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ORIGINAL

Deep Learning-Based Intelligent Supply Chain Management for Optimized Member Selection and Operational Efficiency

Gestión inteligente de la cadena de suministro basada en el aprendizaje profundo para la selección optimizada de miembros y la eficiencia operativa

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ABSTRACT

Introduction: efficient supply chain management (SCM) is crucial for increasing competitiveness, notably through improved member (supplier/partner) selection and operational decision-making. Traditional techniques frequently rely on manual evaluations or static rule-based systems, which have limited scalability, adaptability, and real-time data processing capabilities.
Objective: the goal of this research is to create an intelligent supply chain management (ISCM) framework that uses deep learning (DL) and metaheuristic optimization to improve supplier selection and overall operational efficiency.
Method: a real-world supply chain dataset from open source Kaggle, which includes supplier performance measurements, delivery schedules, demand forecasting, and transaction history. The dataset is preprocessed using min-max normalization. Feature extraction is utilizing Principal Component Analysis (PCA). This research proposes a Flying Fox Optimized Artificial Neural Network (FlyFO-ANN) method based on an Artificial Neural Network (ANN) network, which is suggested for predicting supplier reliability and demand fluctuations. In addition, a Flying Fox Optimization (FFO) is used to modify model hyperparameters and optimize member selection criteria. The proposed FlyFO-ANN model is evaluated against baseline methods.
Results: the experimental results reveal a significant increase in accuracy (0,9233) compared to other methods. The proposed framework is more adaptable and efficient than existing methods.
Conclusions: therefore, combining DL with intelligent optimization improves SCM decision-making by overcoming constraints in static approaches and enabling scalable, data-driven supply chain operations.

Keywords: Supply Chain Management (SCM); Flying Fox Optimized Artificial Neural Network (Flyfo-ANN); Member Selection; Operational Decision-Making; Deep Learning (DL); Intelligent Supply Chain Management (ISCM).

RESUMEN

Introducción: una gestión eficiente de la cadena de suministro (SCM) es fundamental para aumentar la competitividad, especialmente mediante la mejora de la selección de miembros (proveedores/socios) y la toma de decisiones operativas. Las técnicas tradicionales suelen basarse en evaluaciones manuales o en sistemas estáticos basados en reglas, que tienen una escalabilidad, adaptabilidad y capacidad de procesamiento de datos en tiempo real limitadas.
Objetivo: el objetivo de esta investigación es crear un marco de gestión inteligente de la cadena de suministro (ISCM) que utilice el aprendizaje profundo (DL) y la optimización metaheurística para mejorar la selección de proveedores y la eficiencia operativa general.
Método: un conjunto de datos de la cadena de suministro del mundo real procedente de la fuente abierta Kaggle, que incluye mediciones del rendimiento de los proveedores, calendarios de entrega, previsión de la demanda e historial de transacciones. El conjunto de datos se preprocesa utilizando la normalización min-max. La extracción de características se realiza mediante el análisis de componentes principales (PCA). Esta investigación propone un método de red neuronal artificial optimizada Flying Fox (FlyFO-ANN) basado en una red neuronal artificial (ANN), que se sugiere para predecir la fiabilidad de los proveedores y las fluctuaciones de la demanda. Además, se utiliza una optimización Flying Fox (FFO) para modificar los hiperparámetros del modelo y optimizar los criterios de selección de miembros. El modelo FlyFO-ANN propuesto se evalúa en comparación con los métodos de referencia.
Resultados: los resultados experimentales revelan un aumento significativo de la precisión (0,9233) en comparación con otros métodos. El marco propuesto es más adaptable y eficiente que los métodos existentes.
Conclusiones: por lo tanto, la combinación de DL con la optimización inteligente mejora la toma de decisiones en la gestión de la cadena de suministro, ya que supera las limitaciones de los enfoques estáticos y permite operaciones de cadena de suministro escalables y basadas en datos.

Palabras clave: Gestión de la Cadena de Suministro (SCM); Red Neuronal Artificial Optimizada Flying Fox (Flyfo-ANN); Selección de Miembros; Toma de Decisiones Operativas; Aprendizaje Profundo (DL); Gestión Inteligente de la Cadena de Suministro (ISCM).

INTRODUCTION

The supply chain (SC) encompasses manufacturing and distribution routes from suppliers to consumers, aiming to meet consumer demands, increase responsiveness, and build a network of partners.[1] Organizations are focusing on sustainability in supply chain management (SCM) to improve quality, service delivery, and resource efficiency, while integrating artificial intelligence (AI) and internet of things (IoT) for stable operations.[2] AI enhances SCM through fuzzy logic and expert systems, improving decision-making and client relations through evaluation, technology, network reconfiguration, and process optimization.[3] Global Energy-Related Uncertainty Index (GEUI) and Global Supply Chain Pressure Index (GSCPI) are the two indications used for SCM. The GSCPI evaluates global SC conditions, while the GEUI represents global energy efficiency and supply dynamics issues.[4] Multi-echelon systems and communications in SCM can cause data to get confused and damaged, making it harder to forecast unexpected events or threats.[5] SCM systems struggle with accurate consumer demand estimation, but effective forecasting models can improve planning and operational efficiency by providing reliable insights for future demand forecasting and decision-making processes.[6]

SC agility is an organization's capacity to quickly react to unanticipated disturbances while maintaining operations and customer satisfaction, to establish a competitive advantage by decreasing risks and capitalizing on opportunities.[7] Global sourcing and transportation networks are vital for businesses, with supplier performance affecting procurement efficiency. Poor deliveries can disrupt industrial processes, particularly for assembly-based production.[8] SC visibility improvements involve surveying suppliers, using third-party databases, and Radio-Frequency Identification (RFID) technologies, but challenges like confidentiality and lack of reliable verification mechanisms persist.[9] A large manufacturing company developed a technique known as the SC Control Tower (SCCT) to construct an intelligent SCM (ISCM). In addition to innovations, SCCT encompasses interactions with the SCCT team and outside SC players. These socio-technical interactions were managed methodically to establish an ISCM.[10] Machine learning (ML) methods, such as support vector machine (SVM), random forest (RF) and extreme gradient boosting machine (XGBoost) were shown to provide correct forecasts, which increased the effectiveness of ISCM operations. In comparison to the other two models, XGBoost performs better in prediction.[11]

The IoT has made significant advances in the logistics industry, particularly in connectivity, service quality, and SCM. An ISCM system that allows SCM managers to make decisions for successful IoT-based transportation.

[12] Conditional generative adversarial networks (CGANs) were dynamic SCMs used to address classification problems with large selection qualities and small observation samples, preserving classification accuracy while reducing information quantity and variety.[13] Geographic Information System (GIS) technology was utilized to optimize an ISCM logistics information system, enhancing efficiency by assisting in the creation of transportation routes, real-time worker and goods positions, and predicting arrival times.[14] The modified relational deep learning forecasting technique, seasonal auto-regressive integrated moving average, and light-gradient boosted machine (LightGBM) were used to accurately predict product demand, reducing prediction error.[15]

The research aims to develop an ISCM framework using deep learning (DL) and metaheuristic optimization to enhance supplier selection and operational efficiency. The framework utilizes the proposed Flying Fox Optimized Artificial Neural Network (FlyFO-ANN) method for predicting supplier reliability and demand fluctuations.[16,17,18,19,20]

The remaining part of this research should be organized as follow: the next section explains the methodology, which comprises four components namely dataset, preprocessing, feature extraction and the proposed method. The subsequent sections present the result, discussion and conclusion.[21,22,23,24,25,26]

METHOD

The developed ISCM framework employed the proposed FlyFO-ANN for predicting supplier reliability and demand fluctuations with the help of SC dataset. The dataset undergoes the preprocessing process with min max normalization, and feature extraction using Principal Component Analysis (PCA). These processes are clearly explained in the section as well as illustrate in the outline process in figure 1.

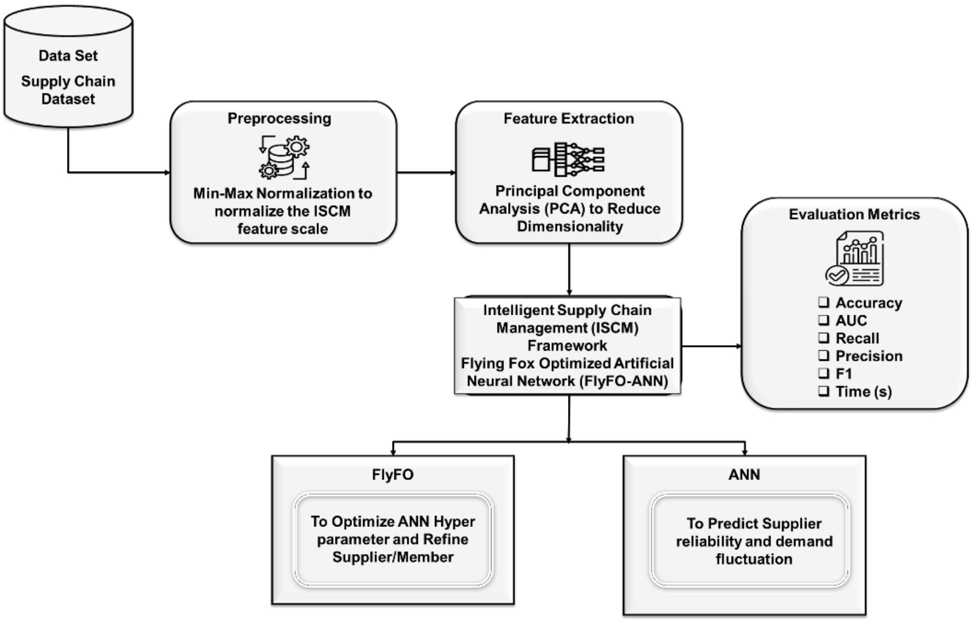

Figure 1. Outline process of proposed methodology

Dataset

The SC dataset was obtained from the Kaggle dataset (https://www.kaggle.com/datasets/programmer3/supply-chain-dataset). The dataset provides detailed insights into real-world SC operations in logistics and manufacturing industries, including supplier performance metrics, delivery patterns, demand forecasting indicators, and historical transactions.

Data Preprocessing and Feature Extraction

Min max normalization: to normalize the SC characteristics by translating values to the smallest values within a predetermined interval, allowing classification algorithms to handle quantitative features, and preserving supplier reliability connections. Equation (1) converts each value in the analysed characteristic into a new standardized value.

$$\acute{w} = \frac{w - min_b}{max_b - min_b}(new\_max_b - new\_min_b) \quad (1)$$

Where the standardized value is ẃ, the initial value is w, and the highest value is max_b. A min_b, represents the minimal value for a specific characteristic in SC. The variables new max_b and new min_b reflect the highest

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and lowest values for the current range predicting supplier reliability and demand fluctuations.

PCA: the PCA is a data augmentation technique that reduces initial supplier selection to speed up computation and increase the risk of excess fitting, while retaining most essential information.

The initial dataset $Y_{p\times q}$ can be represented as a matrix with p rows and qcolumns, where p is the amount of samples and q is the number of variables in the SC dataset, as shown in equation 2.

$$Y_{p\times q} = \left(\frac{x_{11} \dots x_{1q}}{\vdots \quad \ddots \quad \vdots \; x_{p1} \quad \cdots \quad x_{pq}}\right) \qquad (2)$$

The prediction outcomes may be significantly influenced by the significant length variation in each SC input factor. The component $Y_{p\times q}$ is standardized to employ the better use of PCA and transformed into a standardized matrix Y* according to equation 3.

$$Y_{j,k}{}^{*} = \frac{Y_{j,k}-\mu_k}{\sigma_k}, j = 1,2,\dots,p; k = 1,2,\dots,q \qquad (3)$$

$$\eta_j = \frac{\lambda_j}{\sum_{j=1}^{q} \lambda_j} \qquad (4)$$

The standardized value is denoted as $Y_{j,k}{}^{*}$. μ_k and σ_k represent both the average and variance of the original SC data. $M_{p\times q}=Y^{*T}Y^{*}$ is the correlation matrix M. Equation 4 represents the effectiveness rate of each primary component (η).

Predicting Supplier Reliability and Demand Fluctuations Using Flying Fox Optimization-Artificial Neural Network (FlyFO-ANN)

The FlyFO-ANN is a novel form of a DL model that brings together the predictive capabilities of ANN with the global surround of the FFO algorithm. ANN is used by the supplier reliability or demand prediction model in handling nonlinear data relationships. FFO hyperparameters are introduced into the ANN model based on the multi-objective selections. By partnering the ANN with an FFO at the hyperparameter and member selection phase, the model was improved concerning prediction performance, adaptively and implementation efficiency of the resulting assemblage into an ISCM framework.

Artificial Neural Network (ANN): ANN is a unit for supplier selection and efficiency, consisting of multiple cells and a neuron. It serves as the foundation for a the function's operation. ANNs come in various network architectures, such as single-layer nets with input components, one layer of measurements, and output modules, and multi-layer networks with input, hidden, and output components. The optimum architecture is chosen by finding the most effective mix of input and hidden components. However, there is no common approach for ANN modeling in terms of inputs, hidden layers, and nodes in each hidden layer for predicting supplier reliability and demand fluctuations.

ANN modeling employs several functions for activation, including the threshold parameter operation, step engagement function, exponential function, and tangent of hyper function (equation 5).

$$\emptyset(a) = a.\,g(a) \qquad (5)$$

Where g(a) is a tangent of hyper function.

$$g(a) = Tanh(a) = \frac{exp^{a}-exp^{-a}}{exp^{a}+exp^{-a}}.$$

The ANN's outcome is influenced by the weight of cell interactions, which are applied appropriately across neurons in different layers for ISCM.

Flying Fox Optimization (FlyFO): The FlyFO algorithm is a versatile optimization tool that effectively addresses the ISCM challenges by emulating the survival strategies of flying foxes (FF). It offers faster convergence and better regional and global exploration capabilities, focusing on FF migrant habits in hot zones and their starvation and death processes.

The FF moves (SC transportations) to the optimal option to prevent warmth and death, as determined by the application of equation (5). To escape from blockages and exhausting FF moves (SC transportations) and it is represented in equations (6-8).

$$Y_{j,k}^{u+1} = Y_{j,k}^{u} + \propto * rand(cool_{j,k} - Y_{j,k}^{u}) \quad (6)$$
$$mY_{j,k}^{u+1} = Y_{j,k}^{u} + rand_{1,k} * \left(cool_{j,k} - Y_{j,k}^{u}\right) + rand_{2,k} * (Y_{R1,k}^{u} - Y_{R2,k}^{u}) \quad (7)$$
$$Y_{j,k}^{u+1} = \{mY_{j,k}^{u+1}, if\ k = l\ or\ rand_{3,k} \geq pa\ Y_{j,k}^{u},\ \ otherwise \quad (8)$$

Where, $Y_{j,k}^{u}$- representing k-th element of FF individual j in the u-th iteration. $cool_{j,k}$- represents the k-th current position in the overall population related to an individual j. ∝ - Beneficial gravitation constant. rand is a random number in [0,1], $mY_{j,k}^{u+1}$ is a modified position for next generation (u+1).

To forecast supplier dependability and demand changes, overheated FFs are relocated to the coolest node and replaced by younger, more adaptive ones, as described in equation (9).

$$Y_{j,k}^{u+1} = \frac{\sum_{l=1}^{m} \ SL_{l,k}^{u}}{m} \quad (9)$$

The variable m ranges from 2 to the entire number of SL, whereas $SL_{l,k}^{u}$ indicates the k-th element of the l-th individual in the SL of the u-th iteration.

Crowding is handled to predict supplier reliability and demand changes by replacing similar solutions with offspring or deleting underperforming ones using a probability model (equation 10-11).

$$offspring\ 1 = N * C_1 + (1 - N) * C_2 \quad (10)$$
$$offspring\ 2\ = N * C_2 + (1 - N) * C_1 \quad (11)$$

C_1, C_2 are two FF and N being an arbitrary number from 0 to 1. The random number is generated with a 50 % chance, and if it exceeds the probability, the FF survives. If the number is odd, the remaining individual is removed. Algorithm 1 shows the FlyFO-ANN.

Algorithm 1: FlyFO-ANN

```
data = load_data("supplier_dataset.csv")
data = min_max_normalize(data)
features = apply_PCA(data)
ann = initialize_ANN(input_size, hidden_layers, output_size, activation='tanh')
population = initialize_population(num_ff, ann_hyperparams)
alpha = 0,5
pa = 0,2
max_iter = 100
for u in range(max_iter):
  for j in range(len(population)):
for k in range(hyperparam_dims):
      cool = get_best_solution(population)
      Y[j][k] = Y[j][k] + alpha * rand() * (cool[k] - Y[j][k])
      R1, R2 = select_random_indices(population)
mY = Y[j][k] + rand()*(cool[k] - Y[j][k]) + rand()*(Y[R1][k] - Y[R2][k])
      if k == random_index() or rand() >= pa:
        Y[j][k] = mY
  for j in overheated_indices:
    Y[j] = average_of_survivors(SL)
  for j in range(0, len(population), 2):
    if is_similar(Y[j], Y[j+1]):
      N = rand()
      offspring1 = N * Y[j] + (1 - N) * Y[j+1]
      offspring2 = N * Y[j+1] + (1 - N) * Y[j]
replace_or_eliminate(offspring1, offspring2, population)
  for ff in population:
ann.set_hyperparams(ff)
    fitness = ann.train_and_evaluate(features, labels)
update_best(ff, fitness)
best_ann = get_best_ann(population)
```

RESULTS

This section clearly demonstrates the outperformance of the proposed and existing methods with figures and tables as well as system configuration.

Experimental Setup

The experimental setup was performed on a system with an Intel Core i7 processor, 32GB of RAM, running Windows 11 (64-bit). The implementation was achieved in Python using TensorFlow and Scikit-learn libraries. A Kaggle open-source supply chain dataset was used, and the simulations were all executed using FlyFO-ANN.

Evaluation Metrics

To assess the performance of the FlyFO-ANN model as a predictor of supplier reliability and demand variation, six key evaluation metrics were implemented. Accuracy is the model's overall prediction correctness, indicating how often it accurately classifies supplier reliability. AUC (Area Under the Curve) measures model performance in distinguishing reliable and unreliable suppliers. Recall measures the model's ability to identify all actual reliable suppliers, while precision measures the number of predicted reliable suppliers. F1 balances precision and recall, aiming to maximize both. Time (s) indicates model execution efficiency per iteration, particularly important in real-time supply-chain environments. These metrics validate the model's robustness and operational capacity.

Figure 2 shows: (a) delivery modes are uniformly distributed across targets; (b) selected suppliers (flag 1) demonstrate higher on-time delivery performance; (c) quality scores are generally higher for selected suppliers, indicating better overall performance in key metrics.

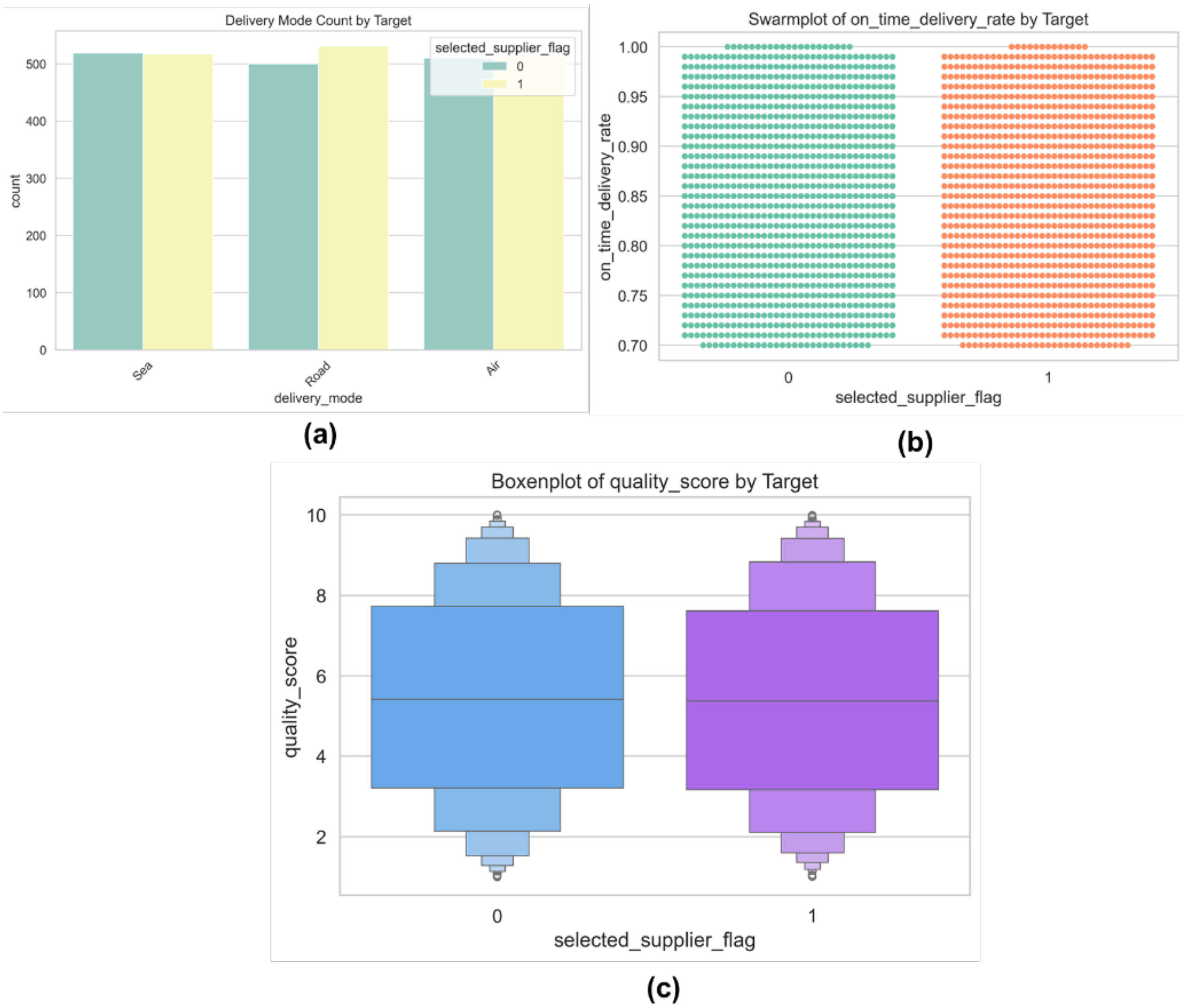

Figure 2. Outcomes of (a) delivery mode count by target, (b) Swarmplot of an time delivery rate by target and (c) boxenplot of quality score by target

Comparison Phase

The proposed method FlyFO-ANN is compared with the existing Random Forest, Extra Trees and CatBoost[16] based on the six evaluation metrics for supplier selection and efficiency.

Table 1 and figure 3-5 display the outcome of evaluation metrics. The proposed method obtains the greater values in accuracy (0,9233), recall (0,8815), AUC (0,9664), F1 (0,8923), and precision (0,9077), as well as lower time (0,005s) than existing methods for SC reliability, and demand fluctuations.

Table 1. Outcome of metrics

Methods	Accuracy	AUC	Recall	Precision	F1	Time(s)
Random Forest[16]	0,8782	0,9328	0,8173	0,8318	0,8241	0,07
Extra Trees[16]	0,8721	0,9202	0,8129	0,8204	0,816	0,07
CatBoost[16]	0,8883	0,9389	0,8185	0,8566	0,8364	0,741
Proposed	0,9233	0,9664	0,8815	0,9077	0,8923	0,005

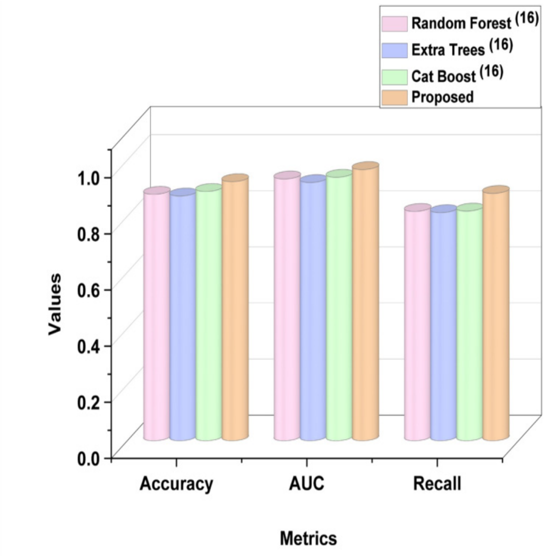

Figure 3. Outcome of accuracy, AUC, recall

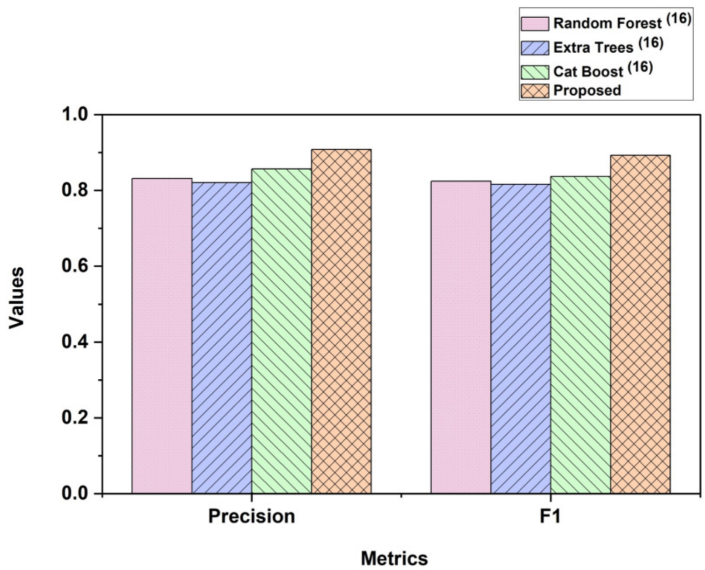

Figure 4. Precision, and F1 for proposed vs existing models

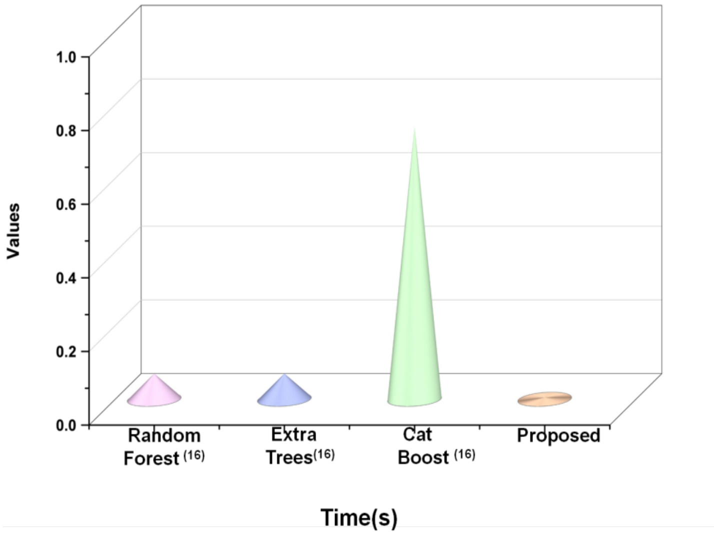

Figure 5. Time for existing vs proposed model

DISCUSSION

In SCM, traditional methods like Random Forest, Extra Trees, and CatBoost[16] have been employed for supplier evaluation but often suffer from limitations, such as poor adaptability to dynamic environments, sensitivity to noisy features, and increased processing time.[27,28,29,30] These limitations hinder real-time decision-making and efficient supplier selection. To address these challenges, the proposed FlyFO-ANN integrates DL with metaheuristic optimization to form a more adaptive and intelligent supply chain management framework. It enhances prediction accuracy, optimizes model parameters, and significantly reduces computational overhead. In the comparison phase, FlyFO-ANN demonstrated superior performance across all evaluation metrics, overcoming the existing methods' weaknesses and establishing itself as a robust and scalable solution for supplier selection and operational efficiency in dynamic supply chain settings.[31,32]

CONCLUSIONS

Research presents a DL-based ISCM framework that effectively addresses the limitations of traditional static and rule-based approaches. The proposed method, FlyFO-ANN, integrates ANN with FlyFO to enhance supplier selection and demand forecasting. Experimental findings demonstrate notable improvements, achieving a rate of accuracy (0,9233), and reduced processing time of 0,005 seconds. Despite its effectiveness, the model requires high computational resources and is sensitive to data quality. Future research can focus on integrating real-time data streams, incorporating blockchain and IoT technologies, and improving interpretability through explainable AI to expand its applicability across diverse SCM environments.

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Authors declare that there is no conflict of interest.

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