Optimized Hybrid CNN-LSTM Model for Agriculture Supply-chain Management System

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Abstract

Agricultural supply-chain management (ASM) has intricated and linked networks that make it possible for agricultural goods to be transported from farms to customers. The integration of deep learning (DL) and blockchain technology has the power to completely transform the agriculture industry by improving sustainability, efficiency, and transparency. But there is still a lot to learn about the scalability and long-term effectiveness of combining blockchain and DL technologies in ASM. In order to tackle these issues, we suggest an Optimized Hybrid CNN-LSTM model for ASM system, to make effective decisions regarding the production and storage of agriculture food products. To fine tune the hyperparameters of CNN-LSTM, the Adaptive White Shark Optimizer (AWSO) algorithm is applied. Before forecasting, Exploratory Data Analysis (EDA) on sales has been performed in which daily, monthly and yearly sales analysis are computed based on store and item features. The sales forecasting is done by means of the proposed optimized CNN-LSTM model and the basic DL models Convolution Neural Network (CNN), Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU) and. The model accuracy is evaluated in terms of the statistical error measures Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE). Experimental results results have shown that the optimized CNN-LSTM model attains least error measures when compared to the other models.

Keywords

Agricultural supply-chain management (ASM), Deep Learning (DL), Adaptive White Shark Optimizer (AWSO), CNN-LSTM model, Statistical error measures

1. Introduction

The transportation of agricultural products from farms to consumers is made possible by the complex and interrelated systems of agricultural supply-chain management (ASM). These networks are essential for guaranteeing food products which are accessible and available everywhere, promoting food security and the welfare of communities everywhere. Their importance is mostly derived from their critical function in preserving food security, since they provide the regular and effective distribution of fresh produce, staple foods, and other agricultural products to consumers. Food shortages, unequal distribution, and price volatility would become more likely in the absence of well-managed supply chains, which might have a negative impact on economies and communities [1].

Reducing food waste also requires effective agricultural supply chains. Food losses can happen at any point in the process, from harvest to consumption, but by guaranteeing the timely delivery of agricultural products, effectively managed supply networks can reduce these losses. This is essential given the significant amount of food wasted globally, which affects both the environment and the economy. Furthermore, agricultural supply networks promote economic stability, particularly in regions where agriculture serves as the primary source of revenue. Through the interconnection of farmers, distributors, merchants, and consumers, these networks promote economic growth, create job possibilities, and maintain a living. Consistent agricultural product flow along these channels supports rural economies and communities., which guarantees farmers receive just recompense for their production [2].

The traceability, efficiency, and transparency of agricultural supply networks could be greatly enhanced by blockchain technology. By monitoring the complete supply chain, consumers, retailers, and regulators can confirm the legitimacy and calibre of food commodities.chain—from planting to harvesting to distribution—on an immutable and visible blockchain. [3]. Smaller farmers can obtain loans more readily by using blockchain-based data, such as past sales and manufacturing figures. Blockchain technology can monitor environmental elements in conjunction with IoT devices, enabling farmers to make informed decisions. Furthermore, blockchain can preserve decentralised records of audits and certificates for certified and organic products, minimising fraud and guaranteeing the integrity of valuable or locally designated agricultural item [4].

In order to handle a variety of agricultural issues that could jeopardise national stability, the agricultural sector of today needs to adopt cutting-edge digital technology like robotics, Artificial Intelligence (AI), and the Internet of Things (IoT). Agricultural products that meet the necessary standards for quantity, quality, and safety are guaranteed to reach customers through efficient agro-industrial supply chain management. This supply chain includes farming, processing, and distribution at every stage from the farm to the table. The lack of information on raw materials for processing, product transparency, production process details, logistics for consumer distribution, and product traceability, quality, documentation, costs, halal status, and value chain are some of the major problems that require answers.

1.1 **Motivation and Objectives**

The integration of deep learning (DL) and blockchain technology possesses the capacity to completely transform the agriculture industry by improving sustainability, efficiency, and transparency. DL models can evaluate and predict market trends, helping farmers and buyers make better-informed decisions about pricing and sales. Achieving efficient traceability and management for agri-food products is difficult because of the complexity and dynamics of agriculture.

Existing solutions often fall short in meeting the comprehensive requirements for traceability and management within agriculture.

The major objectives of our ASM framework are listed below:

- Understanding sales trends to forecast the future sales

- Matching store inventory with actual requirements to reduce storage space
- Optimizing replenishment quantity per order, to minimize the number of replenishments between warehouse and stores
- Determining the factors that affect sales to optimize the business model

To meet these objectives, this paper proposes an optimized hybrid CNN-LSTM model for ASM System. The ASM framework ensures product traceability and ensures decentralized security for agricultural data related to agri-food tracing

2. Literature Review

2.1 ASM using Blockchain technology

'ASBlock,' a blockchain-based decentralised application (dApp) created by Panigrahi et al. [7], is intended to communicate with 4 user types: farmers, retailers, restaurant owners and patrons. In addition to providing integrated support for the MetaMask wallet to ensure convenient and safe payments, this programme has an easy-to-use interface that facilitates efficient and secure communication among users. The programme also assists farmers in realising the worth of their produce, which may boost their productivity and drive. The efficacy of ASBlock was assessed by measuring its gas consumption, key generation time in varying network sizes, and smart contract execution time for diverse use cases.

AgriBlock is a blockchain-based architecture for ASM that was proposed by Acharya et al. [8]. The objective is to develop a decentralised application framework that will enable all stakeholders to manage agricultural supply chains in an open and transparent manner.

ASM using Blockchain and IoTs architecture was introduced by Bhat et al. [9] in order to address concerns with storage, scalability, interoperability, security, and privacy in single-chain agricultural supply systems that are currently in use. They also talked about defence strategies based on blockchain technology and categorised security risks found in IoT infrastructure.

A new blockchain architecture was presented by Mane et al. [10] to safeguard the integrity of agricultural data. Farmers can save their data securely using this architecture, which prevents data modification without adhering to strict guidelines. Smart contracts reduce manipulation risk by automating several operations. By using sensors to collect environmental data and store it in blockchain blocks, the proof of concept improves the agri-supply chain by integrating smart contracts and blockchain technology with conventional agricultural systems. Specialised smart contracts for agriculture automate choices and handle transactions according to programmed rules, resulting in increased security and efficiency.

A blockchain-based and AI-driven smart agricultural framework was presented by Jadav et al. [11] to forecast pesticide levels that surpass thresholds. Blockchain integration makes sure that information about crops grown with the least amount of pesticides is safely stored inside the immutable ledger. The accuracy, blockchain scalability, and latency of the framework were assessed.

During the COVID-19 pandemic, Khan et al. [12] handled the application of blockchain technology in agricultural supply networks, finding advantages and ways to keep things running smoothly. Using interviews with Pakistani agricultural businesses, the study outlined four main obstacles, seven important advantages, and workable solutions. Blockchain was mentioned by almost all responders as being crucial for managing data, preventing fraud, keeping track of shipments, and resolving inconsistencies in global supply chains during the epidemic.

2.2 **ASM using ML or DL Deep learning techniques**

A deep learning strategy based on blockchain was presented by Alla and Thangarasu [13] for the management of the agricultural supply chain sustainably. Their study assesses how deep learning and blockchain technologies can improve the quality assessment of the food supply chain. The accuracy of food traceability was boosted using blockchain, while reaction times were shortened by the Deep Random Forest (DRF) model. The study evaluates the accuracy, responsiveness, and sensitivity of the BC-DRF-based quality assessment system in relation to current techniques for varying block sizes.

A blockchain-based agricultural supply chain (ASC) framework was created by Chen et al. [14] to provide decentralised security and product traceability for agri-food tracing data. Additionally, they unveiled a Deep Reinforcement Learning-based Supply Chain Management (DR-SCM) technique that offers dependable product traceability by optimising manufacturing and storage choices for profit maximisation.

An inventive method for combining blockchain technology and machine learning for quality assessment in agricultural supply chains was put forth by Shaik et al. [15]. A decentralised, tamper-proof ledger system for transparent transaction and product information recording is provided by blockchain, allowing stakeholders to follow agricultural products from farm to table. Blockchain data is analysed by machine learning algorithms to find trends in product quality, forecast possible problems like contamination or spoiling, and send early alerts. By enabling real-time monitoring and verification of product quality, reducing losses, and increasing efficiency to deliver safer, higher-quality products, this system improves transparency, traceability, and confidence.

A blockchain fusion neural network technique was used by Gao and Li [16] to investigate cold chain cooperation in agriculture. Their objective was to enhance the Hadoop Distributed File System (HDFS) to accommodate a multitude of tiny files produced at different phases of the cold chain. Based on the kinds and sizes of files, they suggested an enhanced balanced merging and index caching technique. According to experimental data, utilising this approach for both storing and accessing huge volumes of small files resulted in considerable increases in HDFS performance.

2.3 Research Gaps

Although DL and blockchain-based ASM exhibits potential for improving efficiency, traceability, and transparency, there are still a number of unanswered questions. There is muchl more to learn about the long-term efficacy and scalability of combining blockchain and deep learning technologies in ASM, therefore more thorough research is required. The current barrier to wider adoption is the requirement for standardised protocols and frameworks to guarantee interoperability between various blockchain systems and deep learning models. There are a lot of obstacles to overcome because deep learning and blockchain have high computational and energy costs. These are especially true for small-scale farmers in underdeveloped nations. Additionally, strong solutions are needed to safeguard private data while preserving openness in light of privacy concerns around data sharing and storage on blockchain networks. The lack of real-world case studies and pilot projects emphasises the need for empirical research to verify theoretical frameworks and evaluate their applicability in various agricultural situations.

3. Proposed Methodology

3.1 Overview

The optimized hybrid CNN-LSTM-based ASM method makes effective decisions regarding the production and storage of agri-food products, aimed at optimizing profits. The sales forecasting is done by means of the optimized hybrid CNN-LSTM model and the basic models CNN, LSTM, GRU. To fine tune the hyperparameters of CNN-LSTM, the AWSO algorithm is applied.

The main highlights of the proposed ASM framework are listed below:

- ✓ Produce reasonable forecasts with hyperparameter tuning
- ✓ Demand for lesser data and lesser features
- ✓ Prevents overfitting, and improve the generalization ability
- ✓ Supports parallel selection of split points, thereby increasing the operating speed

3.2 Preprocessing the Dataset

3.2.1 Inclusion of Additional features

The sales training data contains the features of salesdate, store, item, and sale quantity. The following features are included to the training dataset as granular level: day of sales, month of sales, year of sales, day of week, day of year, quarter, daily_avg_sales, monthly_avg_sales, avg_sales_per_store_item. Then Boolean features checking for month starting or month ending, year starting or year ending , quarter starting or quarter ending are included.

3.2.2 Look-back technique for sales series

By using windowing techniques, data analysts can find important patterns in time-series data. Sliding windows are especially effective since they make patterns earlier to identify than with other methods. Look-back or backcast a time series is the process of forecasting in reverse time.

In our sales training data, window of (-30,+30) is applied over the salesdate. (ie) The previous month and the succeeding month of sales are considered for forcasting.

3.2.3 Exploratory Data Analysis (EDA) on Sales

Initially, the itemwise and storewise daily sales analysis is computed and plotted as shown in Figure 1.

Figure 1 Itemwise and Storewise daily sales analysis

Next, the item wise and store wise monthly sales analysis is computed and plotted as shown in Figure 2.

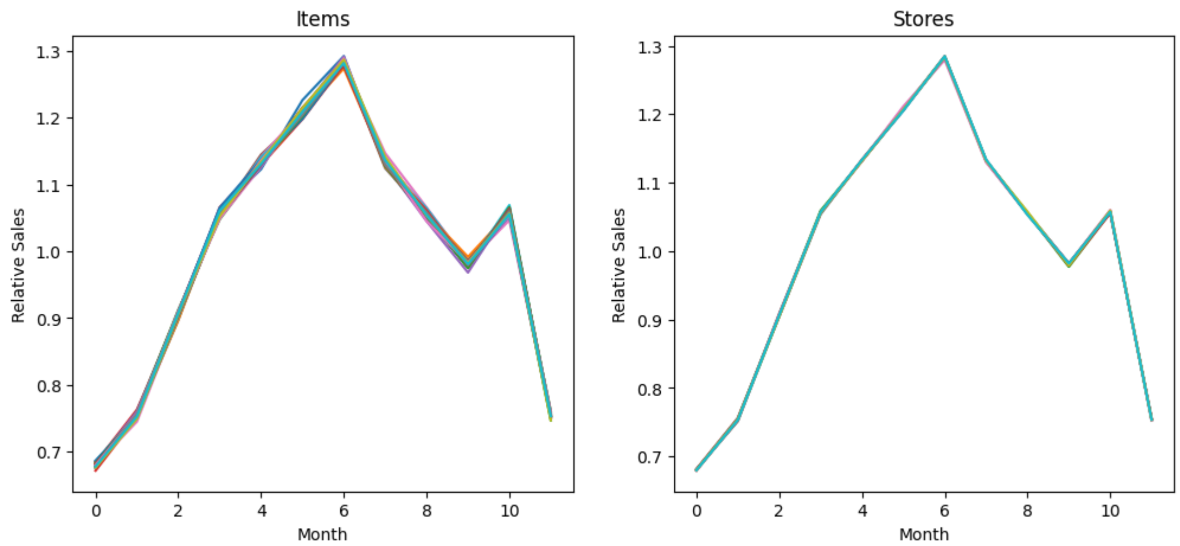

Figure 2 Itemwise and Storewise monthly sales analysis

As seen from Figure 2, all items and stores share a common pattern in sales over the months. There is a steady increase in sales upto 6 months and a steep decrease after that until the 10th month.

Next, the item wise and store wise yearly sales analysis is computed for 4 years and plotted as shown in Figure 3.

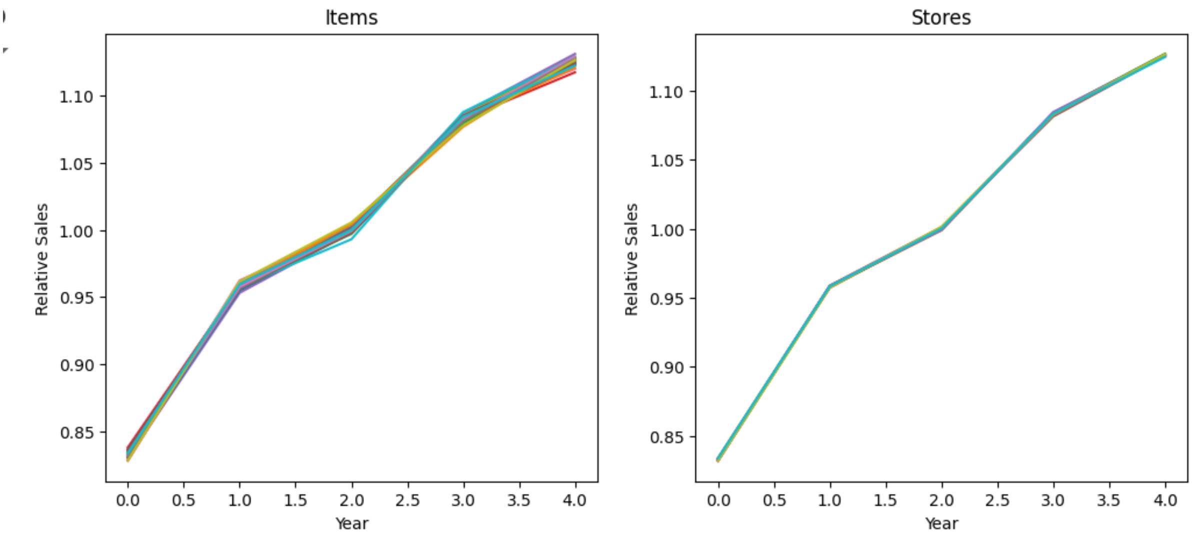

Figure 3 Itemwise and Storewise yearly sales analysis

As shown in Figure,3 all items and stores follow a similar growth in sales over the years. There is a steady increase in sales for all the items for all the 4 years.

3.3 Sales forecasting using CNN-LSTM model

The suggested hybrid model blends LSTM and CNN for sales forecasting, with optimized hyperparameters. A CNN network is primarily utilized for image processing however LSTM is a unique model that is typically employed for time series predictions.

3.3.1 CNN model

Biological brain systems have affected the current popularity of CNN as a DL model. It has fully connected layers as well as convolutional and pooling layers in that order.

Convolutional layer: It generates feature maps as an output after using a sliding-window technique to extract the input signal's high-level properties.

Pooling layer: This provides a traditional down sampling process by combining data from each small subset of the incoming feature systems using pooling operators, and then selecting the most important feature.

Fully connected layer: It generates the final output for the CNN model architecture after receiving the features from the pooling levels.

3.3.2 LSTM model

An enhanced version of a recurrent neural network (RNN) model called LSTM is able to identify long-term correlations. It uses short-term memory to overcome the issue of prolonged reliance. LSTM can process even the largest sequencing data sets without lowering the gradient. Each LSTM unit consists of three primary gates: input, outputs, and forget and storing cells. The cell can be precisely programmed to add or remove data by using these gates

3.3.3 Hybrid CNN-LSTM Model

A CNN can be formed by stacking CNN layers first, followed by LSTM layers and, at the outputs, a dense layer. The CNN-LSTM model contains a time distributed dense layer, followed by LSTM layer.

When dealing with time series data or video frames, a time distributed layer comes in quite handy. It permits using one layer for every input.

A batch size by sequence length by input size array is fed into a time distributed dense layer, which generates a batch size by sequence length by number of classes size array.

Table 1 shows the training summary of CNN-LSTM model with its layers, dimensions and parameters.

Layer	**Shape**	**Parameters**
Time_distributed	(41,64)	128
Time_distributed	(20,64)	
Time_distributed	1280	
LSTM	50	266,200
Dense (Output)	1	51

Table 1 Training Summary of CNN-LSTM Model

3.3.4 Hyperparameter tuning using AWSO Optimization

The effectiveness of the CNN-LSTM network's accuracy is significantly influenced by its hyper-parameters. However, if the hyper-parameters are fine-tuned manually, it takes more time and poses challenges in selecting the most optimal set of hyper-parameters. In an effort to enhance classification performance, this work introduces AWSO [17] and it considers the following fitness function.

$$Fitness = Max(Acc) \qquad (1)$$

The following section provides a concise overview of the mathematical modelling of the AWSO to illustrate the foraging behaviour of WS (white sharks). This behaviour encompasses activities such as hunting and attacking prey. The WS demonstrates the ability to locate its prey even at a considerable distance within the ocean. The WS employs three distinct strategies for prey identification. Firstly, their approach involves locating to prey by capitalizing on the waves' hesitancy induced by the prey's movement. Secondly, they engage in a random search for prey in the depths of the ocean. Thirdly, the behaviour of WS manifests in a deliberate effort to seek the nearby prey.

Initialization: The AWSO belongs to the category of population based model and the solutions of a candidate for an optimized problem, characterized by a size of population p, within a dimension $\dim$, are represented according to the following equation:

$$u = \begin{bmatrix} u_1^1 & u_2^1 & \cdots & u_{\dim}^1 \\ u_1^1 & u_2^2 & \cdots & u_{\dim}^3 \\ \vdots & \vdots & \vdots & \vdots \\ u_1^3 & u_2^3 & \cdots & u_{\dim}^m \end{bmatrix} \qquad (2)$$

where u is every WS position. The random population is initialized by:

$$u_i^m = ll_i + rand(ul_i - ll_i) \quad (3)$$

where $rand$, ul_i and ll_i are the random number, upper and lower limits. $c1, c2, q1, q2, mv, g, s$

Moving to the location of the prey: WS allocate a significant portion of their time to the pursuit and attack of prey, driven by their innate survival instincts. These creatures consistently employ a variety of tactics to trail and monitor prey. When a WS identifies its prey by detecting the wavering movements produced by the prey, it engages in a surging movement and it is given as:

$$v_l^m = \alpha\left[v_{l-1}^m + q_1\left(u_{gb,l-1} - u_l^m\right)\times c1 \times q_2\left(u_b^{v_{l-1}^m} - u_{l-1}^m\right)\times c2\right] \quad (4)$$

where $m = 1,2,3..., p$ is the index of WS, v_{l-1}^m is the new velocity of the m^{th} WS, $l-1$ is the iteration, u_l^m is the new position of WS, $u_{gb,l-1}$ is the best global factor attained at $l-1$ and $u_b^{v_{l-1}^m}$ is the best direction of WS. $q_1, q_2, c1$ and $c2$ are the random parameters. The term v is given as:

$$v = [p \times r(1, p)] + 1 \quad (5)$$

$$q_1 = q_{ul} + (q_{ul} - q_{ll})\exp{-}\left(\frac{4b}{B}\right)^2 \quad (6)$$

$$q_2 = q_{ll} + (q_{ul} - q_{ll})\exp{-}\left(\frac{4b}{B}\right)^2 \quad (7)$$

where b and B are the present and further iterations; q_{ll} and q_{ul} are the low and high velocities. α is the shrinking term and is given as:

$$\alpha = \frac{2}{\left|2 - ac - \sqrt{ac^2 - 4ac}\right|} \tag{8}$$

where ac is the acceleration term.

Moving to optimized prey: Intelligent WS expend a significant portion of their time actively searching for potential prey, irrespective of whether the prey's location is deemed ideal. Consequently, the positions of WS undergo constant fluctuations. Upon either hearing the waves generated by the prey movement or detecting its scent, they instinctively move to the prey and are given as:

$$u_l^m = \begin{cases} u_{l-1}^m \to u_0 + wy + gz & r < mv \\ u_{l-1}^m + \dfrac{v_{l-1}^m}{s} & r < mv \end{cases} \tag{9}$$

where w and g are the upper and lower values; y and z are the values of one dimension binary vectors and they are represented as:

$$y = \text{sgn}\left(u_{l-1}^m - w\right) > 0 \tag{10}$$

$$z = \text{sgn}\left(u_{l-1}^m - g\right) < 0 \tag{11}$$

where u_0 is the logical term and it is given as:

$$u_0 = \oplus(y, z) \tag{12}$$

where s is the WS's frequency and it is given as:

$$s = s_{\min} + \frac{s_{\max} - s_{\min}}{s_{\max} + s_{\min}} \tag{13}$$

where $s_{\min}$ and $s_{\max}$ are the minimum and maximum frequencies. The term mv is given as:

$$mv = \frac{1}{h_0 + \exp\left(\frac{B}{2-b}\right)/h_1} \tag{14}$$

where h_0 and h_1 are the whole numbers and it controls exploration and exploitation.

Moving to the best WS: The WS possesses the capability to consistently maintain concurrence with the optimal targets, which are in close concurrence with their prey.

$$u_l^{m'} = u_{gb,l-1} + r1 \times \vec{D}_u \operatorname{sgn}(r2 - 0.5) r3 < g \tag{15}$$

where g is the efficiency of eyesight and sense of smell, $r1, r2$ and $r3$ are the random numbers, $\vec{D}_u$ is the distance of prey and WS. It is given as:

$$\vec{D}_u = \left| r4 \times \left(u_{gb,l-1} - u_{l-1}^m\right)\right| \tag{16}$$

where $r4$ is the random number and $u_{gb,l-1}$ is the current best position of WS.

Fish school characteristics: The initial two optimal candidates are retained, and the positions of the remaining WS are adjusted based on these optimized locations. This behaviour is given as:

$$u_l^m = \frac{u_l^{m'} + u_{l-1}^m}{2 \times r4} \tag{17}$$

The proposed AWSO is based on the CSA (cuckoo search algorithm) and for every iteration, the Levy's flight is used for generating the new solution. This optimizer overcomes the convergence issue and local optima issue in the standard WSO.

$$v_l^m = v_l^m - \alpha(v_l^m - v_g) \oplus Levy(\beta) = v_l^m + \frac{0.01 j}{|h|^{1/\beta}}\left(v_l^m - v_g\right) \tag{18}$$

where v_l^m is the velocity of the m^{th} WS, α is the step scale, v_g is the best global solution, β is the exponent of Levy's flight and $\oplus$ is the element wise multiplication.

The values of j and h are computed as:

$$j \sim M(0, \sigma_j^2), h \sim M(0, \sigma_h^2) \tag{19}$$

where σ_j^2 and σ_h^2 are the standard deviations. Figure 4 shows the flowchart of AWSO.

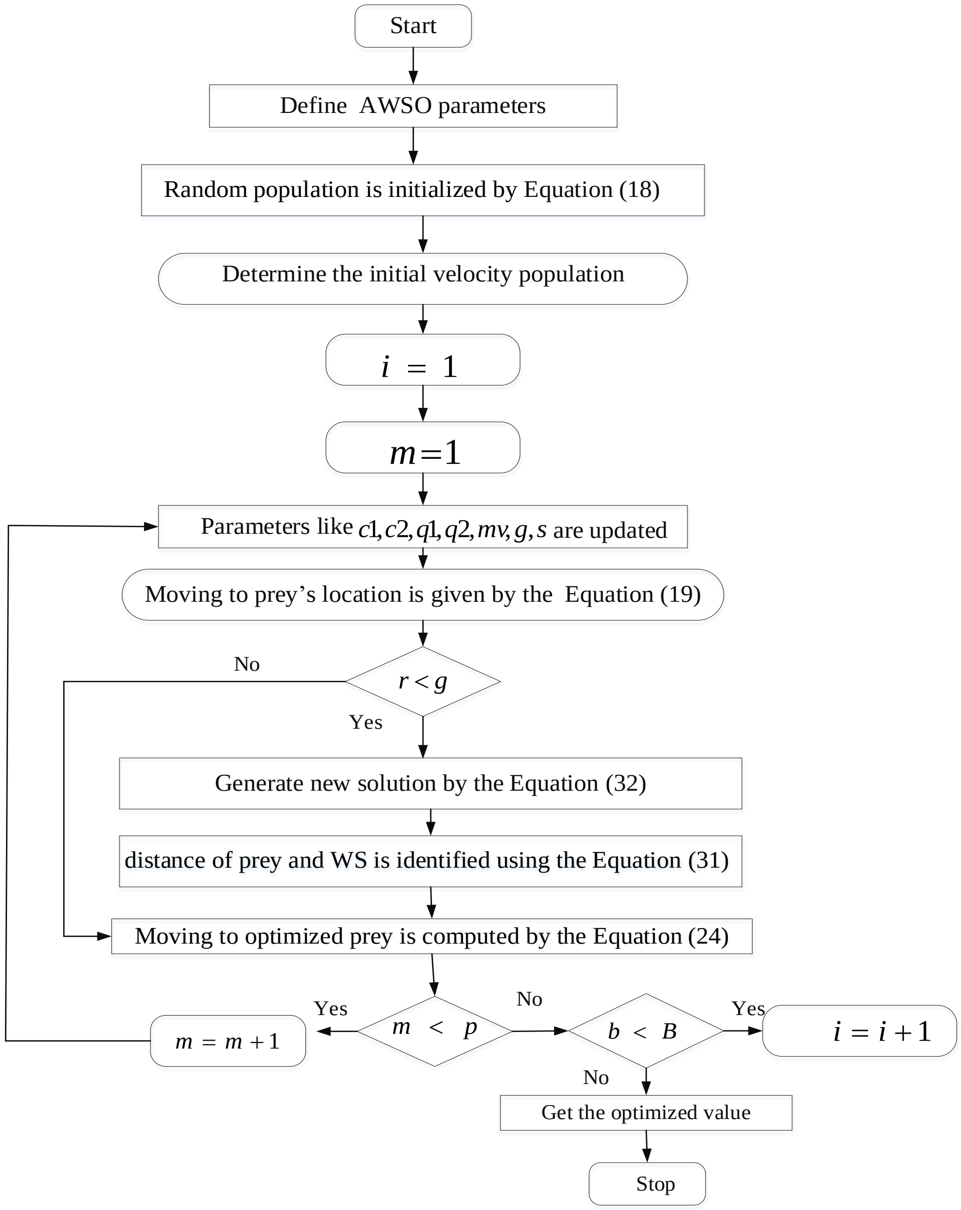

Figure 4 Flowchart of AWSO

4. Experimental Results

The proposed Optimized CNN-LSTM model and the existing CNN,LSTM and GRU model are implemented in Python 3.0.

4.1 CNN Model

Table 2 shows the training summary of CNN model with its layers, dimensions and parameters.

Layer	**Shape**	**Parameters**
Convolution 1D	(40,64)	192
Max Pooling 1D	(20,64)	
Flatten	1280	
Dense	50	64050
Dense (Output)	1	51

Table 2 Training Summary of CNN Model

Figure 5 shows the Training and Validation (TV) loss curves of the CNN model.

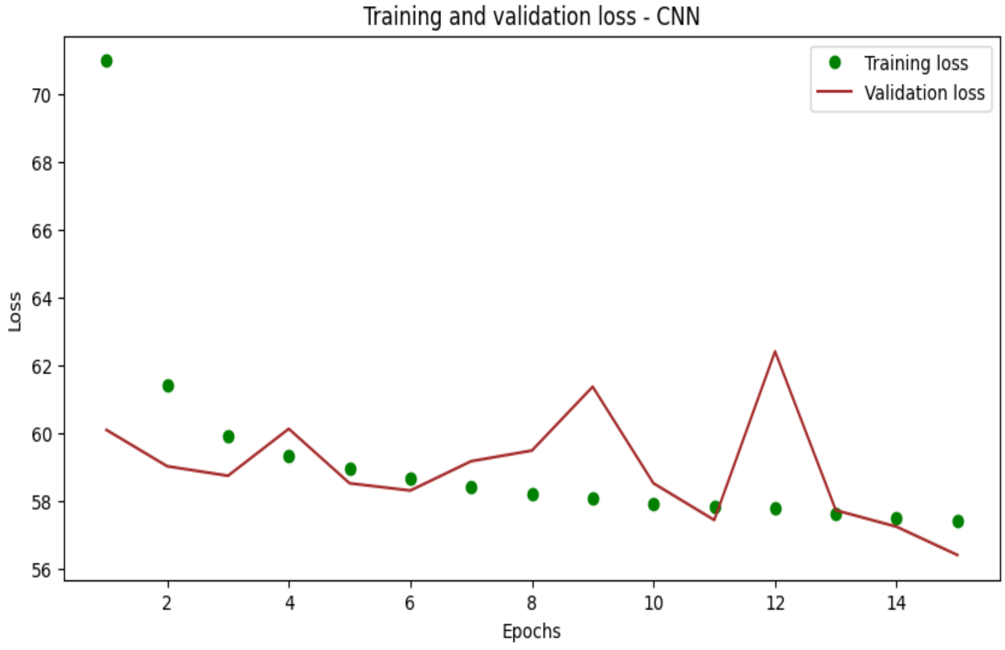

Figure 5 Training & validation Loss for CNN

Figure 6 shows the forcast and original sales values of various time periods, for the CNN model.

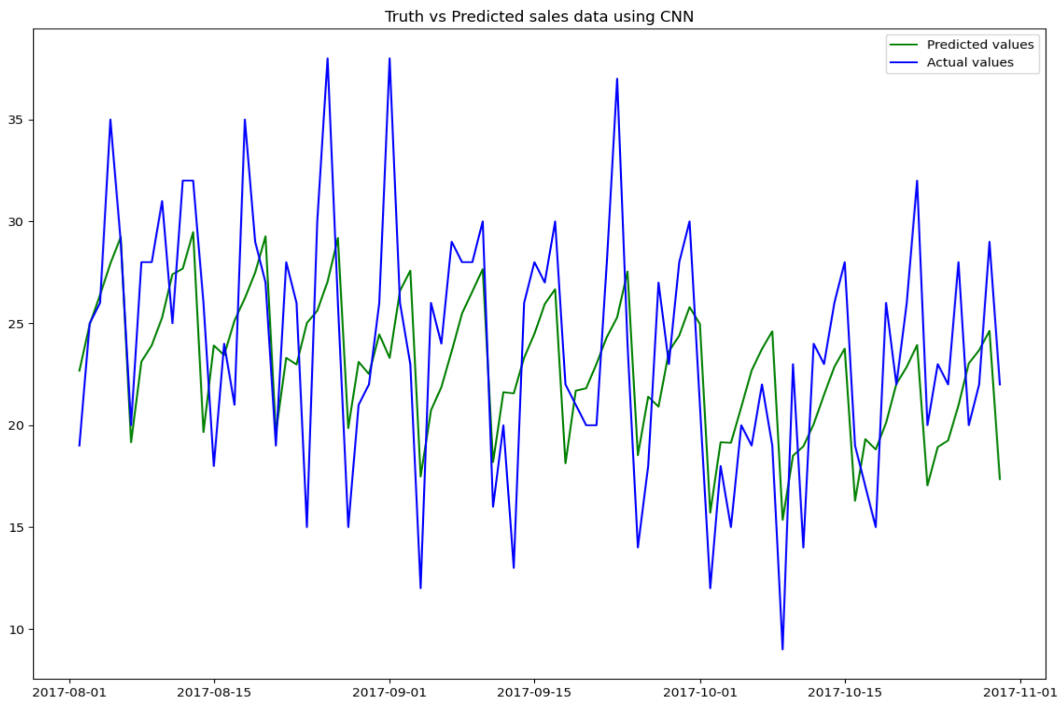

Figure 6 Predicted Vs Actual Sales for CNN

4.2 LSTM Model

Table 3 shows the training summary of LSTM model with its layers, dimensions and parameters.

Layer	Shape	Parameters
LSTM	42	7392
Dense (Output)	1	43

Table 3 Training Summary of LSTM Model

Figure 7 shows the TV loss curves of the LSTM model.

Figure 7 Training & validation Loss for LSTM

Figure 8 shows the orcast and original sales of various time periods, for the LSTM model.

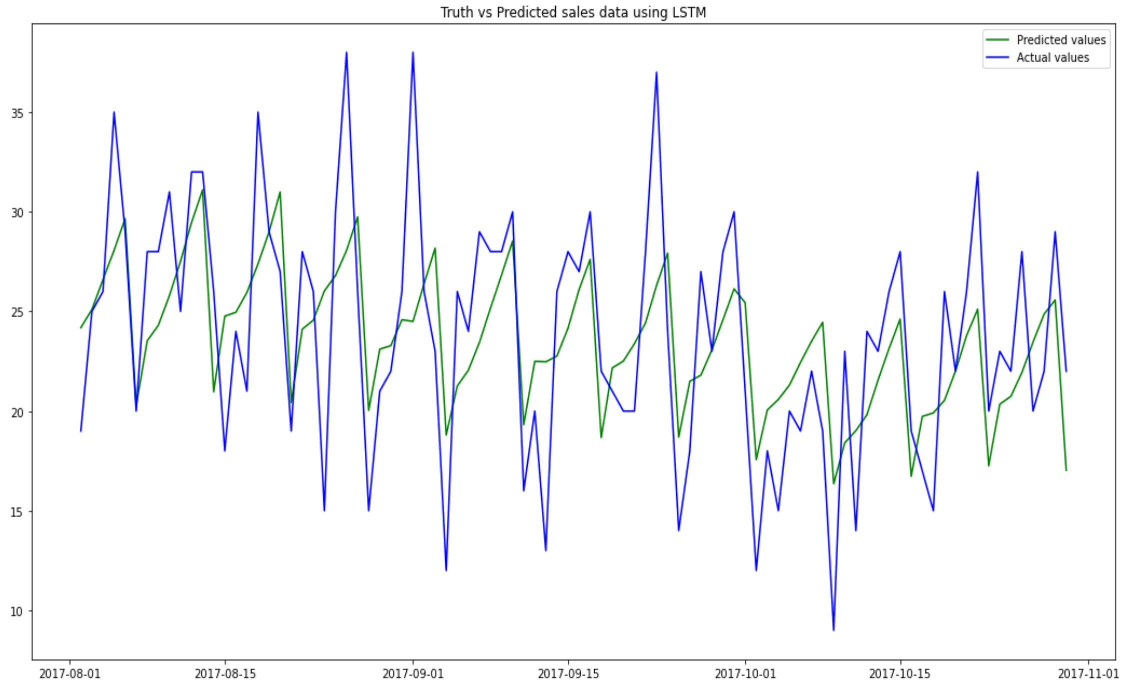

Figure 8 Predicted Vs Actual Sales for LSTM

4.3 GRU Model

Table 4 shows the training summary of GRU model with its layers, dimensions and parameters.

Layer	Shape	Parameters
GRU	(41,75)	17550
GRU	(41,30)	9630
GRU	30	5580
Dense (Output)	1	31

Table 4 Training Summary of GRU Model

Figure 9 shows the TV loss curves of the GRU model.

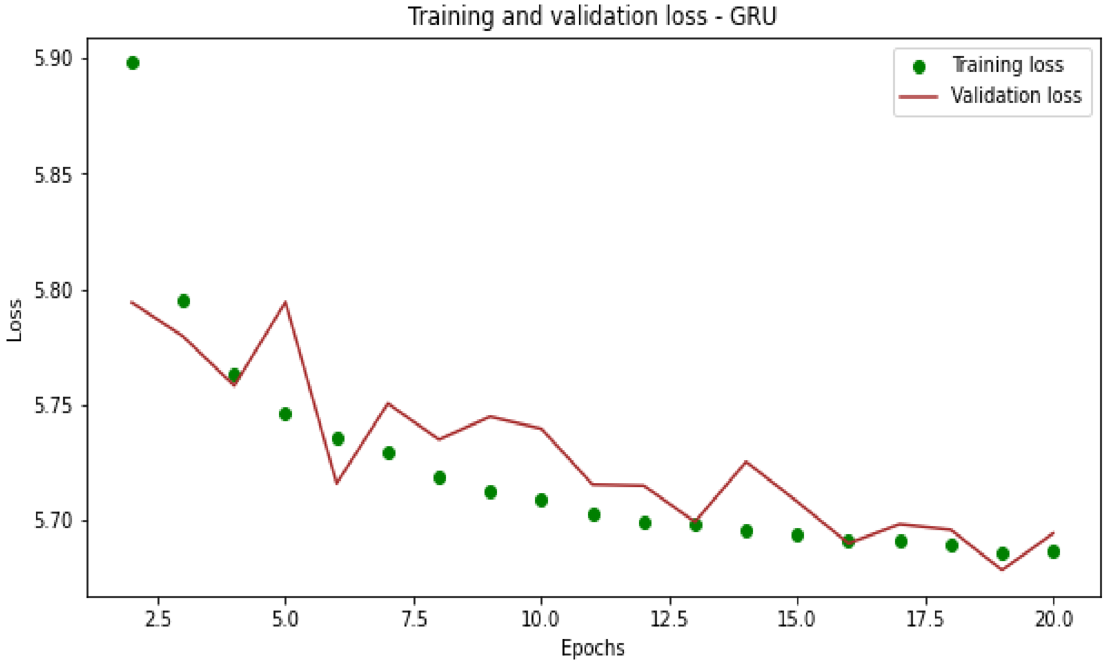

Figure 9 Training & validation Loss for GRU

Figure 10 shows the forcast and original sales of various time periods, for the GRU model.

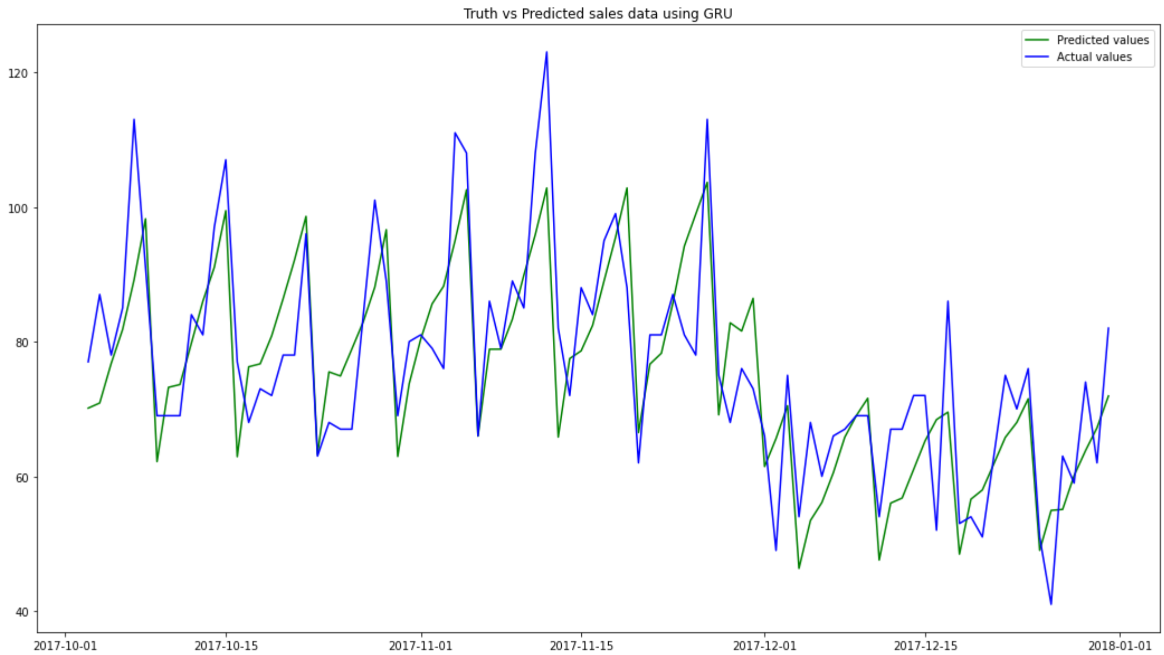

Figure 10 Predicted Vs Actual Sales for GRU

4.4 Optimized hybrid CNN-LSTM Model

Figure 11 shows the TV loss curves of the optimized hybrid CNN-LSTM model.

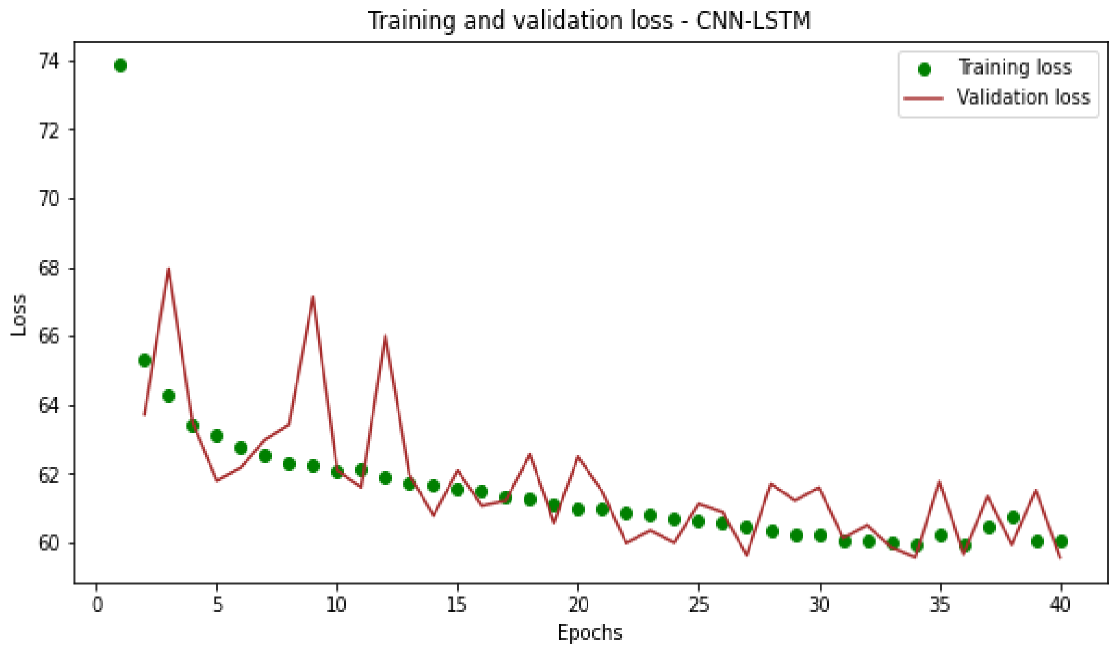

Figure 11 Training & validation Loss for CNN-LSTM

Figure 12 shows the forcast and original sales of various time periods, for the CNN-LSTM model.

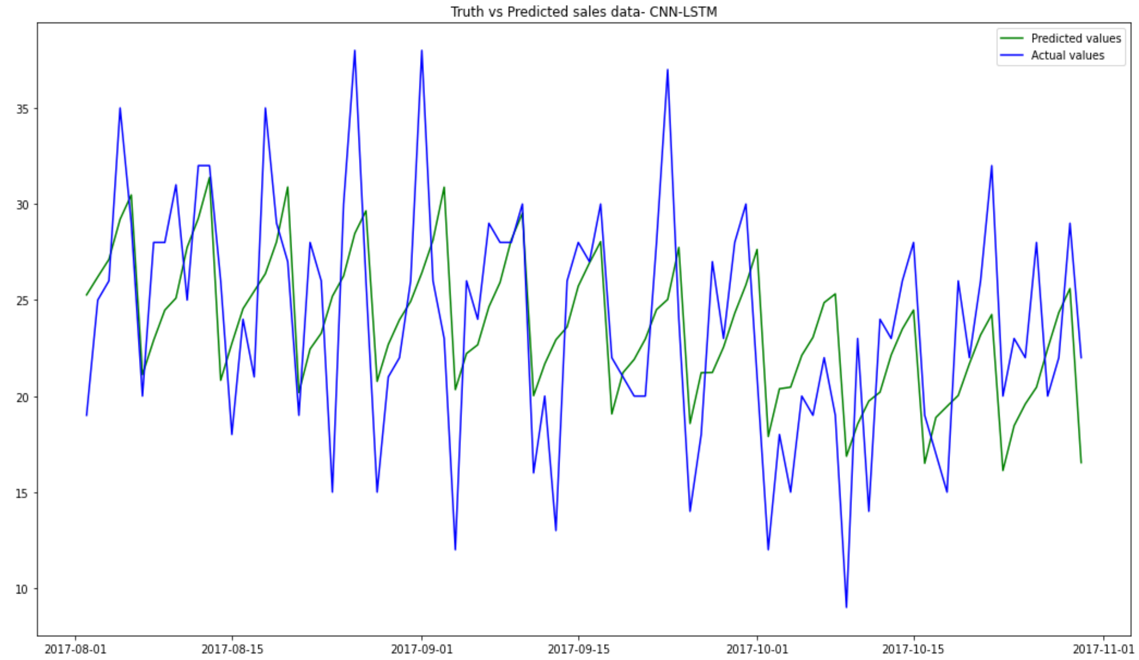

Figure 12 Predicted Vs Actual Sales for Optimized CNN-LSTM

4.5 Performance Metrics

The model accuracy is represented in terms of the statistical error measures, which are defined in Table 5.

Measure	Definition	Formula
Root Mean Square Error(RMSE)	Difference between predicted and measured values are squared and then averaged over the sample for which, the square root is taken.	$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}}$
Mean Absolute Error (MAE)	Average absolute difference between estimated and actual values.	$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert Y_i - \hat{Y}_i \rvert$

Mean Absolute Percentage Error (MAPE)	Percentage error between estimated and actual values.	$$\mathrm{MAPE} = \frac{\sum_{t=1}^{n} \left\| \frac{A_t - F_t}{A_t} \right\|}{n} \times 100$$

Table 5 Statistical error measures for model accuracy

Table 6 and Figure 13 show the statistical error measures of the 4 algorithms.

Algorithm	**RMSE**	**MAE**	**MAPE**
CNN	8.224	6.310	0.125
LSTM	8.640	6.553	0.129
GRU	8.215	6.250	0.123
CNN-LSTM	8.162	6.150	0.122

Table 6 Statistical error measures of all algorithms

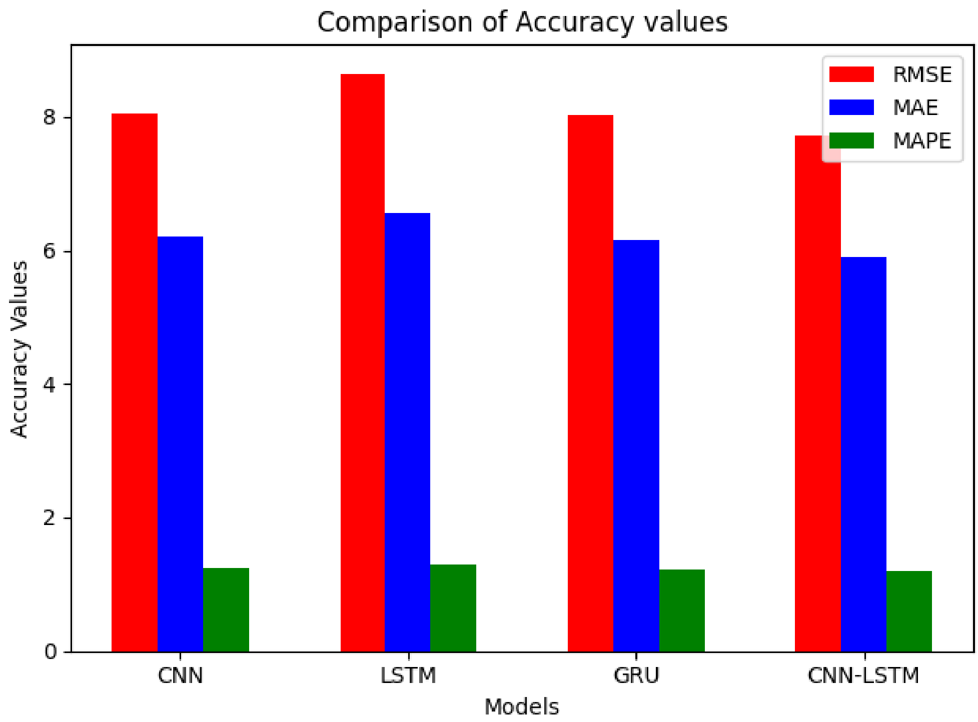

Figure 13 Comparison of Statistical error measures

As seen from Figure 13, optimize CNN-LSTM attains the least error measures leading to enhanced accuracy, when compared to the other models. It has RMSE around 8.16, MAE around 6.15 and MAPE around 0.122, followed by GRU, which has RMSE around 8.21, MAE around 6.25 and MAPE around 0.123. The traditional CNN and LSTM models have very high error measures.

5. Conclusion

In this paper, an optimized CNN-LSTM model for ASM system has been proposed. To fine tune the hyperparameters of CNN-LSTM, the AWSO algorithm is applied. Before forecasting, EDA on sales has been performed in which daily, monthly and yearly sales analysis are computed based on store and item features. The sales forecasting is done by means of the proposed optimized CNN-LSTM model and the basic DL models CNN, LSTM, GRU. The proposed and existing DL models are implemented in Python 3. The model accuracy is evaluated in terms of the statistical error measures RMSE, MAE and MAPE. Experimental results have shown that the optimized CNN-LSTM model attains least error measures when compared to the other models. Thus, the proposed ASM framework produces reasonable forecasts for the agri-food tracing data in agriculture.

Statements and Declarations

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Conflict of Interest: The authors don’t have any conflict of Interest.

Competing Interest: The authors don’t have any competing interest.

Authors Contribution: In this manuscript preparation author 1 prepared the concept and author 2 prepared the implementation part.

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