SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I12P106

Volume 12 Issue 12, 60-74, December 2025

Original Article

Advanced Forecasting of Crop Prices Through Graph Convolutional Model with Gated Recurrent Neural Networks Enhanced by Heuristic Search Optimisation Algorithm

J. Jagadeesan[1], R. Nagarajan[2]

[1,2]Department of Computer and Information Science, Annamalai University, Annamalai Nagar, Chidambaram, Tamil Nadu, India.

[1]Corresponding Author : jagatamil2016@gmail.com

Received: 06 October 2025 Revised: 08 November 2025 Accepted: 07 December 2025 Published: 27 December 2025

Abstract - *Crop price prediction is crucial in reducing market uncertainties and supporting knowledgeable decision-making among farmers, traders, and policymakers. Conventional techniques are relatively simple and easy to understand and implement; however, they provide low prediction performance for non-linear, non-smooth, and high-dimensional data, and they need more a priori knowledge and assumptions. Recently, the Machine Learning (ML) and Deep Learning (DL) models have helped model these non-linear patterns, providing highly reliable and robust crop price prediction. This research paper presents an Advanced Forecasting of Crop Prices through Graph Convolutional Neural Networks by Heuristic Search Optimisation (AFCP-GCNNHSO) approach. The main intention of the AFCP-GCNNHSO approach is to enable effective prediction of crop prices by the use of feature selection and a fine-tuned DL model. To handle high-dimensional data, the AFCP-GCNNHSO method utilizes the Aquila Optimiser (AO) technique for the optimal feature subset selection, which results in reduced complexity and enhanced prediction performance. For effective crop price prediction, the AFCP-GCNNHSO method employs an Enhanced Grasshopper Optimization Algorithm (EGOA) with a Gated Graph Convolution Neural Network (GGCN) technique. The EGOA-based hyperparameter tuning is implemented to optimize the GGCN model by minimizing prediction error. The experimental analysis of the AFCP-GCNNHSO method is performed using the agricultural dataset from the Kaggle repository, and the comparison results highlight its supremacy with a minimal MSE of 0.00038.*

Keywords - *Crop Prices Prediction, Graph Convolutional Neural Network, Enhanced Grasshopper Optimisation Algorithm, Feature Selection.*

1. Introduction

Agriculture is a vital part of the world's economy with a significant influence on employment as well as rural development. According to the Food and Agriculture Organisation (FAO), nearly 33% of the world's population depends on agriculture for their income and survival [1]. Price forecasting plays a crucial economic role by providing valuable insights into market trends and enabling more informed decisions for stakeholders. Without accurate price forecasts, agriculturalists (farmers) may not precisely gauge market interest or anticipated revenue, resulting in inefficient planting strategies and financial instability [2]. Additionally, imperfect price forecasting can disturb supply chains, resulting in market ineffectiveness and impacting food security and consumer affordability [3]. When prices are precisely forecast, agriculturalists are well prepared to adjust their production in response to market demand, thus evading overproduction that results in excessive production and eventual waste. Crop price forecasting assists in balancing supply and demand by enabling agriculturalists to plan production and market timing, thus evading surplus production or shortages [4]. The agriculture industry, which is the pillar of the economy in India, encounters distinctive issues because of its contact with numerous uncertainties [5]. Price unpredictability in agricultural products, caused by factors including seasonal supply patterns, weather fluctuations, global market dynamics, and international trade policies, poses a highly intricate forecasting difficulty [6].

This unpredictability affects various stakeholders, including agriculturalists who must make informed decisions on crop selection and marketing, decision-makers working to stabilize markets and ensure food safety, and traders managing supply chain risks. The intricacy of agricultural price prediction stems from the nature of price movements [7]. Price forecasting holds a vital part in price analysis and commodity trading in the agricultural sector [8]. Traditional methods for crop price prediction strongly rely on historical patterns and the specialist understanding, but still often fail in delivering precise and prompt predictions [9]. The constantly evolving environment of agricultural markets, impacted by reasons such as demand shifts, supply chain disruptions, weather patterns, and geopolitical tensions, challenges the efficiency of conventional methods in understanding the intricacies of price fluctuations [10]. Currently, the arrival of machine learning ML) approaches has transformed the environment of crop price prediction. ML, a division of Artificial Intelligence (AI), assists in comprehending data patterns and makes decisions or predictions without needing code [11]. Employing a massive dataset incorporating different variables, ML models can distinguish complex relations and discover hidden patterns in agricultural market data. Furthermore, DL, a division of ML, has enabled strong forecasting techniques that can address the restrictions of conventional methods.

This research paper presents an Advanced Forecasting of Crop Prices through Graph Convolutional Neural Networks by Heuristic Search Optimisation (AFCP-GCNNHSO) approach. The main intention of the AFCP-GCNNHSO approach is to enable effective prediction of crop prices by the use of feature selection and a fine-tuned DL model. To handle high-dimensional data, the AFCP-GCNNHSO method utilizes the Aquila Optimiser (AO) technique for the optimal feature subset selection, which results in reduced complexity and enhanced prediction performance. For effective crop price prediction, the AFCP-GCNNHSO method utilizes an Enhanced Grasshopper Optimization Algorithm (EGOA) combined with a Gated Graph Convolutional Neural Network (GGCN) technique. The EGOA-based hyperparameter tuning is implemented to optimize the GGCN model by minimizing prediction error. The experimental analysis of the AFCP-GCNNHSO method is conducted using an agricultural dataset. The key contribution is listed below.

- The data pre-processing is performed by implementing data normalization. Additionally, missing values are handled to ensure clean and consistent input for the predictive model, thereby enhancing data quality and reliability. This step also improves the learning efficiency and mitigates errors. The process also contributes to the accurate and precise preparation of the data.
- The AO is employed to choose the optimal feature subset, thus mitigating the computational complexity and data dimensionality. This process also augments effectiveness by giving focus to the most relevant variables. It also strengthens the overall achievement of the crop price forecasting model by enhancing prediction accuracy and reducing redundant data.
- The GGCN method integrated with EGOA enables accurate crop price forecasting. The hybrid approach also assists in capturing intrinsic spatial and temporal relationships, thus improving the predictive capabilities. By integrating graph-based learning with heuristic optimization, it improves the reliability and precision of crop price predictions.
- The EGOA approach is applied for fine-tuning the hyperparameters of GGCN, thus efficiently reducing prediction errors. This process also ensures that the model performs optimally, thus improving the learning efficiency and stability. Refining hyperparameters systematically enhances the accuracy and performance of crop price forecasting.
- The AFCP-GCNNHSO methodology presents a novel integration of AO, EGOA, and GGCN models for addressing both high-dimensional data and intrinsic spatiotemporal relationships. The model also uniquely incorporates advanced feature selection, graph-based deep learning, and heuristic hyperparameter optimization for enhancing prediction accuracy. The method also presents a highly effective and novel solution by mitigating computational complexity and enhancing the model performance.

2. Prior Research on Advanced Forecasting of Crop Prices

Dasanayaka and Perera [12] investigated the usage of an ML approach for predicting crop prices and suggested the best crops. It presents future price forecasting for crops and provides crop recommendations, depending on crucial features: rainfall and soil conditions. The platform's user-friendly interface, integrated with data from several sources and a detailed assessment of available related works, focuses on making sophisticated agricultural forecasting and recommendation devices affordable and accessible. This initiative lines up with global trends in agricultural innovation, promoting data clarity. Choudhary et al. [13] presented an innovative hybrid VMD-LSTM approach, which synergistically integrates Variational Mode Decomposition (VMD), LSTM, and Genetic Algorithm (GA), resulting in improved prediction precision. This presented approach employs GA-optimised VMD that breaks down a time series of prices into Intrinsic Mode Functions (IMFs), resulting in faster convergence.

Lastly, the predictions of every IMF are collected to give a result for the real-time series of prices. Nayak et al. [14] addressed the complex issues linked with prediction. Sari et al. [15] presented an innovative prediction approach by utilizing the Extreme Learning Machine (ELM) method, improved alongside the GA. In predicting commodities, the presented approach, which utilizes the ELM with the GA, surpasses the technique created by incorporating LSTM alongside the GA and the autoregressive integrated moving average method. In [16], an effectual ML-driven approach is introduced in this study to help farmers predict their profit-loss. This study comprises four functional blocks: determination of supply, crop yield prediction, crop price prediction, and demand prediction. Several time series-driven algorithms are employed to predict crop production. Sharma et al. [17] aimed to forecast crop yield using the variables of rainfall, meteorological conditions, crop, production, area, and yield that have presented a critical threat to sustainable farming. Crop yield forecast is a decision-support tool that employs ML and DL to make decisions regarding what type of crop to produce and what to carry out in the crop's growth stage. ML and DL can decide on that accordingly.

Singh and Sindhu [18] addressed the common issues linked with using ML in predicting crop price, namely feature selection, data accessibility, scalability, model interpretability, and generality. Moreover, expect the potential areas of further investigation to focus on improving the precision and efficacy of ML models in forecasting crop prices. Conventional models often strive to provide precise and effective forecasts. Manogna et al. [19] presented a thorough examination of agricultural price fluctuation prediction utilizing a hybrid (STM-Generalised Autoregressive Conditional Heteroskedasticity (GARCH) methodology.

Agrarian price fluctuations pose critical challenges to financial stability, food security, and income sources, especially in emerging countries such as India. Karthik et al. [20] proposed a technique by utilizing the Neural Basis Expansion Assessment for Interpretable Time Series Forecast (N-BEATS) technique, which is compared with Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models. Zhang et al. [21] suggested an approach by capturing both spatial and temporal relationships using a Graph Convolutional Network (GCN), Bidirectional GRU (BiGRU), and Tree-Structured Parzen Estimator (TPE) techniques.

Pandit et al. [22] introduced a technique by utilizing a Complete Ensemble Empirical Mode Decomposition with Adaptive Noise and Time Delay Neural Networking (CEEMDAN-TDNN) hybrid method. Zheng, Li, and Xia [23] improved forecasting by utilizing a hybrid DL technique that incorporates Empirical Wavelet Transform (EWT), multiple Neural Networks (NNs), and a Reinforcement Learning-Assisted Ensemble (RLE) with an Error Correction Module (ECM) technique.

Selvanarayanan and Surendran [24] presented a technique by utilizing a Multi-Variate Time Series Recurrent NN with GRU (RNN-GRU) methodology. They compared its performance with a Bidirectional Recurrent NN (Bi-RNN) model. Jaiswal et al. [25] presented a technique by utilizing a Seasonal Trend Decomposition depending on a Loess and LSTM (STL-LSTM) hybrid model. Rao et al. [26] forecasted brinjal crop yields by implementing an Attention-Based Convolutional NN with Optimised Bidirectional LSTM (ACNN-OBDLSTM) with Shuffling Shepherd Optimisation Approach (SSOA) for tuning. Gülmez [27] predicted stock market prices by employing a GA-Attention-Fuzzy-Stock-Net (GA-Attention-Fuzzy-Stock-Net) methodology.

The existing models exhibit various limitations, although they demonstrate improvements in crop price and yield prediction. Several techniques face difficulty with feature selection, high-dimensional and noisy data, and the integration of spatial-temporal dependencies, restricting prediction accuracy. Furthermore, diverse hybrid techniques need extensive computational resources and lack scalability for massive datasets.

Moreover, while several techniques efficiently capture temporal and spatial correlations, they may not fully optimize hyperparameters or adapt to dynamic market conditions. Stock market and agricultural forecasting models like GA-Attention-Fuzzy-Stock-Net and ACNN-OBDLSTM address uncertainty and pattern extraction, but still encounter threats in interpretability and generalization. The research gap is in developing a combined, computationally effective technique that integrates optimal feature selection, spatial-temporal learning, and heuristic hyperparameter optimization while maintaining high accuracy, scalability, and interpretability across diverse agricultural datasets.

3. Model Design and Techniques

In this research, the AFCP-GCNNHSO technique is proposed. The main aim is to develop a successive prediction architecture for crop prices, which incorporates a new method to enhance the framework for higher accuracy. It has preprocessing, feature selection, crop price prediction, and parameter tuning. Figure 1 indicates the flow of the AFCP-GCNNHSO method.

3.1. Various Levels of Pre-Processing Stages

In the initial phase, pre-processing involves two levels: data normalization and handling of missing values, aimed at enhancing data analysis. In this step, two fundamental tasks are implemented: data normalization and handling missing values [28]. These stages are essential for facilitating model convergence, as the optimizer model can then make constant upgrades through each feature. Normalization is a data scaling procedure that ensures the data is within a particular range. Here, the data was standardized to the interval of $[-1, 1]$.

$$\chi' = 2 \cdot \left(\frac{\chi - \chi_{\min}}{\chi_{\max} - \chi_{\min}}\right) - 1 \tag{1}$$

Whereas χ' Refers to the normalized value, χ denotes the original value; $\chi_{\max}$ and $\chi_{\min}$ indicate the maximum and minimum values in the data.

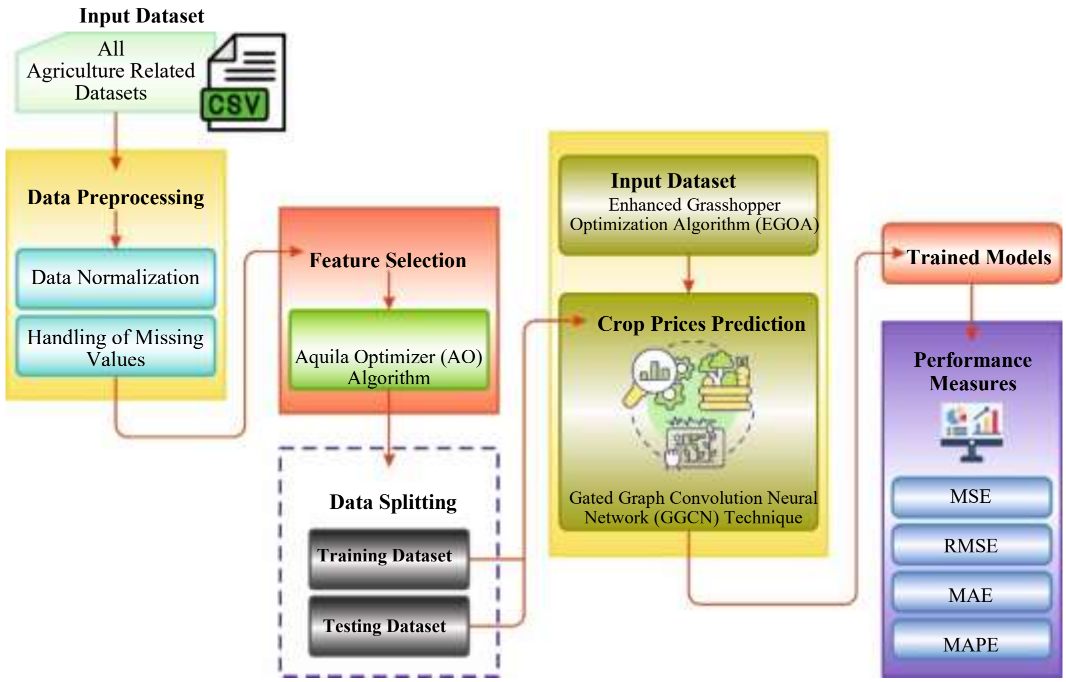

Fig. 1 Flow of the AFCP-GCNNHSO method

To deal with the problem of missing data, linear interpolation is used. It involves approximating the missing data point's value by presuming that the transformation among dual successive data points emulates linear models. This formulation demonstrating this linear interpolation is given below.

$$y = y_1 + \frac{(x-x_1)(y_2-y_1)}{(x_2-x_1)} \quad (2)$$

Wherein the succeeding variables are described. χ specifies the point upon which the data is missed; y means the interpolated value. χ_1 and χ_2 represents identified data points encircle the missing value; y_1 and y_2 indicate consistently recognized values at x_1 and x_2.

3.2. Feature Selection Methods

Moreover, the AO model is primarily utilized in the FS procedure to choose the most relevant features from the dataset. Aquila are frequently seen as predatory birds. Aquila catches prey with its strength, quickness, keen claws, and strong feet [29]. The Aquila employs four searching methods, switching among them based on the situation. The searching model comprises contour flying with a brief glide assault, higher soaring with a vertical stoop, low flying with a gradual descent attack, and walking and grabbing prey. This model is advanced for continuous optimization concerns and succeeds in these steps:

3.2.1. Initialization

In AO, a population-based model, the population is initialized stochastically, a practice that is usual for other metaheuristic models. It creates a population of candidate solutions within the Upper (Ub) and Lower (Lb) bounds of the specified concern in the initial stage. The position of every Individual $\left(X_{i,j}\right)$ in the population.

$$X_{i,j} = r_1 \times (Ub_j - Lb_j) + Lb_j \; i = 1, \dots, n \; j = 1, \dots, m \quad (3)$$

Now r_1 denotes a random number, m signifies the number of decision variables, and n depicts the individuals. X_i represents the i_{th} value of the decision variable. Equation (4) is utilized to transition AO from exploration to exploitation; now T characterizes the overall iteration counts, and t denotes the existing iteration.

$$\begin{cases} Exploration\ phase & if\ r \leq \frac{2}{3} \times T \\ Exploitation\ phase & else \end{cases} \quad (4)$$

3.2.2. Expanded Exploration

The 1st stage $(X_1 It$ involves the aquila flying high, soaring with a vertical stoop to identify the searching area and select the most attractive foraging position.

$$X_1(t+1) = X_b(t) \times \left(1 - \frac{t}{T}\right) + (X_{mean}(t) - X_b(t) \times r_2) \quad (5)$$

$$X_{mean}(t) = \frac{1}{n}\sum_{i=1}^{n} X_i\,(t) \forall j = 1, \dots, m \quad (6)$$

Here, X_b denotes the position of the finest individual in the population, r_2 represents a random number, and X_{mean} Depicts the mean position of individuals.

3.2.3. Narrowed Exploration

In the 2nd stage (X_2), known as contour flight through short glide attacks, they circle above the targeted victim, preparing the regions for strikes.

$$X_2(t+1) = X_b(t) \times Levy(D) + X_R(t) + (y-x) \times r_3 \quad (7)$$

In Equation (7), r_3 signifies random real numbers inside the interval of [0,1], X_R Refers to the place of an arbitrarily chosen individual from the population, $Levy\ (D)$ signifies the Levy flight distribution function, and D indicates the variable number.

$$Levy\ (D) = s \times \frac{u \times \sigma}{|v|} \frac{1}{\beta} \quad (8)$$

$$\sigma = \frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\frac{\beta-1}{2}}} \quad (9)$$

Here, u and σ denote an arbitrary variable in [0,1], and s denotes a constant valued at 0.01. β refers to a constant with a value of 1.5. Variables x and y are employed to create the spiral configuration and are calculated utilizing Equations (10) and (11). U and ω are equal to 0.00565 and 0.005, respectively. $\in$ signifies a number ranging from 1 to 20. D_1 refers to an integer that differs from 1 to the length of the searching space (m).

$$x = \psi x \sin(\theta) \quad (10)$$

$$y = \psi \times \cos(\theta) \quad (11)$$

$$\psi = \varepsilon + U \times D_1 \quad (12)$$

$$\theta = -\omega \times D_1 + \theta_1 \quad (13)$$

$$\theta_1 = \frac{3 \times \pi}{2} \quad (14)$$

3.2.4. Expanded Exploitation

Upon readiness to assault and having precisely recognized a searching position, the aquila descends vertically in preparation for a frontal attack in the 3rd phase. It utilizes random values that range from 0 to 1 for r_4 and r_5. α and δ are constants, both set at a value of 0.1.

$$X_3(t+1) = (X_b(t) - X_{mean}(t)) \times \alpha - r_4 + ((U_b - L_b) \times r_5 + L_b) \times \delta \quad (15)$$

3.2.5. Narrowed Exploitation

Once reaching the prey in the 4th stage, the aquila starts an assault from above, tracking the random movements of prey through land. Equation (16) gives a mathematical model of walking and grasping behaviours connected to prey.

$$X_4(l+1) = X_b(l) \times q_F - (\mathrm{g}_1 \times X(l) \times r_6) - \mathrm{g}_2 \times Levy(D) + r_7 \times \mathrm{g}_1 \quad (16)$$

Here, q_F signifies the quality function and is calculated in Equations (17) and (18), which depict g_1, which is utilized to track prey in escape. g_2 It is employed to track prey throughout an escape, from start to end. The value depicting the eagle's flight slope is evaluated utilizing Equation (19) and shows a decline from 2 to 0. The variables r_6, r_7, and r_8 are arbitrary values that range from 0 to 1.

$$Q_F = t^{\frac{2 \times r_7 - 1}{(1-T)^2}} \quad (17)$$

$$\mathrm{g}_1 = 2 \times r_8 - 1 \quad (18)$$

$$\mathrm{g}_2 = 2 \times \left(1 - \frac{t}{T}\right) \quad (19)$$

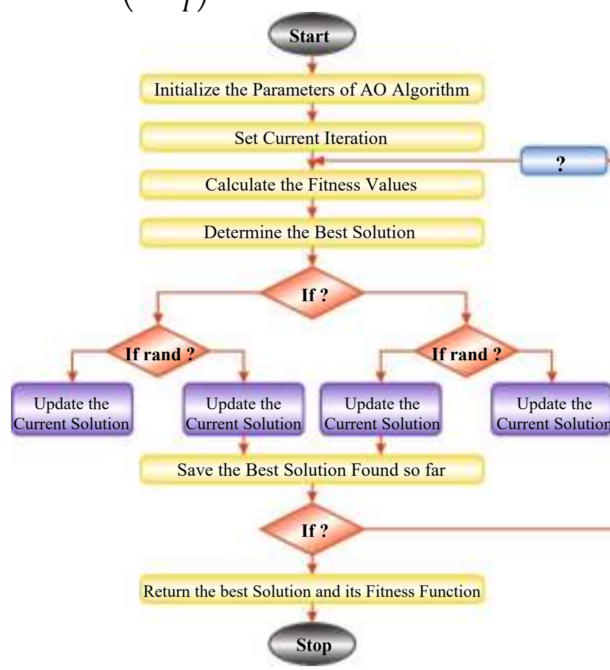

Fig. 2 Flowchart of the AO Technique

The Fitness Function (FF) mimics the classifier precision and the no. of chosen characteristics. It uses the classifier precision and decreases the set size of preferred attributes. Thus, the following FF is applied to evaluate a different solution in Equation (20).

$$Fitness = \alpha * ErrorRate + (1-\alpha) * \frac{\#SF}{\#All\_F} \quad (20)$$

Now, $ErrorRate$ is a classifier error rate and is estimated as the proportion of inappropriate categories, ranging from 0 to 1. $\#SF$ indicates the nominated feature number, and $\#All\_F$ denotes the overall attributes. α is applied for switching the significance of classification excellence and sub-set length. Figure 2 represents the flowchart of the AO model.

3.3. Crop Prices Prediction using GGCN Model

For the crop prices prediction, the GGCN model is implemented. In GCN, the handmade Laplacian matrix of adjacency $\tilde{A}$ Learns a particular variety of data that is not connected with the input [30]. By generating a Laplacian adjacency matrix $\tilde{A}$It depends upon data-driven learning to recognize the relation among graph nodes by lessening errors.

Furthermore, residual connections with the GGCN element are employed to incorporate the GRU and the Graph Convolution Layer (GCL) to concentrate the longer-term dependency within the GCL. It comprises dual layers of GRU and GCL. The l_{th} layer of the GGCN module F_G is specified.

$$F'_G = \sigma_{gru}^{(l)}\left(F_{GCL}^{(l)}, \sigma_{gru}^{(l-1)}\left(F_{GCL}^{(l-1)}\right)\right) \tag{21}$$

$$F_{GCL} = \sigma'\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}\right) \tag{22}$$

Here, σ' signifies the activation function of Leaky ReLu. F_{GCL} Indicates the output feature of GCL. $\sigma_{gru}(\cdot)$ Represents the operation of GRU, Θ implies the weighted matrix. l depicts the counts of both layers, $l = 2$.

Step1 $F_h^r \in R^{M \times C}$ signifies the recreated feature of F_h. Here, $M = HxW$ denotes the counts of graph nodes, and C denotes input channel features. Dual diagonal matrices $\tilde{\wedge}^a$ and $\tilde{\wedge}^b$ were created based on F_h^r To learn the representation of a node.

Particularly, the diagonal matrix $\tilde{\wedge}^a \in R^{C \times C}$ Concentrates the channel data by the distance among the dot products of the input node. The matrix of the diagonal $\tilde{\wedge}^b \in R^{M \times M}$ Represents a spatial weighted matrix that is employed to determine the relationship among diverse nodes. $\tilde{\wedge}^a$ and $\tilde{\wedge}^b$ These are given in Equation (23).

$$\begin{gathered}\tilde{\wedge}^a\ (F_h^r) = \eta\left(Liner\left(AMP(F_h^r)\right)\right)\\ \tilde{\wedge}^b\ (F_h^r) \sim= \eta\left(Conu_{1\times1}\left(AMP(F_h^r)\right)\right)\\ F_h^r = Reshape(F_h) \in R^{M \times C}\end{gathered} \tag{23}$$

While $Linear(\cdot)$ denotes linear layer operation, $AMP(\cdot)$ signifies maximal adaptive pooling operation, $Conu_{1\times1}$ indicates a 1×1 convolution layer and $\tilde{\wedge}(\cdot)$ Refers to the diagonalization operation.

The data-driven matrix of adjacency A is measured by the matrix of diagonal nodes. $\tilde{\wedge}^a$ and $\tilde{\wedge}^b$, the initial matrix of adjacency A.

$$\begin{gathered}A = \psi(F_h^r, \Theta^a) \otimes \tilde{\wedge}^a\ (F_h^r) \otimes \psi(F_h^r, \Theta^a)^T +\\ \phi(F_h^r, \Theta^b) \otimes \phi(F_h^r, \Theta^b)^T \odot \tilde{\wedge}^b\ (F_h^r)\end{gathered} \tag{24}$$

Now, $\otimes$ indicates matrix product, $\odot$ signifies the Hadamard product, Θ^a, Θ^b refers to a learnable weighted matrix, $\psi(F_h^r, \Theta^a) \in R^{M \times C}$ and $\psi(F_h^r, \Theta^b) \in R^{M \times C}$. Reweight the convolution operation 1×1 correspondingly.

Step3 $F'_h \in R^{M \times 1}$ signifies the reconstructed attribute of F_h. To attain the boundary model, $F'_h \in R^{M \times 1}$ is incorporated into $\tilde{\wedge}^b$, which refers to the diagonal matrix of the Laplacian by spatial relation.

$$\begin{gathered}\tilde{\wedge}_f^b\ (F_h^r, F'_h) = Conv_{1\times1}\left(AMP(F_h^r)\right) \otimes\\ Conv_{1\times1}(AMP(F_h^r \odot F'_h))^T\\ F'_h = Reshape(Conv_{1\times1}(F_h) \in \mathbb{R}^{M \times 1})\end{gathered} \tag{25}$$

This method of combining the reconstructed feature F'_h The Laplacian matrix highlights the significance of boundary data by allocating more weight to boundary pixels.

$$\begin{gathered}\tilde{A} = \psi(F_h^r, \Theta^a) \otimes \tilde{\wedge}^a\ (F_h^r) \otimes \psi(F_h^r, \Theta^a)^T +\\ \xi(F_h^r, \Theta^c) \otimes \xi(F_h^r, \Theta^c)^T \odot \tilde{\wedge}_f^b\ (F_h^r, F'_h)\end{gathered} \tag{26}$$

Finally, considering that lower-level attributes comprise prior data, integrating them with higher-level aspects also increases precision.

$$\begin{gathered}F'_h = Conu_{1\times1}(Conu_{1\times1}F'_l = Conu_{1\times1}(F_l)\\ O = SoftMax\left(Up(F'_h) \oplus Up(F'_l) \oplus Up(F_G)\right)\end{gathered} \tag{27}$$

Here, $\oplus$ indicates feature splicing, $Up(\cdot)$ denotes the upsampling process of bilinear interpolation, and $SoftMax(\cdot)$ signifies the classification function.

3.4. EGOA-based Parameter Tuning Process

Finally, the tuning is achieved by implementing the EGOA model for enhancing the prediction performance of the GGCN model [31]. GOA is a meta-heuristic optimizer model that simulates a grasshopper swarm to solve optimization concerns. The insects fly as a group, with each grasshopper at a certain distance from the others, and their movement is modelled.

$$X_i = S_i + G_i + A_i \tag{28}$$

Here, S_i indicates social interaction, A_i denotes wind influence, and X_i represents the position of $the\ i^{th}$ grasshopper.

Interaction plays a vital role in the model, as depicted in Equation (29).

$$S_i = \sum_{1 \le j \le n} s\left(d_i^j\right) \times \tilde{d}_i^j \tag{29}$$

A unit vector $\left(\tilde{d}_i^j\right)$ represents the distance between the i^{th} and j^{th} positions of a grasshopper, and s denotes a function that depicts social force.

$$s_d = f \times e^{\frac{d}{1}} - e^{-d} \tag{30}$$

Now, 1 indicates an attractive length scale, d signifies the distance between grasshoppers, and f denotes attraction intensity.

Nevertheless, an appropriate method for grasshopper movement is utilized to manage the optimization concern. Equation (31) is leveraged in an improved form of the model to solve the issue effectively.

$$x_i^d = c \times \left(\sum_{\substack{1 \le j \le n \\ j \ne 1}} \frac{UB_d - LB_d}{2} \times s\left(\left| x_j^d - x_i^d \right| \times \frac{x_j - x_i}{2} \right) \right) + \tilde{T}_d \quad (31)$$

Now, $\tilde{T}_d$ depicts the targeted location in the D^{th} dimension, and c denotes the volume to manage exploration and exploitation. It should be decreased to increase the iteration number.

$$c = c_{\max} - 1 \times \frac{c_{\max} - c_{\min}}{L} \quad (32)$$

A multi-dimensional Fitness Function (FF) is utilized to retrieve data. To decrease the computation cost and time, a 1D function is proposed. K-best particles denote 'K' data for retrieval.

Additionally, GOA is utilized to manage continuous variables, while a discrete model is required owing to discrete indices. Variables are transformed into a discrete form. Meanwhile, each discrete grasshopper represents a piece of data. In FF, Euclidean distance is established among features and those of grasshoppers.

$$F_i = \sum_{i=1}^{d} ||r - v_i|| \quad (33)$$

Now, r signifies the feature vector of the Query, v_i denotes the i^{th} vector in the feature matrix, and d implies dimensions. The factor i represents the rounded state of grasshopper i.

$$i = [\mathrm{j} + 0.5] \quad (34)$$

Here, j represents the position of the grasshopper and $[.]$ signifies the integer part.

Exploration and exploitation play a crucial role in GOA, enabling a proper search in the probable space and achieving the best outcome, which in turn decreases the FF.

$$x_i = \begin{cases} 10 \times ran \times m_i, if l >> \Theta \\ (19) \\ m_{i'} 1 < \Theta \end{cases} \quad (35)$$

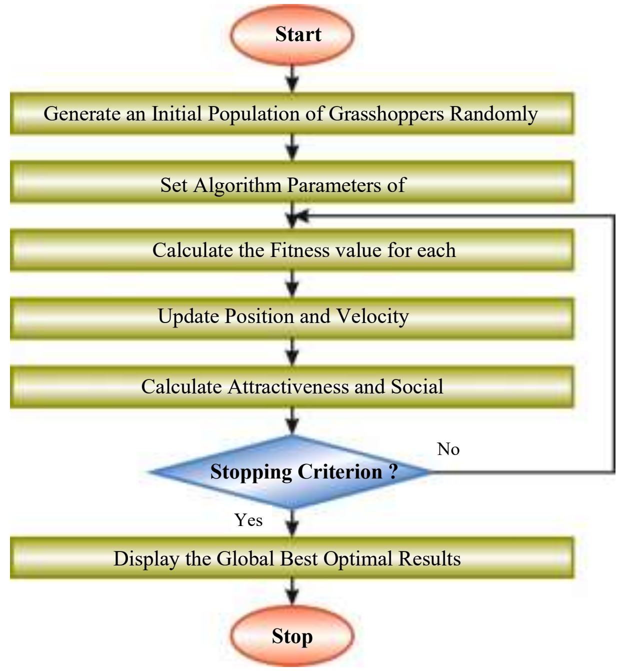

Fig. 3 Flowchart of the GOA method

Now, d is taken as one, and m_i It is similar to Equation (31).

$$m_i = \left(\sum_{\substack{1 \le j \le n \\ j \ne i}} c \times \frac{UB - LB}{2} \times s\left(\left| x_f - x_i \right| \times \frac{x_j - x_i}{d_i^j} \right) \right) + \tilde{T}_d \quad (36)$$

In Equation (35), $10 \times ran$ denotes a number in the range $[0{,}10]$, and ran signifies a variable in the range $[0{,}1]$. The factor 'Θ' is a volume that manages a trade-off between exploration and exploitation. It results in proper searching and exploration, with iteration not exceeding 'Θ', and presents the appropriate answer in the resultant iterations. Figure 3 indicates the flowchart of the GOA method.

The EGOA is used to establish the hyperparameters included in the GGCN model. The MSE is estimated by the function of the objective and is defined as demonstrated.

$$MSE = \frac{1}{T} \sum_{j=1}^{L} \sum_{i=1}^{M} \left(y_j^i - d_j^i \right)^2 \quad (37)$$

Whereas M and L consistently illustrate the data and the resulting layer value, d_j^i and y_j^i Individually suggest the appropriate and attained magnitudes for the j^{th} element from the network's resultant layer at time t.

4. Model Assessment and Results

The experimental assessment of the AFCP-GCNNHSO model is investigated under all agriculture-related datasets for India [32]. This dataset contains a total of nine attributes, but only eight are selected.

Figure 4 depicts the price distribution for the top 10 commodities, revealing two distinct groups: staple vegetables (cabbage, carrot, cauliflower, onion, potato, tomato, and brinjal) with low-to-moderate medians, and paddy (dhan/common), green chilli, and banana, which exhibit superior central prices. Generally, the figure specifies relative price stability for core staples like onion and potato, and pronounced fluctuation risk for green chilli and banana-aligning with research that connects agricultural price variability to climate oscillations and systemic volatility transmission through commodity networks.

Figure 5 verifies the correlation matrix formed by the AFCP-GCNNHSO model. The solution indicates that the AFCP-GCNNHSO approach accurately recognizes and classifies every class label. Figure 6 depicts a performance assessment for the actual vs the predicted AFCP-GCNNHSO approach at epochs 10 to 50. The outcome illustrated that the AFCP-GCNNHSO approach has improved prediction outcomes.

The figure means the actual vs. prediction performance of the AFCP-GCNNHSO model. The outcome specified that the AFCP-GCNNHSO model has revealed improved predicted solutions at all hours of the process. It is well-known that the change between the actual and predicted values is determined at least in part.

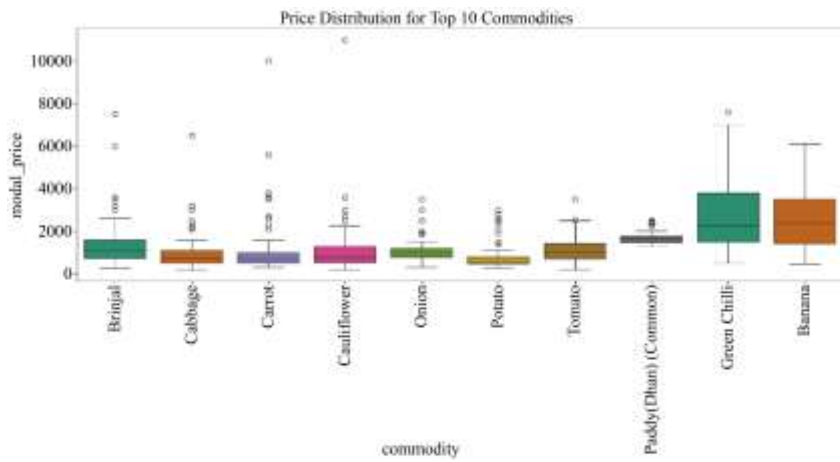

Fig. 4 Price distribution for top 10 commodities

Fig. 5 Correlation matrix of the AFCP-GCNNHSO model

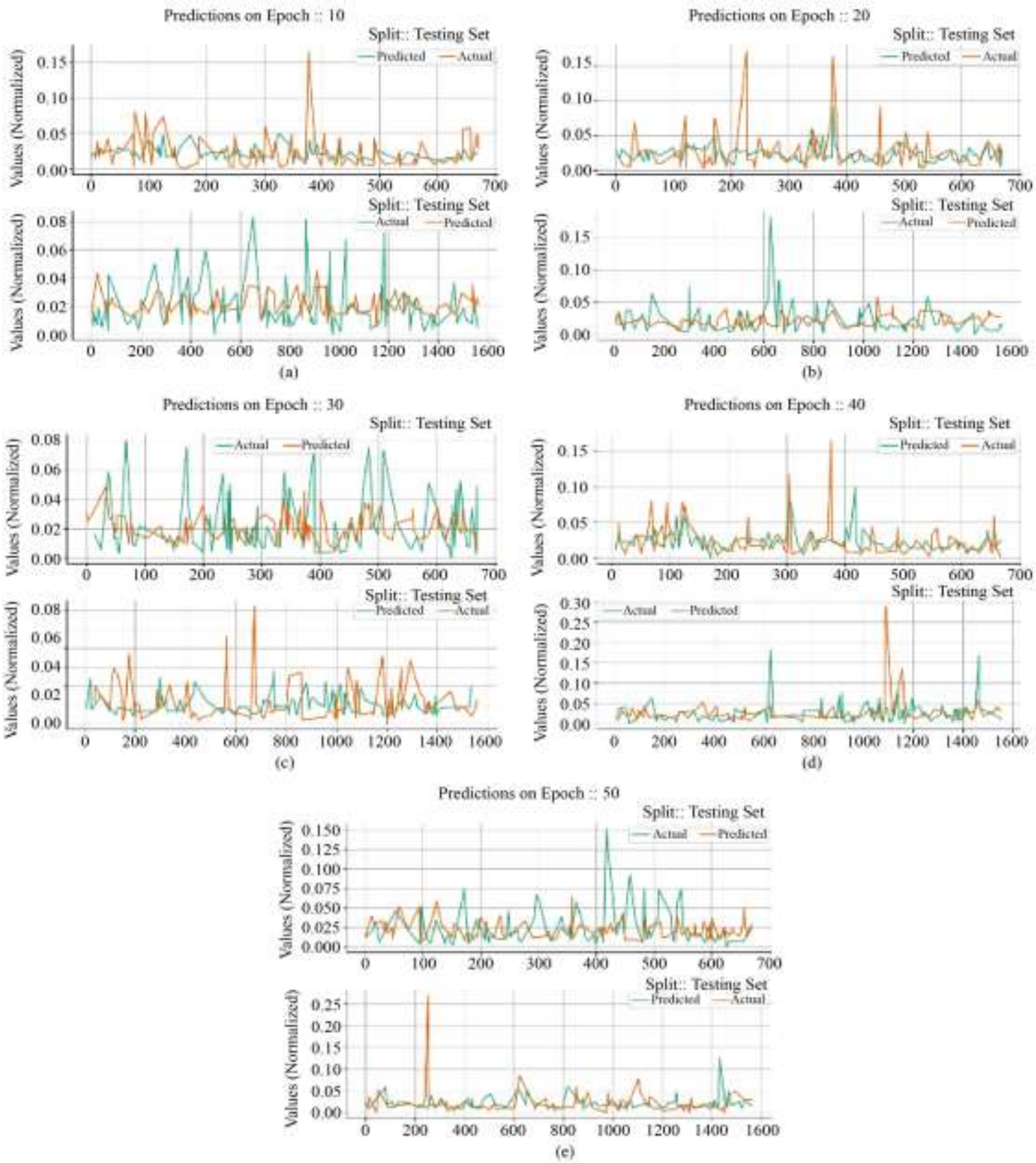

Fig. 6 Actual vs Prediction graph of the AFCP-GCNNHSO technique (a-e), Epoch 10 to 50

Table 1 and Figure 7 indicate the training and testing sets solutions under diverse metrics like MSE, RMSE, MAE, MAPE, and R2 Score. The training set has achieved an MSE of 0.000379, RMSE of 0.019469, MAE of 0.006197, MAPE of 0.027274, and an R^2 score of 0.668797. The testing set has an MSE of 0.000083, an RMSE of 0.009106, an MAE of 0.00568, an MAPE of 0.035496, and an R2 Score of 0.830432.

Table 1. Training and testing sets outcomes under distinct metrics

Metrics	Training Set	Testing Set
"MSE"	0.000379	0.000083
"RMSE"	0.019469	0.009106
"MAE"	0.006197	0.00568
"MAPE"	0.027274	0.035496
"R2 Score"	0.668797	0.830432

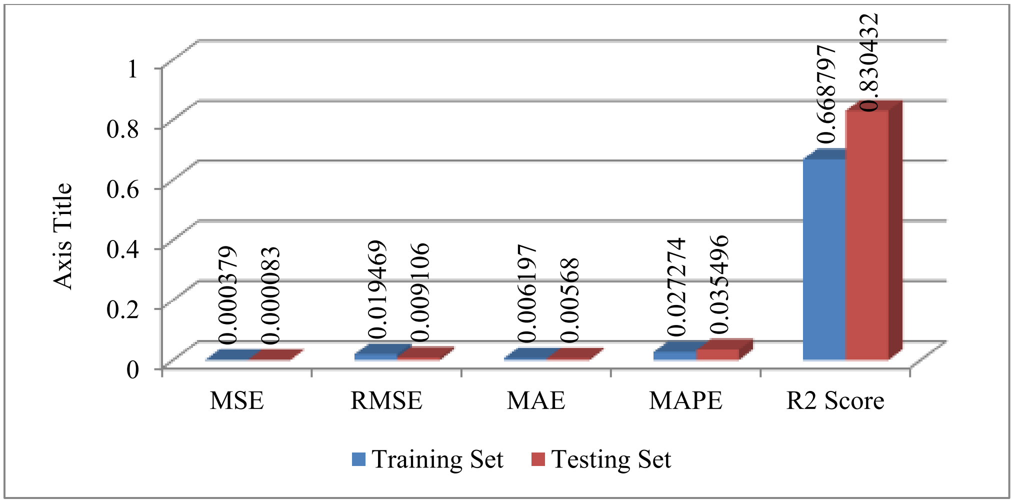

Fig. 7 Training and testing sets outcomes under distinct metrics

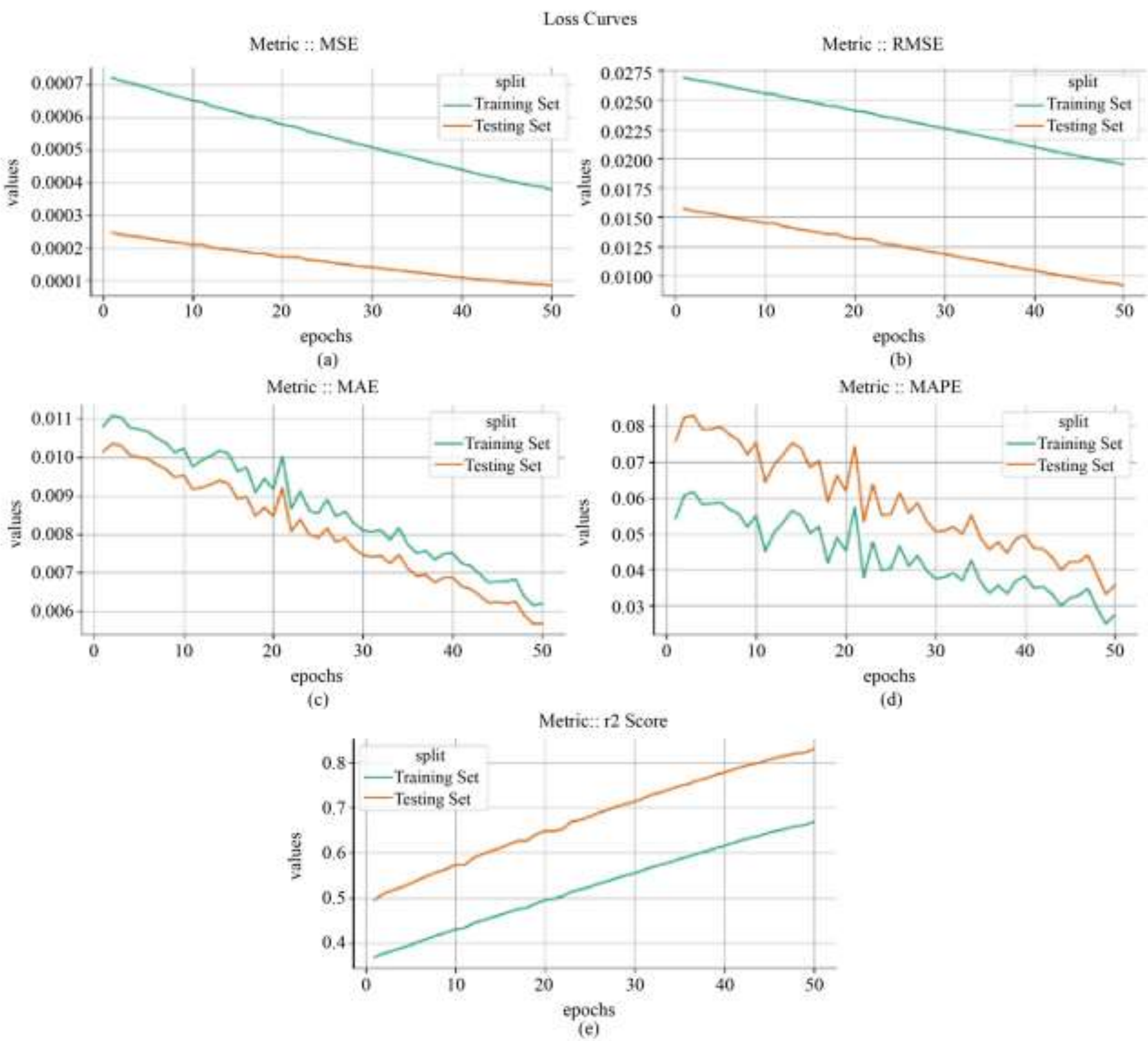

Fig. 8 Loss curves of the AFCP-GCNNHSO technique under distinct metrics

Figure 8 presents the loss curves of the AFCP-GCNNHSO model under various metrics. The values of loss are measured over an interval of 0 to 50 epochs. Both training and testing sets indicate a consistent downward trend, signifying that the method is effectively reducing error in learning.

The testing set remains slightly lower than the training loss through most epochs, recommending better generalization and no signs of overfitting. At the same time, some fluctuations are identified as becoming increasingly consistent and steady.

Table 2 presents the comparison evaluation of the AFCP-GCNNHSO technique with existing models across multiple metrics [7-33]. Figure 9 presents the MSE performance of the AFCP-GCNNHSO technique with recent methods. The solution reveals that the AFCP-GCNNHSO technique has an enhanced outcome. The SVR, ELM, and Full-PSO-CS methods have achieved MSEs of 0.76220, 0.40610, and 0.55480, respectively. The GRNN, SARIMA–LSTM, VMD–TDNN, and Bagging SVR methods have achieved lower MSEs of 0.19190, 0.17170, 0.11530, and 0.13950, respectively. Furthermore, the AFCP-GCNNHSO method has a minimal MSE of 0.00038.

Table 2. Comparative analysis of the AFCP-GCNNHSO technique with existing models

Prediction Techniques	MSE	RMSE	MAE	MAPE
SVR	0.76220	0.09350	0.08640	0.42964
GRNN	0.19190	0.05100	0.03930	0.37417
ELM	0.40610	0.06900	0.04770	0.32120
Full-PSO-CS	0.55480	0.08190	0.07620	0.27107
SARIMA–LSTM	0.17170	0.04840	0.03640	0.19429
VMD–TDNN	0.11530	0.03810	0.03220	0.14125
Bagging SVR	0.13950	0.04190	0.03280	0.08774
AFCP-GCNNHSO	0.00038	0.01947	0.00620	0.02727

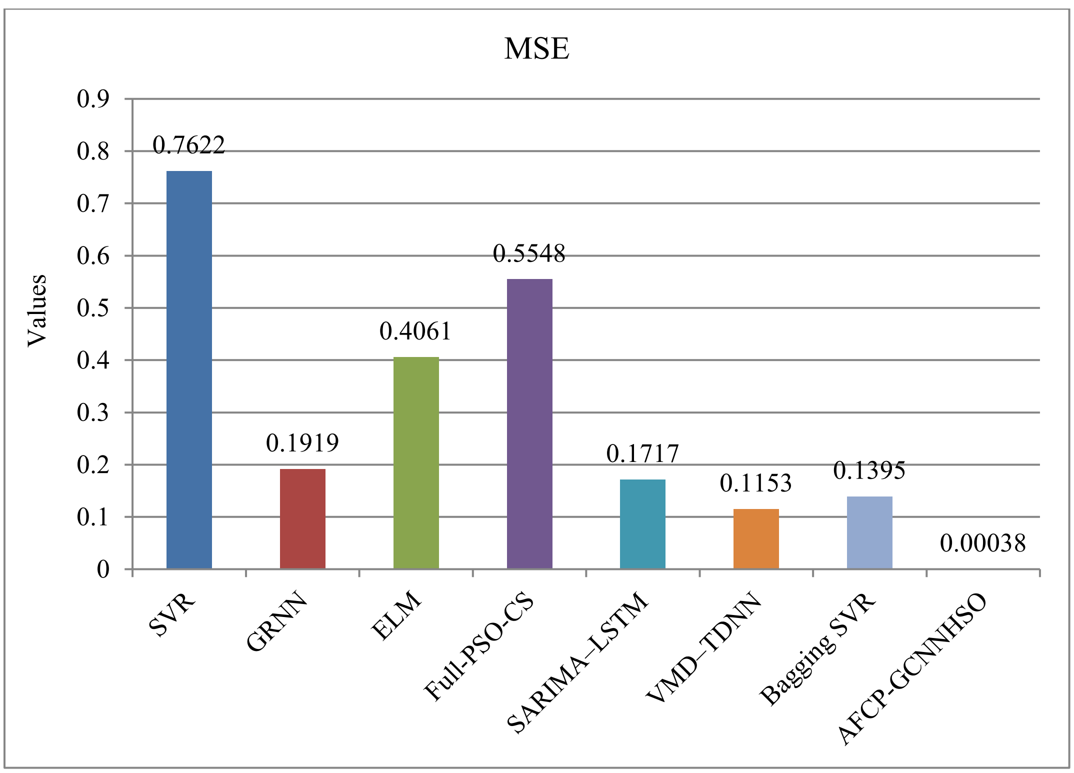

Fig. 9 MSE outcome of the AFCP-GCNNHSO technique with existing models

Figure 10 depicts the RMSE solutions of the AFCP-GCNNHSO technique with prediction approaches. The existing methods, such as SVR, GRNN, ELM, Full-PSO-CS, SARIMA–LSTM, VMD–TDNN, and Bagging SVR, have achieved superior RMSE values of 0.09350, 0.05100, 0.06900, 0.08190, 0.04840, 0.03810, and 0.04190, respectively. The AFCP-GCNNHSO method has a minimal RMSE of 0.01947.

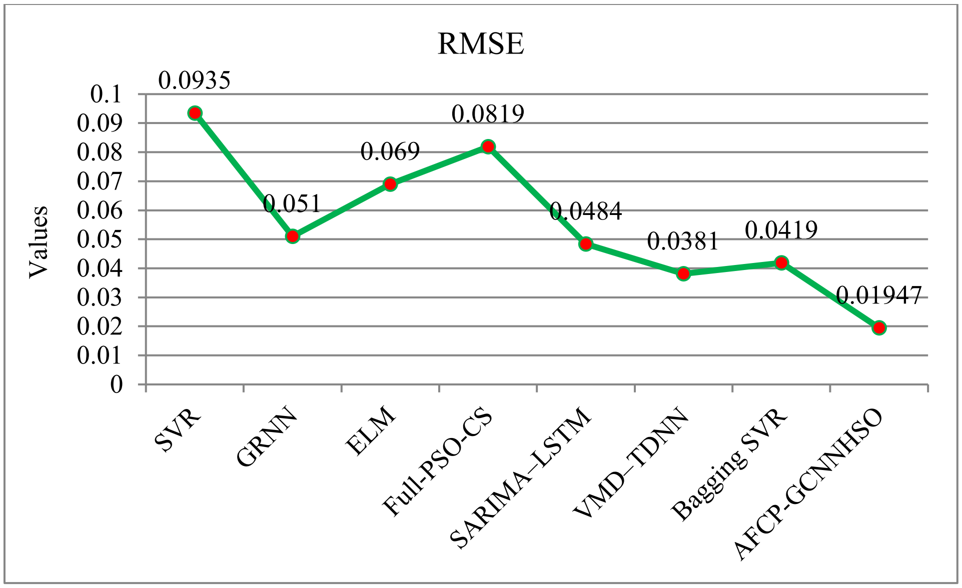

Fig. 10 RMSE outcome of the AFCP-GCNNHSO technique with existing models

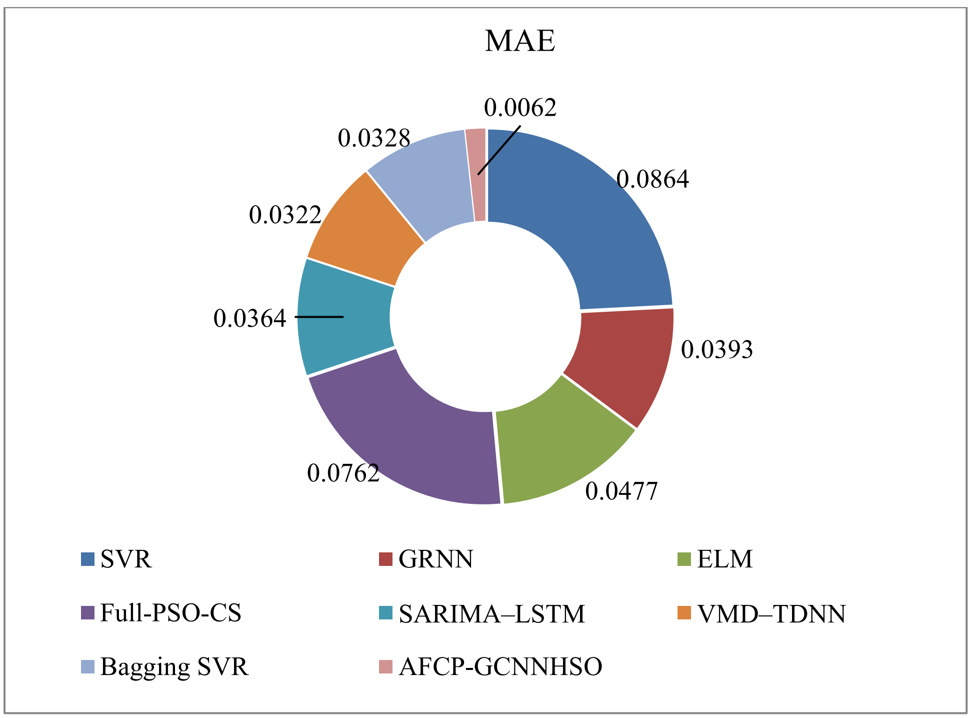

Fig. 11 MAE outcome of the AFCP-GCNNHSO approach with recent methods

The MAE results of the AFCP-GCNNHSO approach, compared to the existing method, are presented in Figure 11. The table values indicate that the AFCP-GCNNHSO methodology has achieved an enhanced outcome with a minimal MAE of 0.00620. Simultaneously, the existing prediction approaches, such as SVR, GRNN, ELM, Full-PSO-CS, SARIMA–LSTM, VMD–TDNN, and Bagging SVR models, have attained maximal MAE of 0.08640, 0.03930, 0.04770, 0.07620, 0.03640, 0.03220, and 0.03280, correspondingly.

Figure 12 shows a comparison analysis of the AFCP-GCNNHSO approach with prediction techniques under MAPE. The SVR, GRNN, ELM, and Full-PSO-CS have achieved MAPEs of 0.42964, 0.37417, 0.32120, and 0.27107, respectively. However, the SARIMA–LSTM, VMD–TDNN, and Bagging SVR approaches have a somewhat lower MAPE of 0.19429, 0.14125, and 0.08774, respectively. Additionally, the AFCP-GCNNHSO methodology has a significantly lower MAPE of 0.02727.

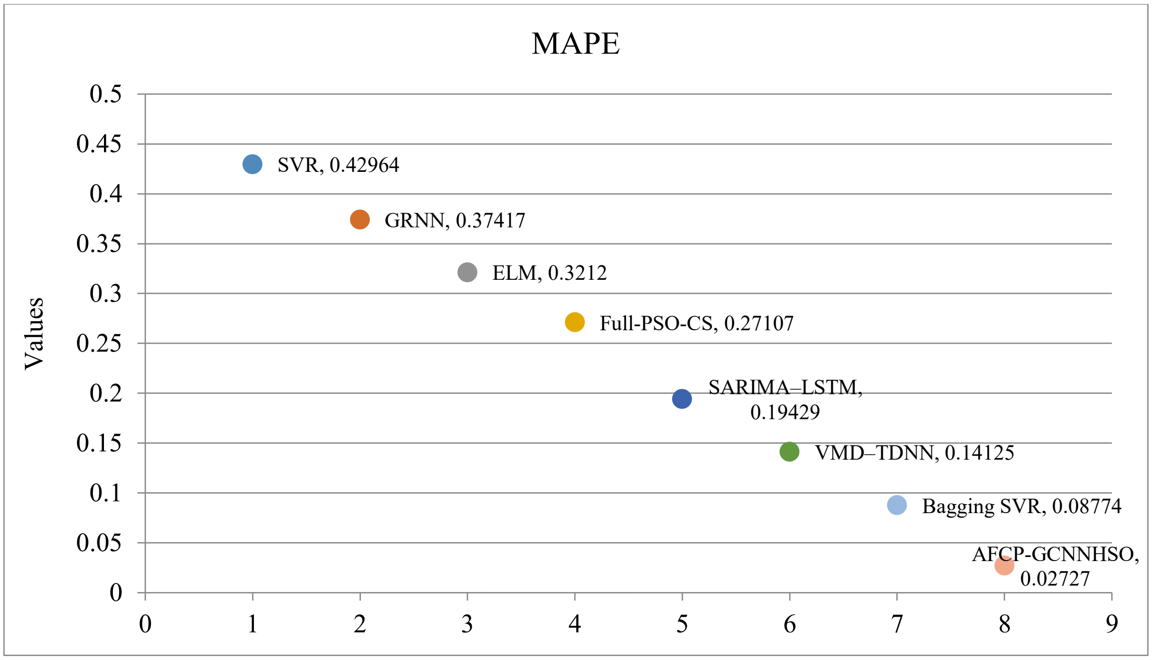

Fig. 12 MAPE Outcome of the AFCP-GCNNHSO Approach with Recent Methods

These results highlighted that the AFCP-GCNNHSO model accomplishes better prediction results compared to other methods.

5. Conclusion

In this research paper, an effective AFCP-GCNNHSO method is proposed for accurate forecasting of crop prices. The AFCP-GCNNHSO method encompasses a series of subprocesses, namely pre-processing, AO-based feature selection, GGCN-based prediction, and EGOA-based hyperparameter selection. The preprocessing stage involves two key operations: data normalization and handling of missing values, which convert the data into a compatible format for the prediction process. Moreover, the design of the AO approach enables the optimal selection of features from the pre-processed data, thereby reducing overall computational complexity and enhancing prediction performance. Furthermore, the EGOA with the GGCN technique adequately predicts the crop process, and the use of EGOA helps to obtain reduced prediction error. The utilization of AO assured the selection of highly related features, and the EGOA results in faster convergence and high generalization. The experimental validation of the AFCP-GCNNHSO methodology is tested on benchmark agricultural data from the Kaggle repository. The comparison results indicated the enhanced performance of the AFCP-GCNNHSO methodology over other existing approaches. Therefore, the AFCP-GCNNHSO methodology is employed as a reliable tool to support decision-making in the agricultural market. Future work can focus on the design of hybrid DL models or transformer-based architectures for capturing temporal dependencies in crop prices. Also, external factors like weather patterns, government policies, and global market trends are incorporated to boost prediction performance accuracy and applicability.

Data Availability Statement

The data that support the findings of this research paper are openly available in the Kaggle repository at https://www.kaggle.com/datasets/thammuio/all-agriculture-related-datasets-for-india, reference number [32].

References

[1] Ranjit Kumar Pau et al., “Machine Learning Techniques for Forecasting Agricultural Prices: A Case of Brinjal in Odisha, India,” *Plos one*, vol. 17, no. 7, pp. 1-17, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] Luyao Wang et al., “Agricultural Product Price Forecasting Methods: Research Advances and Trend,” *British Food Journal*, vol. 122, no. 7, pp. 2121-2138, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[3] Ersin Elbasi et al., “Crop Prediction Model using Machine Learning Algorithms,” *Applied Sciences*, vol. 13, no. 16, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] G. Murugesan, and B. Radha, “An Extrapolative Model for Price Prediction of Crops Using Hybrid Ensemble Learning Techniques,” *International Journal of Advanced Technology and Engineering Exploration*, vol. 10, no. 98, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] R.L. Manogna, Vijay Dharmaji, and S. Sarang, "Enhancing Agricultural Commodity Price Forecasting with Deep Learning," *Scientific Reports*, vol. 15, pp. 1-24, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[6] G.H. Harish Nayak et al., "Exogenous Variable Driven Deep Learning Models for Improved Price Forecasting of TOP Crops in India," *Scientific Reports*, vol. 14, pp. 1-26, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Asterios Theofilou et al., "Predicting Prices of Staple Crops Using Machine Learning: A Systematic Review of Studies on Wheat, Corn, and Rice," *Sustainability*, vol. 17, no. 12, pp. 1-34, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[8] Anket Patil et al., "Forecasting Prices of Agricultural Commodities using Machine Learning for Global Food Security: Towards Sustainable Development Goal 2," *International Journal of Engineering Trends and Technology*, vol. 71, no. 12, pp. 277-291, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Kiran M. Sabu, and T.K. Manoj Kumar, "Predictive Analytics in Agriculture: Forecasting Prices of Arecanuts in Kerala," *Procedia Computer Science*, vol. 171, pp. 699-708, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] R. Ramesh, and M. Jeyakarthic, "Enhanced Price Prediction of Seasonal Agricultural Products Using Ensemble Learning," *NeuroQuantology*, vol. 20, no. 6, pp. 101433-101442, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Rajesh Kumar Panda et al., "Agri-horticulture Commodity Price Prediction by Deep Learning Techniques," *2024 2nd International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES), Paralakhemundi Campus, Centurion University of Technology and Management*, Odisha., India, pp. 1-6, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] D.M.I.S. Dasanayaka, and G.R. Perera, "Smart Agriculture System Leveraging Machine Learning Technology for Price Forecasting and Crop Recommendation," *International Conference on Transformative Applied Research 2024*, Sri Lanka, 2025. [Google Scholar]

[13] Kapil Choudhary et al., "A Genetic Algorithm Optimized Hybrid Model for Agricultural Price Forecasting based on VMD and LSTM Network," *Scientific Reports*, vol. 15, pp. 1-20, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[14] G.H. Harish Nayak et al., "N-BEATS Deep Learning Architecture for Agricultural Commodity Price Forecasting," *Potato Research*, vol. 68, pp. 1437-1457, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Murat Sari et al., "Various Optimized Machine Learning Techniques to Predict Agricultural Commodity Prices," *Neural Computing and Applications*, vol. 36, pp. 11439-11459, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Manas Kumar Mohanty, Parag Kumar Guha Thakurta, and Samarjit Kar, "Agricultural Commodity Price Prediction Model: A Machine Learning Framework," *Neural Computing and Applications*, vol. 35, pp. 15109-15128, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Priyanka Sharma et al., "Predicting Agriculture Yields Based on Machine Learning Using Regression and Deep Learning," *IEEE Access*, vol. 11, pp. 111255-111264, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Nitesh Singh, and Ritu Sindhu, "Crop Price Prediction using Machine Learning," *Journal of Electrical Systems*, vol. 20, no. 7, pp. 2258-2269, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] R.L. Manogna, Vijay Dharmaji, and S. Sarang, "A Novel Hybrid Neural Network-based Volatility Forecasting of Agricultural Commodity Prices: Empirical Evidence from India," *Journal of Big Data*, vol. 12, pp. 1-19, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[20] V.C. Karthik et al., "Advanced Potato Price Prediction through N-BEATS Deep Learning Architecture," *Journal of Experimental Agriculture International*, vol. 46, no. 9, pp. 362-375, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[21] Dabin Zhang et al., "Integrated GCN–BiGRU–TPE Agricultural Product Futures Prices Prediction Based on Multi-graph Construction," *Computational Economics*, vol. 66, pp. 3927-3955, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[22] Pramit Pandit et al., "Hybrid Modeling approaches for Agricultural Commodity Prices using CEEMDAN and Time Delay Neural Networks," *Scientific Reports*, vol. 14, pp. 1-19, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Guangji Zheng, Ye Li, and Yu Xia, "Crude Oil Price Forecasting Model Based on Neural Networks and Error Correction," *Applied Sciences*, vol. 15, no. 3, pp. 1-25, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[24] Raveena Selvanarayanan, and R. Surendran, "Predicting Coffee Prices Trends and Demand Hit Record using Multi-Variate Time Series-RNN for Mitigating Supply Chain Risks," *8th IET Smart Cities Symposium (SCS 2024), Hybrid Conference*, Bahrain, pp. 792-797, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] Ronit Jaiswal et al., "STL-LSTM Hybrid Model for Forecasting Seasonal Agricultural Price Series," *Annals of Data Science*, pp.1-24, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[26] M. Venkateswara Rao et al., "Brinjal Crop yield prediction using Shuffled Shepherd Optimization Algorithm based ACNN-OBDLSTM Model in Smart Agriculture," *Journal of Integrated Science and Technology*, vol. 12, no. 1, pp. 1-7, 2024. [Google Scholar] [Publisher Link]

[27] Burak Gülmez, "GA-Attention-Fuzzy-Stock-Net: An Optimized Neuro-Fuzzy System for Stock Market Price Prediction with Genetic Algorithm and Attention Mechanism," *Heliyon*, vol. 11, no. 3, pp. 1-23, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[28] Eko Sediyono et al., "An Integrated Framework for Multi-Commodity Agricultural Price Forecasting and Anomaly Detection using Attention-Boosted Models," *Journal of Agriculture and Food Research*, vol. 22, pp. 1-14, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[29] Gülnur Yıldızdan, “Binary Aquila Optimizer with Taper-Shaped Transfer Function: An Application for Merkle-Hellman Knapsack Cryptosystems,” *Intelligent Methods in Engineering Sciences*, vol. 4, no. 2, pp. 29-37, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[30] Huiqing Pei et al., “Combined Gated Graph Convolution Neural Networks with Multi-Modal Geospatial Data for Forest Type Classification,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 136, pp. 1-15, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[31] N. Sundaravalli et al., “An Enhanced Diagnostic and Classification Process of Covid-19 Chest X-Ray Images Using Ensemble Convolutional Neural Network (ECNN),” *Explorium - Bulletin of the Center for Nuclear Mining Technology*, vol. 46, no. 1, pp. 1-23, 2025. [Google Scholar] [Publisher Link]

[32] All Agriculture Related Datasets for India, Kaggle. [Online]. Available: https://www.kaggle.com/datasets/thammuio/all-agriculture-related-datasets-for-india

[33] Bo Li, and Yuanqiang Lian, “A Forecasting Approach for Wholesale Market Agricultural Product Prices Based on Combined Residual Correction,” *Applied Sciences*, vol. 15, no. 10, pp. 1-21, 2025. [CrossRef] [Google Scholar] [Publisher Link]