DEVELOPMENT OF CROP YIELD PREDICTION MODEL IN AGRICULTURE USING IMPROVED EXTREME LEARNING MACHINE

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Abstract

The finest utility sector is agriculture, particularly in emerging nations like India. Utilizing historical data in agriculture may change the context of decision-making and increase farmer productivity. Approximately a part of India's population is employed in agriculture, however this sector contributes just 14% of India's GDP. This may be explained in part by farmers not making sufficient decisions on yield forecast. Increased agricultural yield is the outcome of accurate crop forecast. With this goal in mind, this work proposes the Improved Extreme Learning Machine (IELM) approach, which aims to forecast the best-yielding crop for a specific region by analyzing a variety of atmospheric factors, such as rainfall, temperature, humidity, etc., and land factors, such as soil pH and soil type, as well as historical data on crops grown. In this study, feature selection strategies are used to forecast crops using classification algorithms that recommend the best crop(s) for a given plot of land. After pre-processing the data to eliminate any undesirable information like NULL and other entries, this system is meant to forecast the best yield based on the dataset it has been given. Weak characteristics are eliminated using the Recursive Feature Elimination (RFE) feature selection approach until the necessary attributes are fulfilled. The IELM classifier beats the other learning strategies, according on the experimental findings.

Keywords – Agriculture, crop yield prediction, Improved Extreme Learning Machine, rainfall, temperature, humidity, land factors, feature selection and Recursive Feature Elimination

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1. INTRODUCTION

The agricultural industry is essential to human survival and the economy. Crop selection in traditional agricultural methods relied on farmers' rudimentary understanding. Most often, farmers want to choose the crop that is most popular in their locality or neighborhood. The fertility of soils is negatively impacted by a lack of scientific understanding about farming and a lack of crop rotation. Soil nutrients, groundwater level, and fertilizer type are major determinants of crop quality. A traditional farmer deals with ongoing difficulties. The improper crops chosen and insufficient soil nutrients may cause the acidity of the soil to grow [1]. The biggest element affecting crop quality and productivity is the unstable climate. For the best crop selection and the health of the crop, soil fertility is crucial.

The goal of the study is to identify issues that farmers have while trying to grow quality, robust crops. We provide a crop production prediction model based on an ML algorithm to address the aforementioned difficulties in agriculture. It aims to solve a few existing agricultural problems brought on by ineffective methods. As shown in Fig. 1, it takes into account metrological elements such as temperature, humidity, rainfall, CO2 level in the air, soil pH, EC, and soil type. Plant development and output are directly impacted by metrological conditions [2]. Soil analysis is carried out to evaluate the soil's fertility. The macronutrients of soil, nitrogen, phosphorus, and potassium, are taken into account for soil analysis. These three essential elements are crucial for the health of plants and the prevention of illness. By regulating nutrient chemical reactions and forms, the soil pH controls soil nutrient available for crops and reveals how alkaline the soil.

The growth of the plant is impacted by higher and lower soil EC values. Additionally, it shows the soil's salinity, water quality, and fertility. The amount of CO2 in the air has a significant impact on crop health. It is used during the process of plant dataynthesis. Both clay and loamy soil may be used with the suggested model. These kinds of soil contain the proper levels of moisture and humidity for most crops. The amount of rainfall is also crucial for crop health [3], since various crops may need varying amounts of water. Before planting the crop, knowing the season's normal rainfall is quite helpful. Although it is difficult to anticipate, machine learning systems have shown encouraging outcomes. Crop output may increase from 50% to 90% by switching to precision farming methods. Precision farming is a methodical approach to rational decision-making and efficient resource use [2]. By using this strategy, soil fertility may be maintained. IoT can play a significant role in enabling precision agriculture.

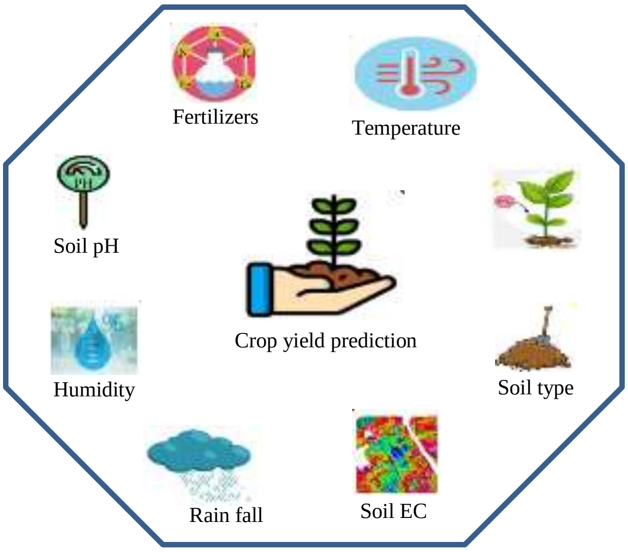


Fig. 1. SmartArt diagram for crop selection for yield prediction features.

An IoT-based agricultural system may provide efficient decision-making and steer clear of unpleasant circumstances. Smart agriculture uses automation systems, which are less costly than conventional agricultural methods yet more exact. Three layers make up the framework of IoT systems: perception, network, and application. Physical tools like sensors, RFID tags, and cameras are employed to gather data on the perception layer. Data transmission and forwarding are done at the network layer. IoT and a particular domain of use are combined via the application layer. [4].

A fascinating use of artificial intelligence is machine learning. It offers the opportunity to learn from encounters without the need of a formal curriculum [5]. The suggested strategy is built on simple, reasonably priced technology that farmers and agricultural officials may utilize to increase crop output. SCS model is tested after being trained by categorizing data. An ML classifier's effectiveness and accuracy are solely dependent on the kind and volume of the data [6]. In this research, I want to provide a classifier-based approach to agricultural production prediction. The three steps of the proposed agricultural yield prediction are pre-processing, feature reduction, and prediction. The input data is often inaccurate and missing specific behaviors or patterns, contradictory, and/or insufficient. Pre-processing data is a tried-and-true way to fix these problems. A good data pre-processing takes less time and results in a better model. The suggested technique's subsequent step involves feature selection using RFE. Finally, the suggested technique employs a classifier to forecast crop production. The IELM is used as the basis for the forecast. Predictions correctness and error value are used to assess how well the suggested strategy performs.

The remainder of the essay is organized as follows. Briefly describe relevant works in Section 2. Explain the suggested system in Section 3. highlighted and reviewed the findings in Section 4. Section 5 draws findings and suggests more research.

2. RELATED WORKS

For quick decision-making, crop yield forecast is a crucial responsibility for decision-makers at the national and regional levels (such as the EU level). Farmers may choose what to produce and when to grow it with the aid of an accurate crop production prediction model. There are several methods for predicting agricultural yields. This review section has looked at the research on agricultural yield prediction using machine learning that has been done in the literature. According to the study design, Patil et al. [7] suggested using a hybrid technique that combines logistic regression and random forest (LRRF) to forecast agricultural output based on yearly rainfall. Reinforcement Random Forest, a novel hybrid regression-based algorithm suggested by Elavarasan & Durai Raj Vincent [8], outperforms more well-known machine learning methods including random forest, decision tree, gradient boosting, artificial neural network, and deep Q-learning. The novel approach employs reinforcement learning at each choice of a splitting characteristic during tree building to make the most use of the samples that are available. The results showed that the suggested method works better with lower error measures and increased accuracy of 92.2%.

Guo & Xue [9] In this paper, a paradigm for modeling and predicting agricultural yields is provided. By addressing agricultural output and related variables as a non-temporal collection, it provides a complementing method to standard time series analysis on modeling and forecasting. In order to clean up the data and, if required, expand it for neural network training and testing, statistics are utilized to discover the highly linked factor(s) among various crop yield correlates. This incorporative technique is tested using the wheat production, related plantation area, rainfall, and temperature data from Queensland, Australia, over a 100-year period. To illustrate the advantages of regional agricultural output forecasting in Europe, Paudel et al. [10] created a general machine learning methodology. We anticipate crop yields for 35 case studies, nine of which are important producers of six crops, in order to assess the accuracy and utility of regional predictions.

With Wilcoxon p-values of 3e-7 for 60 days before harvest and 2e-7 at the end of the season, respectively, machine learning models at the regional level showed lower normalized root mean squared errors (NRMSE) and uncertainty than a linear trend model. In 18 out of 35 instances, regional machine learning predictions aggregated to the national level, 60 days before harvest, showed lower NRMSEs than forecasts from an operational system, with a Wilcoxon p-value of 0.95 suggesting equivalent performance. To find the most crucial factors for forecasting coffee output and to determine how to balance the nutritional state of the plants, such as Mg, Fe, and Ca levels to maximize yield, de Carvalho Alves [11] suggested a random forest model. For calculating coffee production in the field, characteristics pertaining to the nutritional condition of the coffee were more crucial than remote sensing variables. The occurring more frequently of each machine learning algorithm modeling was used in terms of the benefits of each methodology's results synergic in favor of carefully identifying the finest approach and techniques for crop management, even though the random forest model (rf) had a greater precision for predicting coffee yield when comparison to the rpart1SE model.

Pant et al., [12] employed machine learning to forecast four widely-cultivated yields that are mostly grown in India. Once the crop yield for a certain location has been estimated, inputs like pesticides may be administered differently based on the anticipated crop and soil demands. In this paper, we create a trained model for crop forecasting using machine learning methodologies to find trends in the data. In this work, machine learning is used to forecast the yields of the four most widely grown crops in India. These crops include wheat, potatoes, paddy rice, and corn. For five crops—soft wheat, spring barley, sunflower, sugar beet, and potatoes—and three nations—the Netherlands (NL), Germany (DE), and France (FR), Paudel et al[13] .'s forecasted production at the regional level. We contrasted the results with a straightforward approach that lacked any predictive ability and projected either a linear yield trend or the mean of the training set. Additionally, we combined the estimates to a national level and contrasted them with earlier MCYFS forecasts. By incorporating additional data sources, creating more predictive characteristics, and testing various machine learning methods, the baseline may be enhanced. The starting point will encourage the use of machine learning for extensive agricultural production forecasts.

Gong et al., [9] To identify the input weights and hidden biases of an extreme learning machine (ELM), two optimization techniques, swarm optimization (PSO) and genetic algorithms (GA)—were presented. Two innovative hybrid GA-ELM and PSO-ELM models were also constructed for ETo predictions with limited input data. 96 meteorology locations throughout China's diverse climates provided daily climatic data from 1994 to 2016 that was used to train and test the models utilizing a temporally and geographical technique that may prevent inaccurate or only partly correct findings. The findings showed that GA-ELM and PSO-ELM could measure ETo on a daily, monthly, and yearly time frame, with GA-ELM outperforming PSO-ELM in all environments. In order to create crop development and cultivating plans that are more production and wealth, Sakthipriya and Naresh [15] suggested a decision tree and a support vector machine approach that takes environmental factors, such as temperature and the nitrogen content of the soil, into consideration.

Pantazi et al., [16] Based on online multi-layer soil data and satellite crop growth parameters, forecast wheat yield within-field variance. By applying an unsupervised learning method, supervised self-organizing maps were created that are capable of managing data from various soil and crop sensors. For a single cropping season, the effectiveness of XY-fused Networks (XY-Fs), Supervised Kohonen Networks (SKNs), and counter-propagation artificial neural networks (CP-ANNs) were tested for forecasting wheat production in a 22 ha field in Bedfordshire, UK. To anticipate crop yields, Johnson et al. [17] used MODIS-NDVI, MODIS-EVI, and NOAA-NDVI as predictors using multiple linear regression (MLR) and two nonlinear machine learning models: Bayesian neural networks (BNN) and model-based recursive partitioning (MOB). The cross-validated mean absolute error skill score (in relation to climatological predictions) was used to assess crop production forecasts generated using predictors from July and earlier throughout the period 2000–2011. For all three crops, MODIS-NDVI was determined to be the best predictor, however adding MODIS-EVI as a second predictor improved forecasting abilities.

Inference: When diverse input patterns are analyzed, the over-fitting issues with the conventional machine learning models might result in unexpectedly significant forecast failures. In this work, the ELM approach was really created to address the knowledge gaps and shortcomings of existing predictive modeling techniques. The ELM has been shown to be an effective method and a promising algorithm for resolving over-fitting issues. The shortcomings of both conventional and machine learning prediction modeling approaches are really addressed by the ELM's process. The ELM's method makes it possible to significantly reduce the chance of suffering over-fitting during training, leading to constant forecast performance for unanticipated input patterns. Additionally, the random projections approach used in parallel computing techniques enhances the likelihood of a good converging operation and reduces the amount of time required to reach the efficiency objective.

3. METHODOLOGY

Human face is a critical facet as far as social cThe precise yield prediction for the several crops included in the planning is a critical concern for agricultural planning intentions. Data mining methods are a critical component of any strategy for achieving realistic and efficient solutions to this issue. Big data has a clear objective in agriculture. It is now more important than ever for farmers to utilize information and get assistance when making important agricultural choices because of changing environmental factors, soil variability, input levels, and commodity pricing. This effort focuses on the analysis of agricultural data and identifying the best settings to employ IELM to provide the highest crop yield possible. Optimizing productivity and strengthening agriculture's resistance to climate change requires analyzing new, non-experimental data as well as mining the vast amounts of current crop, soil, and weather data.

3.1 Input dataet description

Crop production data: The information relates to production and crop covered area (Hectare) statistics broken down by district, crop, season, and year (Tonnes). the data collection that may be found at https://data.world/thatzprem/agriculture-india.

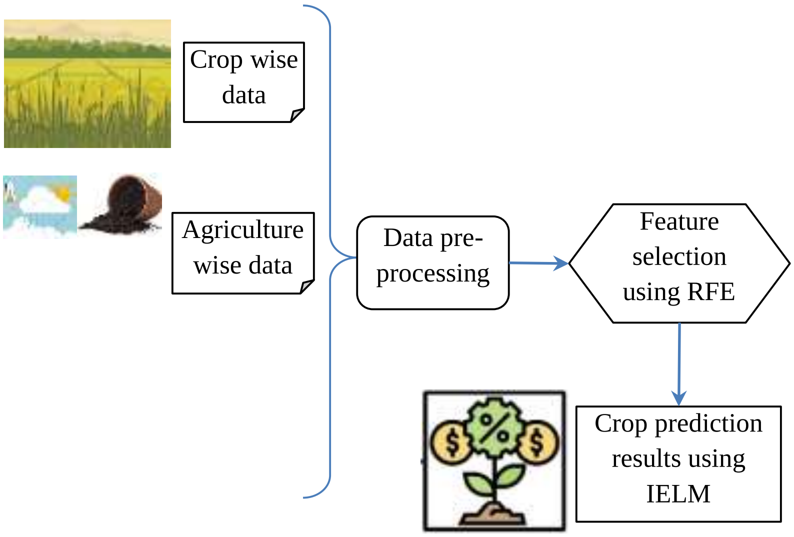


Fig. 2. General Framework diagram

The data is being utilized to research and analyze agricultural productivity, the importance of manufacturing to regions, states, and countries, the performance of agroclimatic zones, the order of high yielding crops, crop growth patterns, and crop diversification. The system is also an essential tool for developing crop-related plans and evaluating their effects. State Name, District Name, Crop, Year, Season, Crop, Cropclass, Area, and Production are the qualities.

Climate Link: The data is gathered from the official Indian website, Through the site collect minimum temperature (°C), maximum temperature (°(C), average temperature (°(C), precipitation(mm), humidity (%), pressure, dew point °C, wind. (m/s). The attributes are Max-Temp, Min-Temp, Avg-Temp, Precipitation, Humidity, Dew points, wind and pressure.

The data in the proposed study is clustered based on districts with comparable temperature, rainfall, and soil type using a modified IELM technique. Based on these evaluations, we are determining the ideal crop production parameters, and the yearly crop output is predicted using the IELM approach. In this work, RFE used for feature extraction process.

3.2 Data pre-processing and RFE based feature selection

The BMI attribute in the retrieved dataset has null values, which must be eliminated. If these values are present, the model's correctness may suffer. Additionally, the

'LabelBinarizer' technique is used to encode the category values into numerical values since training is only possible on numerical values because it entails standardizing the characteristics. It is necessary to find the relevant aspects that have a strong and positive connection with features of interest for crop production prediction after calculating the missing values. Construction of a reliable diagnostic model is hindered by the elimination of unnecessary and worthless characteristics during the vector feature extraction process [18]. In this work, the most crucial elements of a prediction were extracted using the RFE approach. Due to its simplicity of usage and setups, as well as its efficiency in picking characteristics in training datasets important to detecting goal parameters and removing weak characteristics, the Recursive Feature Elimination (RFE) method is particularly well-liked. By identifying strong connection among certain characteristics and the goal, the RFE approach is used to choose the most important features (labels). The following are the steps for:

Step 1: Train the models with all available characteristics.
Step 2: Analyse the accurateness
Step 3: Identify each feature's significance to the model.
Step 4: for each subset size Si, i = 1. . .N do
- Keep the Si most crucial characteristics
- Training the model using Si features
- Analyze the model's precision

Step 5: Determine the pr ecision profile throughout the Si
Step 6: Choose the right amount of characteristics.
Step 7: Utilize the model that represents the ideal S.

Algorithm 1 RFE-based feature selection

3.3 Improved Extreme Learning Machine based crop yield prediction

Extreme Learning Machine, a learning algorithm that can pick up new information considerably more quickly than other learning algorithms, is employed as the classifier in the present work [19]. With this learning approach for feedforward neural networks, the greatest generalization efficiency is attained. This technique is a very effective learning algorithm for single-hidden layer feed forward neural networks, despite its simplicity (SLFNs). It is capable of selecting the input weights at random and without bias while making an analytical decision on the output weights of SLFNs. A common finding is that the ELM learning method may be used to train SLFNs with a variety of non-differentiable and non-regular activation functions [32]. The output weights of a single-hidden layer feedforward network (SLFN) are analytically determined in the Extreme Machine Learning method utilizing the Moore-Penrose (MP) generalized inverse rather than an iterative learning technique [20]. Figure 3 shows the topology of an Extreme Learning Machine-based single-hidden layer feed-forward network. In here, lw_{1n}, lw_{2n}, and lw_{rn} are weights vector connecting the kth hidden neuron and the input neurons, w the weight vector between the kth hidden neuron with the output neuron, and $af(\cdot)$ is the activation function.

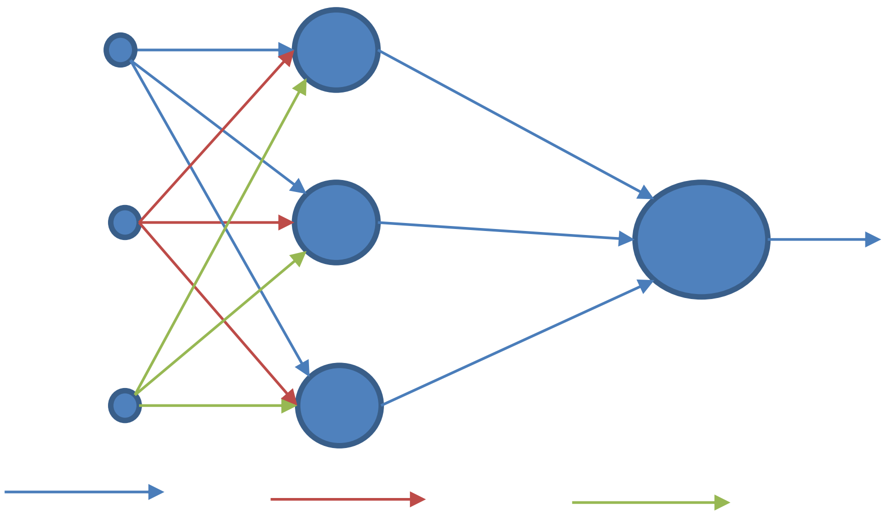


Fig.3. The structure of Extreme Machine Learning.

The most significant features of ELM: The learning rate in the ELM framework is really quick. As a result, ELM may be used to train a single hidden layer feedforward network. This results in the creation of an ELM learning approach, which is quicker than other traditional learning methods. Because the ELM learning method performs well for neural networks, the goal of utilizing it is to acquire less training error and less weight norms. The ELM learning technique is employed in the single-hidden layer feed forward network's topology together with non-differentiable activation functions. To enter the ELM structure, the simple solutions are attempted [19]. The following are the outputs of an ELM with n neurons and an activation function generated with weight and bias b.

$$out_j = \sum_{i=1}^{n} \beta_i af(lw_i x_r + b_i)$$

Compared to traditional neural networks, the ELM learning algorithm offers a quicker learning rate. Additionally, it outperforms them in terms of generalization performance. Researchers who study ELM have become more prevalent in modern times [19]. The hidden layer's initial settings in the ELM learning algorithm don't need to be adjusted. All nonlinear piecewise continuous functions are used as hidden neurons in the ELM method. Therefore, for N crop data samples $\{(r_j, m_j) | r_j \in Q^l, n_j \in Q^k, j = 1, \dots, N\}$, the output function in ELM by using k hidden neurons is

$$u_k(r) = \sum_{j=1}^{k} Sw_j v_j(r) = v(r)Sw$$

Where $v = [v_1(r), v_2(r), \dots, v_k(r)]$ when compared to the input crop data, is the hidden layer's output vector r, $Sw = [Sw_1, Sw_2, \dots, Sw_k]$ the hidden layer of the vector containing the output weights k both input and output neurons. Data is changed from input space to the ELM feature space using a vector [19]. To reduce the training error in the ELM method, the output weights and training error should be decreased simultaneously. Thus, neural network adaptation efficiency improves:

$$\text{minimize } \|\mathrm{Hout}\cdot\mathrm{Sw}-\mathrm{Eout}\|, \|\mathrm{Sw}\|$$

This equation can be solved by using

$$\mathrm{Sw}=\mathrm{Hout}^{\mathrm{T}}\left(\frac{1}{\mathrm{RC}}+\mathrm{Hout}\cdot\mathrm{Hout}^{\mathrm{T}}\right)^{-1}\times\mathrm{Eout}$$

where RC , Hout, which represents the output matrix of the hidden layer, and Eout, which represents the anticipated output matrix of the samples, are each given. As a result, the ELM learning algorithm's output function is as follows:

$$\mathrm{u}(\mathrm{r})=\mathrm{v}(\mathrm{r})\cdot\mathrm{Sw}$$

If the feature vector v(r) is unknown, it is possible to construct the kernel matrix of ELM using Mercer's criteria MC as follows.:

$$\mathrm{KM}=\mathrm{Hout}\cdot\mathrm{Hout}^{\mathrm{T}}: \mathrm{k}_{\mathrm{jz}}=\mathrm{v}(\mathrm{r}_{\mathrm{j}})\mathrm{v}(\mathrm{r}_{\mathrm{z}})=\mathrm{b}(\mathrm{r}_{\mathrm{j}},\mathrm{r}_{\mathrm{z}})$$

Thus, the Improved Extreme Learning Machine's (IELM) output function u(r) may be expressed as follows:

$$\mathrm{u}(\mathrm{r})=[\mathrm{b}(\mathrm{r},\mathrm{r}_1),\mathrm{b}(\mathrm{r},\mathrm{r}_2),\ldots,\mathrm{b}(\mathrm{r},\mathrm{r}_{\mathrm{n}})]\left(\frac{1}{\mathrm{RC}}+\mathrm{KM}\right)^{-1}\times\mathrm{Eout}$$

In there, KM and $\mathrm{b}(\mathrm{r},\mathrm{g})$ is the Extreme Learning Machine's core operation. The linear kernel, polynomial kernel, gaussian kernel, and exponential kernel are a few kernel functions that are suitable for the Mercer condition in ELM [19]. For the simulation and performance evaluation of IELM in this work, the wavelet kernel function is utilized:

$$\mathrm{b}(\mathrm{r},\mathrm{g})=\cos\cos\left(\omega\cdot\frac{\|\mathrm{r}-\mathrm{g}\|}{\mathrm{x}}\right)\exp\exp\left(-\frac{\|\mathrm{r}-\mathrm{g}\|^2}{\mathrm{y}}\right)$$

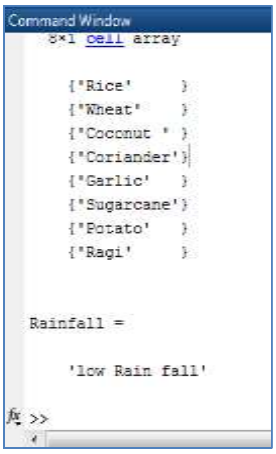
According to the findings of these applicability tests, the wavelet kernel function indicated in $\mathrm{b}(\mathrm{r},\mathrm{g})$ performs higher in training and assessment than the linear kernel, polynomial kernel, Gaussian kernel, and exponential classical kernel functions, respectively. For the effectiveness of ELM's training, the values of the configurable parameters x, y, and ω are crucial. In order to solve the issue, values for these parameters need be carefully calibrated. The number of hidden neurons and the knowledge of the hidden layer feature mapping are not requirements for IELM methods. Additionally, the IELM learning algorithm outperforms the traditional ELM learning method in terms of adaptation efficiency. Additionally, it was shown that IELM is more stable than traditional ELM for predicting crop production.

4. EXPERIMENTS, RESULTS AND DISCUSSION

The performance of this work's suggested model is the main topic of this section. Compare IELM in the experiment to two widely used techniques for crop selection identification, LRRF [7] and CP-ANNs [16]. The experiment's findings demonstrate that the residual network with multidimensional feature comparison presented in this study outperforms conventional models. Performance criteria such as precision, sensitivity/recall, specificity, f-measure, and accuracy were used to assess the suggested model's performance. True Positives (TPs) are accurately classified positive Crop, whereas False Negatives (FNs) are negatively classified Crop selection and crop yield prediction as shown in Fig.4. Negative Crop selection are referred to as TNs (True Negatives), whereas their classification as positive suggests that they are FPs (False Positives). The proposed method's qualitative results are precise in identifying the crops for yield prediction. In comparison to previous classification approaches, the contour's convergence rate is improved. The numerical value of proposed and exiting methods are shown in Table 1.

Table 1.The numerical value of proposed and existing methods

	LRF	**CP-ANN**	**IELM**
Accuracy	**80.1000**	**85.2100**	**91.8879**
Precision	**79.8000**	**81.2341**	**84.1016**
Recall	**81.6000**	**83.6547**	**92.0292**
E-Measure	**80.2400**	**82.3241**	**87.8870**



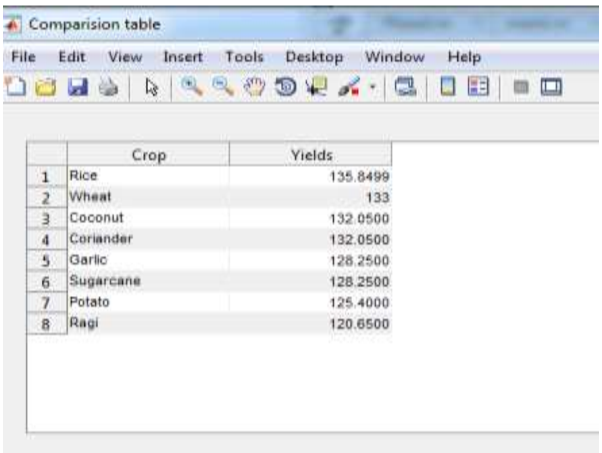


Fig.4. Crop selection and yield prediction results

Recall: the proportion of true positive values that are accurately identified and computed as

$$\mathrm{recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{TN}}$$

Precision: Ratio of accurately identified positive samples to the overall positive sample count predictions on samples and calculated as

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{FP} + \mathrm{TP}}$$

F-measure: It represents the harmonic mean of recollection and accuracy, also called $\mathrm{F_1}$-score and calculated as

$$\mathrm{F} - \mathrm{measure} = \frac{2 * (\mathrm{Recall}\ * \ \mathrm{Precision})}{(\mathrm{Recall}\ +\ \mathrm{Precision})}$$

Classification Accuracy: Proportion of samples that were properly categorized to all samples count as

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

The precision coefficient comparison findings for the suggested LRRF, CP-ANN and IELM are shown in Fig.5. When there are more data, the precision value increases linearly as the number of attributes increases.

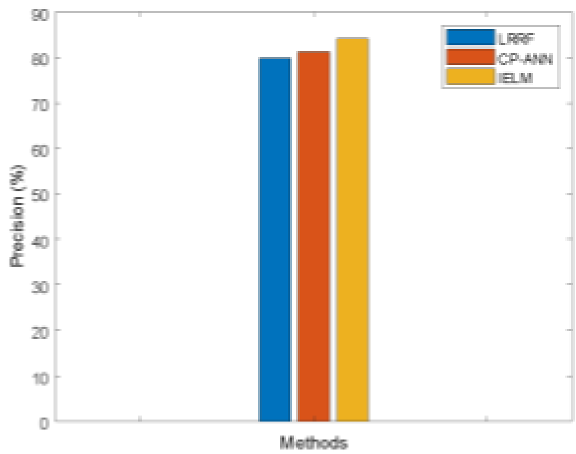


Fig.5. Precision Comparison Results between Existing and Proposed Method

This graph demonstrates that the proposed approach segments the crops with a high degree of precision of 84.1016%. Low precision of 79.8000% and 81.2341%, respectively, is produced by the LRRF and CP-ANN. As a result, the suggested method was applied to a particular data with known information and showed good results. It was also successful when applied to natural data without any prior knowledge. This is due to the fact that the IELM model can extract more fine-grained characteristics from the crop data, and these fine-grained features are highly helpful to recognize crop selection.

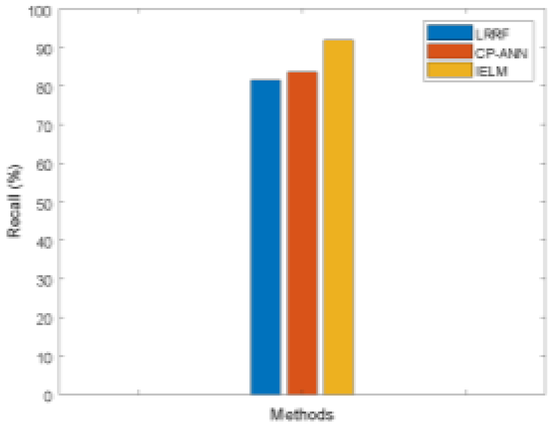


Fig.6: Recall Comparison Results between Existing and Proposed Method

The recall analysis of the methods for the number of attributes is shown in Fig.6. The techniques of the LRRF, CP-ANN and IELM were all applied. The LRRF and CP-ANN achieve recall values of 81.6000% and 83.6547%, respectively, whereas the proposed method's recall rate is 92.0292%. IELM may reportedly outperform the standard single residual networks model for categorizing crops for future crop production prediction since researchers often implement identification systems using the model parameters that provide the best performance. It has therefore concluded from this finding that it can produce superior results for crop selection classification and yield prediction. As the number of epochs was enhanced, the correctness was enhanced to its highest level while the training loss reduced to its lowest level. According to the findings, the proposed method produced successful crop selection classification results because it was adaptable, precise, reliable, and quick.

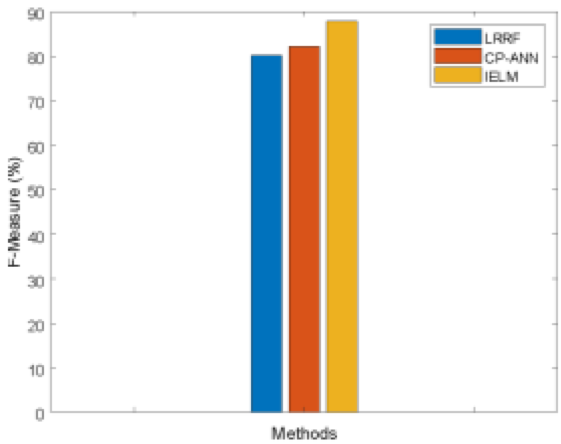


Fig.7: F-measure Comparison Results between Existing and Proposed Method

The F-measure findings of approaches for the number of attributes are shown in Fig.7. The techniques of the LRRF, CP-ANN and IELM were all applied. The suggested approach's F-measure rate is 87.8870%, while the F-measure rates for current methods like the LRRF and CP-ANN are 80.2400% and 82.3241%, respectively. It has concluded from the findings that it could improve crop selection classification results. This demonstrates that the method not only lowers the difficulty of model training and increases the program's training effectiveness, but also prevents the outcomes' quality from deteriorating. These findings demonstrate that the crop yield identification accuracy of this algorithm is the best, and the method's training effectiveness has not significantly decreased.

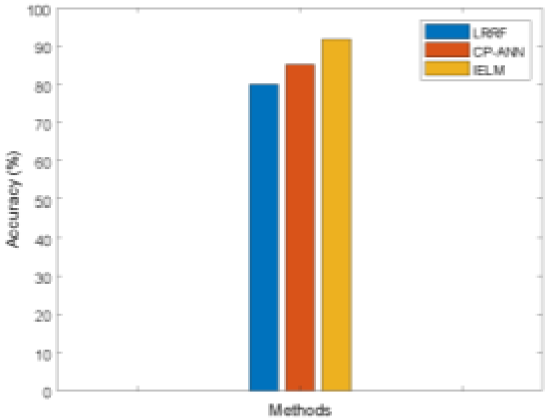


Fig.8: Classification Accuracy Comparison Results between Existing and Proposed Method

The classification accuracy results for the normalised graph cut method, GVF, and the suggested graph cut based on min-cut/max-flow approaches are compared in Fig.12. According to classification accuracy, the value decreases linearly as the quantity of qualities grows. This graph demonstrates that the suggested strategy predicts crop yield with a high level of 91.8879% accuracy. Low classification accuracy of 80.1000% and 85.2100%, respectively, is produced by LRRF and CP-ANN. According to the findings, the suggested is very suitable for efficient Crop selection classification and yield prediction.

5. CONCLUSION

An efficient face recognition method from face images called, GDC-SKEL is designed by exploring and inspecting the affinity points selected from the given dataset. To minimize the face recognition time and improve the face recognition accuracy therefore paving means for face recognition, Gravitational Center Loss-based Face Alignment is first applied to the selected face input image, focusing on occluded images. Second with the occlusion-removed face images provided as input salient features for further processing are extracted using the Convoluted Tikhonov Regularization function. Finally, with the extracted facial regions, Stacked Kernel Extreme Learning-based Classification is performed to obtain the final face image recognition output. For the experimentation, the Cross-Age Celebrity Dataset (CACD) dataset is used. The performance of the GDC-SKEL method is evaluated with different metrics such as face recognition accuracy, face recognition time, PSNR and False Positive Rate. From the result, it is clearly understood that the proposed GDC-SKEL method outperforms well in the face recognition process with higher detection rate and minimum time when compared to the state-of-the-art methods. In general, face recognition is only suitable for offline applications. In order to recognize human faces in online applications, a higher computing system is required. Thus, future work is developed for recognizing the human face in online applications

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