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Forecasting Auto Spare Parts Demand in Iran: A Hybrid Neural Network Approach with Meta-heuristic Optimization

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Abstract

The automotive industry serves as a cornerstone of Iran's economy, with auto spare parts demand playing a vital role in its transportation infrastructure. Traditional forecasting methods often struggle to capture the intricacies of Iran's dynamic market dynamics, prompting the adoption of advanced computational techniques. This study explores the efficacy of hybrid neural networks, particularly the combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, optimized with genetic algorithm, in forecasting auto spare parts demand. Empirical evaluation demonstrates the superiority of the CNN-LSTM-GA model over traditional algorithms, showcasing its potential to drive operational efficiency and cost-effectiveness in the automotive supply chain. The findings underscore the significance of embracing innovative methodologies and present avenues for future research to explore broader applicability and scalability in diverse contexts.

Keywords: Auto spare parts, Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Genetic Algorithm (GA).

1.Introduction

The automotive industry stands as a cornerstone of Iran's economy, playing an indispensable role in the nation's transportation infrastructure. This industry not only contributes significantly to the gross domestic product (GDP) of Iran, but also creates employment opportunities and supports the growth of subsidiary industries. Central to this industry is the demand for auto spare parts, which directly influences vehicle maintenance, repair, and overall operational efficiency (Huang & Wang, 2023). The efficient management of spare parts is critical for maintaining the operational readiness of vehicles, especially in a country where the automotive sector plays a vital role in both public and private transportation. Accurate forecasting of this demand is paramount for stakeholders across the supply chain spectrum, from manufacturers to retailers and service providers, enabling them to optimize inventory management, production planning, and supply chain operations (Kuroiwa, Techakanont, & Keola, 2024; Paksaz, Salamian, & Jolai, 1400). However, traditional forecasting methods, such as time series analysis and econometric models, often fall short in capturing the intricate nonlinear relationships and dynamic patterns inherent in Iran's rapidly evolving market dynamics. Moreover, the presence of exogenous factors like economic fluctuations and regulatory changes further complicates the forecasting process. These fluctuations, including currency devaluation, sanctions, and changing import regulations, introduce a level of unpredictability that challenges traditional forecasting models.

To address these challenges and elevate forecasting accuracy, advanced computational techniques have gained prominence, particularly neural networks and meta-heuristic optimization algorithms. Neural networks offer the flexibility to model complex nonlinear relationships and temporal dependencies in the data, making them ideal for demand forecasting tasks (Eskandari, Saadatmand, Ramzan, & Mousapour, 2024). One of the primary advantages of

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neural networks lies in their ability to self-learn and improve their predictions by continuously adjusting their internal parameters based on feedback from the data, making them adaptable to changing market conditions. A hybrid neural network combines multiple neural network architectures or techniques to leverage the strengths of each component and enhance overall performance (Xiao, Cao, Wang, Cheng, & Yuan, 2024). By integrating different types of neural networks, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and feedforward networks, a hybrid approach can effectively capture diverse patterns and features present in complex data. For example, combining the sequential processing capabilities of RNNs with the spatial feature extraction capabilities of CNNs can improve the model's ability to handle sequential and spatial data simultaneously (Cheng, Gao, Zhao, & Yang, 2024). Additionally, hybrid neural networks may incorporate meta-heuristic optimization algorithms to automatically adjust model parameters and improve predictive accuracy (Mallik et al., 2024). This combination allows for a more robust model capable of handling both the spatial dependencies (such as relationships between different regions or markets) and temporal dependencies (such as time-based demand fluctuations) inherent in auto spare parts demand.

Simultaneously, meta-heuristic optimization algorithms provide a means of fine-tuning neural network parameters to enhance predictive performance (Singh, Sandhu, & Kumar, 2024). Meta-heuristic optimization algorithms can be effectively applied for hyperparameter optimization in neural networks and other machine learning models. These algorithms, inspired by biological processes such as evolution and swarm intelligence, help overcome the challenges associated with the large search space and high-dimensionality of hyperparameters. Hyperparameters are parameters that define the structure and behavior of the model, such as the learning rate, batch size, and number of hidden layers. Tuning these hyperparameters is crucial for optimizing model performance, but it can be challenging due to the high-dimensional and nonlinear nature of the optimization problem. In the context of neural networks, meta-heuristic optimization algorithms can be used to search for the optimal combination of hyperparameters that minimize a chosen objective function, such as loss function or validation error (Mamoudan, Jafari, Mohammadnazari, Nasiri, & Yazdani, 2023; Muttio et al., 2024). By iteratively evaluating different hyperparameter configurations and updating the population based on their performance, these algorithms can efficiently navigate the hyperparameter space and identify configurations that yield the best model performance. As a result, meta-heuristic algorithms not only improve the performance of forecasting models but also reduce the computational resources required to achieve optimal model settings. This is especially valuable in industrial environments where data complexity and computational resources are limited.

Our study proposes a novel approach for forecasting auto spare parts demand in Iran by harnessing a hybrid neural network framework optimized with meta-heuristic algorithms. This approach integrates various neural network architectures, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), into a unified framework to capture diverse demand patterns and features effectively. Furthermore, the utilization of meta-heuristic optimization techniques, such as genetic algorithms, automates the tuning of neural network meta-parameters, thereby improving forecasting accuracy and robustness. The use of these techniques enables the model to automatically respond to data changes and allows predictive modeling with greater confidence, even in times of economic and market fluctuations. In this context, this study seeks to explore how the accuracy of forecasting auto spare parts demand in the Iranian market can be improved using hybrid neural networks (CNN-LSTM), what advantages meta-heuristic algorithms such as genetic algorithms offer in optimizing the parameters of demand forecasting models, and how this approach can help mitigate the effects of economic volatility and sudden market changes.

The primary objective of this research is to demonstrate the effectiveness of our proposed hybrid approach in accurately predicting auto spare parts demand in Iran. By assisting industry stakeholders in making informed decisions regarding inventory management, production scheduling, and resource allocation, our approach aims to drive operational efficiency and cost-effectiveness. This improvement in efficiency can help reduce excess storage costs, prevent shortages of spare parts, and ensure a continuous flow of production. Additionally, the use of accurate forecasts enables supply chain managers to make strategic decisions regarding material procurement and production planning. Through empirical evaluation and comparative analysis, we seek to validate the superiority of our approach over traditional forecasting methods, showcasing its potential for practical implementation in real-world scenarios.

In the subsequent sections, we provide a comprehensive overview of the methodology employed in our study, including data collection, model development, and parameter optimization. We then present the results of our experiments and discuss their implications for the automotive industry in Iran. Finally, we offer concluding remarks and suggestions for future research directions in the field of demand forecasting for auto spare parts.

2.Literature Review

In this section, we review the literature on the applications of CNN-LSTM models across various domains, including load forecasting, anomaly detection, structural health monitoring, and complex data analysis. Additionally, we examine the relevant literature related to the automotive industry, focusing on the challenges and the use of forecasting models in supply chain management and automotive spare parts demand prediction.

2.1.Neural networks

In recent years, the combination of CNN-LSTM models has emerged as a powerful approach for solving complex forecasting and data analysis problems, with applications spanning various fields. Du et al. (2024) developed a real-time end-to-end deep learning model for structural health monitoring (SHM) of composite materials. Using CNN for feature extraction and LSTM for processing acoustic emission signals, the model achieved a high accuracy of 98%, significantly outperforming basic CNN and RNN models. This study demonstrated the strength of the CNN-LSTM model in diagnosing impact damage in composite structures.

Hu, Wang, Lee, Wang, and Wang (2024) applied a 1D-CNN-LSTM hybrid model for wear prediction of high-performance rolling bearings. By utilizing a large dataset and comparing CNN with CNN-LSTM, the study found that the latter offered superior predictive accuracy, significantly reducing both time and costs associated with traditional life testing of bearings. This approach provided a robust solution for industrial applications by improving the prediction of wear over time. In another study, Ryan (2020) proposed a CNN-LSTM-AM model for electric vehicle (EV) load forecasting. The model leveraged convolutional layers for feature extraction and LSTM combined with an attention mechanism for handling time series data, achieving better results than standalone models. The CNN-LSTM-AM model excelled in multi-step-ahead forecasting and was validated on real-world EV data, showing superior accuracy in comparison with other models.

Ishida, Ercan, Nagasato, Kiyama, and Amagasaki (2024) explored rainfall-runoff modeling using a CNN-LSTM approach, combining the power of CNN to reduce input data size and LSTM to capture short-term dependencies in meteorological data. Their model demonstrated significant improvements in accuracy over traditional models, reducing the root mean square error (RMSE) by up to 51% compared to CNN-only models. This study highlighted the effectiveness of CNN-LSTM in hydrological applications, particularly for flood management and hydraulic structure design. In the realm of power load forecasting, C. Wang et al. (2024) introduced a CNN-LSTM model to capture both local and long-term dependencies in historical load data. This method outperformed other deep learning models, delivering highly accurate predictions across various timeframes. The results underscored the versatility of CNN-LSTM in handling complex load prediction tasks in power systems. Yu, Liu, Peng, Gan, and Wan (2024) applied a CNN-LSTM-Attention model for impact localization in CFRP structures. Using fiber Bragg grating sensors, the model successfully detected impact locations with high precision by integrating convolutional layers, LSTM, and an attention mechanism. This approach proved effective in monitoring the health of CFRP structures and preventing potential failures.

In a study focusing on diesel engine oil temperature prediction, Yu et al. (2024) proposed an attention-enhanced CNN-LSTM model. By combining CNN for capturing local correlations and LSTM for long-term dependencies, the model achieved highly accurate temperature predictions using real-world sensor data. This research provided an efficient solution for monitoring and optimizing diesel engine performance in locomotives. Wang, Liu, and Bai (2024) explored wind energy production forecasting with CNN-LSTM, where they compared various machine learning models. Their results showed that the CNN-LSTM model outperformed other approaches, making it an ideal choice for predicting wind power generation and contributing to the transition toward sustainable energy sources.

In the textile industry, Malakouti et al. (2024) used a CNN-LSTM model for the rapid and accurate quantitative analysis of cotton-polyester blended fabrics. The model significantly outperformed traditional methods like partial least squares (PLS) in determining fiber content, offering a fast and non-invasive solution for fabric quality control. Finally, Nguyen-Da, Nguyen-Thanh, and Cho (2024) developed a real-time anomaly detection system for industrial diesel generators using CNN-LSTM. Their model, integrated into an AIoT system, successfully identified abnormal conditions in diesel generators, improving the efficiency and reducing the costs of maintenance services. The study demonstrated the superior diagnostic capabilities of CNN-LSTM in complex industrial environments.

2.2.The automotive industry

The automotive industry relies heavily on efficient spare parts management to ensure smooth operations and customer satisfaction. Effective demand forecasting for automotive spare parts is paramount for optimizing inventory levels, reducing costs, and meeting customer needs promptly. Over the years, researchers have explored various methodologies and approaches to improve the accuracy of demand forecasting in this domain. This literature review aims to examine recent advancements and key studies in automotive spare parts demand forecasting. By synthesizing findings from diverse research endeavors, this review seeks to identify current trends, methodologies, challenges, and research gaps in the field. Through a comprehensive analysis of existing literature, this review will contribute to a deeper understanding of the complexities involved in forecasting automotive spare parts demand and provide insights for future research directions and practical applications in the automotive supply chain. Huang and Wang (2023) proposed a hybrid forecasting model for short-term auto parts demand. It combines EEMD-CNN-BiLSTM-Attention to handle non-stationarity and non-linearity in demand data. The model effectively decomposes data, analyzes each component separately, and utilizes an attention mechanism for improved prediction accuracy. Focusing on the auto aftermarket, Yang and Chen (2012) developed a nonnegative variable weight combination model for auto parts demand forecasting in China. It integrates ARIMA, multiple regression, and Support Vector Regression methods, proving higher accuracy and stability through a case study. Examining demand forecasting in remanufacturing, Matsumoto and Komatsu (2015) evaluated methods like Holt-Winters and ARIMA models. It addresses the complexities of remanufacturing production planning, emphasizing the importance of handling demand seasonality. Results show significant improvement over traditional methods.

Focusing on value chains, Sun, Wu, Bo, Duan, and Zhang (2019) presented a collaboration mechanism based on sales prediction for auto parts. Utilizing colored Petri nets and Monte Carlo simulations, it demonstrates the effectiveness of maximizing value across multiple value chains through accurate demand forecasts. Other study proposes integrating ABC analysis and rough set theory for inventory control in the auto spare parts supply chain (Mehdizadeh, 2020). By considering criteria such as the number of sold cars and their mileages, the model improves demand forecasting and ordering decisions, leading to enhanced service levels and inventory management. Gamasaee and Fazel Zarandi (2018) tackled the bullwhip effect in supply chains by considering multiple factors simultaneously: demand, pricing, ordering, and lead time. It dynamically models demand, orders, and prices, utilizing game theory for optimal pricing and reducing the bullwhip effect significantly, as demonstrated in a numerical experiment focusing on auto-parts supply chains.

Addressing the challenges of parts-procurement planning in mass customization scenarios, Fattahi, Dasu, and Ahmadi (2022) focused on accurately forecasting demand for configurable options in vehicles. It introduces a model to minimize procurement costs arising from inaccurate range estimates, significantly improving range estimation quality and reducing joint-parts ranges, thus enhancing inventory management efficiency. Other study proposes a deep learning approach using Recurrent Neural Networks (RNN) and Long-Short Term Memory (LSTM) with a modified Adam optimizer for forecasting automobile spare parts demand (Chandriah & Naraganahalli, 2021). The model demonstrates superior performance compared to traditional methods, offering minimal errors and improved inventory management effectiveness, thus proving its suitability for demand prediction in the automotive industry. Focusing on improving short-term traffic flow prediction, Gehret, Weir, Johnson, and Jacques (2020) compared various recurrent neural network (RNN) architectures for forecasting traffic flow. It concludes that simpler RNN units such as simple recurrent units and GRU outperform LSTM in terms of accuracy and training time, offering insights into optimizing traffic prediction models for intelligent transportation systems.

Salais-Fierro, Saucedo-Martinez, Rodriguez-Aguilar, and Vela-Haro (2020) presented a hybrid method for demand forecasting in the automotive industry. By combining expert judgments and historical data, the proposed approach improves demand planning activities, highlighting the efficacy of machine learning techniques in integrating qualitative and quantitative variables for accurate demand projections. Ma, Wang, and Zhang (2021) investigated the application of deep learning algorithms for forecasting automotive spare parts demand, crucial for inventory management and customer satisfaction. Comparing various deep learning models like FCN, CNN, LSTM, GRU, and transformer networks using real historical data, the study assesses their accuracy in demand prediction, addressing the challenge of small training data and high data volatility. Introducing a novel approach for predicting the all-time demand of new automotive spare parts, Steuer, Hutterer, Korevaar, and Fromm (2018) proposed leveraging similarity in demand patterns with comparable parts from the past. By clustering historical demand patterns and training a classification model, it accurately predicts the demand for new parts based on their characteristics, offering a practical solution validated with standard quality measures. Zareian, Baradaran, and Rashidi (2024) presented an integrated data-driven approach to production planning in auto parts manufacturing.

One notable research gap in the field of automotive spare parts demand forecasting lies in the integration of real-time external factors and contextual data into predictive models. While existing studies primarily focus on historical sales data and internal inventory information, they often overlook the dynamic nature of external influences such as economic conditions, market trends, and weather patterns, which can significantly impact demand fluctuations. Incorporating these factors into forecasting models could enhance their accuracy and robustness, enabling companies to adapt their inventory management strategies more effectively in response to changing market conditions. Additionally, there is a lack of research on the optimization of spare parts inventory replenishment considering environmental sustainability objectives, such as minimizing carbon emissions associated with transportation and production processes. Investigating how to balance demand forecasting accuracy with sustainable inventory management practices presents a promising avenue for future research in the automotive spare parts supply chain domain.

3. Methodology

In this methodology section, we begin by reviewing the data utilized for forecasting auto spare parts demand in Iran. We then delve into the details of our proposed algorithm, CNN-LSTM, which combines Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) to capture both spatial and temporal dependencies in the data. Lastly, we scrutinize the genetic optimization method employed to fine-tune the meta-parameters of the CNN-LSTM model, optimizing its performance for accurate demand forecasting. Figure 1 shows the steps of this article.

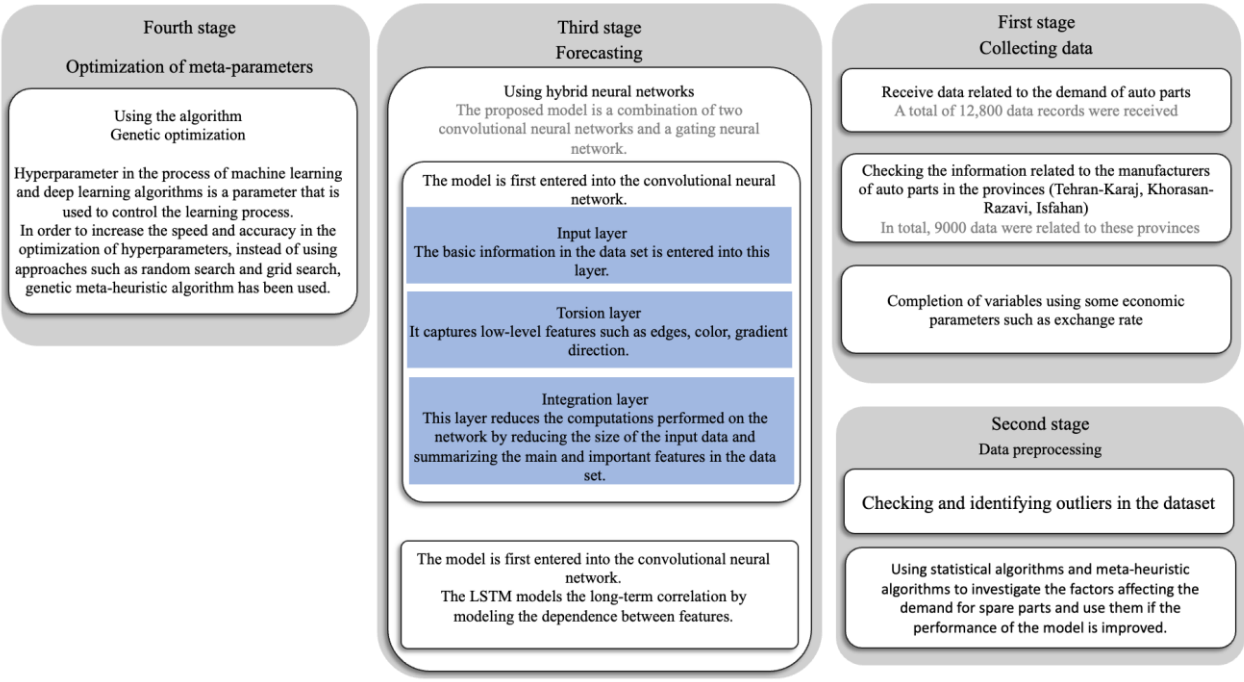

Figure 1. Study roadmap

The proposed CNN-LSTM-GA model represents a significant advancement in forecasting auto spare parts demand within the context of Iran's automotive industry. This superiority stems from several key aspects inherent to the model's design and implementation. By combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, the model leverages the strengths of both architectures. CNNs are adept at capturing spatial and temporal patterns in data, while LSTMs excel at modeling sequential dependencies. This hybrid approach allows the model to effectively capture the complex and nonlinear relationships present in auto spare parts demand data.

The incorporation of genetic algorithm optimization further enhances the model's performance. Genetic algorithms provide a robust optimization framework that iteratively refines model parameters to minimize forecast error. This adaptive optimization process ensures that the CNN-LSTM-GA model is finely tuned to the specific characteristics of Iran's automotive market, leading to more accurate and reliable demand forecasts. Empirical evaluation of the CNN-LSTM-GA model against traditional forecasting algorithms provides compelling evidence of its superiority.

The model consistently outperforms conventional methods by yielding more accurate predictions of auto spare parts demand. This superior performance not only validates the effectiveness of the proposed approach but also highlights its potential to drive operational efficiency and cost-effectiveness within the automotive supply chain. By delivering more accurate demand forecasts, the CNN-LSTM-GA model enables automotive manufacturers and suppliers to optimize inventory management, production planning, and resource allocation. This, in turn, leads to improved operational efficiency and cost-effectiveness throughout the supply chain.

By minimizing excess inventory and avoiding stockouts, businesses can reduce carrying costs and maximize profitability. The findings of this study underscore the importance of embracing innovative methodologies in forecasting auto spare parts demand. They also highlight the need for further research to explore the broader applicability and scalability of the CNN-LSTM-GA model in diverse contexts beyond Iran's automotive industry. Future studies could investigate its effectiveness in other geographical regions, industry sectors, or supply chain scenarios, providing valuable insights into its potential for widespread adoption and impact.

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3.1.Data Description

The models proposed in this study have been meticulously applied in a case-by-case manner using data pertaining to the demand for auto parts within Sazeh Gostar Saipa Company. Sazeh Gostar Saipa is a privately held joint-stock enterprise entrenched in the automotive sector. Originating on July 10, 1364, it stands as a subsidiary of the esteemed Saipa Automobile Group. Initially focusing on casting and forging productions, the company expanded its scope in 1373 to include the design, engineering, and procurement of Saipa car components. The dataset utilized for this study originates from Sazeh Gostar Company's car demand forecasting department, boasting a total of 12,861 meticulously curated records. These records encapsulate six key variables, namely product description, manufacturer company name, customer name, product number, manufacturer city, and customer city, each of which is further stratified into distinct segments. For instance, the customer name variable encompasses entities such as Sanat Khodro Development Foundation, Pars Khodro, Megamotor, Zamiad, Saipa, Saipapress, Saipa Citroen, Saipa Yadak, and Idcopress.

In the following, external parameters and factors such as the exchange rate, oil price, and gold price are also considered as indicators for evaluating and predicting the demand for auto spare parts.

3.2.Prediction Integrated Model

In this section, we will delve into an examination of the proposed hybrid algorithm.

3.2.1.Convolutional Neural Network

CNNs can be described as neural networks (NNs) characterized by deep structures (Mousapour Mamoudan, Ostadi, Pourkhodabakhsh, Fathollahi-Fard, & Soleimani, 2023). A typical CNN consists of five layers: an input layer, a convolution layer, a pooling layer, a fully connected layer, and an output layer. The output layer generates outputs based on the received properties. Equation (1) depicts the CNN structure and its calculation formula. In this equation, the output size is denoted by Output, the input size by Input, the convolution kernel size by Kernel, the padding value size by Padding, and the step size by Stride.

$$N = (W - F - 2P)/S + 1 \qquad (1)$$

Features are extracted from input data by the convolution layer (Liu et al., 2022). Convolution layers typically comprise convolution kernels, parameters, and activation functions. Convolution, a pivotal layer in CNNs, utilizes kernels to extract features from inputs. Kernels, smaller in scale than input matrices, generate feature maps via convolution operations. Equation (2) illustrates the calculation of each element in the feature map (Kattenborn, Leitloff, Schiefer, & Hinz, 2021; Mamoudan, Forouzanfar, Mohammadnazari, Aghsami, & Jolai, 2023). In this equation, Output(*i*,*j*) represents the value in row *i* and column *j* of the feature map, Input(*i*,*j*) denotes the value in row *i* and column *j* of the input matrix, the activation function is denoted by f, and Kernel(*m*,*n*) represents the weight in row m and column n for the convolution kernel. Additionally, the bias of the convolution kernel is shown as Bias.

$$x_{i.j}^{out} = f_{cov}\left(\sum_{m=0}^{k}\sum_{n=0}^{k} w_{m,n}\, x_{i+m,j+n}^{in} + b\right) \qquad (2)$$

The convolution layer utilizes multiple kernels to extract features from the input matrix, producing a feature map. The pooling layer then reduces the dimensions of the feature map, enhancing computational efficiency through down sampling. This layer aids in reducing the output feature vectors while potentially improving results. CNNs excel in extracting features from grid data, where m variables of any type are expanded to n stations, resulting in an $m \times n$ matrix.

3.2.2.Long Short-Term Memory

Recurrent Neural Networks (RNNs) are renowned for their capabilities in data learning, classification, and prediction, making them particularly suitable for tasks involving time series data analysis. However, RNNs face challenges in retaining input information over long sequences, leading to issues like gradient vanishing or explosion as subsequent nodes lose track of past data. This long-term dependency problem significantly affects the performance of conventional RNNs. Long Short-Term Memory (LSTM) networks were developed to address this issue, focusing on mitigating gradient vanishing problems and ensuring sustained information retention over extended periods, thus enhancing reliability (Mamoudan, Mohammadnazari, Ostadi, & Esfahbodi, 2022). LSTM has demonstrated remarkable success in capturing both short-term and long-term dependencies across various tasks. In LSTM, specialized units known as "cells" play a crucial role in information processing, acting as advanced versions of neurons found in typical Multilayer Perceptrons (MLP). These cells can be interconnected and stacked to facilitate the transmission of temporal information. LSTM employs mechanisms called gates, including the input gate, forget gate, and output gate, to effectively manage the flow of information within the network, enabling reading, writing, and resetting functions.

$$f_t = sigmoid(W_f[d_{t-1}, X_t] + b_f) \quad (3)$$

As the RNN progresses, the input gate mechanism in LSTM networks supplements the latest memory from the current input to counteract the tendency to "forget" part of the previous state. This function is achieved through the "input gate," consisting of two primary components: a sigmoid layer known as the "input threshold layer" determining which values need updating, and a hyperbolic tangent (tanh) layer generating a new candidate vector $\widetilde{C_t}$, which is then added to the current state. Equations (4) to (6) depict these relationships, where W_n represents the weight matrix, b_n represents the bias element, W_m signifies the weight matrix used to update the unit's status, b_m represents the bias element used to update the unit's status, and C_t denotes the status of the updated memory unit.

$$h_t = \sigma(W_n.[d_{t-1}, X_t] + b_n) \quad (4)$$

$$\widetilde{C_t} = \tanh(W_m.[d_{t-1}, X_t] + b_m) \quad (5)$$

$$C_t = F_t * C_{t-1} + h_t * \widetilde{C_t} \quad (6)$$

Equation (7) illustrates how the gate h_t and $\widetilde{C_t}$ are subjected to a dot product to determine whether to update the state of the memory unit at the current time step, while the forgetting gate F_t is multiplied by C_{t-1} to decide whether to retain the initial state of the memory unit at the current time step. The output gate in LSTM generates the current time output after computing the new status and controlling the level of filtering of the storage unit status within this layer. Its calculation formula, presented in Equations (7) and (8), entails applying the sigmoid activation function to obtain O_t, followed by multiplying C_t by the tanh activation function, and then by O_t, yielding the output of this layer. The value dt is influenced not only by the input X_t at time step t and the activation value d_{t-1} of the hidden layer at the previous time step, but also by the state of the memory unit $C_t$at the current time step.

$$d_t = O_t * \tanh(C_t) \quad (7)$$

$$O_t = \sigma(W_o[d_{t-1}, X_t] + b_o) \quad (8)$$

3.3. Hyper-parameter Optimization

Genetic algorithms (GAs) are optimization techniques inspired by the process of natural selection and genetics. In the context of hyperparameter optimization for machine learning models, GAs are used to search through a potentially vast space of hyperparameters to find the combination that maximizes the performance of the model on a given dataset.

The process begins with the initialization of a population of potential solutions, where each solution represents a set of hyperparameters for the model. These solutions are typically generated randomly or using some heuristic method. Each solution is then evaluated using a fitness function, which measures how well the model performs with those specific hyperparameters. This fitness function could be based on metrics like cross-validation score, accuracy, or loss function.

Based on their fitness scores, solutions are selected from the population for reproduction. Solutions with higher fitness scores are more likely to be selected, mimicking the concept of "survival of the fittest" in natural selection. These selected solutions, also known as parents, undergo genetic operations such as recombination (crossover) and mutation to produce offspring solutions.

During recombination, parts of the hyperparameters from two or more parent solutions are combined to create new offspring solutions. This process helps explore different combinations of hyperparameters and potentially discover better solutions. Mutation introduces random changes to the hyperparameters of the offspring, adding diversity to the population and allowing exploration of new regions in the search space.

The offspring solutions, along with some of the existing solutions from the previous generation, form the next generation population. This replacement process ensures that the population evolves over time, favoring solutions with higher fitness while maintaining diversity to prevent premature convergence.

The algorithm continues iterating through these steps for a certain number of generations or until a stopping criterion is met. This criterion could be reaching a maximum number of iterations, convergence of the fitness function, or a predetermined threshold for performance improvement.

Through this iterative process of selection, recombination, and mutation, genetic algorithms efficiently explore the hyperparameter space to find optimal or near-optimal solutions for machine learning models. Despite their computational cost and potential for premature convergence, genetic algorithms offer a robust approach to hyperparameter optimization, especially in scenarios where the search space is large or the objective function is complex and nonlinear.

Utilizing principles from genetics and evolutionary biology, the Genetic Algorithm emerges as a specialized Meta-Heuristic Algorithm employed in the identification of optimal patterns or predictions (Pourkhodabakhsh, Mamoudan, & Bozorgi-Amiri, 2023). With a particular affinity for regression-based prediction techniques, Genetic Algorithms mirror genetic evolution in their problem-solving and optimization approaches. In this study, the Genetic Algorithm is tasked with determining integer values for crucial parameters such as kernel size, neuron count, and activation function type, pivotal for effective model training. The iterative process integrates selection, mutation, and crossover operations until convergence criteria are met. Specifically tailored for optimizing hyperparameters within the CNN-LSTM architecture, the Genetic Algorithm addresses factors including the number of kernels in the CNN layer, neurons in the LSTM layer, and activation functions for both layers. The study adopts a population size of 50, a crossover rate of 0.4, and a mutation rate of 0.1. The exploration of kernel and neuron spaces ranges from 2 to 128, encompassing activation functions such as relu, selu, tanh, and linear. The Algorithmic structure is shown in algorithm structure 1.

Algorithm structure1. Genetic algorithm

Algorithm 1: ***Genetic Algorithm (GA)***

Parameter(s): S – select of blocks
Output: superstring of set s
Initialization:
$t \leftarrow 0$
Initialize p_t to random individuals from s^*
EVALUATE-FITNESS-GA(S, P_T)
While termination condition not met

Do $\begin{cases} select\ indivisuals\ form\ p_t(fitness\ proporationate) \\ recombine\ individuals \\ mutate\ individuals \\ evaluate\ fitness\ GA(s, modified\ individuals) \\ p_{t+1} \leftarrow newly\ created\ individuals \\ t \leftarrow t+1 \end{cases}$

Return (superstring derived from best individual in p_t)
Procedure EVALUATE-FITNESS-GA (s, p)
S – set of blocks
P – population of individuals
For each individual $i \in p$

Do $\begin{cases} generate\ drived\ string\ s(i) \\ m \leftarrow all\ blocks\ forms\ that\ are\ not\ coverd\ by\ s(i) \\ s'(i) \leftarrow concateration\ of\ s(i) and\ m \\ fitness(i) \leftarrow \frac{1}{\|s'(i)\|^2} \end{cases}$

3.4. Model Evaluation

In this study, the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE), and R-square (R^2) were employed to assess and evaluate the proposed model for forecasting auto parts demand. The mathematical formulations for these metrics are presented in equations (9) to (12). Generally, MAE, RMSE, and MSE are utilized to quantify the error in the forecast. A lower error rate signifies higher accuracy and performance of the model; hence, minimizing these metrics enhances forecasting precision. Conversely, R^2 indicates the model's accuracy in predicting auto parts demand, with values ranging between 0 and 1. A higher R^2value signifies superior accuracy and performance of the model (Momeni et al., 2024). In all equations pertaining to evaluation criteria, y_i represents the predicted value, x_i represents the actual value, and $\overline{y_i}$ denotes the average value in R^2calculations.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i| \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \tag{10}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \tag{11}$$

$$R^2 = 1 - \frac{(\sum_{i=1}^{n}(y_i - x_i)^2)/n}{(\sum_{i=1}^{n}(\overline{y_i} - x_i)^2)/n} \tag{12}$$

4.Results

In analyzing the histogram plots of the Dollar rate, oil prices, gold prices, and demand for automotive spare parts, several insights can be drawn. The histogram for the Dollar rate reveals its distribution over a certain period, indicating fluctuations and potential trends. Fluctuations in the Dollar rate can significantly impact the cost of importing spare parts, thereby affecting the overall pricing structure within the automotive industry. Similarly, the histogram for oil prices showcases its distribution pattern, highlighting periods of volatility or stability. Since oil is a crucial component in manufacturing and transportation, fluctuations in oil prices can directly influence production costs and, consequently, the prices of automotive spare parts. Furthermore, the histogram for gold prices provides insights into its volatility and market demand, as gold often serves as a hedge against economic uncertainty. Changes in gold prices may indirectly affect consumer sentiment and purchasing power, subsequently impacting the demand for automotive spare parts. Finally, the histogram representing demand for automotive spare parts reflects consumer behavior and market trends. Analyzing this histogram can help identify peak periods of demand, allowing manufacturers and suppliers to adjust their production and inventory management strategies accordingly. Overall, these histograms collectively provide a comprehensive understanding of the interplay between economic indicators and market dynamics within the automotive spare parts industry.

Figure 2 displays the histogram, illustrating the distribution patterns of the Dollar rate, oil prices, gold prices, and demand for automotive spare parts over a specified time period. In Figure 3, the trend chart depicts the temporal evolution of these variables, offering insights into their long-term movements and potential trends. Finally, Figure 4 showcases the correlation matrix, elucidating the relationships between these variables and highlighting any significant correlations that may exist among them. Together, these figures provide a comprehensive analysis of the interplay between economic indicators and market dynamics within the automotive spare parts industry, aiding in strategic decision-making and forecasting.

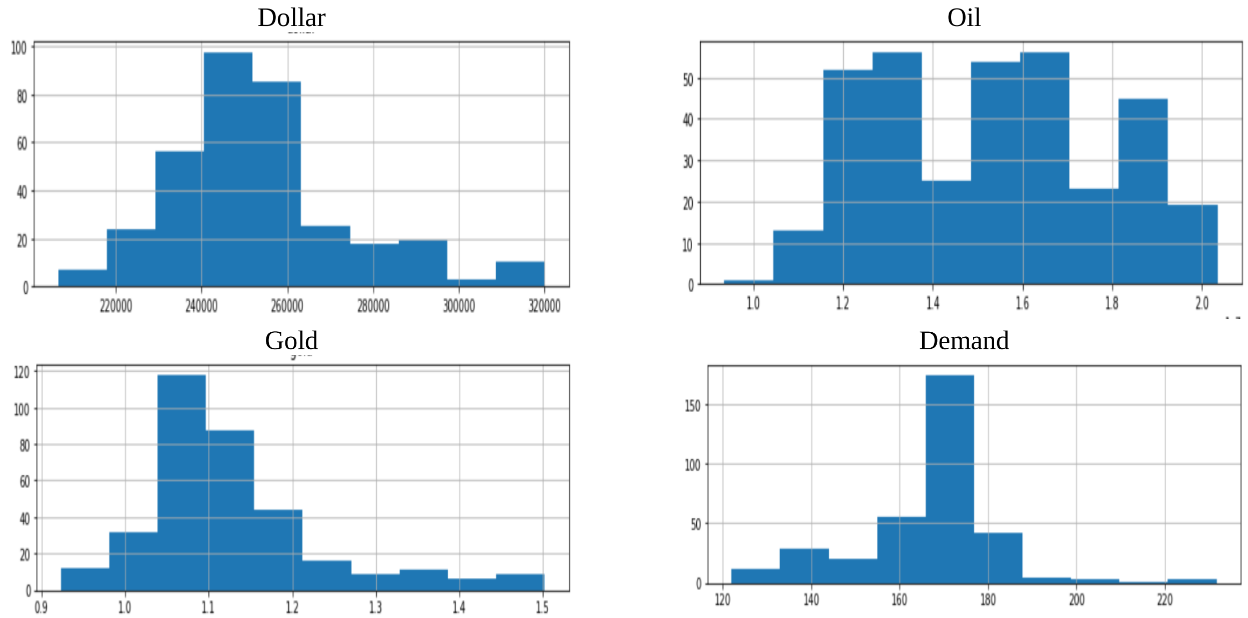
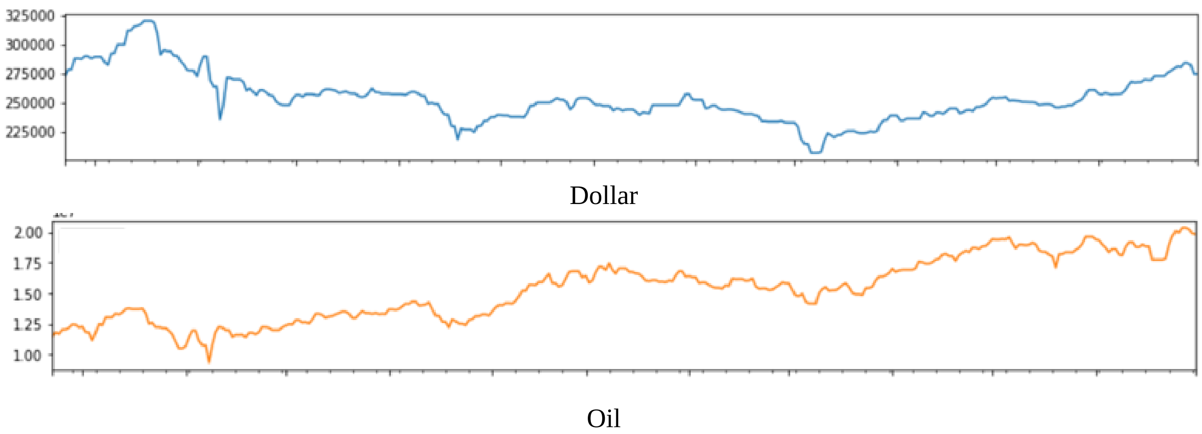
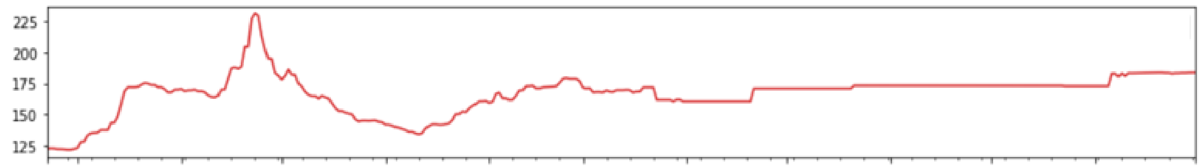
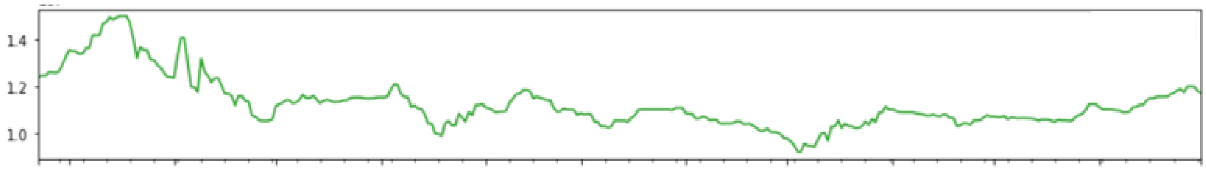


Figure 2. Histogram Diagram





Gold



Demand

Figure 3. Trends Graph

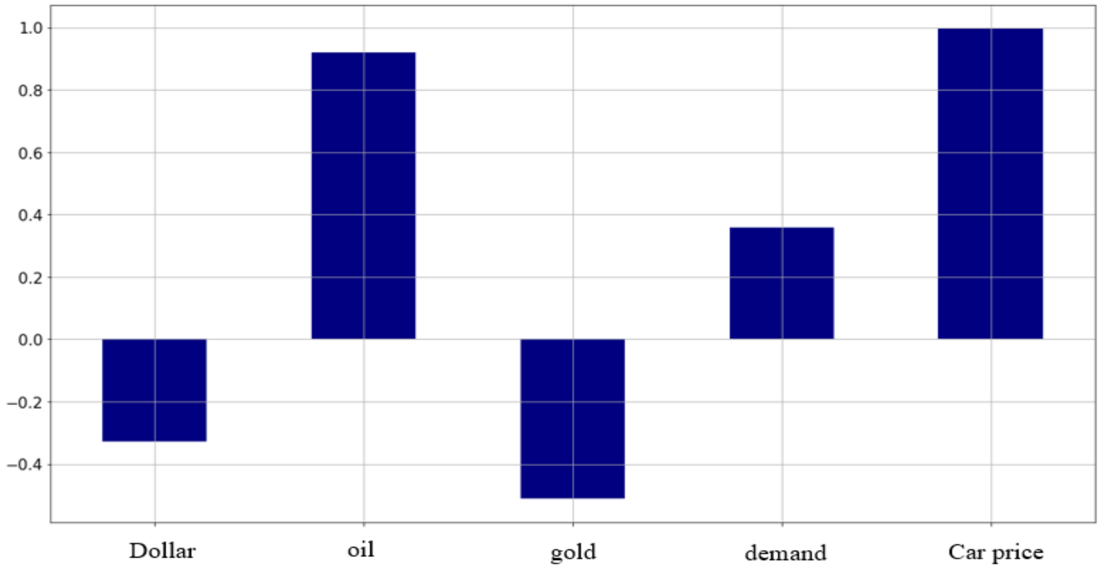


Figure 4. Correlation

Some other deep learning and machine learning algorithms that are able to predict the demand for auto spare parts have been used in this study. The results shown in Table 2, and Figure 5 show that the proposed model (CNN-LSTM) performs better than other deep learning and machine learning algorithms. These algorithms include recurrent neural network (RNN), and Gated recurrent units (GRUs). In other words, compared to other algorithms, the proposed model has the least error and the most accuracy. This table appears to be comparing different machine learning models based on their performance metrics.

This column lists the different types of models that were evaluated, such as CNN (Convolutional Neural Network), LSTM (Long Short-Term Memory), RNN (Recurrent Neural Network), CNN-LSTM (Combination of Convolutional Neural Network and Long Short-Term Memory), LSTM-GRU (Combination of Long Short-Term Memory and Gated Recurrent Unit), and CNN-GRU (Combination of Convolutional Neural Network and Gated Recurrent Unit).

MSE (Mean Squared Error): This metric measures the average squared difference between the actual and predicted values. Lower values indicate better performance in terms of how close the predicted values are to the actual values.

MAE (Mean Absolute Error): This metric measures the average absolute difference between the actual and predicted values. Like MSE, lower values indicate better performance.

R2-Score (Coefficient of Determination): This metric indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. It ranges from 0 to 1, where 1 indicates perfect predictions and 0 indicates that the model does not explain any of the variability of the response data around its mean. Higher values are desirable.

RMSE (Root Mean Squared Error): This is the square root of the MSE, and it represents the average magnitude of the error between predicted and actual values. Again, lower values indicate better performance.

Based on the values in the table, you can see the performance of each model across these metrics. For example, the CNN-LSTM model appears to have the lowest MSE, MAE, and RMSE values, as well as the highest R2 Score, suggesting it performs the best among the models listed.

Comparing the performance of various models based on Mean Squared Error (MSE), Mean Absolute Error (MAE), R2 Score, and Root Mean Squared Error (RMSE), the CNN-LSTM model emerges as the top performer across all metrics. With the lowest MSE, MAE, and RMSE values of 3.266507, 2.312415, and 2.914158, respectively, along with the highest R2 Score of 0.945122, CNN-LSTM consistently demonstrates superior predictive accuracy and a better fit to the data compared to other models such as CNN, LSTM, RNN, LSTM-GRU, CNN-GRU, and CNN-RNN. This suggests that the combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture is particularly effective for the given task, offering the most precise predictions and the highest explanatory power.

Table 1. Prediction Results

Model	MSE	MAE	R2_Score	RMSE
CNN	4.317524	2.945713	0.900412	5.541238
LSTM	5.449721	4.793546	0.923421	3.783217
RNN	6.241556	5.278219	0.901741	3.646528
CNN-LSTM	**3.266507**	**2.312415**	**0.945122**	**2.914158**
LSTM-GRU	4.246138	3.416452	0.812726	4.612532
CNN-GRU	4.762135	3.821446	0.813460	5.974261
CNN-RNN	4.239355	2.791927	0.841327	3.111524

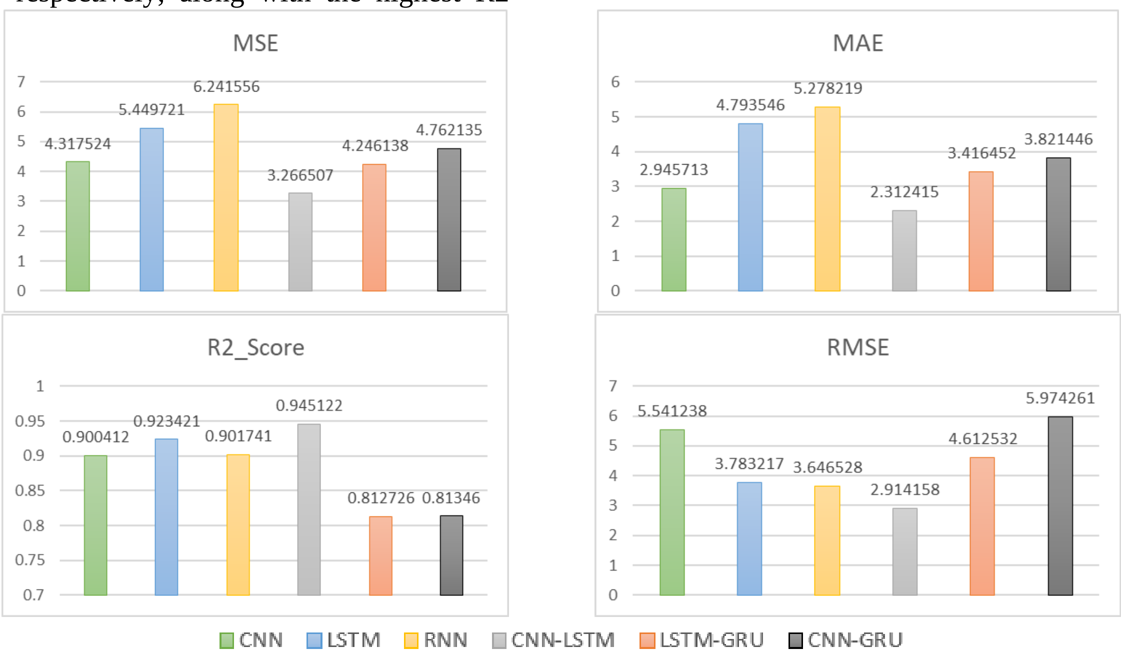


Figure 5. results of prediction models

In order to check the performance of the proposed meta-heuristic algorithm (Genetic Algorithm) in order to increase the accuracy and performance of the model in predicting the demand of car parts, some other meta-heuristic algorithms such as Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and BAT algorithm (BA) have also been used. The results obtained from the hyperparameter optimization of the algorithms show that the proposed algorithm (GA) has been able to show the best performance.

As shown in Table 3, the optimized CNN-LSTM algorithm using the proposed meta-heuristic algorithm (GA) has shown better results than other algorithms. The CNN-LSTM-GA algorithm in MSE, MAE and RMSE has been able to show a value equal to 4.239355, 2.791927 and 3.14521, respectively, which have lower results than other models. Also, this

R2 algorithm was able to obtain a value of 0.95982, which is more compared to other algorithms.

Comparing the performance of different variations of the CNN-LSTM model based on Mean Squared Error (MSE), Mean Absolute Error (MAE), R2 Score, and Root Mean Squared Error (RMSE), the CNN-LSTM-GA variant emerges as the top performer across all metrics. With the lowest MSE, MAE, and RMSE values of 2.124215, 2.174216, and 2.682712, respectively, along with a high R2 Score of 0.946714, CNN-LSTM-GA consistently demonstrates superior predictive accuracy and a strong fit to the data. Following closely, CNN-LSTM-PSO and CNN-LSTM-GWO exhibit similar performance with slightly higher MSE, MAE, and RMSE values but still maintain respectable R2 Scores above 0.94. CNN-LSTM-BA, despite achieving an exceptionally low MAE of 0.229498, shows a slightly higher MSE and RMSE compared to other variants, resulting in a slightly lower R2 Score. Overall, these variations of the CNN-LSTM model showcase the effectiveness of different optimization algorithms in enhancing predictive accuracy, with CNN-LSTM-GA standing out as the most effective variant for the given task.

Table 3. Optimal CNN-LSTM

Model	MSE	MAE	R2_Score	RMSE
CNN-LSTM	3.266507	2.312415	0.945122	2.914158
CNN-LSTM-GA	**2.124215**	**2.174216**	**0.946714**	**2.682712**
CNN-LSTM-PSO	3.212716	2.302716	0.940017	2.841225
CNN-LSTM-GWO	3.254182	2.226478	0.946140	2.694127
CNN-LSTM-BA	3.611478	0.229498	0.945712	2.722549

Furthermore, the loss function plot is presented in Figure 6, demonstrating the performance of the predictive model utilized in analyzing the aforementioned variables. By examining the loss function plot, one can assess the model's accuracy and effectiveness in capturing the underlying patterns and dynamics of the Dollar rate, oil prices, gold prices, and demand for automotive spare parts. This additional visualization enhances the analytical capabilities and robustness of the research findings, enabling stakeholders to make informed decisions based on reliable predictive modeling outcomes.

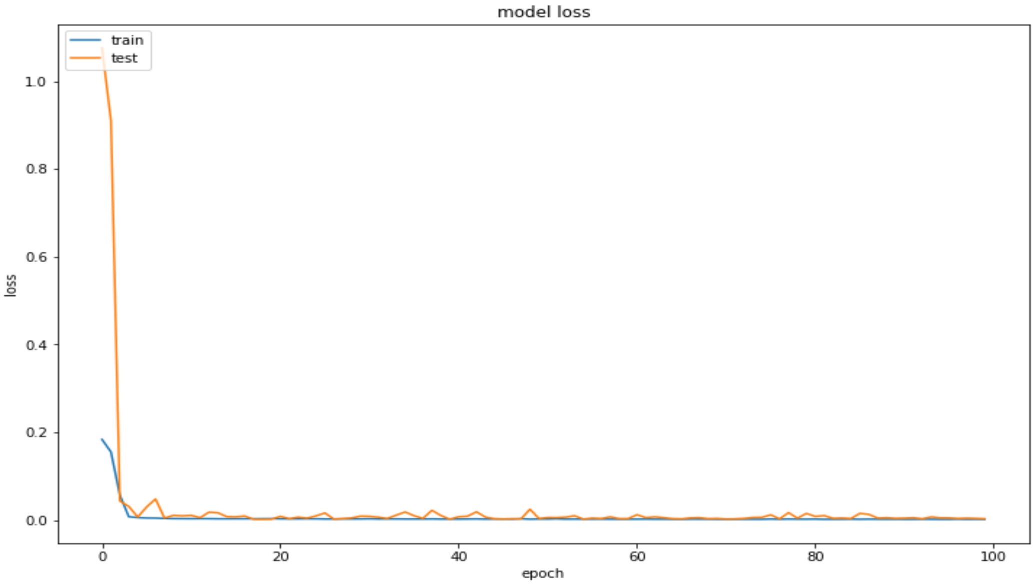


Figure 6. Model loss function

5. Discussion

In this study, the demand for automotive spare parts was forecasted using various machine learning models, including CNN, LSTM, RNN, and hybrid models such as CNN-LSTM. The performance metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), R^2 Score, and Root Mean Squared Error (RMSE), were used to evaluate the effectiveness of each model. Among the models evaluated, the CNN-LSTM model, particularly when optimized with Genetic Algorithm (GA), exhibited superior performance with the lowest MSE, MAE, and RMSE values, and the highest R^2 score, outperforming traditional models and even advanced recurrent networks. These findings are consistent with those of Chandriah et al. (2021), who employed a Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) model optimized using a modified Adam optimizer for the same forecasting task.

However, while both studies demonstrate the utility of deep learning architectures in forecasting automotive spare parts demand, the CNN-LSTM-GA model proposed in this study offers several distinct advantages over the RNN-LSTM with modified Adam optimizer model of Chandriah et al. (2021). First, the CNN-LSTM model integrates both convolutional and recurrent layers, allowing it to capture both spatial and temporal dependencies in the data. This architecture enables the model to detect intricate patterns in demand that may be missed by pure RNN-LSTM models, which only focus on temporal relationships.

Moreover, the use of meta-heuristic algorithms, such as the Genetic Algorithm (GA) for hyperparameter optimization, further enhances the predictive performance of the CNN-LSTM model. In contrast, Chandriah et al. (2021) relied solely on the modified Adam optimizer, which, while effective, is more susceptible to issues such as slower convergence and suboptimal tuning of learning rates. The CNN-LSTM-GA model, by contrast, consistently achieved lower error rates across all metrics, with an MSE of 2.124, MAE of 2.174, and R^2 score of 0.947, compared to the RNN-LSTM with modified Adam model, which reported higher error rates, particularly in cases of intermittent demand patterns.

Additionally, Chandriah et al. (2021) focused primarily on minimizing the holding and backordering volumes in the inventory system, which is crucial for cost control but might not fully capture the complexities of real-world demand fluctuations. While their model showed improvements in inventory performance, the CNN-LSTM-GA model proposed in this study provides a more comprehensive solution by focusing on predictive accuracy, which directly translates into better demand forecasting and inventory management. The CNN-LSTM-GA model, with its robust optimization technique, reduces both the forecast error and the stock-out risks, thereby contributing more significantly to efficient supply chain management in the automotive industry.

In conclusion, while both studies highlight the relevance of deep learning models in forecasting automotive spare parts demand, the CNN-LSTM-GA model presented in this research outperforms the RNN-LSTM with modified Adam optimizer by Chandriah et al. (2021) in terms of prediction accuracy, error minimization, and practical applicability in handling complex and fluctuating demand patterns. The integration of convolutional layers with recurrent networks, combined with advanced optimization techniques, underscores the robustness and versatility of the proposed model in managing spare parts demand forecasting.

6.Conclusion

The automotive industry in Iran stands as a pivotal pillar of the nation's economy, crucial for its transportation infrastructure. Central to this industry is the demand for auto spare parts, influencing vehicle maintenance, repair, and operational efficiency. Accurate forecasting of this demand is essential for stakeholders across the supply chain spectrum, facilitating optimized inventory management, production planning, and supply chain operations. However, traditional forecasting methods often struggle to capture the intricate nonlinear relationships and dynamic patterns inherent in Iran's rapidly evolving market dynamics, exacerbated by exogenous factors like economic fluctuations and regulatory changes.

This study investigates the forecasting of auto spare parts demand within Iran's automotive industry, emphasizing the necessity for accurate predictions to optimize supply chain operations. Traditional forecasting methods often fall short in capturing the intricate dynamics of Iran's rapidly evolving market, prompting the adoption of advanced computational techniques such as hybrid neural networks and meta-heuristic optimization algorithms. The proposed approach integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks within a hybrid framework, optimized with Genetic Algorithm (GA), to enhance predictive accuracy. Empirical evaluation showcases the superiority of the CNN-LSTM-GA model over traditional algorithms, demonstrating its potential to drive operational efficiency and cost-effectiveness in the automotive supply chain.

In conclusion, our study addresses the critical task of forecasting auto spare parts demand in Iran's automotive industry by leveraging advanced deep learning models and meta-heuristic optimization algorithms. Through empirical evaluation, we have demonstrated the effectiveness of the proposed hybrid CNN-LSTM model in accurately predicting demand patterns, outperforming traditional machine learning algorithms such as CNN, LSTM, and RNN. The

CNN-LSTM architecture exhibits superior predictive accuracy and robustness, capturing complex nonlinear relationships and dynamic patterns inherent in the automotive market. Moreover, the integration of meta-heuristic optimization algorithms, particularly Genetic Algorithm (GA), further enhances the performance of the CNN-LSTM model, resulting in even more precise predictions and improved model fit. Our findings highlight the significant impact of GA in automating the tuning of model hyperparameters, leading to superior forecasting accuracy and reliability.

The practical implications of our research extend to stakeholders across the automotive supply chain, including manufacturers, retailers, and service providers. By providing accurate forecasts of auto spare parts demand, our approach facilitates informed decision-making regarding inventory management, production scheduling, and resource allocation, ultimately driving operational efficiency and cost-effectiveness.

Looking ahead, future research directions could explore the applicability of our approach in other industries and regions, as well as the integration of additional data sources and features to further enhance forecasting accuracy. Additionally, investigating novel meta-heuristic optimization techniques and their synergies with deep learning models could yield further improvements in predictive performance.

In summary, our study contributes to advancing the field of demand forecasting in the automotive industry, demonstrating the effectiveness of hybrid deep learning models optimized with meta-heuristic algorithms. By combining state-of-the-art technologies, we pave the way for more accurate and reliable forecasting methodologies, with implications for optimizing supply chain operations and driving economic growth.

The findings of this study underscore the significance of embracing advanced computational techniques, particularly hybrid neural networks optimized with meta-heuristic algorithms, in forecasting auto spare parts demand within Iran's automotive industry. Managers within the sector can leverage these insights to enhance decision-making processes pertaining to inventory management, production planning, and resource allocation. By adopting the proposed CNN-LSTM-GA model, organizations can attain superior predictive accuracy, enabling proactive adjustments to meet fluctuating demand patterns and optimize operational efficiency. Furthermore, the integration of meta-heuristic optimization algorithms automates the fine-tuning of model parameters, streamlining the forecasting process and minimizing resource-intensive manual interventions. Embracing such innovative methodologies not only fosters competitive advantage but also cultivates resilience in navigating the complexities of Iran's dynamic automotive market landscape.

Despite the advancements achieved in this study regarding the forecasting of auto spare parts demand in Iran's automotive industry, several avenues for future research remain unexplored. One notable research gap pertains to the investigation of the applicability of the proposed hybrid neural network framework and meta-heuristic optimization algorithms in other industries or geographic regions with similar or distinct market dynamics. Additionally, future studies could delve deeper into the integration of alternative meta-heuristic algorithms beyond Genetic Algorithm (GA), such as Particle Swarm Optimization (PSO) or Grey Wolf Optimization (GWO), to ascertain their comparative efficacy in enhancing predictive accuracy. Furthermore, exploring the impact of incorporating additional data sources, such as customer sentiment analysis or geopolitical factors, could further enrich the forecasting models, yielding more comprehensive insights for industry stakeholders. Addressing these research gaps would not only contribute to advancing the field of demand forecasting but also foster broader applicability and scalability of the proposed methodologies in diverse contexts.

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