

Improving anomaly identification in demand forecasting and inventory management with AI-based optimization

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Abstract Numerous intelligent applications have been made possible in many different areas because to the development of technologies like data mining and machine learning. Supply chain management and communication are two important topics of study related to the Global internet. Among these, inventory management (IM) is gaining significance as a crucial component of the complete life cycle management system of supply chains. However, the lengthy supply chain life cycles, the complexity of supply chain management and the ever-changing customer expectations all contribute to the high logistics and communication costs encountered. By improving the IM process, this effort attempts to reduce costs throughout the supply chain's life cycle. Initially, described as a mathematical model, the main goal of the IM process is to maximize revenues while minimizing logistic costs. The Optimized Hierarchical Clustered Sequential Recurrent Neural Network (OHC-SRNN) is presented as the IM technique to solve this problem in order to achieve this aim. When compared to other cutting-edge techniques, the IM model achieves an excellent average accuracy of approximately 90.2% in predicting inventory requirements. This degree of precision has the potential to improve supply chain efficiency by spotting unexpected inventory activities and reducing inventory expenses by approximately 30%.

Keywords: supply chain, internet of things (IoT), (OHC-SRNN), logistic cost

1. Introduction

The profitability and customer happiness of a firm are directly impacted by demand forecasting and inventory management, which are essential components of supply chain operations. Histogram algorithms and historical data have been used by firms to manage their inventories and generate forecasts. For better demand forecasting accuracy, artificial intelligence (AI) systems can examine enormous amounts of data and spot trends and generate forecasts in real time. AI may dynamically change reordering points and safety stock levels to optimize inventory levels and reduce carrying costs while maintaining the availability of products.

1.1. Effects of digital technologies on logistic management

The performance of logistic technology in the past has been impacted by the rise of big data, artificial intelligence, data mining, and other methods, as well as the sudden growth of computing equipment achievements with big data analysis technologies; thus, it is possible to maximize the effective lifespan of the whole logistic chain (Lv et al., 2022). However, data mining technologies can be used to identify potential product buyers to increase earnings. The only steps in the conventional supply chain process are managing inventory, manufacturing and transport. With the current expansion of information technology, clients who were first excluded from procedures for managing supply chains have gained importance (Ullah et al., 2021). Purchase, inventory, production and distribution are the only steps in the conventional supply chain process. Consumers who were once excluded from logistic chain management have taken on particular importance due to the development of digital technologies (Kartskhiya et al., 2020).

1.2. Inventory Management and Demand Forecasting

The tasks of operation, control, and optimization are necessary during each procedure. Additionally, cooperation between these processes is necessary (Akçay et al., 2022). Furthermore, consumers are involved in the supply chain management process; the uncertainty of critical product availability will increase due to their ever-shifting expectations

(Stoychev et al., 2020). The main component of supply chain management, inventory handling, is crucial for reducing the overall cost of network logistics management. Usually, having too much or too little inventory may be undesirable (Li, 2021). As a result, maintaining the majority of the items in storage for an extended period would also result in high inventory costs, which would drive businesses to utilize their resources too gradually or not enough. A lack of inventories might result in an inability to meet consumer expectations, which could create product scarcity, a decline in customer confidence and even a loss of profit (Pinçe, 2021). Because good inventory management will lower costs and boost profits, it has become increasingly crucial for supply chain management. Based on this thought, the study of inventory management and optimization is receiving greater interest. The ability to foresee future client requests has a large impact on performance and function (Gijsbrechts et al., 2022).

1.3. Hardware Demand Forecasting

The original feature space and the Euclidean distance are used in the clustering procedure when dealing with amplitude irregularities (Gonçalves et al., 2021). The autocorrelation representation of time series is used to eliminate temporal shifts from the data and collect shape information for anomalies. Then, the similarity of time series data in the new feature space is measured using the distance function (Pang et al., 2021). Difference recognition is a method of locating data samples that differ from the majority of data occurrences. Innovation identification refers to innovation identification of outliers. For many years, anomaly detection has been a focus of active study, beginning with initial explorations (Ma et al., 2021). Finding anomalies in data, which is the process of finding unanticipated objects or events, has drawn the attention of many scholars and practitioners and is one of the key tasks in data mining and quality assurance (Cholodowicz et al., 2023). Clustering, neural networks, and support vector regression (SVR) are methods for predicting time-series data and are among the techniques that they categorize along with their applications in supply chain management (Seyedan et al., 2020). Demand forecasting in closed-loop supply chains (CLSCs) is another gap in the literature. This is an inclusive overview and quantitative study of the available research on forecasting techniques for spare parts demand. First, they examine each research stream and illustrate the evolution time in the field of research. Then, using data from accessible studies, they conducted a quantitative analysis to provide specific insights into which forecasting approach should be used (Fernando, 2021).

A multivariate technique is introduced to anticipate the element produce supply over numerous forecasting periods utilizing various indicators of demand changes and a comparison between machine learning (ML) models and the context of time series forecasting. External inputs could represent exogenous variables. They assess multivariate regression models' forecasting and supply chain performance during an element's lifetime using a real-world case study (Kim 2019). The wider application of fragmented demand techniques for predicting exceptional events has been promoted as a less complicated and more reliable substitute for non-OR models that are more intricate. Furthermore, they provide a unique approach for determining the strategic planning horizon for phenomena likely to give rise to exceptional occurrences in a foresight environment (Nikolopoulos et al., 2021). A technique that makes use of an ANN to anticipate demand. The model uses a multilayer feed-forward neural network with back propagation for forecasting analysis. ML can be useful in dealing with exchanges in consumer interest. When the expected and current demand varies significantly, certain spending is eliminated (Praveen 2019). By planning and forecasting decisions and eliminating suboptimal decisions, they investigated the interaction between two models. In this work, two computational models are presented, one of which calculates the stock level, the allocation of spare part orders to traders, the allocation of equipment repairs and the number of intervals during the arranging session. The SVM prediction copy is the second form (Babaveisi et al., 2023). LSTM/RNNs with component weight vectors are produced in this LSTM network in a corresponding manner. Modified Adam is a weight optimization approach that is used. The experimental results consider both the reliability of the forecast and the inventory's performance (Naraganahalli, 2021). The recommended replenishment amount is calculated from the input characteristics utilizing deep learning models in an end-to-end (E2E) architecture. The end-to-end model has been refined to depict how the optimum dynamic software solution behaves given prior information (Qi et al., 2023). The hybrid approach we have suggested delivers reliable forecasts and stable efficiency of the materials through series with different levels of variability. They emphasize the need for deconstruction for erratic demand series. To examine the forecasting accuracy and storage performance of a variety of well-known statistical and ML methods, demand series have been developed (Abolghasemi et al., 2020). The difficulty for industrial organizations is making precise decisions about what, when, where and how much inventory to purchase and store. In the past, SMEs have handled this process manually, as traditional approaches rely on the skills of employees and are subject to human error. Inaccurate estimations and over/understocking might occur as a result of human mistakes (Osman, 2022). AI-based optimization algorithms that evaluate historical demand data for spot anomalies and outliers are utilized. The forecasting model can be adapted to handle abnormal patterns by using machine learning techniques to learn from previous anomalies. A dynamic optimization goal that strikes a balance between service levels, inventory costs, and anomaly detection precision is created.

2. Materials and methods

The major emphasis of this part is developing the inventory management and optimization model, which includes the constraints, the purpose and the inventory management issue for wireless communications and mobile computing. Figure 1 shows the flowchart of the suggested approaches.

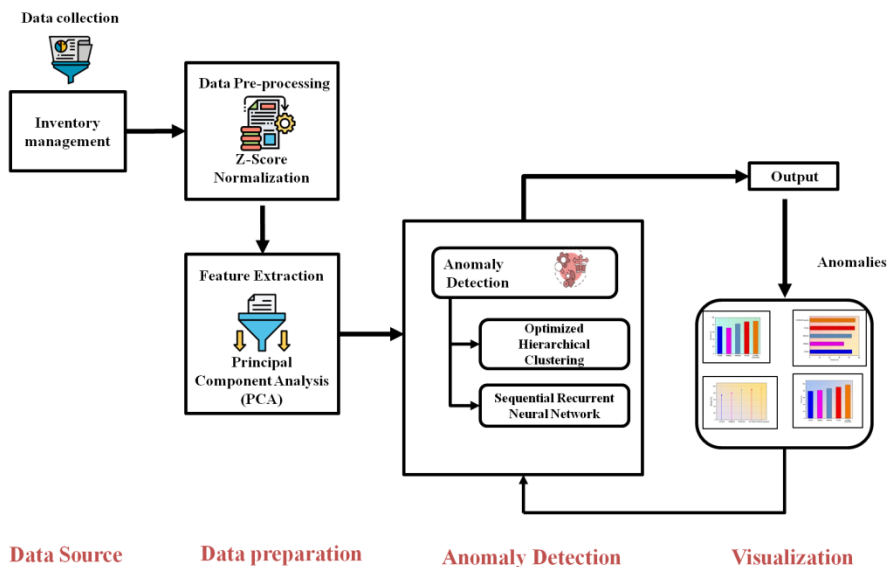


Figure 1 Flow of the suggested approach.

2.1. Data collection

For the reasons listed below, these datasets were selected for further research. Table 1 summarizes each dataset, including the dimensionality, proportion of anomalies, and anomaly detection scenario. Forty-one characteristics are present in the first dataset from the machine learning repository at UCI. Each training sample has three characteristics and a number that indicates that the internet connection is secured. Of the 4,898,431 entries in the original dataset, 3,925,651 assaults (80.1%) were found. This dataset is a forgery of outlier detection with density-based scoring (ODDS). (Kamaraj et al., 2019).

Table 1 A brief overview of the dataset.

Dataset	KDD Cup	Digits	Gestures
Dimensionality	567497x3	30000x784	11674x64
% of anomalies	0.35%	11%	25.3%
Anomaly type	Attack on the network	Digits 0	A hand contraction of patient
IoT scenario	Intrusion detection	Anomalous image detection	Health monitoring

Source: (Kamaraj et al., 2019).

2.2. Data preprocessing using Z score normalization

Z score normalization, one of the most important first steps in the data analysis process, is data preprocessing. This approach entails boosting the quality of the data and organizing the raw data through cleaning, transformation and organization. The management of missing values, the elimination of outliers and the standardization of variables during data preparation guarantees that the conclusions drawn from later studies are accurate and insightful. In a vector matrix with 'l' columns and 'm' rows, where 'l' is the number of characteristics and 'm' is the number of patients, the patient data are arranged. It is used to normalize variables using different scales or measurement units. For the Z score normalization, each data point is subtracted from the dataset's normal before the result is divided by the normative variation. The formula below was used for calculations. The Z scores of the data points in the dataset are presented as the mean and deviation $z=(y-\sigma)/\mu$. Additionally, normalizing the z score feature during meta-training, which is simple yet effective, is recommended.

$$(Z - score)_T = \frac{(y_{th}-\sigma)}{\mu} \tag{1}$$

The difference between the characteristic mean and standard deviation—the upper threshold, or T_{th} —is used to determine the highest permissible Z score in the equation above.

2.3. Feature extraction using principal component analysis (PCA)

Many significant aspects can be transformed using PCA into no significant index to reduce the size of the novel index if a function reduces redundant information and provides a complete index connected to the likelihood of sporting activities. The



steps in PCA are as follows: A indices are chosen for the value of the research field, and the sample matrix of the index F is set for obtaining the value.

$$F = (F_{ij})C * B \tag{2}$$

where $j = 1, 2, \dots, A, j = 1.2 \dots, B$

R_{b*b} denotes a value for the correlation matrices where the eigenvalues fall within the necessary range $1 \geq b \geq 0$. The procedure for the PCA is as follows:

$$T_i = F_{ej} \tag{3}$$

T_i The matrix that represents the main component of the correlation coefficient and the normalized eigenvector is e_j . If the variation in the participation rate of the $j - th$ primary element exceeds 86%, the first P principal elements are selected T_1, T_2, \dots, T_o . At this stage, P can represent B the beginning positions in full together with the contribution rate as a consequence.

$$C = \sum_{i=1}^q c_j \tag{4}$$

For the sports event in question, the detailed risk rating Y is as follows:

$$x = aY_1 + cY_2 + \dots + bY_x \tag{5}$$

where Y represents an eigenvalue of the eigenvector b and x , which represents the initial data of the normalized value.

2.4. Anomaly identification using an optimized hierarchical clustered sequential recurrent neural network (OHC-SRNN)

The OHC-SRNN uses a hierarchical framework to record complex relationships and patterns in sequential data. The network learns models at many levels of complexity using this modular technique, leading to a greater comprehension of the fundamental facts.

2.4.1. Optimized hierarchical clustering (OHC)

Compared to nonhierarchical clustering, optimized hierarchical clustering creates a layered tree of partitions that are represented by a deprogram, which provides more information. Without repeating the hierarchical clustering technique, alternative clustering results can be achieved by cutting the deprogramme, and the single-linkage, complete-linkage and average-linkage agglomerative hierarchical clustering algorithms are equivalent. Other significant clustering criteria include Ward's minimal variance approach.

Algorithm 1: Optimized hierarchical clustering (AHC)

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Input:
    The input dataset  $Y = \{y_1, y_2, \dots, y_m\}$ ;
    The linkage function  $t$ ;
    The desired number of clusters  $r$ ;
Output:
    Cluster partition  $V = \{V_1, V_2, \dots, V_r\}$ .
1: Initially,  $m$  clusters are formed, and each cluster has one data
   Point, i.e.,  $V_j = y_j$  and  $r' = m$ ;
2: While  $r' > r$  do
3:     the  $i - th$  and the  $j - th$  cluster (similarity  $G_{ji}$  is calculated by the linkage
   function  $t$ );
4:     Seek two closest clusters  $V_b$  and  $V_o$  and merge  $V_k$ , i.e.,  $V_k = V_b \cup V_o$ :
5:     Let  $r' = r' - 1$ ;
6: end while
7: return  $V = \{V_1, V_2, \dots, V_r\}$ .
    
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2.4.2. Sequential recurrent neural network (SRNN)

SRNNs employ sequential information as their main principle. We presume that all inputs and outputs are independent of one another in conventional neural networks. This is a poor approach for many activities. Despite the fact that RNNs may employ arbitrary lengthy sequence information, the issue of gradient explosion and gradient disappearance limits the ability



of RNNs to look backward in real time. Equation 1 shows the path direction of the j th value. If the plane travels directly Ω , then Ω becomes 0 to determine one lateral stability index.

$$\Omega = \frac{\sum_{j=i}^{i+M-1} |\psi_{j+1} - \psi_j|}{M-1} \tag{8}$$

A single GRU unit has the inputs $y[d]$ and the outputs $z[d]$. $z[d]$ is also used for the calculation of $z[d - 1]$, and the following forms display accurate computations.

$$k = \sigma(U_k y[d] + W_k z[d - 1]) \tag{9}$$

$$h = \sigma(U_h y[d] + W_h z[d - 1]) \tag{10}$$

$$\hat{z} = \tanh(U y[d] + W(k \odot z[d - 1])) \tag{11}$$

$$z[d] = (1 - h) \odot z[d - 1] + h \odot \hat{z} \tag{12}$$

$$\sigma(y) = \frac{1}{1 + \exp(-y)} \tag{13}$$

$$Sil = \frac{1}{m} \sum_{j=1}^r \sum_{y \in V_j} \frac{p(y) - e(y)}{\max(e(y), p(y))} \tag{14}$$

Four criteria govern the units (U_k, U_h, U_y, U) and retain previous data, requiring more parameters than a straightforward unit. This unit's inputs and results are independent of those used in calculations, such as those for a regular synapse.

3. Performance analysis

To access the data rapidly, a computer with 8.00 GB of RAM, an Intel® Core i9 CPU, and Windows 11 was used. The optional system is contrasted with techniques such as decision trees, global networks, K-nearest neighbors, and logistic regression. Metrics, including precision, accuracy, recall and F1 score, are used in our evaluations. The suggested techniques include precision, recall, F1-score, and accuracy. These techniques include LR (Elmrabit et al., 2020), GNB (Elmrabit et al., 2020), KNN (Elmrabit et al., 2020), and DT (Elmrabit et al., 2020). The accuracy is a statistical metric used to evaluate the precision of forecasts. A comparison of the proposed method with existing methods revealed that our proposed method achieves 90.2% accuracy.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{15}$$

Existing methods such as LR, GNB, KNN and DT achieve 75.3%, 71.6%, 82.9% and 88.5%, respectively. This demonstrates that our suggested technique improves upon the present method. A comparison between the suggested and present systems is shown in Figure 2 and Table 2. As a result, our method is effective for anomaly detection.

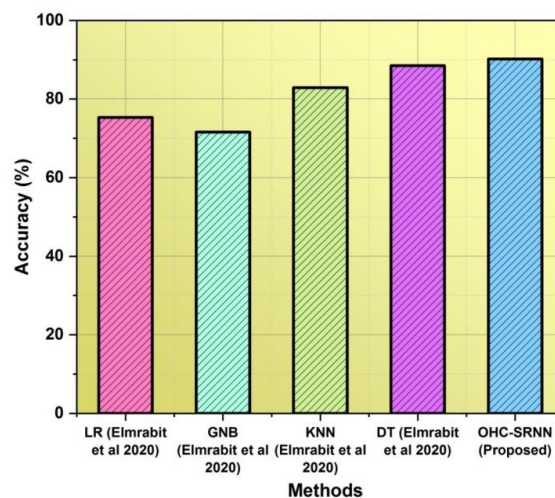


Figure 2 Results for accuracy.

Table 2 Numerical outcome for accuracy.

Method	Accuracy (%)
LR	75.3



GNB	71.6
KNN	82.9
DT	88.5
OHC-RNN (Proposed)	90.2

Precision is defined as the ratio of cases that are successfully categorized to positive data occurrences. A comparison of the proposed method with existing methods shows that our proposed method achieves 92.3% accuracy.

$$\text{precision} = \frac{TP}{TP+FP} \tag{9}$$

The existing methods, such as LR, GNB, KNN, and DT, have precision values of 75.3%, 71.6%, 82.9%, and 88.5%, respectively. A comparison between the suggested and recent systems is displayed in Figure 3 and Table 3. This demonstrates that our suggested technique improves the excision method.

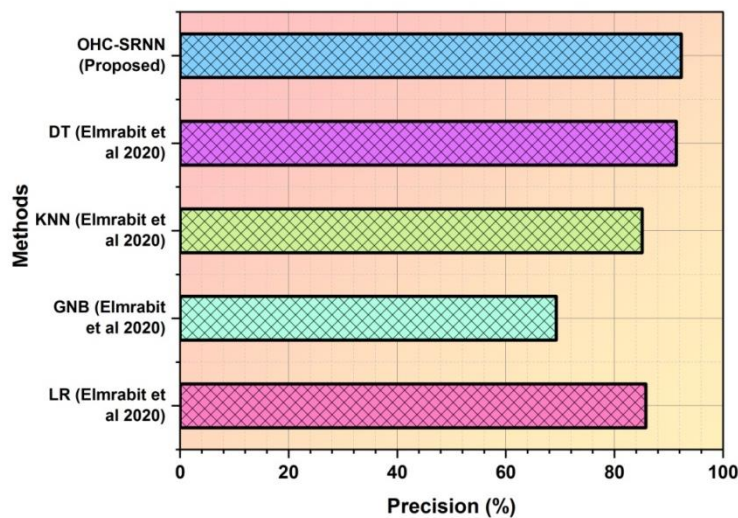


Figure 3 Results for precision.

Table 3 Numerical outcome for precision.

Method	Precision (%)
LR	85.8
GNB	69.3
KNN	85.1
DT	91.4
OHC-SRNN (Proposed)	92.3

The ability of a model to identify every significant sample included in a data collection is referred to as its recall. Recall that the referred sensitivity or the proportion of true positives is a statistical metric that assesses a classification model's capacity to distinguish true positives from false positives when there are many positive cases.

$$\text{Recall} = \frac{FN}{FN+TP} \tag{10}$$

A comparison of the proposed method with existing methods revealed that our proposed method achieved 92.3% accuracy and that existing methods, such as LR, GNB, KNN and DT, achieved 85.8%, 69.3%, 85.1% and 91.4%, respectively. As a result, our method is effective for anomaly detection.

The precision and recall of the F1 scores are utilized to assess the performance of an algorithm in binary classification tasks. To provide a fair assessment of the model's accuracy, these two criteria are combined into a single value. For the proposed approach, "recall and precision" are combined into a single metric known as the f1-score by computing the harmonic mean. A comparison of the proposed method with existing methods, as shown in Figure 4 and Table 4, reveals that our proposed method achieves 93.7% accuracy, and that of existing methods such as the LR, GNB, KNN and DT methods achieve 73.5%, 79.7%, 88.8%, and 90.6%, respectively. This demonstrates that our suggested technique improves upon the current method. An evaluation of the compared planned or current systems is shown in Figure 5 and Table 5. As a result, our method is effective for anomaly detection.



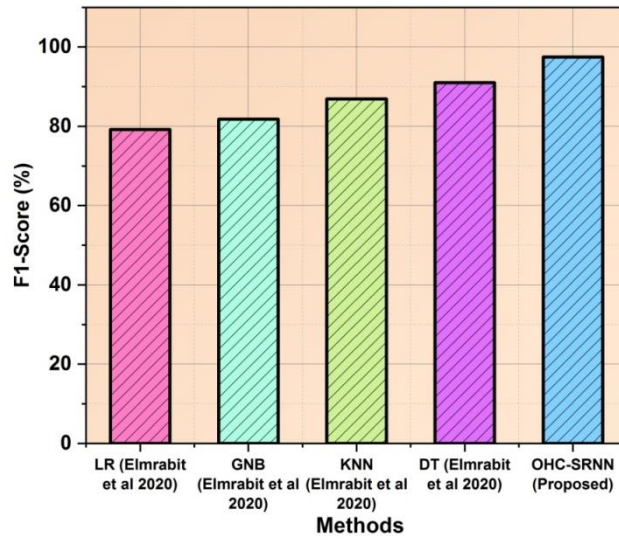


Figure 5 Results for the F1 score.

Table 5 Numerical outcome of the F1 score.

Method	F1-Score (%)
LR	79.2
GNB	81.8
KNN	86.9
DT	91.2
OHC-SRNN (Proposed)	97.5

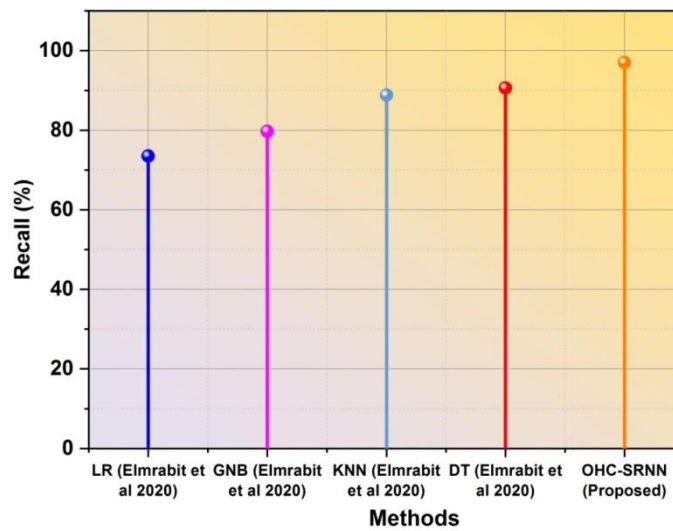


Figure 4 Results for recall.

Table 4 Numerical outcome for recall.

Method	Recall (%)
LR	73.5
GNB	79.7
KNN	88.8
DT	90.6
OHC-SRNN (Proposed)	93.7

$$F1 - score = \frac{(recall) \times (precision) \times 2}{recall + precision} \tag{11}$$

4. Discussion

The LR technique (Ullah 2021) represents the relationship between a dependent variable and one or more independent variables by modeling a linear calculation of the observed data. A type of linear filter known as GNB (Ullah, 2021) is employed in computer vision and image processing. By gathering data on spatial frequencies and orientations, they are intended to evaluate and depict textures inside pictures. The texture-based characteristics of the data may be extracted using GNB. These characteristics can characterize the local texture patterns of the data. The supervised machine learning method K-NN (Ullah, 2021) is used for classification and regression applications for data analysis and structure detection. A nonparametric, instance-based method for learning is K-NN. A DT (Ullah, 2021) is a well-liked ML technique for various applications. It is a graphical description of options and possible results, such as utility, resource costs, and results from random events. Predictive modeling and decision analysis are two applications of DTs. These methods were compared to overcome the issues proposed.

5. Conclusion

Artificial intelligence-based optimization methods can improve the accuracy and efficacy of anomaly finding in demand forecasting and inventory control. This study aims to minimize costs and maximize profits in this regard by first formulating a method for managing stocks via an equation. In light of this, this research project develops a stock management procedure with the objectives of reducing cost and generating profit. Based on this, the IM is suggested, which uses the OHC-SRNN theory to provide effective inventory management to maximize the anomaly detection management process. To obtain a high level of prediction accuracy, the IM integrates the time series and back-propagating pattern. As a result, we introduced the OHC-SRNN for the recognition of anomalies. Performance metrics such as accuracy, recall, precision, and F1-score are evaluated and compared with existing technologies such as LR (75.3%), GNB (85.8%), KNN (8.88%), and DT (9.10%). The potential to use AI-based optimization to enhance anomaly identification in demand forecasting and inventory management is enormous and encouraging. Large-scale logistics, warehousing, and distribution issues related to managing stock are potential research areas.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

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