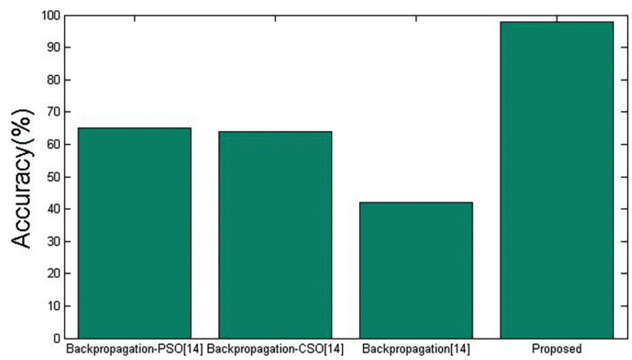


Figure 7: Output of Accuracy

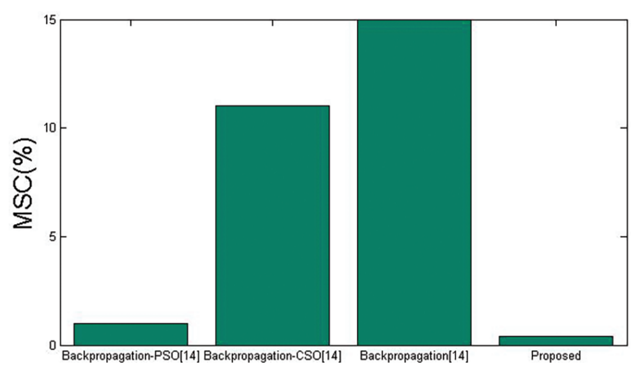


Figure 8: Output of MSE

Tab. 4 shows that the proposed methodology was compared to three other recently proposed methodologies. Analysis shows that the proposed approach has superior precision, recall, accuracy, and mean square error (MSE) than alternative methods.

Table 4: Comparative analysis

Parameters	Backpropagation + PSO [14]	Backpropagation + CSO [14]	Backpropagation [14]	Discrete hybrid deep belief network with VGG (Proposed)
Precision	0.83	0.84	0.64	0.97
Recall	0.63	0.61	0.44	0.94
Accuracy	0.67	0.68	0.42	0.98
MSE	0.15	0.45	0.55	0.1

The F-score, also known as the F1-score, may be used to measure the model's accuracy. This approach is used to classify input as either "positive" or "negative" in a binary system. Using the harmonic mean of the model's accuracy and recall, it may be characterized as a way of integrating precision and recall. The detailed analysis of F1 score shown in Tab. 5.

Table 5: Analysis of F1 score

Methods	F1 score
SVM [17]	0.68
RF [17]	0.67
XG-Boost [17]	0.69
LSTM Based [17]	0.67
Conv 1-D-based [17]	0.73
MLP [17]	0.69
Discrete Hybrid deep belief network with VGG (Proposed)	**0.88**

The overall performance metrics shown in Fig. 9 are part of the present approach. An example of AROC, which is 0.9677, may be seen in Fig. 10. If the AROC score is 0.9677, it means that the classifier accurately identified the class as shown in Fig. 10. The sensitivity/specificity pairs presented at each position on the AROC curve may be used to define decision thresholds. To test how successfully a parameter distinguishes between various crops, the area under the AROC curve is used. It is obvious from the findings that the suggested technique outperforms the present method in comparison.

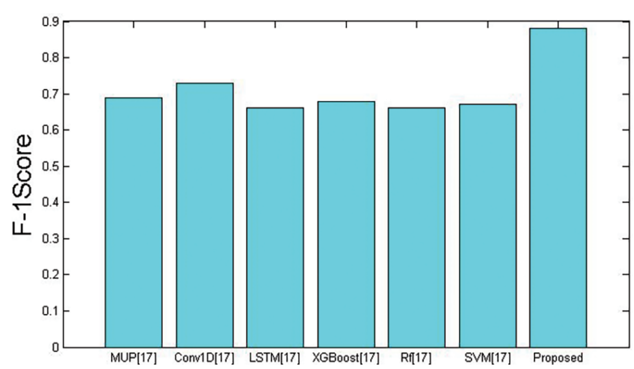


Figure 9: Efficiency of the implemented model

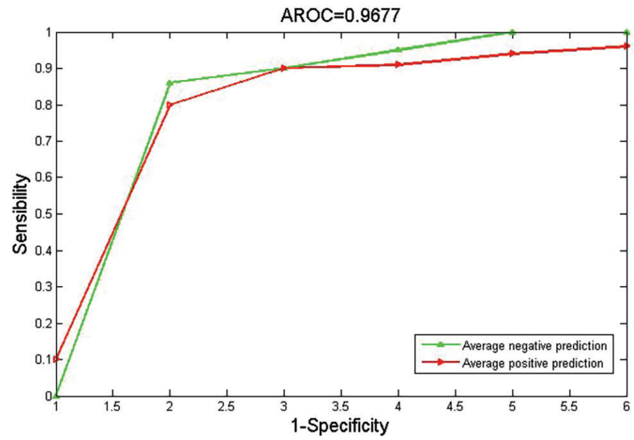


Figure 10: Performance of AROC

6 Conclusion

A deep learning-based strategy for agricultural yield prediction was suggested in this study, which accurately predicted crop yields throughout the complete dataset utilizing environmental data and management strategies. Based on the planting schedule, we employ a Discrete Hybrid Deep belief network using VGG NET algorithm to identify crops. The proposed approach may be used in three different datasets. Crop separation improvement in planting-based timetables may be accomplished by focusing on a theoretical model in this application. The implemented technique is compared to three other previously disclosed methods in order to determine its efficacy. When compared to other ways, the performance of the suggested method is effective. In this case, it is evident that the suggested method selects the most profitable crop.

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References

[1] J. H. Jeong, J. P. Resop, N. D. Mueller, D. H. Fleisher, K. Yun *et al.,* “Random forests for global and regional crop yield predictions,” *PLoS One*, vol. 11, no. 5, pp. 156571, 2016.

[2] S. Fukuda, W. Spreer, E. Yasunaga, K. Yuge, V. Sardsud *et al.,* “Random Forests modelling for the estimation of mango (Mangifera indica L. cv. Chok Anan) fruit yields under different irrigation regimes,” *Agricultural Water Management*, vol. 116, no. 2, pp. 142–150, 2013.

[3] O. M. Adisa, J. O. Botai, A. M. Adeola, A. Hassen, C. M. Botai *et al.,* “Application of artificial neural network for predicting maize production in South Africa,” *Multidisciplinary Digital Publishing Institute*, vol. 11, no. 6, pp. 1145, 2019.

[4] C. J. Ransom, N. R. Kitchen, J. J. Camberato, P. R. Carter, R. B. Ferguson *et al.,* “Statistical and machine learning methods evaluated for incorporating soil and weather into corn nitrogen recommendations,” *Computers and Electronics in Agriculture*, vol. 164, no. 4, pp. 104872, 2019.

[5] S. Nosratabadi, K. Szell, B. Beszedes, F. Imre, S. Ardabili *et al.,* “Comparative analysis of ANN-ICA and ANN-GWO for crop yield prediction,” in *Int. Conf. on Computing and Communication Technologies (RIVF)*, Ho Chi Minh City, Vietnam, IEEE, vol. 12, no. 8, pp. 1–5, 2020.

[6] M. Shahhosseini, R. A. Martinez-Feria, G. Hu and S. V. Archontoulis, “Maize yield and nitrate loss prediction with machine learning algorithms,” *Environmental Research Letters*, vol. 14, no. 3, pp. 124026, 2019.

[7] M. M. Awad, "Toward precision in crop yield estimation using remote sensing and optimization techniques," *Precision Agriculture*, vol. 9, no. 8, pp. 54, 2019.

[8] M. S. Khan, M. Semwal, A. Sharma and R. K. Verma, "An artificial neural network model for estimating Mentha crop biomass yield using Landsat 8 OLI," *Precision Agriculture*, vol. 21, no. 20, pp. 18–33, 2020.

[9] J. R. Romero, P. F. Roncallo, P. C. Akkiraju, I. Ponzoni, V. C. Echenique *et al.,* "Using classification algorithms for predicting durum wheat yield in the province of Buenos Aires," *Computers and Electronics in Agriculture*, vol. 96, no. 9, pp. 173–179, 2013.

[10] Y. Ma, Z. Zhang, Y. Kang and M. Özdoğan, "Corn yield prediction and uncertainty analysis based on remotely sensed variables using a Bayesian neural network approach," *Remote Sensing of Environment*, vol. 259, no. 7, pp. 112408, 2021.

[11] A. Kross, E. Znoj, D. Callegari, G. Kaur, M. Sunohara *et al.,* "Using artificial neural networks and remotely sensed data to evaluate the relative importance of variables for prediction of within-field corn and soybean yields," *Multidisciplinary Digital Publishing Institute*, vol. 12, no. 9, pp. 2230, 2020.

[12] A. Kaneko, T. Kennedy, L. Mei, C. Sintek, M. Burke *et al.,* "Deep learning for crop yield prediction in Africa," in *ICML Workshop on Artificial Intelligence for Social Good*, Long Beach, United States, vol. 16, no. 7, pp. 33–37, 2019.

[13] Z. Jiang, C. Liu, N. P. Hendricks, B. Ganapathysubramanian, D. J. Hayes *et al.,* "Predicting county level corn yields using deep long short term memory models," arXiv preprint, vol. 7, no. 2, pp. 1805, 2018.

[14] R. Layona, S. Suharjito, Y. Tunardi and D. Tanoto, "Optimization of land suitability for food crops using neural network and swarm optimization algorithm," *International Review on Computers and Software (IRECOS)*, vol. 11, no. 8, pp. 1, 2016.

[15] C. Saranya and N. Nagarajan, "Efficient agricultural yield prediction using metaheuristic optimized artificial neural network using Hadoop framework," *Soft Computing*, vol. 24, no. 7, pp. 12659–12669, 2020.

[16] B. Peng, K. Guan, W. Zhou, C. Jiang, C. Frankenberg *et al.,* "Assessing the benefit of satellite-based solar-induced chlorophyll fluorescence in crop yield prediction," *International Journal of Applied Earth Observation and Geoinformation*, vol. 90, no. 8, pp. 102126, 2020.

[17] L. Zhong, L. Hu and H. Zhou, "Deep learning based multi-temporal crop classification," *Remote Sensing of Environment*, vol. 221, no. 9, pp. 430–443, 2019.