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Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 3 (2025)

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Article History:

Received: *03-08-2024*

Revised: *25-09-2024*

Accepted: *07-10-2024*

Abstract:

Predicting farm-level crop yields (CYP) is crucial for the import and export of farmed commodities and raising farmers' incomes. Crop breeding has always required substantial effort and financial investment. CYP is designed to predict increased agricultural yield. This research presents effective deep learning & dimensionality reduction (DR) methodologies for crop yield prediction (CYP) in Indian regional agriculture. This work consisted of three phases: pre-processing, dimensionality reduction, and classifying. The agricultural information from the southern Indian area is first extracted from the dataset. Subsequently, pre-processing is performed on the gathered dataset via data cleaning and normalisation. Subsequently, dimensionality reduction is executed utilising squared exponential kernel-based principal component analysis (SEKPCA). CYP uses a weight-tuned deep convolutional neural networks (WTDCNN) to forecast high agricultural production profitability. The results indicate the suggested technique achieves enhanced performing for CYP relative to existing systems, with an accuracy of 98.97%. The innovation of the suggested methodology is in the integration of deep learning, dimensionality reduction, and wavelet transform deep convolutional neural network methods for precise agricultural production forecasting, particularly designed for regional crops in India.

Keywords: Importing and Exporting, Crop breeding, financial investment, CYP, SEKPCA.

1. Introduction

The goal of agricultural yield prediction is to estimate how much food will be harvested from a certain plot of land. In order to make educated judgements on agricultural output, it is a crucial tool for farmers, governments, and enterprises. Predicting crop yields in India is difficult because of the country's varied climate, geography, and farming techniques. Nonetheless, one may anticipate crop production based on a variety of criteria, such as:

Weather: One of the key elements influencing agricultural productivity is the weather. Plant growth is influenced by temperature, humidity, and rainfall.

Soil: The soil type and its fertility influence crop productivity.

Variety of Crop: Crop variety is another factor that might influence yield. When it comes to pests and illnesses, some kinds are resistant than others.

Practices for farm management: Crop output is also affected by farm management. One way to increase crop output is to use good agricultural management methods like watering and insect control.

These elements may be taken into consideration when predicting crop production using crop yield prediction models. These models may use machine learning, statistical approaches, or a mix of the two. Soil sensors, weather stations, and remote sensing have all contributed to a dramatic increase in the quantity of data used in agriculture in recent years. Building predictive models for managing and estimating crop yields is possible with this data. Data analysis and modelling face substantial obstacles from the huge amount and complexity of data used in agriculture. Thus, to enhance crop production prediction and management, efficient and effective techniques of analysing and modelling agricultural data are required. For India's massive population, agriculture provides both sustenance and economic stability. The significant climatic changes and fast population expansion in India make it imperative to keep the supply of food and demand chain in good working order. In a pivotal research, agronomic specialists mapped, monitored, analysed, and managed yield variability to maximise agricultural output. One tactic that may aid in crop management is the use of crop production projections. In the food industry, CYP plays a vital role. Because of its importance in national and international programming, CYP for important plants including wheat, rice, and maize is an intriguing area of study for agrometeorologists. Consequently, systems that evaluate accuracy using weather data do exist. Policymakers on a worldwide and regional scale are presently facing a challenging problem when it comes to agricultural production forecasting. The best way for farmers to know when and what to plant is using a trustworthy crop production prediction model.

A number of approaches exist for the purpose of predicting crop yields. Machine learning (ML) is a technology used to predict agricultural yields, alongside support vector machines (SVM), random forests (RF), decision trees (DT), and others. Calibration models for crops are more readily adopted than simulated crop models due to their lack of need for specialist expertise or user proficiency, reduced execution durations, and lower data storage constraints. Although several machine learning models have been developed to enhance forecast accuracy, the spatial as well as temporal non-stationarity inherent to several geographical phenomena is never included into agricultural production modelling. Recently, deep learning has been utilised to create several effective computations, as it facilitates the selection of the most appropriate crop from various alternatives. It is a machine learning class including numerous layers of neural networks that can learn from data. By determining the connections between the input and response variables, it hopes to provide predictions. But DL's dependence on hyper-parameters is a major drawback that may be circumvented to get better outcomes. In the past, experts in DL approaches have often had to hand-design structures in order to forecast agricultural yields. Their lack of understanding of agriculture prevents them from creating excellent buildings. Consequently, our study offered a realistic deep-learning strategy for regional crops in India, including with appropriate hyperparameter adjustment for CYP. The following are the primary benefits of the work:

- Data cleaning and normalisation provide the basis of the pre-processing steps used to eliminate noise and standardise the dataset.
- To execute the DR, first decrease the dimensionality of the data using the SEKPCA technique.
- The WTDCNN model is used to forecast the most lucrative crop production, and the EWOA is used to determine the DCNN weights effectively.

2. Related Works

The authors introduced a CYP method using proximate sensing and ML techniques. Training was done using four publicly accessible datasets: PE-2019, PE-2021, NB-2019, and NB-2021. For agricultural yield prediction, k-nearest neighbour (KNN), support vector regression (SVR), linear regression (LR), and elastic net (EN) ML models were trained on the given data. The SVR outperformed other techniques on all four datasets with reduced RMSE. Multiple CYP machine-learning models were given. Initial Irish potatoes and maize data set were obtained, followed by pre-processing activities such as null value removal and correlation determination to improve system performance. CYP classification was then done utilising three ML models: polynomial regression (PR), support vector machine (SVM), and a random forest (RF). Results indicate that the RF model outperformed SVM and PR in forecasting potato and maize crop yields, with RMSEs of 510.9 as well as 129.8 on tested datasets. The use of CYP is best accomplished using a combination of DL methods, including temporal convolutional networks & recurrent neural networks. The data was gathered from many actual tomato-growing greenhouses. We normalised the acquired data first, and then we sent it to the RNN so it could analyse the normalised sequence data. At last, the TCN for tomatoes CYP received the RNN's output. With a decreased RMSE, the strategy outperformed analogous methods that were previously used on the datasets that were gathered. They introduced a hybrid method for CYP with agricultural parameters, which they called reinforced RF. At first, the system retrieved information about crops from the agricultural dataset and then sent it to the reinforced RF hybrid DL model.

For each internal node, the reinforced RF employed the reinforcement learning technique to assess the input data's relevance. After that, the RF classified crop production using the most important variables found by the reinforcement model. Results were better with the hybrid technique compared to the current machine learning models for CYP, including SVM, LR, & KNN. They proposed a best CYP deep-learning model. The pre-processed data were used to extract important characteristics utilising principal component analysis. The chosen characteristics were optimised utilising an updated chicken swarm technique to increase classifier performance. Final classifier is using a discrete DBN-VGG Net classifier. The method outperformed state-of-the-art models with 98% accuracy and 0.02 % MSE. Their large-scale CYP machine-learning models were shown. The system first gathered agricultural yield data from several sources, including crop growth simulations, weather measurements, and yield statistics. The information was cleaned for categorisation. After feature design, some input data was given into the classifier. ML classifiers including KNN, SVM, regression with ridges, as well as decision trees with gradient boost were used for CYP. A weighted combined linear model was proposed to investigate the potential for saffron farming in India using remote sensing & geospatial analytic approaches. Though straightforward, the approach misses intricate nonlinear interactions between the factors affecting appropriateness. Utilising SAR information, the height and biomass of India's rice fields are estimated. Relevance vector regression (RVR), multiple linear regression, (MLR), support vector regression (SVR), and other machine learning methods were used; RVR produced the best results. creates and assesses a particular image- and classifier-based flood detection technique. Ground truth data, such as that gathered from high-resolution optical images or ground sensors, is used to verify the precision of the flood detection system.

The suggested strategy for fast ADCS performance sizing in EO-satellites uses matching diagrams to cut down on time and effort while maintaining an adequate degree of accuracy. To facilitate estimate, a method was suggested for optimally extracting features from POLSAR pictures. To enhance the outcomes with the addition of polarimetric channels, a method based on the rapid independent component analysis (rapid ICA) technique is suggested. They suggested a multiple scale double-branch residual spectrum-spatial net that prioritises the hyper spectral photos classification model to enhance accuracy in situations when the amount of training data is limited. The study conducted in India identified soil types and locations that are conducive to saffron cultivation by utilising the Weighted Linear Composition technique and remote sensing information. Using classic machine-learning methods for CYP has been the focus of earlier studies. In order to predict agricultural output according to predetermined parameters, traditional ML models are trained using limited amounts of data. But it's not without its flaws. For instance, conventional ML models' poorer yield performance can be due to characteristics that weren't the most accurate or representative when gathered from data. It has to be able to process complicated or massive amounts of data with ease. Consequently, the authors advocated using DL methods, even if the model's prediction rate and computational complexity may need some improvement. In addition, prior efforts should have prioritised DR, which eliminates the need to interpret DL characteristics and directly forecasts crop yield from the dataset; yet, it requires more storage capacity.

3. Methodology

In this research, an ideal DL system with DR techniques for CYP of regional crops in India is proposed. South Indian agricultural statistics, including rainfall, crop production, soil composition, and meteorological information, are first gathered from publicly accessible data sources. Next, data cleaning and data normalisation are used to complete the pre-processing of the data. Subsequently, DR is generated by SEKPCA, yielding reduced dimensional elements for CYP. Lastly, WTDCNN is used to create CYP. Fig. 1 depicts the planned work's process.

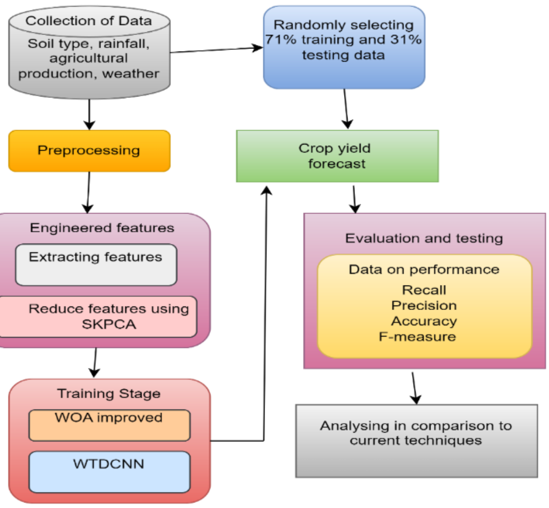

Figure. 1 Planned work's process

3.1 Preprocessing

The south Indian region's agricultural statistics, including information on rainfall, crop production, soil composition, and meteorological conditions, are first gathered from publicly accessible data sources. After that, as data is gathered from several sources, preparation or preprocessing is done. Since it is gathered in raw form, analysis is not appropriate. Therefore, in order to increase the prediction rate, preprocessing is crucial before estimating crop production. The following is an explanation of the preprocessing procedures.

Step:1 Cleaning data

The data is cleaned by estimation for missing values and removal of errors after it has been gathered from sources. The precision of the model in the data is impacted by missing variables. The median or mean values of the whole dataset or another summary statistic are then used to replace the missing values. In order to minimise noise in the dataset, missing value imputation is followed by outlier reduction. Delete: Removing outlier from the data collection is the simplest method to do so and enhances the quality of the data. Matrix dimensions of (3355, 1, 22) indicate the number of information samples used with a 1 kernel and 22 features in CNN. The dataset consists of 3355 row (input sample) and 22 columns (features).

Step:2 Normalisation

The dataset is normalised after data cleaning is completed. The goal of normalisation is to make data comparable in distribution and dimensionless. The mathematical expression for it is as follows:

$$C'_{\rightarrow Norm} = \frac{C'_{\rightarrow} - C'_{\rightarrow min}}{C'_{\rightarrow max} - C'_{\rightarrow min}} \quad (1)$$

Here, $C'_{\rightarrow Norm}$ denotes the data that has been normalised, $C'_{\rightarrow}$ represents the original information, and $C'_{\rightarrow min}$ min and $C'_{\rightarrow max}$ denote lowest and highest values found in the data set, respectively. This min-max normalisation places the values of the dataset between 0 and 1.

Step:3 Splitting data sets

Pre-processed data is divided into datasets for training and testing so that the suggested approach may be put into practice. For testing and training, the suggested system selects 71% and 31% of the data, respectively, at random.

3.2 A reduction of dimensions

The dataset's DR is made utilising squared exponentially kernel-based analysis of principal components after it has been pre-processed. This takes high-dimensional data and turns it into low-dimensional data. In principle component analysis (PCA), the basis is changed after the principal components are computed. It resolves the association between the variables and may greatly enhance the recognition and diagnosis of high-dimensional information in agricultural yields during real production. Still, very uncorrelated variables are a must for PCA to work. Also, PCA isn't great at spotting models in nonlinear data. Due to the nonlinear nature of the feature-to-feature connection in the pre-processed dataset, the suggested method enhances the performance of the system by effectively recognising the nonlinear data and DR in the dataset via the use of squared exponentially kernels in traditional principal component analysis (PCA). To start, take a look at the dimensional pre-processed dataset and apply Eq. (2) to the mean vector for each dimension:

$$\underset{\rightarrow_{sv}}{V} = \frac{\underset{\rightarrow_{ds}}{P} - \mu}{\sigma} \tag{2}$$

In this context, $\underset{\rightarrow_{sv}}{V}$ is related to the scaled value, $\underset{\rightarrow_{ds}}{P}$ denote the pre-processed dataset, while μ and σ signify the standard deviation and mean, respectively. The SEK, a well-known kernel function for estimating covariance matrices, is then used to compute the resulting covariance matrix. Utilising the SEK produces a smooth prior for positions that are obtained from the calculation of covariance. In summary, the SEK function, SEK (v_x, v_y),characterises the covariance among each pair in $\underset{\rightarrow_{sv}}{V}$, and is articulated as follows:

$$\sum = SEK\ (v_x, v_y) \tag{3}$$

$$SEK(v_x, v_y) = \sigma^2 \exp\left(\frac{-\left|\left| v_x - v_y)\right|\right|^2}{2r^2}\right) \tag{4}$$

The length scale is denoted by r, while σ^2 is the total variance. Then, we can calculate the covariance matrix's eigenvalues and eigenvectors by following these steps:

$$\sum = \underset{\rightarrow}{M} \Delta \left(\underset{\rightarrow}{M}\right) T \tag{5}$$

The matrix $\underset{\rightarrow}{M}$, which is made up of eigenvectors, and the eigenvalue diagonal matrix Λ are referenced here. The lengths of these eigenvectors are 1 since they are unit eigen vectors. In the next step, the eigenvectors of the covariance matrix are arranged in descending order of eigenvalue. In this list, the components are arranged in decreasing order of significance. Therefore, it is necessary to attend to the less important parts. Here is the mathematical expression:

$$\underset{\rightarrow s}{DR} = \left\{ \underset{\rightarrow}{m_1}, \underset{\rightarrow}{m_2}, \underset{\rightarrow}{m_3}, \ldots \ldots . \underset{\rightarrow}{m_n} \right\} \tag{6}$$

Here, $\underset{\rightarrow s}{DR}$ is a collection of features that have been reduced in dimensionality and include important eigenvectors, and n → represents the total number of dimensions that have been chosen.

3.3 Predicting yields of crops

The following procedure, CYP, is performed using a weight-tuned deep convolutional neural network. Each of the many layers that make up a DCNN performs a convolutional transform calculation before going on to the next layer, which handles nonlinearities and pooling operators. Backpropagation training in DCNN makes use of random weight and bias values, increasing the likelihood of suboptimal outputs and larger prediction loss. To improve detection accuracy and decrease network loss, it is vital to tune the network's weights and biases correctly. Consequently, the suggested method uses an EWOA to establish the bias and weights of the network, which minimises the network's prediction loss and vanishing gradient saturation for CYP, leading to optimum outcomes. The overall architecture of DCNN is shown in Fig. 2.

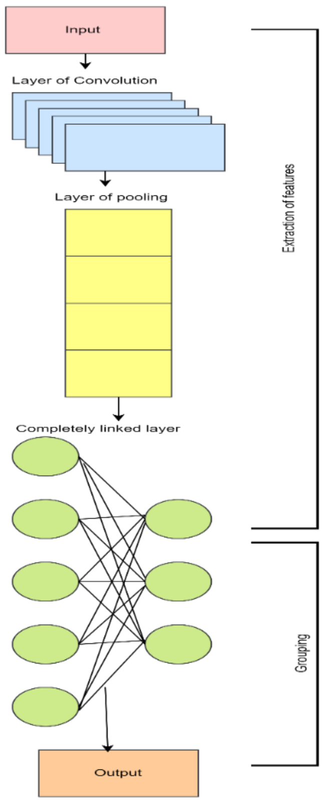

Figure. 2 Overall architecture of DCNN

The '4' layers that make up a DCNN architecture are the fully linked layer, activation, pooling, and convolution. For backpropagation training, DCNN uses a randomly selected network weight and biases. The suggested method improves the network's yield prediction performance by selecting them optimally using EWOA, as opposed to randomly. The WOA is an innovative swarm-based optimisation system that takes cues from the way humpback whales hunt. It takes three operators—encircling, studying, and attacking—for WOA to locate prey. A reduction in converging efficiency and

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 3 (2025)

algorithm quality leading to optimum global solutions is seen when whales are initialised with a random population in their early stages. Furthermore, the algorithm's speed drops as it proceeds through the search process because it becomes trapped on optimum local problems. Starting with a Tent chaotic map enhances the algorithm's convergence efficiency and variety of the population, which is why it is recommended to utilise this approach. Also, the system can't identify locally optimum solutions since the levy flying mechanism is used to update the whales' positions later on in the algorithm. Both of these improvements to traditional WOA are known as EWOA. In order to extract features, VWCNN uses a deep learning-based approach. With Relu connecting each convolutional layer to an activation layer, the network has a total of fifteen layers: five convolutional, five pooling, and three fully linked. Each map of features is 6 x 6, with a total of 128 feature maps, resulting in an output size of 6 × 6 × 128 after 5th pooling and convolution layers, from an input picture with dimensions of 200 × 200 × 3. Following the first two completely linked layers, a vector of 1024 dimensions is produced as an output. The Soft max classifier takes a 5-dimensional vector as input and output after the last fully connected layer. Utilising a chaotic tent map, the method first initialises the number of people in the search space. Tent chaotic maps lessen the impact of the original population distribution while increasing search speed and improving uniformity of population dispersion. It is expressed as follows:

$$\underset{\rightarrow}{Z_{\tau+1}} = \begin{cases} 2\underset{\rightarrow}{Z_\tau} & 0 \leq \underset{\rightarrow}{Z} \leq 0.5 \\ 2\left(1 - \underset{\rightarrow}{Z_\tau}\right), & 0.5 < \underset{\rightarrow}{Z} \leq 1 \end{cases} \qquad (7)$$

In this context, $\underset{\rightarrow}{Z_{\tau+1}}$ denotes the initial population of whales as determined by a tent map, whereas $\underset{\rightarrow}{Z_\tau}$ represents the randomised populations. Next, the classifier's mean square error is used to estimate fitness ($\underset{\rightarrow}{FN}\ cal$) of the whale in the initialised population. To calculate MSE, one must subtract the classifier's anticipated output from the actual output when predicting yield. Here is how it is stated:

$$\underset{\rightarrow}{FN}\ cal = Min\ (MSE) \qquad (8)$$

$$MSE = \frac{1}{d}\sum_{p=1}^{d}(q_{val} - q_{val}^{*}) \qquad (9)$$

Where d − is the number of samples in the training data set and q_{val} and q_{val}^{*} are the actual and predicted values of the classifier, respectively. After that, you may find out where the whales are and encircle them. In the present population, the whale closest to the prey site is deemed the best whale $\underset{\rightarrow}{Z^*}$, and the positioning of other whales is adjusted accordingly.

$$\underset{\rightarrow}{DT} = \left|\beta \times \underset{\rightarrow}{Z^*}(\tau) - \underset{\rightarrow}{Z}(\tau)\right| \qquad (10)$$

$$\underset{\rightarrow}{Z}\ (\tau + 1) = \underset{\rightarrow}{Z^*}(\tau) - \alpha \times \underset{\rightarrow}{DT} \qquad (11)$$

The distance between the whale $\underset{\rightarrow}{Z}(\tau)$ and the prey $\underset{\rightarrow}{Z^*}(\tau)$ is represented by $\underset{\rightarrow}{DT}$, and τ represents the current iteration. Furthermore, α and β denote the vector calculation is using Eqs. (12) and (13) respectively.

Algorithm: 1

Proposed weight-tuned deep convolutional neural network algorithm.

Require: Input of crop yield images image

Ensure: Class level for each image

Initialize with weight and bias of the pre-trained weight-tuned CNN model.

Initialize the population of whales by using Eq. (5,7).

Compute the fitness of each individual by using Eq. (5,8).

While

For each search agent

Calculate the coefficients and

If

If

Update the position of the current whale using Eq. (5,11).

Else

Update the position of the current whale using Eq. (5,16).

End if

End if

Update the position of the current whale using Eq. (5,14)

End if

End for

Update if there is a better solution

End while

End

Defines the learning rate, batch size and number of epochs for training.

Rescale the input image to a fixed size of 224 x 224.

for each rescaled image x^i do

Rotate (x^i, θ); where $\theta \varepsilon [30^\circ, 30^\circ]$

Add a randomly initialised new head to the weight-tuned architecture

Freeze the body of the network and train the newly added head of previous step using RMSProp with learning rate 10^{-3}.

Unfreeze the body of the network and continue the training process using SGD optimizer with a learning rate 10^{-3}.

end for

Evaluate the fine-tuned network and serialize the weights to disk.

$$\alpha = 2 \times\ l_d\ \times\ R_{num} -\ l_d\ (\tau) \qquad (12)$$

$$\beta = 2 \times\ R_{num} \qquad (13)$$

After updating the bubble-net behaviour of the humpback whales using the following equation, where R_{num} denotes a random number ranging between [0, 1] and ld decreases linearly from 2 to 0 throughout the number of iterations:

$$\underset{\rightarrow}{Z}\ (\tau+1) = \begin{cases} \underset{\rightarrow}{Z} * (\tau) - \alpha \times \underset{\rightarrow}{DT} & if\ p < 0.5 \\ \left(\underset{\rightarrow}{DT'}\right) \times e^{h_k g_{lk}} \times \cos(2 \times \pi \times g_{lk}) + \underset{\rightarrow}{Z * (\tau)} & if\ p \geq 0.5 \end{cases} \qquad (14)$$

In contrast, p is an arbitrarily integer between 0 and 1 that indicates the probability of tracking whale positions using either the spiral updating position or the shrinking encircling technique (if p is greater than or equal to 0.5), g_{lk} is an arbitrarily integer between -1 and 1, and h_k is the shape of the spiral movement. Next, the whales begin their worldwide search and exploration, which ends when their absolute vectors value is one or larger. If not, the algorithm will go onto the exploitation step. The following expression describes the use of the random variable $\underset{\rightarrow}{Z} rand$ to update the locations of whales during the exploration phase, as opposed to the best whale $\underset{\rightarrow}{Z} *$.

$$\underset{\rightarrow}{DT} = \left|\beta \times \underset{\rightarrow}{Z} rand - \underset{\rightarrow}{Z} (\tau)\ \right| \qquad (15)$$

$$\underset{\rightarrow}{Z} (\tau+1) = \underset{\rightarrow}{Z} rand - \alpha \times \underset{\rightarrow}{Dt} \times L_f(\xi) \qquad (16)$$

In this case, $\underset{\rightarrow}{Z} rand$ denotes the randomly selected whale from the existing population, and $L_f(\xi)$ is a levy flight mechanism that improves algorithm's exploration and exploitation capabilities. It is expressed as follows: It is a random walk with steps indicated in terms of step lengths and a specific probability distribution.

$$L_f(\xi) \sim\ \left|\xi\ \right|^{-1-\lambda} \qquad (17)$$

$$\xi = \frac{N_{ud}}{\left|\ N_{vd}\ \right|^{1/\lambda}} \qquad (18)$$

Whereas ξ denotes the step length, λ ($0 < \lambda \leq 2$) denotes an index, and N_{ud} and N_{vd} stand for drawn from normal distributions, respectively. The layer of convolution retrieves related features from the dimensionality-reduced data set after selecting weights and biases efficiently. The probability of a better model steadily increases as biases and weights take into account the best value at every stage of the process.

$$\text{Feature Vector} = \sum \left(\underset{\rightarrow}{DR}_s +\ \breve{O} *_{d \times d}\right) + \breve{B} * \qquad (19)$$

In this context, $\underset{\rightarrow}{DR}_s$ symbolises the dataset subjected to dimensionality reduction for the convolutional operation, $\breve{O} *_{d \times d}$ represents the optimum filter weights, and $\breve{B} *$ signifies the bias determined by EWOA, while d − indicates the kernel size. After that, the activation layer receives the feature vector as a result and uses it to make the output more nonlinear. The active layer's activation function is ReLU, which generates the input instantly for positive input values. On the other hand, it could provide no output at all. To decrease the data size, the activation-convolution layer feeds its output into the pooling layer. In order to provide output, these polling layers sample the smaller rectangular boxes taken from the convolution layer. The fully linked layer uses the Soft Max activation function for categorisation and receives the data from the polling layers. To help farmers choose crops with the best potential for future production, the classifier predicts how productive different crops would be in different parts of India throughout different seasons.

4. Result and Discussion

The experimental outcomes of the suggested yield prediction for regional crops in India utilising effective DL and DR methodologies are examined in the next section. Regarding categorisation metrics, the suggested technique is contrasted with the CYP schemes that are now in place. Using an Intel Core i7-8550 CPU, an NVIDIA GeForce MX130 graphics card, and 8.0 GB of RAM, the predictions were produced using Python.

4.1 Descriptions of datasets

The crop production data, which includes District Name, Production Yield, Year, Crop class, Area, Crop, State Name, Season, and Crop, was gathered using the proposed system utilising agriculture-India, a publicly accessible data source. Additionally, meteorological data are gathered from the Indian website and include the following: precipitation, humidity, pressure, dew point, wind, lowest temperature, highest temperature, average temperature, and humidity.

4.2 Analysis of performance

They compare the results of the suggested classification method (WTDCNN) to those of present-day classification schemes, including DCNN, RF, DBN, and ELM. Measures like as accuracy (AC), recall (RC), f-measure (FM), false positive rate (FPR), root mean square error (RMSE), and precision (PR) are used to assess the techniques. The following are the formulae for the dimensions given above.

$$PR = \frac{Tp}{Tp+Fp}$$

$$RC = \frac{Tp}{Tp+Fn}$$

$$AC = \frac{Tp}{Tp+Tn+Fp+Fn}$$

$$FM = \frac{Tp}{Tp+1/2(Fp+Fn)}$$

$$FPR = \frac{Fp}{Fp+Tn}$$

$$FNR = \frac{Fn}{Fn+Tp}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(A-B)^2$$

$$RMSE = \sqrt{MSE}$$

This has indicated that deep learning may significantly influence CYP, and our findings corroborate this assertion. Although grounded on fundamental performance criteria, the results can be compared with other cutting-edge techniques. The proposed WTDCNN yields superior results compared to the current models. The current DCNN attains recall, f-measure, accuracy, and precision of 96.99%, 96.28%, 97.04%, and 96.79%, respectively. The current RF achieves an accuracy of 89.22%, precision of 89.06%, recall of 89.33%, and f-measure of 89.20%, all of which are inferior to the suggested model, which attains a maximum accuracy of 98.97%, precision of 98.67%, recall of 99.04%, and f-measure of 98.88%. Likewise, when evaluating other approaches (DBN and ELM), the suggested approach demonstrates superior performance. Consequently, the results demonstrated that the new strategy surpassed the traditional approach. Figure 3 illustrates the diagrammatic form. Figure 3 displays the results of the methods for AC, PR, RC, and FM. The graphic clearly shows that the suggested approach outperforms the current systems. Compared to DCNN (96.28), DBN (94.17), ELM (90.03), and RF (89.22), the suggested WTDCNN achieves a PR of 98.68. Similarly, the proposed technique outperforms other current systems in terms of accuracy. For example, WTDCNN achieves an AC of 98.97, whereas RF, ELM, DBN, and DCNN achieve lesser AC values of 96.99, 94.44, 90.35, and 89.22, respectively.

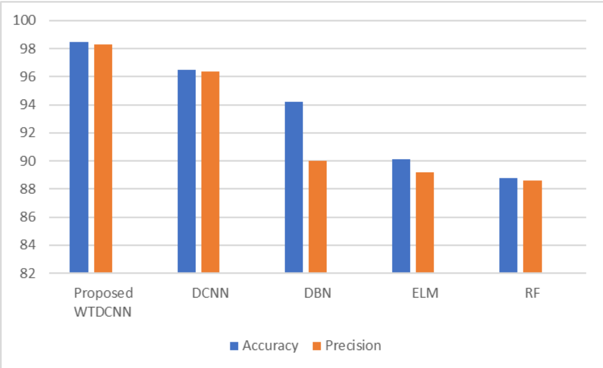

Figure. 3 Evaluation of AC and PR.

Figure 4 displays the results of the methods with respect to FM and RC. The suggested model outperforms the current systems, as can be seen from the picture. Compared to DCNN (96.79), DBN (94.36), ELM (90.28), and RF (89.20), the suggested WTDCNN achieves an FM of 98.88. The WTDCNN achieves the maximum RC of 99.04, whereas ELM, RF, DCNN, and DBN achieve lesser RCs of 97.04, 94.67, 90.47, and 89.33, respectively. This means that the suggested approach outperforms other current systems.

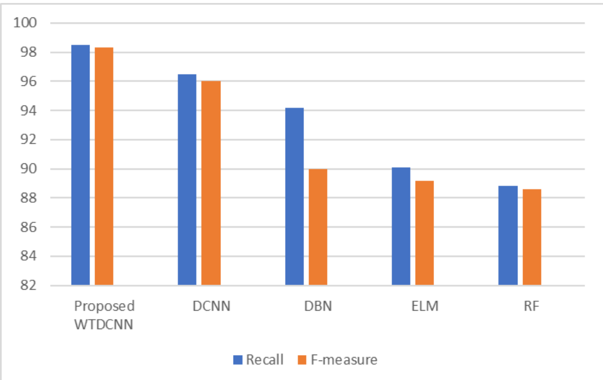

Figure. 4 FM and RC analysis.

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 3 (2025)

The suggested one's results are then examined using error metrics, such as FRR, FPR, RMSE, FNR, and MSE metrics. Comparing the results of the proposed technique to those of the current DCNN, DBN, ELM, and RF approaches in terms of MSE, RMSE, FPR, FNR, and FRR. By reducing classification error values, the findings shown that the suggested strategy outperforms the current models. Since the current approaches had greater error values, the suggested method demonstrated superior performance with FRR, MSE, FNR, FPR, and RMSE values of 0.035, 0.220, 0.030, 0.066, and 0.062, respectively. A sound system, on the other hand, will have lower error levels. The results showed that the suggested approach outperformed the state-of-the-art methods for precise CYP. In Figures 5 and 6, you can see a graphical depiction.

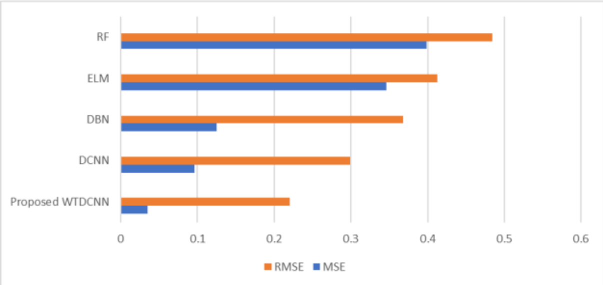

Figure. 5 Analysis of MSE and RMSE.

Figure 5 illustrates the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) of both the proposed and current classifiers. The new model demonstrably outperforms the previous approaches. The suggested WTDCNN achieves a mean squared error (MSE) of 0.035, which is superior to that of DCNN (0.096), DBN (0.125), ELM (0.346), and RF (0.399). Similarly, RMSE achieved by the proposed method is lower than that of other existing schemes; for example, the RMSE achieved by the WTDCNN is 0.220, while the RMSEs obtained by the current schemes, namely DCNN, DBN, ELM, and RF, are 0.413, 0.483, 0.368, and 0.299, respectively.

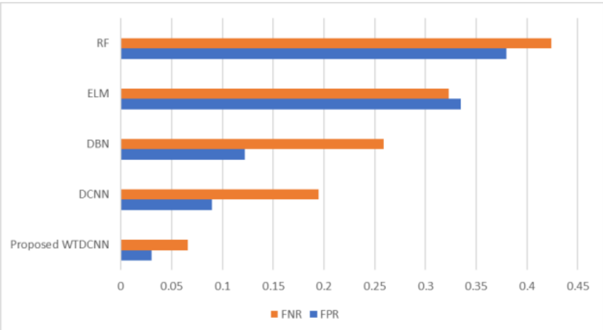

Figure. 6 FNR and FPR evaluation.

Both the current and proposed classifiers' FPR and FNR are shown in Figure 6. It was obvious that the suggested model outperformed the previous approaches. Compared to DCNN (0.090), DBN (0.122), ELM (0.335), and RF (0.380), suggest the WTDCNN achieves a lower FPR of 0.030. Just as the WTDCNN achieves the lowest FNR of 0.065, the suggested approach also achieves the lowest RMSE compared to other current systems like DCNN, DBN, ELM, and RF, which are 0.259, 0.323, 0.424, and 0.195, respectively. Our model's superior performance compared to WTDCNN shows how our suggested work is unique thanks to the correct data preparation techniques, architecture, and settings for the hyperparameters. The suggested one makes effective use of the DR approach and preprocesses the data set before making predictions. Consequently, these methods provide better forecasts.

5. Conclusion and future work

In order to improve CYP efficiency for regional crops in India, this study proposes DL and DR methods. There are 'three' primary steps to the suggested system: preprocessing, data reduction, and classification. In terms of recall, f-measure, accuracy, precision, FPR, FNR, MSE, FRR, and RMSE, the suggested work's findings are compared against those of the traditional ELM, DBN, RF, and DCNN. Because it attains a maximum accuracy of 98.97%, 98.68% precision, 99.04% recall, and 98.88% f-measure, the suggested one produces much better results. With reduced error levels of 0.035 MSE, 0.220 RMSE, 0.031 FPR, 0.066 and FNR, the suggested one outperforms the others. The suggested optimum DL technique with a realistic DR approach outperforms state-of-the-art CYP systems. To make the model more generalisable, the scientists advise applying the strategy to additional areas and crops. To strengthen the suggested technique, they advise adding satellite photos and sensor data. In conclusion, the authors advocate using the suggested technique to create systems that support decisions for farmers to make educated crops management and production choices. Integrating the suggested technique with precision agricultural technology would let farmers anticipate crop yields and make decisions in real time. They can create a web-based tool to help farmers and policymakers make agricultural production and import-export choices using the suggested technique.

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