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An Efficient Recommendation System in E-commerce Using Passer Learning Optimization Based on Bi-LSTM

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Abstract: Online reviews play a crucial role in shaping consumer decisions, especially in the context of e-commerce. However, the quality and reliability of these reviews can vary significantly. Some reviews contain misleading or unhelpful information, such as advertisements, fake content, or irrelevant details. These issues pose significant challenges for recommendation systems, which rely on user-generated reviews to provide personalized suggestions. This article introduces a recommendation system based on a Passer Learning Optimization-enhanced Bidirectional Long Short-Term Memory network classifier applicable to e-commerce recommendation systems with improved accuracy and efficiency compared to state-of-the-art models. More specifically, the proposed model achieves a high accuracy of 98.03%, F1 score of 98.03%, precision of 98.49%, recall of 97.57%, and minimum mean square error of 1.97 based on training percentage using the patio lawn garden dataset. These results, made possible by advanced graph embedding for effective knowledge extraction and fine-tuning of classifier parameters by the hybrid PLO algorithm, establish the suitability of the proposed PLO-Bi-LSTM model in various e-commerce environments.

Keywords: recommendation system, e-commerce, Passer Learning Optimization, Bi-LSTM classifier, TF-IDF

1. Introduction

Online shopping has become very common because of the increased use of the Internet and mobile phones in recent years [1–5]. This growth has nurtured the emergence of electronic commerce, which has granted people the ability to buy, sell, and barter goods and services based on Internet-enabled platforms [6–8]. In e-commerce, understanding consumer behavior is considered the cornerstone of preference, decision, and interaction on the platforms. Recommender systems help drive this ecosystem by leveraging user data on browsing history, search queries, and purchase patterns to offer suggestions for personalization that increase customer satisfaction and drive conversions.

E-commerce encompasses a wide variety of business models, including business-to-consumer sites (such as Amazon) and C2C marketplaces (such as eBay), and monetization approaches that leverage advertising and subscriptions in addition to freemium models. These areas of strategy, from pricing to supply chain optimization to data security, are keys to thriving and growing in a global economy. Recommendation systems form the core of solving key challenges around customer engagement, conversion optimization, and product relevance. These systems study user behavior and make the shopping experience better, optimize conversions, and personalize products. Although impactful, several recommendation approaches exist that involve several trade-offs: for example, fuzzy logic-based systems improve diversity at the cost of confidence [9]; hybrid models that combine collaborative and content-based filtering address the issue of accuracy but not cold starts [10].

More advanced scalable implementations include deep learning based [11], cross-domain matrix factorization [12], and self-complementary collaborative filtering [13]. Nevertheless, all of these have challenges, including high computational complexity and limited data generalization [14]. To overcome these challenges, the proposed Bidirectional Long Short-Term Memory network (BiLSTM) is developed with passer learning optimization to address cold-start and scalability issues in e-commerce recommendation systems. The main contributions of this research are mentioned as follows:

Passer Learning Optimization (PLO): The research introduces the Passer learning optimization algorithm, a hybrid approach that merges the automatic learning capacity of a teacher-learner algorithm with sparrow-inspired principles. The foraging behaviors are merged to find the optimal solution with less loss. This distinctive blend improves convergence rates and performance, differentiating it from conventional optimization techniques.

PL-optimized BiLSTM: The refined version of the Bi-LSTM architecture offers enhanced sequence modelling capabilities, making

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it particularly valuable for tasks involving sequential data, such as natural language processing and time series analysis. The optimizations introduced contribute to improved performance, including accuracy and convergence speed, improving e-commerce through better product review analysis and personalized recommendations.

This paper is organized as follows: The proposed methodology for the e-commerce recommendation system is described in Section 2, and the Passer learning optimization technique and related mathematical models are discussed in Section 3. The experimental findings of the proposed method are presented in Section 4, and the conclusion and suggestions for future work comprise Section 5.

2. Literature Review

The previous model's recommendation system in e-commerce is discussed in the section below, and a new fuzzy logic-based product suggestion system was developed by Jain and Gupta [15] that utilizes users' present interests to anticipate which products are the most pertinent to them when they purchase online. This approach raised the diversity and product rating score but decreased the recommendation system's level of confidence. A deep learning and distributed expression-based application solution for e-commerce product advertising recommendations was created by Zhou [11]. This approach had great flexibility and minimized calculating complexity, but it was exceedingly expensive and time-consuming. Zheng et al. [16] proposed a heterogeneous product system by combining user, item, and interaction information. This strategy increased quality and decreased rating prediction error but converged too slowly. Sharma et al. [10] introduced a hybrid recommendation system that anticipates recommendations. The suggested method combined collaborative filtering with content-based filtering. Although this method's recommendations were more accurate, it had a cold start issue. The cross-domain situation of user overlap in an e-commerce system [12, 17] created a domain matrix factorization that predicted the rating of a product for a frequent user with a fixed cold start issue. Although this method's convergence is excessively sluggish and does not predict all testing data, it does minimize the time complexity. Esmeli et al. [18] presented the session similarity-based strategy to address the issue of cold-start sessions in the e-commerce area, where no interactive objects in the sessions can aid in discovering users' preferences. This approach lessened the effects of the cold-start movie issue. Self-complementary collaborative filtering is a framework proposed by Xie et al. [13] and can make recommendations in real time using both global and local information. This technique lowered the size of the model and helped with overfitting, but it is time-consuming and cannot be used in large-scale applications. Zhang et al. [19] presented a novel strategy that is effectively a hybrid probabilistic matrix model. Although this method had a high computational complexity and a high computing cost, it minimized errors.

2.1. Materials and methods

The following is a list of the challenges encountered during the current research:

Improved accuracy and efficiency: Our PLO-BiLSTM model will overcome the shortcomings of the available techniques in reducing computational complexity and enhancing the convergence speed, hence finding applications in real-time dynamic e-commerce environments.

Performance improvement: The performance of the integration of Passer Learning Optimization with Bi-LSTM outperforms others, reducing mean square error (MSE) to 1.24%, and increasing F1 scores to 88.58% on key datasets, outperforming traditional models.

Real-time capabilities: Our approach provides the rapidity of decision-making demanded by real-time applications by optimizing computational efficiency common weakness with systems involving heterogeneous products.

Cost-effectiveness: The PLO-Bi-LSTM slashes deep learning systems' time and money, hence very well viable on a large-scale e-commerce platform without hurting recommendation quality.

Algorithm efficiency: The proposed model will maintain high user satisfaction while enhancing algorithm efficiency, and balancing context-aware personalization with demands for scalability and performance.

Moreover, the proposed BiLSTM model is incorporated with Passer Learning Optimization, which aims to overcome the cold-start and scalability issues in e-commerce recommendation systems by integrating Passer Learning Optimization with the Bi-LSTM architecture. Moreover, the Passer learning optimization is a fusion of teaching-learning-based optimization (TLBO) and sparrow search algorithm (SSA), which helps to ensure enhanced accuracy of recommendations, scalability, and fast convergence rate with tracking data nature and user preference compliance.

3. Proposed Methodology for Recommendation System in E-commerce

This research primarily aims to create an e-commerce recommendation system employing a Passer learning optimization-based Bi-LSTM classifier. Initially, the recommendation dataset is input, and the data are preprocessed to enhance quality. The preprocessing phase includes stemming, lemmatization, and tokenization processes, improving data quality. The preprocessed data is forwarded to content and collaboration-based feature extraction, where the term frequency-inverse document frequency (TF-IDF) and the graph embedding-enabled features are extracted. The graph embedding enables the extraction of the data features in the form of a discrete graph, which is represented in vector form, and the TF-IDF features measure the relationship between Word and the document. Extracting these features reduces the data's dimensionality by eliminating irrelevant features, and it reduces data dimensionality by eliminating nonrelevant features. This feature extraction also enhances the model's classification accuracy. Finally, recommendations of a valid product to the users from the extracted features are made by the collaborative Bi-LSTM classifiers. Bi-LSTM is useful, especially for processing sequences of data. Considering both past and future contexts during prediction is of great value in understanding user behavior and preferences. This helps in the efficient recommendation of the products to the users. The Bi-LSTM classifier is tuned using the Passer learning optimization, created using two common optimizations, TLBO [20] and SSA [21], improving the performance of the Bi-LSTM classifier. The architecture of the proposed recommendation system in an e-commerce model is shown in Figure 1.

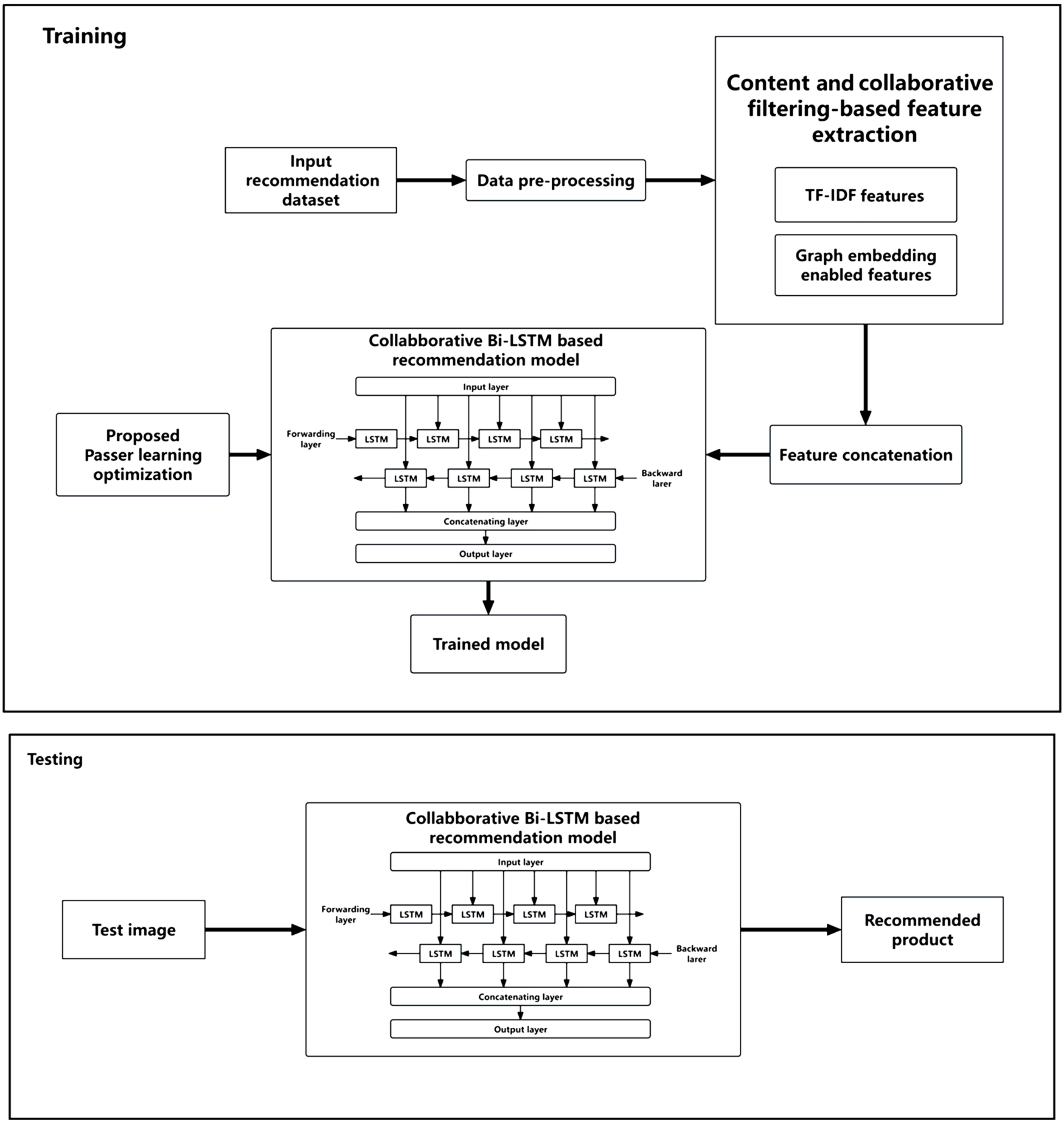
3.1. Input data

The input data is collected from the baby dataset, the digital music dataset, and the patio lawn garden dataset sourced from the Amazon dataset for the recommendation model is mathematically formulated as the following equation:

$$R = \sum_{i=1}^{a} R_i \tag{1}$$

where the recommendation dataset is denoted as R, and R_i denotes text present in the dataset, ranging from 1 to a.

Figure 1
The architecture of the proposed recommendation system in the e-commerce model



Note: TF-IDF = term frequency-inverse document frequency.

3.2. Data preprocessing

The input text data is applied in the preprocessing phase, which uses text processing techniques such as stemming, lemmatization, and tokenization processes for preprocessing, which is processing the input text for the classification process in the e-commerce recommendation system. The techniques are explained as follows.

Tokenization: Tokenization is the process of splitting text into individual words or tokens, making it easier for computers to understand and analyze the content. This essential step in natural language processing breaks down complex sentences or paragraphs into manageable units for subsequent analysis.

Stemming: Stemming is a process of standardizing the text by removing the last few characters from a word or suffixes, often leading to incorrect meanings and spelling.

Lemmatization: Lemmatization also enhances text processing by reducing words to their meaning, ensuring consistency in word representations, and aiding in identifying common semantic meanings within the text data. The preprocessed data is mathematically represented as

$$R = \sum_{i=1}^{a} R_i^* \tag{2}$$

where the preprocessed text is denoted as R_i^*.

3.3. Content and collaborative filtering-based feature extraction

Eliminating unnecessary features is an essential phase of feature selection, which avoids overfitting problems by lowering the size of the features and reducing cold start problems. To accurately categorize the polarity, the algorithm is trained for a certain feature that is used to represent the data. The class attribute is thus represented in the smaller feature space by feature selection, which chooses the fewest significant characteristics. The techniques for feature selection can considerably increase classification accuracy and provide users with better knowledge of key class traits, helping to interpret the data. The two steps used in this research to extract TF-IDF features and graph embedding-enabled features are discussed in depth below.

3.3.1. TF-IDF features

The TF-IDF is one of the most popular weighting metrics for detecting the link between words and documents, commonly used in the process of collecting word features. We can quantify the importance of every phrase in a document by assigning it a numerical value with the aid of TF-IDF. The inverse document rate (IDF) quantifies the frequency of words appearing across the whole corpus. A term appearing only occasionally in the corpus can still be considered a feature because it has great differentiation potential [22]. As TF-IDF merely computes the importance of each word in a document or collection of documents rather than evaluating each document's entire content, search engines can rank texts with less computational effort. The equation for the TF-mathematical IDF is calculated as follows:

$$Vt_{i,j} = \frac{o_{i,j}}{\sum_a o_{a,j}} \tag{3}$$

$$idt_i = log\frac{|Q|}{|\{j: w_i \in v_j\}|} \tag{4}$$

The denominator of Equation (3) is the total number of times all the words appear in the text, and the value in the numerator of the formula is the number of times each word appears in the document. Equation (4) |Q| shows the overall number of documents in the corpus or the entire number of documents comprising the phrases. If the feature word's *TF-IDFt*$_1$ value equals the word's value when $Vt_{i,j}$ is multiplied by idt_i, the weight of the feature word can also be determined using Equation (5).

$$TF - IDFt_1 = vt_{i,j} \times idt_i \tag{5}$$

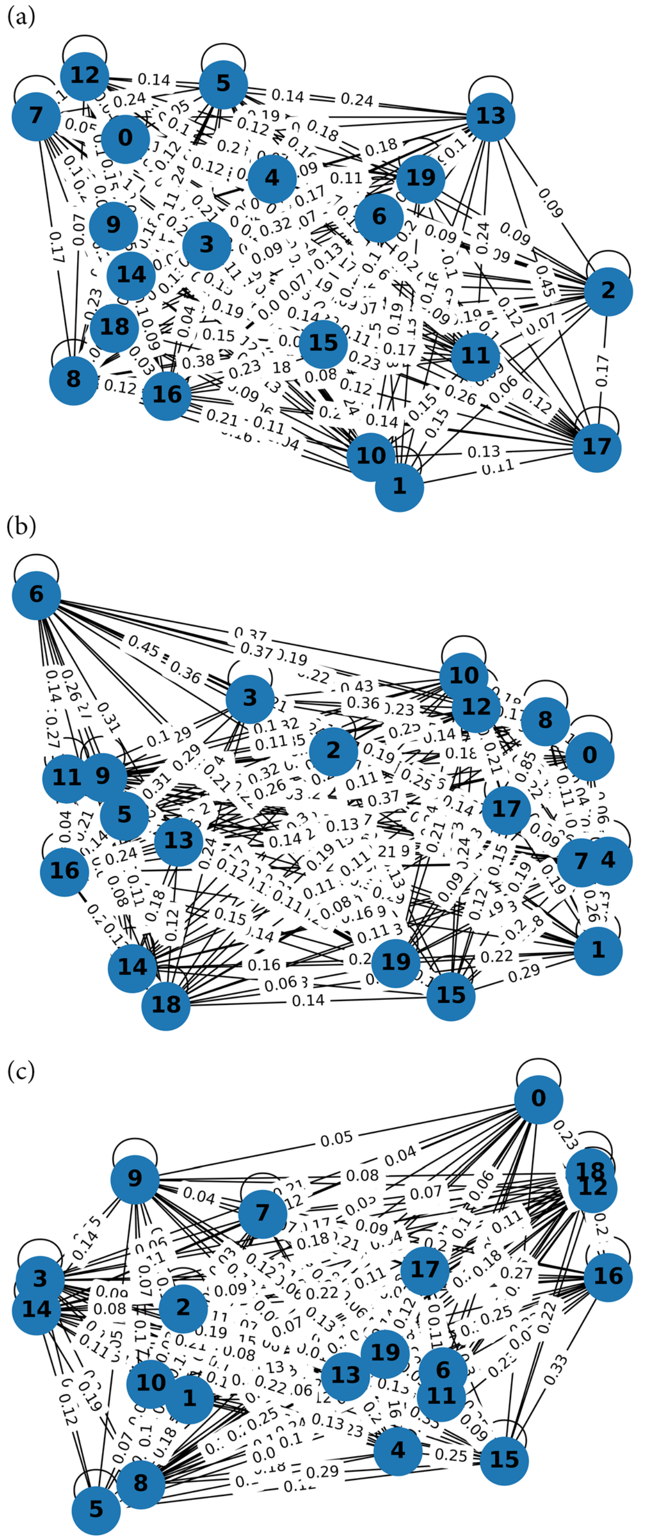
3.3.2. Graph embedding-enabled features

Graph embedding refers to the processes that convert property graphs into a vector or a collection of vectors. Graph topology, vertex-to-vertex relationships, and other pertinent details about graphs, subgraphs, and vertices should all be captured during embedding.

As graph embedding techniques compress every node's attribute in a vector with a smaller dimension, node similarity in the original complicated irregular spaces may be readily measured in the embedded vector spaces using common metrics.

The benefits of graphical representation include time-saving and easier understanding of data. Graph embedding is a dimensionality reduction technique that extracts the most meaningful information from graph data while significantly lowering the computational burden and complexity accompanying large dimensions. This graph-embedding feature for Datasets 1, 2, and 3 is shown in Figure 2.

Figure 2
Graph embedding-based features for (a) the baby dataset, (b) the digital music dataset, and (c) the patio lawn garden dataset



Feature concatenation: After numerous features with the same dimensions are extracted to the Bi-LSTM classifier for analysis, they are merged using the feature concatenation approach. The various original information are significantly conserved throughout the concatenation method due to the integrated perspective representation of all the concatenated features. The Passer learning optimization-based Bi-LSTM classifier receives the output of feature concatenation and improves the performance during the recommendation system. The optimization method discovers the most effective solution while the overall number of parameters in the features is minimized. Consequently, the model's performance is assessed and trained, using both the test and trained data as modelling input. A training dataset is used to train the model with the dimension of 1 × 2,000, and the model's accuracy determines the test data.

3.4. Collaborative Bi-LSTM-based recommendation model

Bi-LSTM plays an important role in the recommendation system by making personalized product recommendations for users with the help of sequential information and context. It considers content features TF-IDF, graph embedding, and collaborative information for making informed suggestions. Adding Passer learning optimization further refines the performance of Bi-LSTM, making the recommendations quite accurate and effective. After extraction, the features are fed to collaborative Bi-LSTM classifiers that shall wield the power of Bidirectional Long Short-Term Memory for recommendations. Bi-LSTM is particularly helpful in handling the processing of sequences in NLP tasks or sequential recommendations. It offers an ability to predict, considering past and future contexts—a useful insight for understanding user behaviors and preferences. The performance of the Bi-LSTM classifier is further improved by the system using Passer learning optimization. The Passer learning optimization is an algorithm that combines the characteristics of a teacher-student relationship inspired by sparrow behavior and is designed to improve convergence rates and performance. It fine-tunes the parameters of the Bi-LSTM classifier to make more accurate recommendations [1].

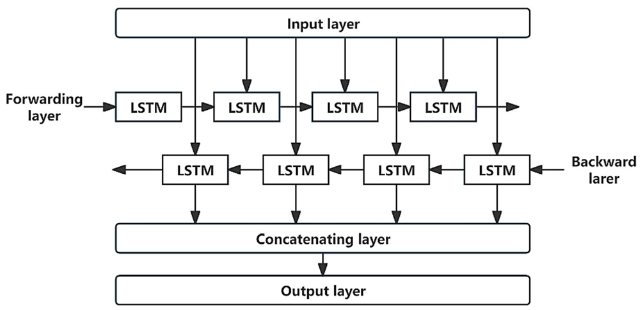
Figure 3 displays the Bi-LSTM classifier recommendation system. This architecture is comprised of input layers, forwarding layers, backward layers, totally connected layers, and output layers. The Bi-LSTM classifier effectively manages the error gradient by making gates available and providing long-term dependencies, significantly reducing the vanishing gradient problem. The equation demonstrates how the Bi-LSTM classifier is conceptualized mathematically.

$$B_X = A(w_c \cdot x_Y + O_Y \cdot c_{Y-1} + b_c) \tag{6}$$

The features expressed as $R^*_{i,f}$ are carried by the current word embedding represented by B_X. The weights for the Bi-LSTM classifier are given *byw*$_c$ and O_Y, whereas $A(X)$ stands for the nonlinear function, b_c determines the bias, and, $c_{Y\text{-}1}$ signifies the hidden state. The classifier's weights and biases are optimized using the Passer learning optimization, which also successfully adjusts the hyperparameters.

$$E_Y = \sigma(w_E \cdot y_Y + O_E \cdot c_{Y-1} + b_E) \tag{7}$$

Figure 3
Bi-LSTM architecture



Note: Bi-LSTM = Bidirectional Long Short-Term Memory, and LSTM = Long Short-Term Memory.

$$J_Y = \sigma(w_J \cdot y_Y + O_J \cdot c_{Y-1} + b_J) \tag{8}$$

$$P_Y = \sigma(w_P \cdot y_Y + O_P \cdot c_{Y-1} + c_P) \tag{9}$$

$$m_Y = E_Y \cdot m_{Y-1} + J_Y \cdot tanh(w_m \cdot x_Y + O_m \cdot c_{Y-1} + c_m) \tag{10}$$

$$c_Y = P_Y \cdot tanh(m_X) \tag{11}$$

Here, E_Y, J_Y, and P_Y stand for the input gate, forget gate, and memory cell, respectively. m_Y stands for the memory cell, P_Y for the Hadamard product, and σ for the sigmoid function. Although the forget gate assists in forgetting previous knowledge, the memory cell in the input gate keeps the currently important information. The output gate determines which information is presented in the internal memory cell and enables many retrievals of crucial information.

3.5. Proposed Passer Learning Optimization

To make the Bi-LSTM classifier work effectively, an effective passer learning optimization is incorporated with the classifier to fine-tune the parameters based on weight and bias. Thus, the sparrow optimization [21] and TLBO [20], which are developed with built-in automatic learning features, should be combined with the passer to increase speed, convergence rate, and improvement in performance order.

A basic explanation of an algorithm, along with a mathematical notational description, is furnished further in the subsequent sections.

Motivation: PLO is the hybrid algorithm proposed in this work, which incorporates the teaching capabilities of a "teacher" with inspiration from the sparrow behavior of the SSA to enhance the performance and convergence rate. The sparrow is believed to be one of the most intelligent birds, classified into "producers," "scroungers," and "investigators." Producers have energy reserves that help lead scavengers to the food, while scroungers follow the best food providers. The algorithm also implements a security mechanism whereby sparrows chirp to raise an alarm, and producers lead the scavengers to safety if the alarm threshold is violated. This strategy has been adopted from the foraging strategy of sparrows. TLBO is a population-based algorithm that draws inspiration from classroom dynamics. It has two phases: the teacher phase and the learner phase. In the teacher phase, students learn from a knowledgeable teacher and try to improve their knowledge. In the learner phase, students share and improve their knowledge through interactions such as group discussions and learning from more knowledgeable peers. TLBO emulates the teaching-learning process in a classroom environment. These algorithms, PL and TLBO, draw from the natural behaviors of sparrows and classroom dynamics in order to enhance convergence and learning within optimization problems.

3.5.1. Mathematical model of the proposed Passer Learning Optimization

The producer, scrounger, and investigator are the three categories used to represent the mathematical model of the proposed Passer learning optimization, and those behaviors are mathematically formulated in the sections as follows:

1) Initialization

The solutions of the developed optimization are randomly initialized with the lower bound and upper bound. The initialized solutions are presented as

$$x^t_{ij} = rand \cdot (ub - lb) + lb \tag{12}$$

where $rand$ is the random number and x^t_{ij} is the solution position at iteration *t*.

2) Evaluation of fitness

The optimal solution establishes the fitness of the developed optimization. The solution with the minimum MSE is the best fitness and can be stated as

$$fit\left(x_{ij}^{t}\right) = \min\left(MSE\left(x_{ij}^{t}\right)\right) \tag{13}$$

3) Solution update

After determining the fitness functions, the solutions are updated using different phases, which are presented as follows:

a. Phase I: Position update of the producer

The producers in Sparrow are responsible for finding food and controlling the movement of the entire population, though producers with higher fitness ratings have priority when it comes to finding food. Consequently, the producers have access to a greater range of food sources than the scroungers, and the teachers' teaching characteristics improve the producers' capability to explore more search areas. When the sparrows see a predator, they immediately begin chirping as an alert. If the alarm value beats the safety level, the producers are required to direct all scavengers to a safe area. The location update of the producer's mathematical formula is as follows:

$$x_{ij}^{t+1} = \begin{cases} x_{ij}^{t} \cdot ex\left(\frac{-h}{\alpha_1 \cdot t_{max}}\right) + \left(M_{ij}^{t} - x_{ij}^{t}\right) R_2 < AP \\ \left(x_{ij}^{t} + r_i * fl\right) \times \left(M_{ij}^{t} - x_{ij}^{t}\right) R_2 \geq AP \end{cases} \tag{14}$$

The current iteration is denoted as h, the random number as α_1, which ranges from 0 to 1, the flight length as fl, the uniform random number as r_i, which ranges from 0 to 1, the maximum number of iterations as M, the alarm value as R_2, and awareness probability as AP. x_{ij}^{t} represents the current position of the j^{th} dimension of the i^{th} sparrow at the iteration t. When $R_2 < AP$, it indicates that there are no predators nearby. All sparrows must immediately fly to other safe regions if $R_2 \geq AP$. This indicates that some sparrows have identified the predator.

b. Phase II: Position update of the investigators

In the sparrow system, the investigators are randomly selected from the population. They emit signals to prompt sparrows to move safely when predators enter the area. However, the sparrow's automatic prediction capacity is not properly interpreted, leading to a slower performance and a poor convergence rate. To improve convergence rate and performance, the automatic learning capability of the teacher learning system is integrated with the sparrow's abilities, enabling independent predator identification. This integration enhances global convergence and minimizes time complexity. The mathematical formula for the combined algorithm is as follows:

$$x_{ij}^{t+1} = |x| \cdot A^{+} \cdot L - \alpha M_{ij}^{t} \tag{15}$$

$$x_{ij}^{t+1} = \alpha x_{ij}^{t} - \frac{1}{2}\alpha x_{ij}^{t-1} + \left|A^{+} \cdot L - \alpha M_{ij}^{t}\right| \tag{16}$$

where A stands for a $1 \times d$ matrix, each of whose elements is given a random value of 1 or 1, and $A^{+} = AT(AAT)^{-1}$. L displays a matrix of $1 \times d$, whose elements are all 1.

c. Phase III: Position update of the scrounger

Some scavengers keep a close eye on the producers and engage in feeding competition with them to increase the pace of their predation, and the teaching traits of the teachers make the scavengers move to the next location with its capabilities of improving the means of the class. As soon as they discover that the producer has located delicious food, they promptly leave their current location to compete for food. If they are successful, they can get the food right away; if not, the process continues. The scrounger's position update formula is as follows:

$$x_{ij}^{t+1} = \begin{cases} Q \cdot ex\left(\frac{M_{ij}^{t-1} - x_{ij}^{t}}{i^2}\right) + rand\left(\frac{x_p^{t} - x_{ij}^{t}}{f\left(x_{ij}^{t+1}\right)}\right) \\ x_{ij}^{t} + k\left(\frac{x_{ij}^{t} - M_{ij}^{t}}{f\left(x_{ij}^{t}\right) - x_{ij}^{t-1}}\right) + Q \cdot v_{ij}^{t} \end{cases} \tag{17}$$

where Q is a random number that follows the normal distribution, the producer's best solution is denoted as x_p^{t}, the i^{th} sparrow's velocity in the j^{th} dimension at iteration t is denoted as v_{ij}^{t}, the sparrow's direction of motion and the step size controls are both denoted as k and the fitness functions of the current, next, and previous iterations are denoted as $f\left(x_{ij}^{t}\right)$ $f\left(x_{ij}^{t+1}\right)$ and $f\left(x_{ij}^{t-1}\right)$.

The best solution must be determined by reevaluating the solutions' fitness values once the solutions have been updated.

4) Termination

The optimization process iterates further, validating the condition ($t < t_{max}$) and reevaluating fitness to get the optimum solution. Further, the algorithm stops when the iteration reaches its maximum stage or obtains the optimal solution. The pseudo-code for the proposed Passer learning optimization is provided in Algorithm 1.

Algorithm 1
Pseudo-code for the proposed Passer learning optimization

S.No	Pseudocode for the proposed Passer learning optimization
1.	Initialization
2.	M: maximum number of iterations
3.	R_2: alert value
4.	Q: random value
5.	Initialize population
6.	$t = 1$
7.	While $(t < t_{max})$
8.	Update the position of the producer.
9.	$x_{ij}^{t+1} = \begin{cases} x_{ij}^{t} \cdot ex\left(\frac{-h}{\alpha_1 \cdot M}\right) + \left(M_{ij}^{t} - x_{ij}^{t}\right) R_2 < AP \\ \left(x_{ij}^{t} + r_i * fl\right) \times \left(M_{ij}^{t} - x_{ij}^{t}\right) R_2 \geq AP \end{cases}$
10.	$R_2 = rand(1)$
11.	$for(i = 1)$
12.	Update the position of the scrounger
13.	$x_{ij}^{t+1} = \begin{cases} Q \cdot ex\left(\frac{M_{ij}^{t-1} - x_{ij}^{t}}{i^2}\right) + rand\left(\frac{x_p^{t} - x_{ij}^{t}}{f\left(x_{ij}^{t+1}\right)}\right) \\ x_{ij}^{t} + k\left(\frac{x_{ij}^{t} - M_{ij}^{t}}{f\left(x_{ij}^{t}\right) - f\left(x_{ij}^{t-1}\right)}\right) + Q \cdot v_{ij}^{t} \end{cases}$
14.	End for
15.	$for(i = N + 1)$
16.	Update the position of the investigators.
17.	$x_{ij}^{t+1} = \alpha x_{ij}^{t} - \frac{1}{2}\alpha x_{ij}^{t-1} + \left|A^{+} \cdot L - \alpha M_{ij}^{t}\right|$
18.	End for
19.	Re-evaluate the fitness
20.	Declare the best solution
21.	End while

4. Results and Discussion

The results derived by employing the PLO-BiLSTM for the e-commerce recommendation system are discussed below.

4.1. Experimental setup

The proposed PLO-BiLSTM for e-commerce recommendation is performed utilizing 8 GB of RAM with Python software with Pycharm tool implemented in the Windows 10 Operating system. The initial hyperparameters involve the activation function of "ReLU," kernel initializer of "Random normal," recurrent activation of "hard sigmoid," loss function of MAE, a learning rate of 0.001, batch size of 32 with epochs 500, regularization of "L2," dropout rate of 0.2, Bios initializer of "zeros," a population size of 50, and default optimizer Adam.

4.2. Dataset description

Product recommendation dataset: The recommendation collection in this research comprises product reviews and associated metadata sourced from Amazon, the source link of which is available in the section on data availability. These reviews are extensive, totalling 143.7 million, and span a period from May 1996 to July 2014. The dataset includes not only reviews but also product metadata and links. The research focuses on three specific datasets: the baby dataset containing 160,792 reviews, the digital music dataset containing 64,706 reviews, and the patio lawn garden dataset containing 13,272 reviews. These datasets form the basis of the analysis and recommendations in this research.

4.3. Performance metrics

The performance of the proposed method is evaluated based on performance metrics such as accuracy, precision, F1-score, and MSE, which are explained in the following section.

Accuracy: Computes the performance of the PLO-BiLSTM model for accurate recommendations based on the entire prediction results, which is mathematically calculated as

$$C_{accuracy} = \frac{T_rP + T_rN}{T_rP + T_rN + F_aP + F_aN} \tag{18}$$

where T_rP represents the true positive, F_aP represents the false positive, F_aN represents the false negative, and T_rN represents the true negative.

Precision: Precision C_precision is defined as the ratio of correctly predicted positive results to all positively predicted by the PLO-BiLSTM.

$$C_{pre} = \frac{T_rP}{T_rP + F_aP} \tag{19}$$

Recall: Recall C_{recall} is calculated by dividing the sum of true positives and false negatives by the total number of true positives.

$$C_{recall} = \frac{T_rP}{T_rP + F_aN} \tag{20}$$

F1 score: Defined as the harmonic mean between recall and precision, and is represented as follows:

$$C_{f1-score} = 2\frac{C_{pre} \times C_{recall}}{C_{pre} + C_{recall}} \tag{21}$$

MSE: When comparing real and estimated data, the difference is known as MSE. It helps in differentiating actual and predicted ratings in the recommendation model, which is mathematically expressed as

$$MSE = \frac{1}{n}\sum\left(A_cV - P_rV\right)^2 \tag{22}$$

where n represents the number of data, A_cV represents the actual value, and P_rV denotes predicted value.

4.4. Performance evaluation

For testing the classifier's performance during different epochs, the PLO-BiLSTM classifier is put through a performance evaluation. The performance evaluation presents the efficacy of PLO-BiLSTM on three datasets: baby, digital music, and patio lawn garden, across different training percentages such as 40%, 50%, 60%, 70%, 80%, and 90% at epochs 100, 200, 300, 400, and 500.

4.4.1. Performance evaluation with baby dataset

In the baby dataset, at 90% training percentage, the performance metrics achieved maximum values at 90% training percentage. The proposed model achieved high accuracy of 91.34%, 92.85%, 93.94%, 96.07%, and 98% at epochs 100, 200, 300, 400, and 500. Similarly, F1-score of 91.33%, 92.85%, 93.94%, 96.06%, and 97.99%. The proposed model achieved a precision of 91.21%, 92.51%, 93.46%, 97.15%, and 98.56%. Also, recall of 91.46%, 93.19%, 94.42%, 94.99%, and 97.43% and minimum MSE of 8.66, 7.15, 6.06, 3.93, and 2 at various epochs, indicating very good recommendation accuracy with low error rates. The precision and recall metrics are seen to increase consistently with increasing training percentages, hence showing the capability of the model to learn effectively and adapt to various types of e-commerce data, ensuring highly accurate recommendations. Figure 4 illustrates the performance analysis of the PLO-BiLSTM model at various epochs.

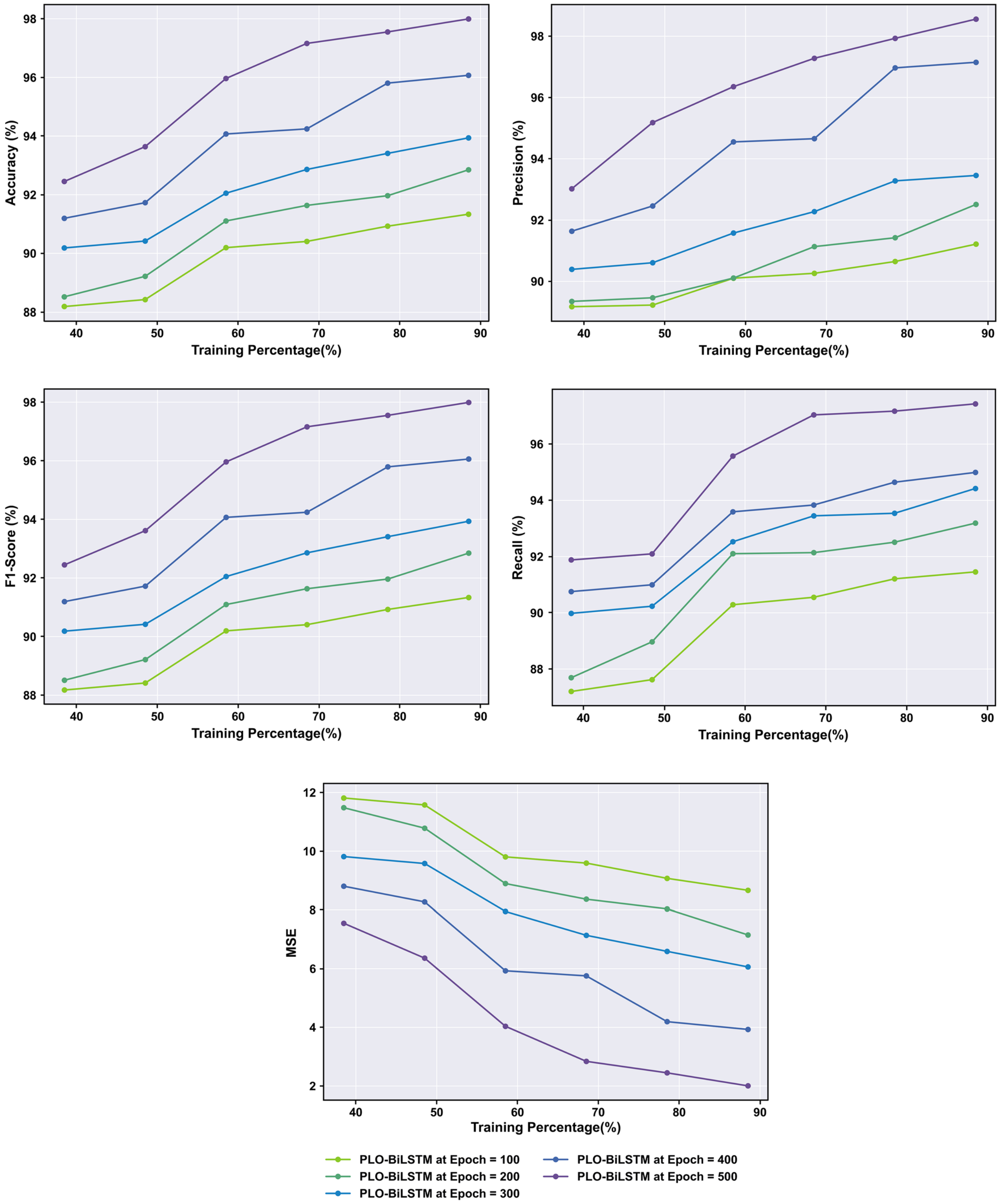
4.4.2. Performance evaluation with digital music dataset

At 90% training percentage, the digital music dataset is evaluated using the performance metrics, which achieved maximum accuracy. The proposed model achieved high accuracy of 91.24%, 93.88%, 94.89%, 96.56%, and 97.94% at epochs 100, 200, 300, 400, and 500. Similarly, F1-score achieved 91.22%, 93.83%, 94.88%, 96.55%, and 97.94%. The proposed model achieved high precision of 92.59%, 95.99%, 96.04%, 97.12%, and 98.45%. Accordingly, the model achieved a recall of 89.88%, 91.77%, 93.74%, 95.99%, and 97.44% and achieved a minimum MSE of 8.76, 6.12, 5.11, 3.44, and 2.06 at epochs 100, 200, 300, 400, and 500, indicating very good recommendation accuracy with low error rates. The precision and recall metrics are seen to increase consistently with increasing training percentages, hence showing the capability of the model to learn effectively and adapt to various types of e-commerce data, ensuring highly accurate recommendations. Figure 5 illustrates the performance analysis of the PLO-BiLSTM model for the digital music dataset.

4.4.3. Performance evaluation with patio lawn garden dataset

At 90% training percentage, the patio lawn garden dataset is evaluated using the performance metrics, which achieved maximum accuracy. The proposed model achieved high accuracy of 91%, 93.04%, 94.89%, 95.22%, and 98.03% at epochs 100, 200, 300, 400, and 500. Similarly, F1-score of 90.99%, 93.04%, 94.89%, 95.22%, and 98.03%. The proposed model achieved high precision of 90.21%, 93.37%, 94.40%, 94.66%, and 98.49%. Accordingly, the model achieved a recall of 91.79%, 92.70%, 95.39%, 95.79%, and 97.57% and achieved minimum MSE of 9, 6.96, 5.11, 4.78, and 1.97 at epochs 100, 200, 300, 400, and 500, indicating very good recommendation accuracy with low error rates. The precision and recall metrics are seen to increase consistently with increasing training percentages, hence showing the capability of the model to learn effectively and adapt to various types of e-commerce data, ensuring highly accurate recommendations. Figure 6 illustrates the performance analysis of the PLO-BiLSTM model for the patio lawn garden dataset.

Figure 4
Performance analysis using the baby dataset



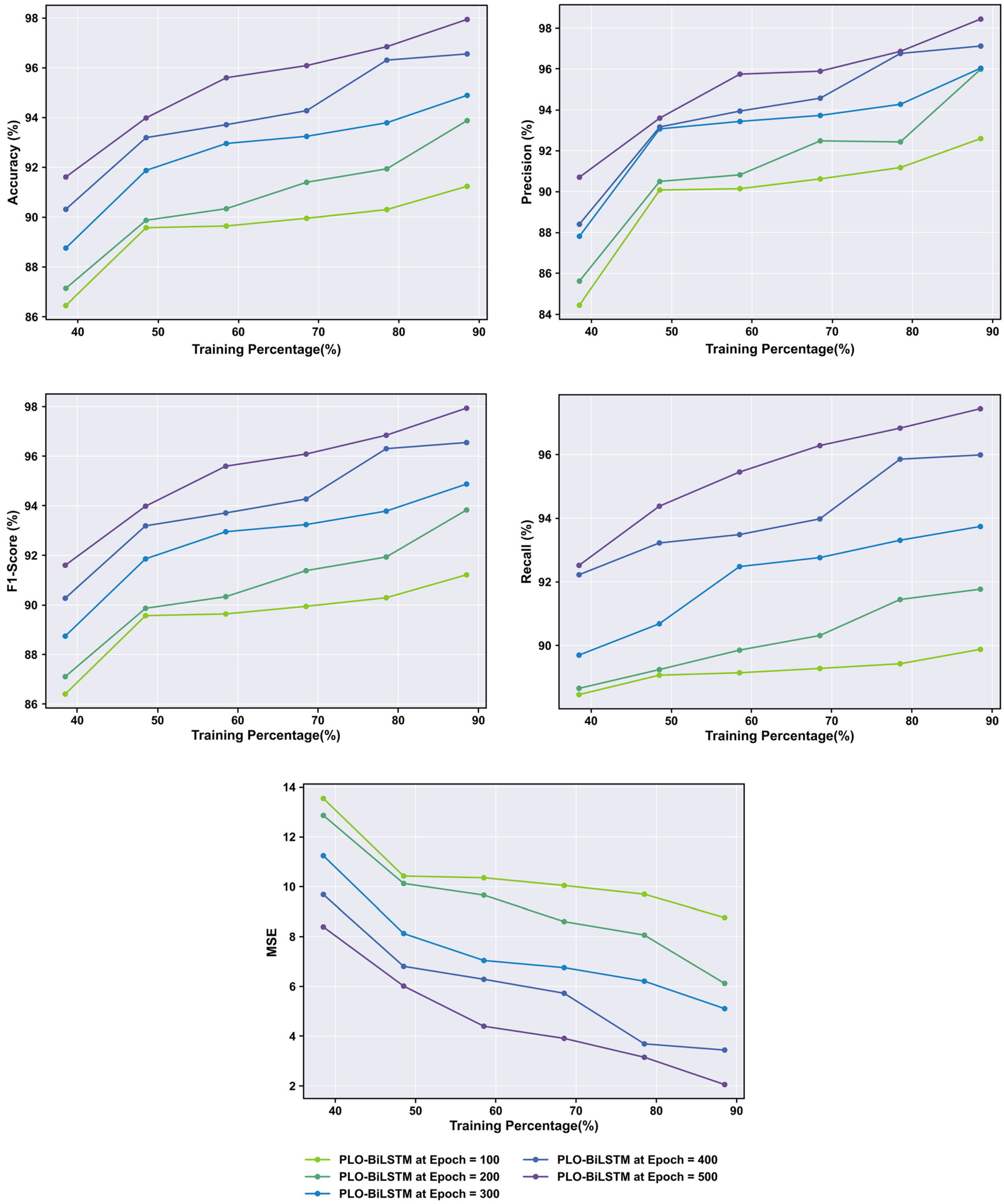
4.5. Comparative evaluation based on training percentage

The proposed PLO-BiLSTM model is evaluated based on training percentage of 90% and compared with other existing models such as HPMFM [19], SCCF [23], A3NCF [22], BiLSTM [24], EIR-GCN [25], LCNA [17], HHO-BiLSTM [26], and PSO-BiLSTM [27] to improve the efficiency of the model.

4.5.1. Comparative evaluation with the baby dataset

The proposed PLO-BiLSTM model is evaluated using the baby dataset and compared with other existing models based on a training percentage of 90% to improve the efficiency of the model for e-commerce recommendation. The comparative analysis of the proposed PLO-BiLSTM model achieved a high accuracy of 98%, which shows an improvement of 1.22% with the LCNA model. Similarly, the proposed model achieved a high F1-score value of 97.99% and gained

Figure 5
Performance analysis using the digital music dataset

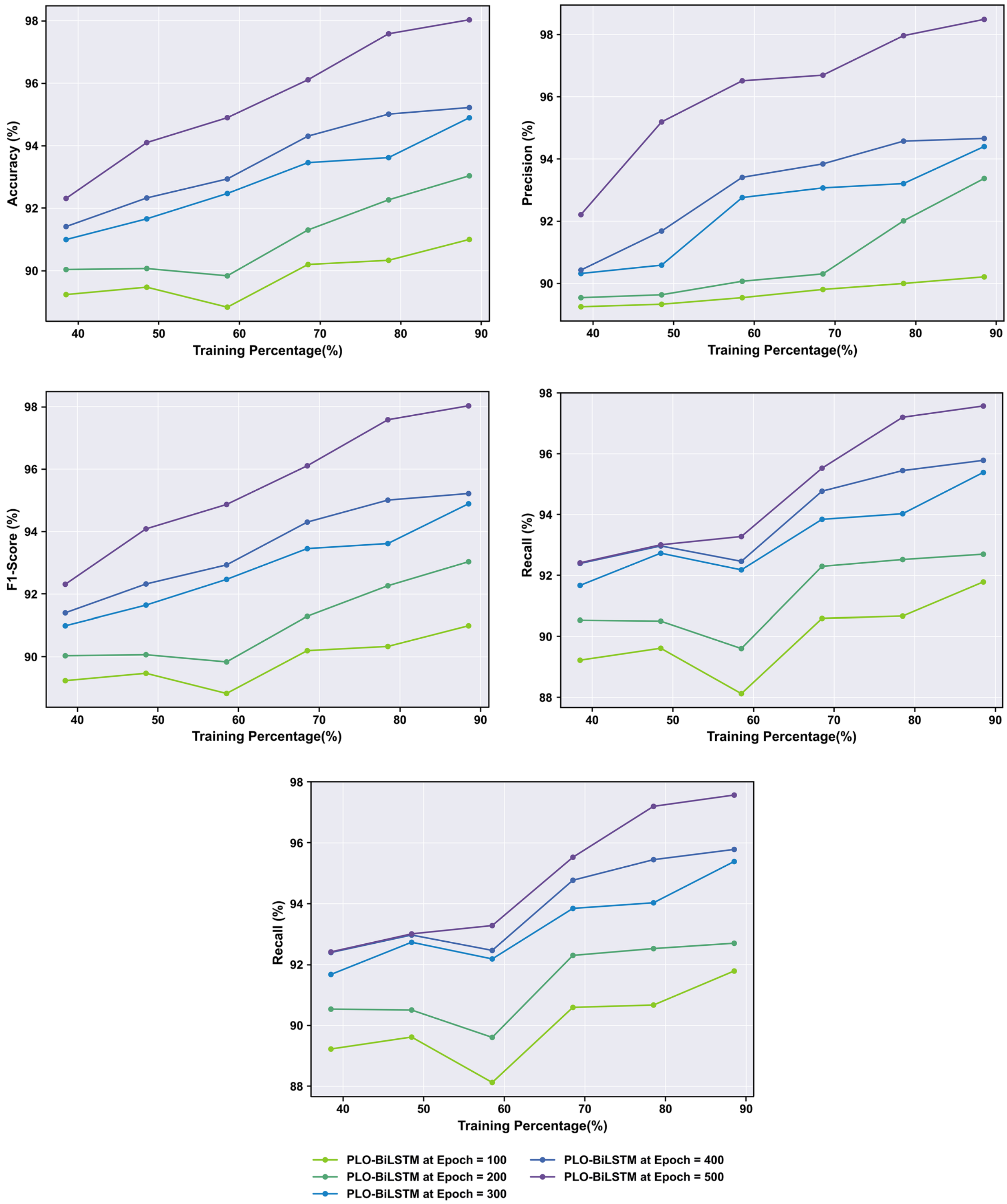


an improvement of 1.23% with the LCNA model. The proposed model attained a minimum MSE of 2 and got an error difference of 1.2 with the LCNA model. Also, the model gained a precision of 98.56%, attaining an improvement of 1.01% with the LCNA model. Moreover, the proposed PLO-BiLSTM model achieved a high recall of 97.43%, compared with the LCNA model got an improvement of 1.45% for 90% training. Figure 7 depicts the comparative analysis of the model using the baby dataset.

4.5.2. Comparative evaluation with digital music dataset

The proposed PLO-BiLSTM model is evaluated using the digital music dataset and compared with other existing models based on a training percentage of 90% to improve the efficiency of the model for e-commerce recommendation. The comparative analysis of the proposed PLO-BiLSTM model achieved a high accuracy of 97.94%, which shows an improvement of 0.46% with the LCNA model. Similarly, the proposed model achieved a high F1-score value of 97.94% and gained

Figure 6
Performance analysis using patio lawn garden dataset

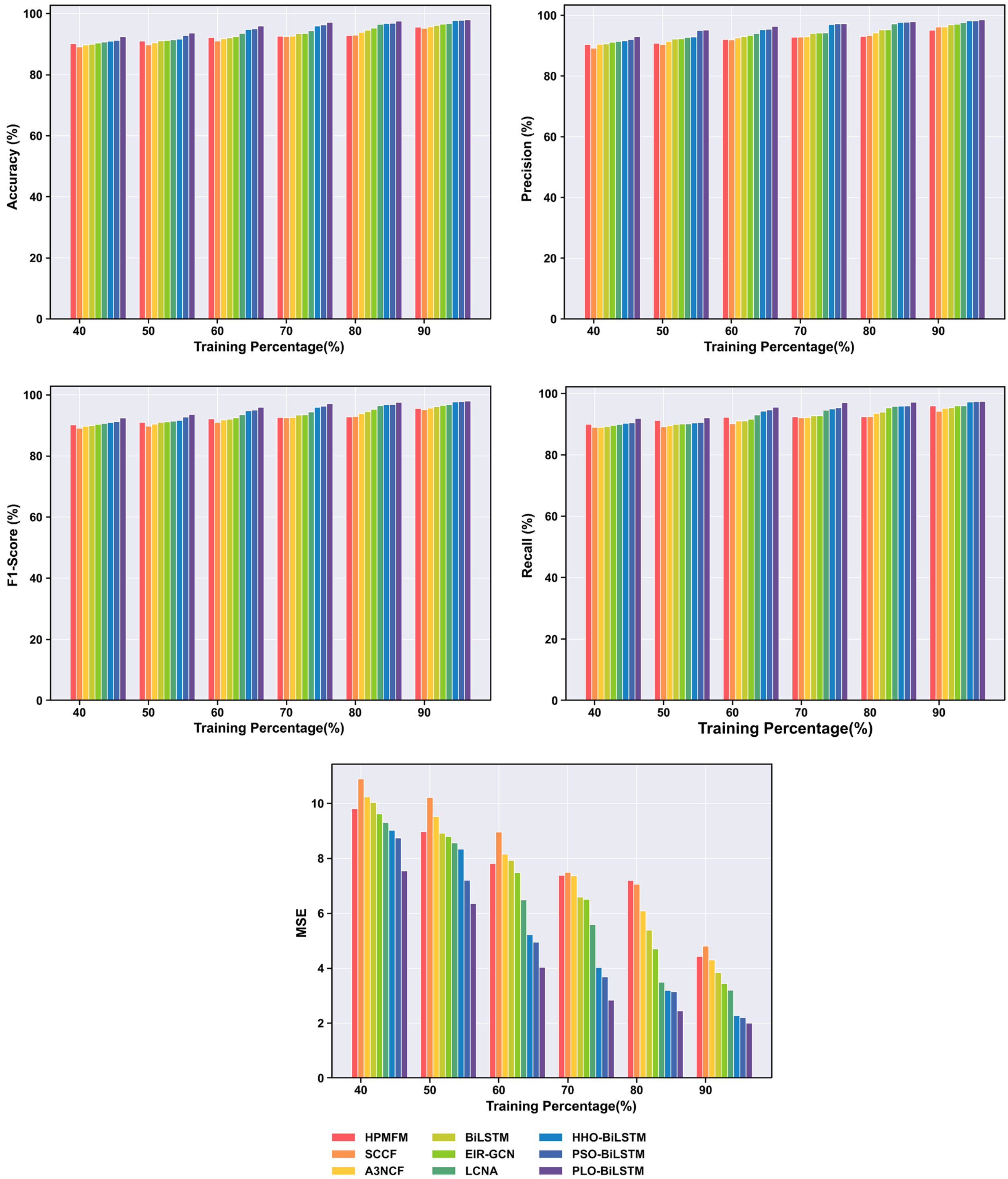


an improvement of 0.46% with the LCNA model. The proposed model attained a minimum MSE of 2.06 and got an error difference of 0.45 with the LCNA model. Also, the model gained a precision of 98.45%, attaining an improvement of 0.68% with the LCNA model. Moreover, the proposed PLO-BiLSTM model achieved a high recall of 97.44%, compared with the LCNA model got an improvement of 0.24% for 90% training. Figure 8 depicts the comparative analysis of the model using the digital music dataset.

4.5.3. Comparative evaluation with patio lawn garden dataset

The proposed PLO-BiLSTM model is evaluated using the patio lawn garden dataset and compared with other existing models based on

Figure 7
Comparative analysis using baby dataset

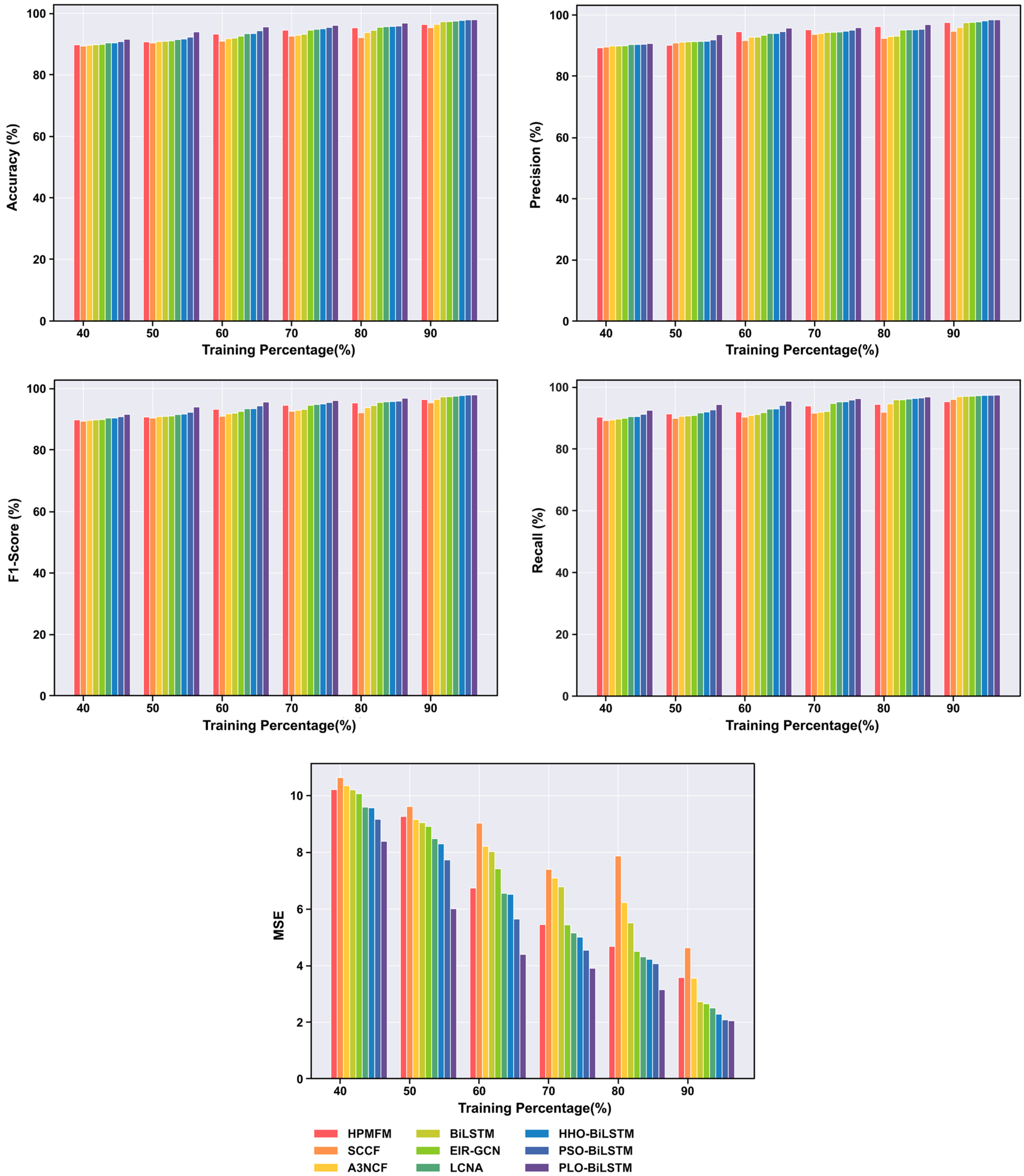


a training percentage of 90% to improve the efficiency of the model for e-commerce recommendation. The comparative analysis of the proposed PLO-BiLSTM model achieved a high accuracy of 98.03%, which shows an improvement of 1.09% with the LCNA model. Similarly, the proposed model achieved a high F1-score value of 98.03%, gaining an improvement of 1.09% with the LCNA model. The proposed model attained a minimum MSE of 1.97 and got an error difference of 1.07 with the LCNA model. Also, the model gained a precision of 98.49%, attaining an improvement of 1.36% with the LCNA model. Moreover, the proposed PLO-BiLSTM model achieved a high recall of 97.57%, compared with the LCNA model got an improvement of 0.81% for 90% training. Figure 9 depicts the comparative analysis of the model using the patio lawn garden dataset.

4.6. Comparative evaluation based on K-fold value

The proposed PLO-BiLSTM model is evaluated based on a K-fold value of 10 and compared with other existing models, such as

Figure 8
Comparative analysis using digital music dataset

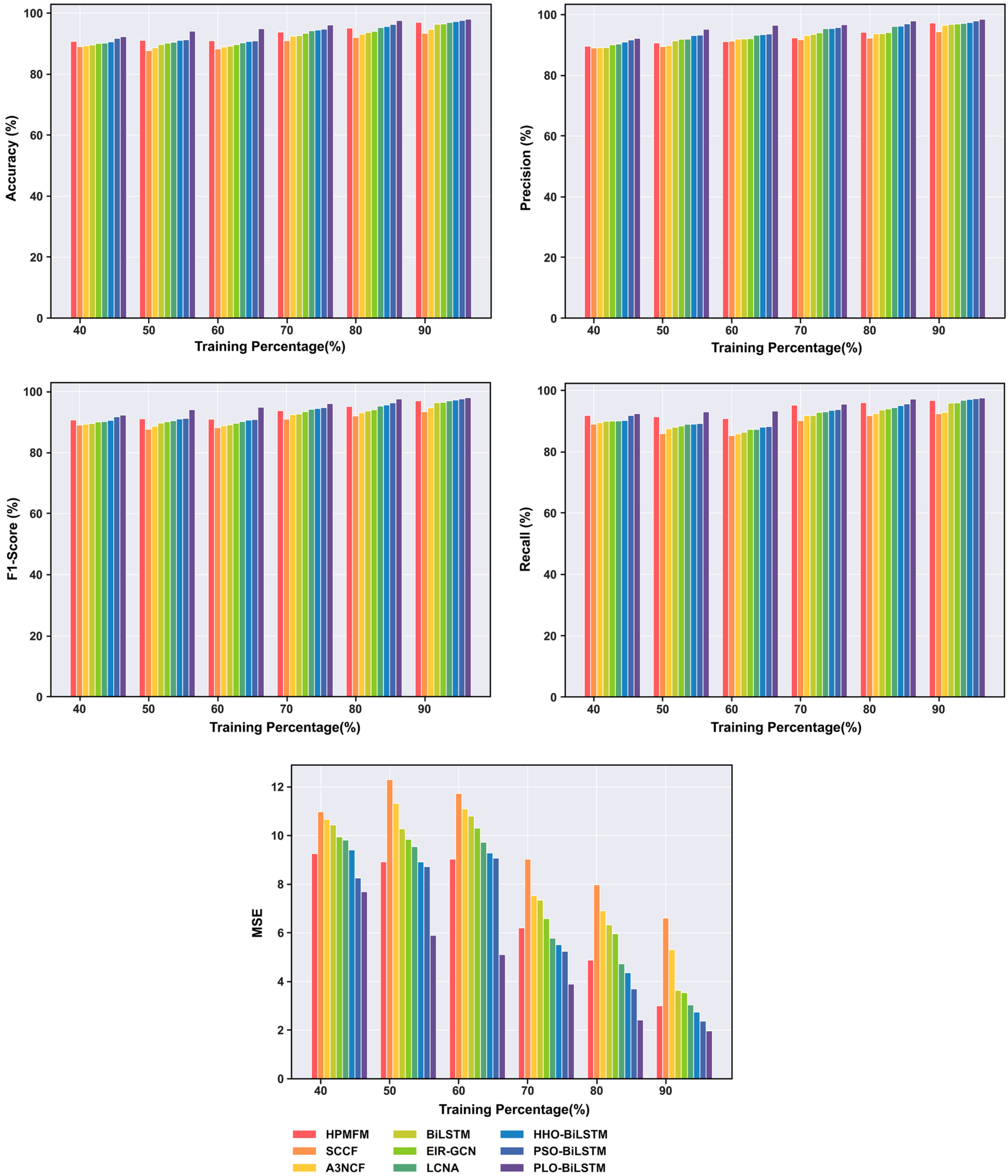


HPMFM [19], SCCF [23], A3NCF [22], BiLSTM [24, 28], EIR-GCN [25], LCNA [17], HHO-BiLSTM [26], and PSO-BiLSTM [27], to improve the efficiency of the model.

4.6.1. Comparative evaluation with the baby dataset

The proposed PLO-BiLSTM model is evaluated using the baby dataset and compared with other existing models based on a K-fold value of 10, to improve the efficiency of the model for e-commerce recommendation. The comparative analysis of the proposed PLO-BiLSTM model achieved a high accuracy of 97.63%, which shows an improvement of 1.06% with the LCNA model. Similarly, the proposed model achieved a high F1-score value of 97.62% and gained an improvement of 1.06% with the LCNA model. The proposed model attained a minimum MSE of 2.37 and got an error difference of 1.03 with the LCNA model. Also, the model gained a precision of 97.81%, attaining an improvement of 1.69% with the LCNA model. Moreover, the proposed PLO-BiLSTM model achieved a high recall of 97.44%, compared with the LCNA model got an improvement of 0.41% for 90% training. Figure 10 depicts the comparative analysis of the model using the baby dataset.

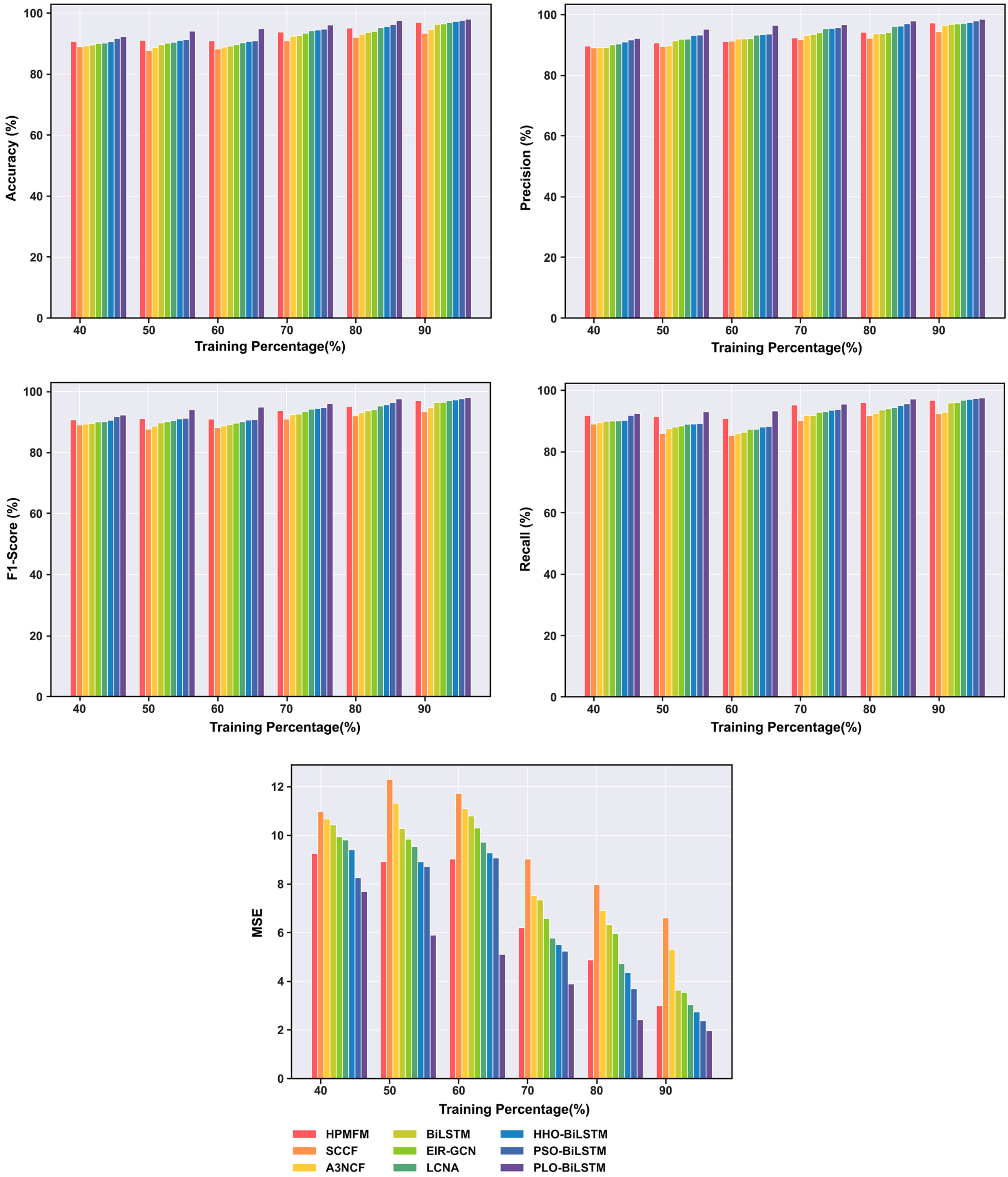
Figure 9
Comparative analysis using the patio lawn garden dataset



4.6.2. Comparative evaluation with digital music dataset

The proposed PLO-BiLSTM model is evaluated using the digital music dataset and compared with other existing models based on a K-fold value of 10, to improve the efficiency of the model for e-commerce recommendation. The comparative analysis of the proposed PLO-BiLSTM model achieved a high accuracy of 97.93%, which shows an improvement of 0.55% with the LCNA model. Similarly, the proposed model achieved a high F1-score value of 97.93% and gained an improvement of 0.55% with the LCNA model. The proposed model attained a minimum MSE of 2.07 and got an error difference of 0.54 with the LCNA model. Also, the model gained a precision of 98.51%, attaining an improvement of 0.74% with the LCNA model. Moreover, the proposed PLO-BiLSTM model achieved a high recall of 97.36%, compared with the LCNA model got an improvement of 0.37% for 90% training. Figure 11 depicts the comparative analysis of the model using the digital music dataset.

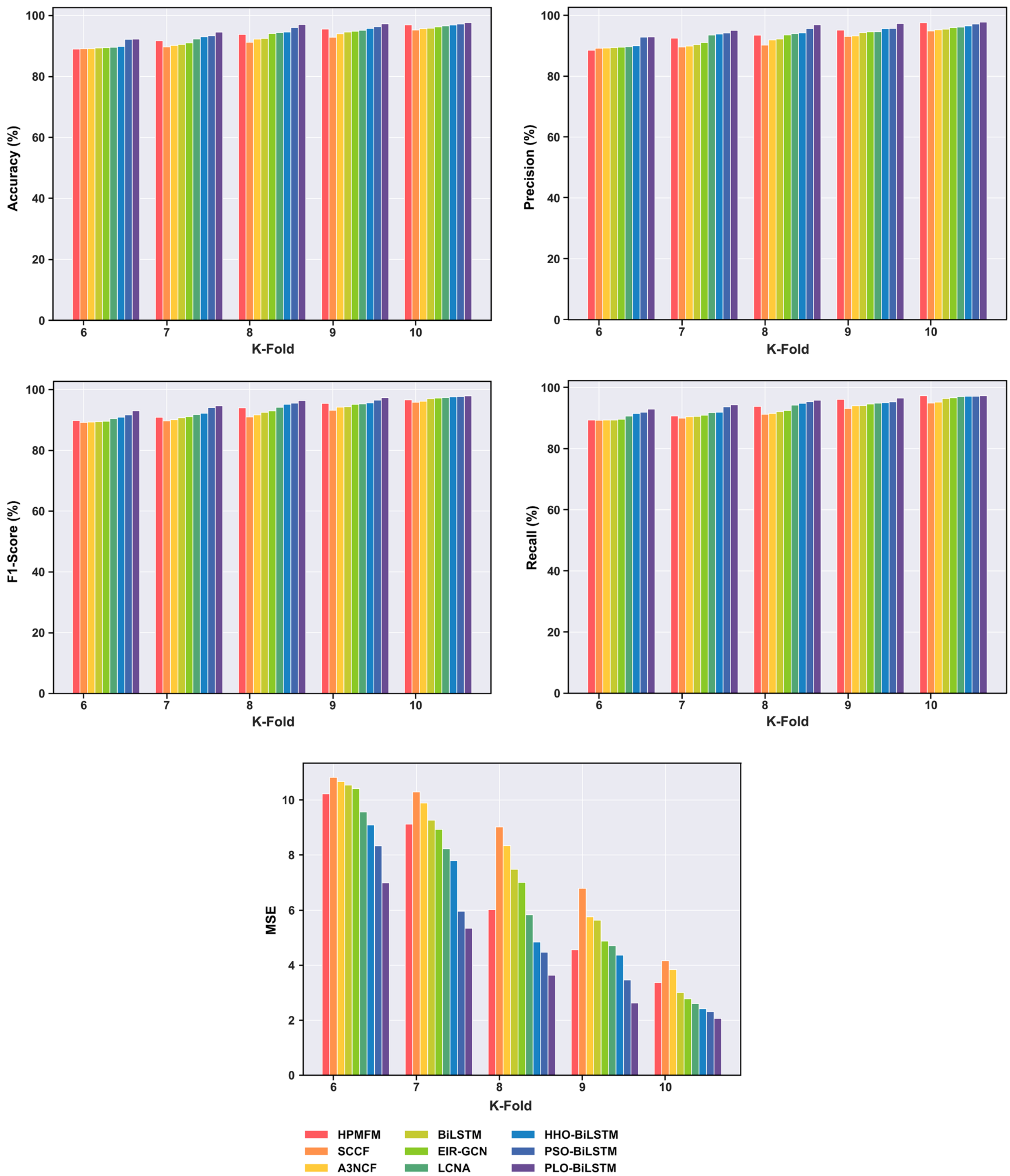
Figure 10
Comparative analysis using the baby dataset



4.6.3. Comparative evaluation with patio lawn garden dataset

The proposed PLO-BiLSTM model is evaluated using the patio lawn garden dataset and compared with other existing models based on a K-fold value of 10, to improve the efficiency of the model for e-commerce recommendation. The comparative analysis of the proposed PLO-BiLSTM model achieved a high accuracy of 97.8% outperforming the other existing models, which shows an improvement of 0.76% with the LCNA model. Similarly, the proposed model achieved a high F1-score value of 97.79% and gained an improvement of 0.77% with the LCNA model. The proposed model attained a minimum MSE of 2.2 and got an error difference of 0.75 with the LCNA model. Also, the model gained a precision of 98.51%, attaining an improvement of 0.74% with the LCNA model. Moreover, the proposed PLO-BiLSTM model achieved a high recall of 98.4%, compared with the LCNA model got an improvement of 0.62% for 90% training. Figure 12 depicts the comparative analysis of the model using the patio lawn garden dataset.

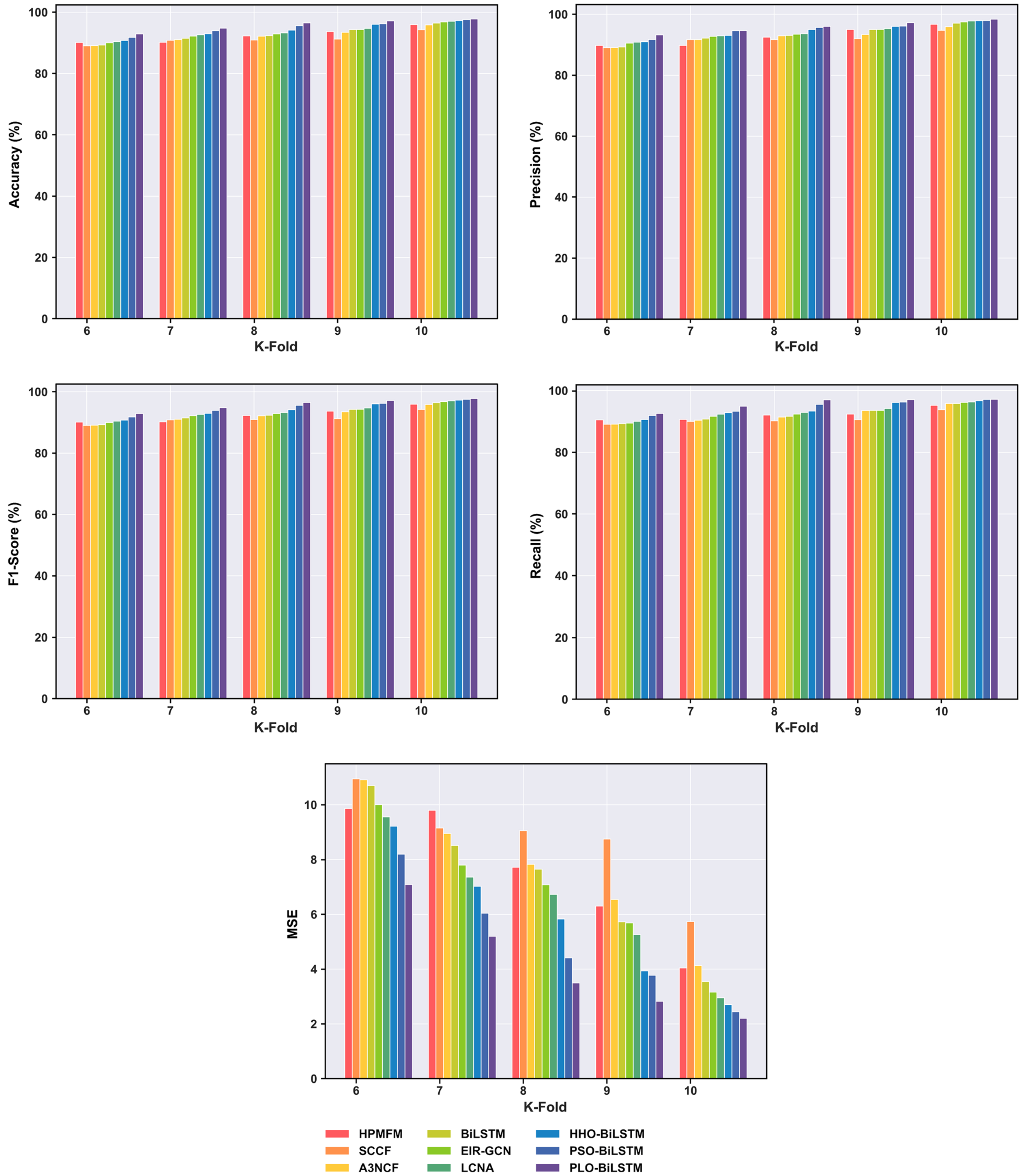
Figure 11
Comparative analysis using the digital music dataset



4.7. Comparative discussion

The proposed model is evaluated using three datasets: the baby dataset, the digital music dataset, and the patio lawn garden dataset. The proposed PLO-BiLSTM model outperforms the other existing models in terms of accuracy, F1-score, MSE, Precision, and Recall at a 90% training percentage and K-fold value of 10. Most specifically, the proposed model achieved a high accuracy of 98.03%, F1-score of 98.03%, precision of 98.49%, recall of 97.57%, and minimum MSE of 1.97 based on training percentage using the patio lawn garden dataset. Table 1 illustrates the comparative analysis of the proposed model based on training percentage. Similarly, the proposed model attained a high accuracy of 97.93%, F1-score of 97.93%, precision of 98.51%, recall of 97.36%, and a minimum MSE of 2.07 based on the K-fold value using the digital music dataset, which shows the excellence in the recommendation predictions. Table 2 depicts the comparative

Figure 12
Comparative analysis using the patio lawn garden dataset



evaluation of the model based on the K-fold value. The model also shows the lowest MSE rates, thus showing its precision in modelling with minimized errors. Precision and Recall metrics confirm its robustness, with scores considerably higher than those from competing methods, thus illustrating its ability to provide highly relevant and accurate recommendations across diverse e-commerce settings. This comparative analysis has indicated the advanced capability of the proposed PLO-BiLSTM model in handling complex recommendation tasks with better results than the conventional and other optimized LSTM models. The other existing models have some limitations, such as high computation cost, longer computation time, poor efficiency, cold start issues, computational complexity, and poor data generalization. The proposed model addressed these challenges with the integration of Passer learning optimization with the BiLSTM model. To overcome these challenges, the proposed PLO-BiLSTM model utilized hybrid optimization as the PLO algorithm with a deep learning model is utilized for the e-commerce recommendation system. The inclusion of the feature extraction process with the Content and Collaborative Filtering includes the content feature extraction with TF-IDF, graph embedding, and collaborative information for making accurate

Table 1
Comparative analysis of the PLO-BiLSTM model based on training percentage

Dataset	Methods/ Metrics	HPMFM	SCCF	A3NCF	BiLSTM	EIR-GCN	LCNA	HHO-BiLSTM	PSO-BiLSTM	PLO-BiLSTM
90% Training Percentage										
The baby dataset	Accuracy (%)	95.57	95.19	95.70	96.15	96.55	96.80	97.72	97.79	**98.00**
	F1-score (%)	95.57	95.18	95.69	96.15	96.55	96.79	97.72	97.79	**97.99**
	MSE	4.43	4.81	4.30	3.85	3.45	3.20	2.28	2.21	**2.00**
	Precision (%)	95.12	96.14	96.20	96.89	97.09	97.57	98.17	98.19	**98.56**
	Recall (%)	96.01	94.24	95.19	95.42	96.02	96.03	97.27	97.40	**97.43**
The digital music	Accuracy (%)	96.42	95.36	96.44	97.27	97.34	97.49	97.71	97.91	**97.94**
	F1-score (%)	96.40	95.36	96.43	97.27	97.34	97.49	97.71	97.91	**97.94**
	MSE	3.58	4.64	3.56	2.73	2.66	2.51	2.29	2.09	**2.06**
	Precision (%)	97.56	94.71	95.93	97.51	97.63	97.78	98.08	98.44	**98.45**
	Recall (%)	95.27	96.02	96.94	97.03	97.05	97.21	97.34	97.38	**97.44**
The patio lawn garden	Accuracy (%)	97.00	93.39	94.69	96.37	96.46	96.96	97.26	97.63	**98.03**
	F1-score (%)	97.00	93.38	94.66	96.37	96.46	96.96	97.26	97.63	**98.03**
	MSE	3.00	6.61	5.31	3.63	3.54	3.04	2.74	2.37	**1.97**
	Precision (%)	97.26	94.39	96.47	96.83	96.95	97.15	97.42	97.94	**98.49**
	Recall (%)	96.74	92.40	92.91	95.91	95.97	96.78	97.09	97.32	**97.57**

Table 2
Comparative discussion of the proposed PLO-BiLSTM model based on K-fold

Dataset	Methods/ Metrics	HPMFM	SCCF	A3NCF	BiLSTM	EIR-GCN	LCNA	HHO-BiLSTM	PSO-BiLSTM	PLO-BiLSTM
90% Training Percentage										
The baby dataset	Accuracy (%)	96.90	95.23	95.69	95.81	96.26	96.60	96.88	97.21	**97.63**
	F1-score (%)	96.90	95.23	95.69	95.81	96.26	96.59	96.88	97.21	**97.62**
	MSE	3.10	4.77	4.31	4.19	3.74	3.40	3.12	2.79	**2.37**
	Precision (%)	97.57	94.88	95.27	95.48	96.01	96.15	96.55	97.17	**97.81**
	Recall (%)	96.23	95.59	96.10	96.14	96.51	97.04	97.20	97.24	**97.44**
The digital music	Accuracy (%)	96.63	95.83	96.16	96.99	97.22	97.39	97.58	97.69	**97.93**
	F1-score (%)	96.62	95.83	96.15	96.99	97.22	97.39	97.58	97.68	**97.93**
	MSE	3.37	4.17	3.84	3.01	2.78	2.61	2.42	2.31	**2.07**
	Precision (%)	95.92	96.72	97.08	97.56	97.77	97.79	98.01	98.20	**98.51**
	Recall (%)	97.33	94.95	95.24	96.42	96.66	97.00	97.16	97.17	**97.36**
The patio lawn garden	Accuracy (%)	95.96	94.27	95.87	96.46	96.84	97.05	97.29	97.56	**97.80**
	F1-score (%)	95.95	94.26	95.87	96.45	96.83	97.05	97.29	97.56	**97.79**
	MSE	4.04	5.73	4.13	3.54	3.16	2.95	2.71	2.44	**2.20**
	Precision (%)	96.72	94.74	95.92	97.09	97.49	97.79	97.88	97.96	**98.40**
	Recall (%)	95.20	93.79	95.82	95.83	96.18	96.31	96.70	97.16	**97.19**

recommendations in E-commerce. The utilization of the advanced feature extraction techniques extracts relevant features and removes irrelevant data with minimal user interaction data which improves the cold start issue. The PLO-BiLSTM model enhances not only the accuracy and efficiency of the recommendations but also scalability and challenging cold-start situations. By incorporating advanced graph embedding techniques and Passer Learning Optimization, the model achieved a minimum error and less computational complexity. The inclusion of these techniques develops a scalable, accurate, and robust system that can operate effectively in diverse, dynamic e-commerce environments. The comparative analysis based on training percentage and K-fold is depicted in Tables 1 and 2.

4.8. Computational complexity

The computational time complexity of the proposed PLO-BiLSTM model is estimated with other existing models based on the weight and bias in the hyperparameters present in the Bi-LSTM classifier that are tuned by the proposed PLO algorithm for 100 epochs. The optimization algorithm helps to attain the optimal solution with multiple iterations and achieves minimum computational time, leading to a high convergence rate. The proposed model attained a less computational time of 54.67 ms, which enhances the efficiency for e-commerce recommendation. Comparatively, other existing models gained average computation time, such as HPMFM is 55.82 ms, SCCF is 55.24 ms, A3NCF is 55.37 ms, BiLSTM is 55.62 ms, EIR-GCN is 55.65 ms, LCNA is 55.66 ms, HHO-BiLSTM is 55.74 ms, and PSO-BiLSTM is 55.76 ms, which is visually represented in Figure 13.

4.9. Ablation study

The Passer learning algorithm is a hybrid of sparrow optimization and teacher-learner optimization. The existing algorithms, such as PSO and HHO algorithms, are designed to achieve high accuracy. However, the PSO and HHO algorithm has low convergence rates in high-dimensional search spaces, and face complexity with large datasets. Hence, the integration of a hybrid Passer learning algorithm with BiLSTM improves the faster convergence rate and also provides a balance between exploration and exploitation with accurate prediction, leading to high efficiency. The proposed PLO optimization fine-tunes the BiLSTM model for achieving optimal solutions with minimum computation time. However, the evaluation results show that the HHO model achieved an average accuracy of 97.72%, and the PSO algorithm attained 97.79%. The proposed PLO algorithm achieved a high accuracy of 98%, which shows the effective performance of the optimization. Figure 14 illustrates the comparison of the PLO algorithm with other optimization algorithms.

4.9.1. Ablation study with comparison of feature extraction technique

The ablation study evaluates the proposed PLO-BiLSTM model's performance by varying the different features. The analysis of graph embedding features with the BiLSTM model is carried out and evaluated in terms of accuracy. As a result, the proposed PLO-BiLSTM model achieved a maximum accuracy of 98% with the graph embedding technique and an average accuracy of 96.15% without the graph embedding technique. Moreover, the proposed PLO-BiLSTM model provides superior performance with content-collaborative features as it integrates the advantages of TF-IDF features and Graph embedding features, which is illustrated in Figure 15.

Figure 13
Computational complexity

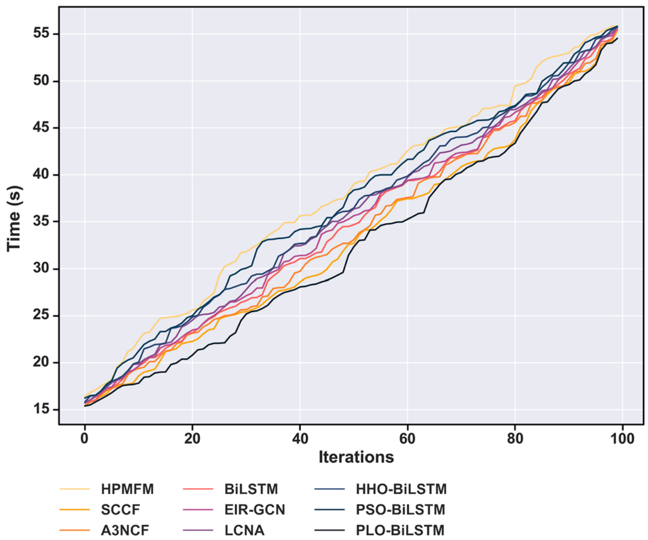


Figure 14
Ablation study of the proposed PLO algorithm

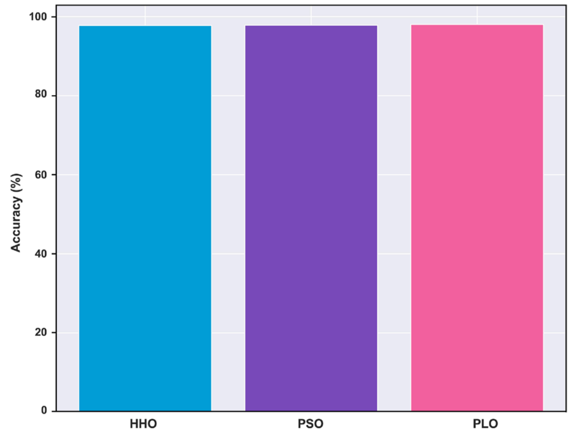
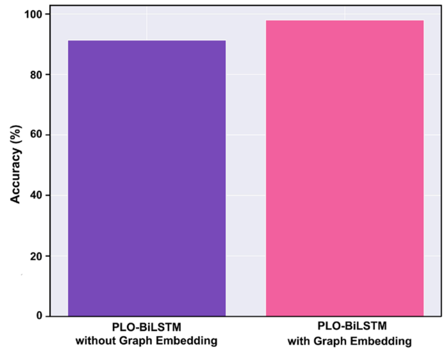


Figure 15
Comparative analysis of feature extraction techniques



4.10. Statistical analysis

The statistical analysis of the proposed PLO-BiLSTM model is evaluated with other existing models. The proposed PLO-BiLSTM model obtained the best, mean, variance, and standard deviation for the evaluation metrics such as accuracy, precision, F1-score, Recall, and MSE. Further, the PLO-BiLSTM attained high values compared with other competent models that declare the efficiency of the proposed PLO-BiLSTM model for e-commerce recommendation. The statistical analysis of the PLO-BiLSTM model using the baby dataset is depicted in Table 3.

4.10.1. Statistical T-test analysis

Statistical T-test analysis is conducted in this research to evaluate the significant difference in the model results. In the analysis of the results, a p-value <0.05 indicates that the relevant features have a significant difference in the recommendation, whereas a p-value >0.05 indicates that the relevant features have a non-significant mean difference in a recommendation. Consequently, the T-test analysis reveals the high efficiency of the proposed PLO-BiLSTM model compared to other existing techniques. Table 4 demonstrates the T-test analysis of the model with other existing models.

4.11. Error analysis

The error analysis helps in diagnosing the errors or suboptimal solutions that occurred in the proposed PLO-BiLSTM model, which affects the efficiency of the model in e-commerce recommendation. Figure 16 illustrates the accuracy and loss curve of the proposed model, which is plotted with iterations ranging from 0 to 500. The proposed

Table 3
Statistical analysis of the proposed PLO-BiLSTM model

	Methods/ Metrics	HPMFM	SCCF	A3NCF	BiLSTM	EIR-GCN	LCNA	HHO-BiLSTM	PSO-BiLSTM	PLO-BiLSTM
Accuracy	Best	95.57	95.19	95.70	96.15	96.55	96.80	97.72	97.79	**98.00**
	Mean	92.40	91.76	92.38	92.88	93.24	93.89	94.65	95.01	**95.79**
	Variance	2.84	4.20	4.04	4.40	4.69	5.33	6.38	5.31	**4.27**
	Standard Deviation	1.69	2.05	2.01	2.10	2.17	2.31	2.53	2.30	**2.07**
F1-score	Best	95.57	95.18	95.69	96.15	96.55	96.79	97.72	97.79	97.99
	Mean	92.40	91.76	92.38	92.87	93.23	93.89	94.64	95.00	95.79
	Variance	2.84	4.19	4.05	4.41	4.70	5.34	6.39	5.35	4.29
	Standard Deviation	1.69	2.05	2.01	2.10	2.17	2.31	2.53	2.31	2.07
MSE	Best	9.81	10.90	10.25	10.04	9.62	9.31	9.02	8.75	7.55
	Mean	7.60	8.24	7.62	7.12	6.76	6.11	5.35	4.99	4.21
	Variance	2.84	4.20	4.04	4.40	4.69	5.33	6.38	5.31	4.27
	Standard Deviation	1.69	2.05	2.01	2.10	2.17	2.31	2.53	2.30	2.07
Precision	Best	95.12	96.14	96.20	96.89	97.09	97.57	98.17	98.19	98.56
	Mean	92.39	92.31	93.00	93.68	93.89	94.53	95.44	95.95	96.39
	Variance	2.46	4.93	3.46	4.16	3.76	4.92	5.97	4.38	3.45
	Standard Deviatiom	1.57	2.22	1.86	2.04	1.94	2.22	2.44	2.09	1.86
Recall	Best	96.01	94.24	95.19	95.42	96.02	96.03	97.27	97.40	97.43
	Mean	92.41	91.21	91.77	92.08	92.58	93.25	93.86	94.07	95.20
	Variance	3.37	3.65	4.71	4.70	5.87	6.13	6.93	7.01	5.51
	Standard Deviation	1.83	1.91	2.17	2.17	2.42	2.48	2.63	2.65	2.35

Table 4
Statistical T-test analysis of the proposed PLO-BiLSTM model

	Methods/ Metrics	HPMFM	SCCF	A3NCF	BiLSTM	EIR-GCN	LCNA	HHO-BiLSTM	PSO-BiLSTM	PLO-BiLSTM
Accuracy	T-statistic	2.93	2.90	2.93	3.11	2.95	3.10	3.25	3.64	**3.62**
	P-value	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.01	**0.02**
F1-score	T-statistic	2.93	2.90	2.93	3.11	2.95	3.10	3.25	3.62	3.60
	P-value	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02
MSE	T-statistic	4.204	3.742	3.687	3.490	3.421	2.814	2.718	2.702	2.382
	P-value	0.008	0.013	0.014	0.017	0.019	0.037	0.042	0.043	0.063
Precision	T-statistic	2.852	3.138	3.014	3.364	3.182	3.125	3.474	4.169	4.055
	P-value	0.036	0.026	0.030	0.020	0.024	0.026	0.018	0.009	0.010
Recall	T-statistic	2.942	2.573	2.839	2.859	2.731	2.980	3.017	3.049	3.162
	P-value	0.032	0.050	0.036	0.035	0.041	0.031	0.030	0.028	0.025

PLO-BiLSTM model attained a minimum loss of 0.01 at epoch 500. Moreover, the accuracy curve reveals a high accuracy of 0.99%, which means the model achieved high efficiency with minimum loss.

4.12. ROC analysis

The ROC analysis of the proposed PLO-BiLSTM model is conducted with other existing models to evaluate the performance of the model for correctly predicting recommendations in terms of True Positive Rate (TPR) and False Positive Rate (FPR). Here, TPR denotes the sensitivity of the model that correctly predicted the recommendation, and FPR denotes the proportion of incorrectly predicted recommendations. The proposed PLO-BiLSTM model achieved a high sensitivity of 0.99% for the baby dataset, the digital music dataset, and the patio lawn garden dataset, which explicates the model's high efficiency and outperforms the other existing models.

Figure 16
Convergence analysis

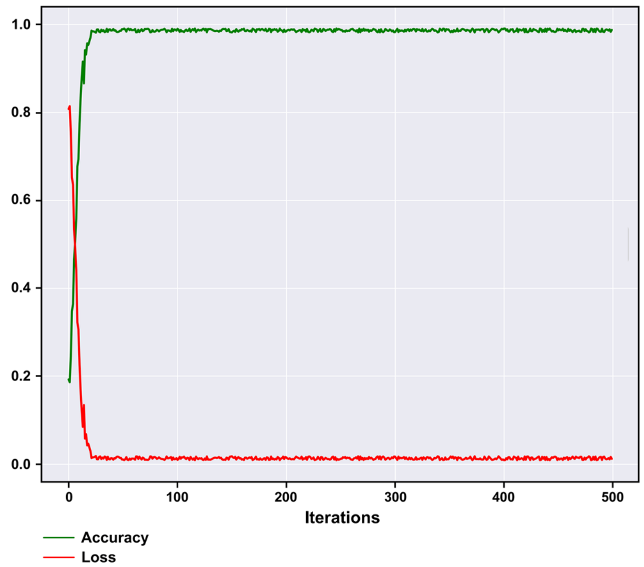
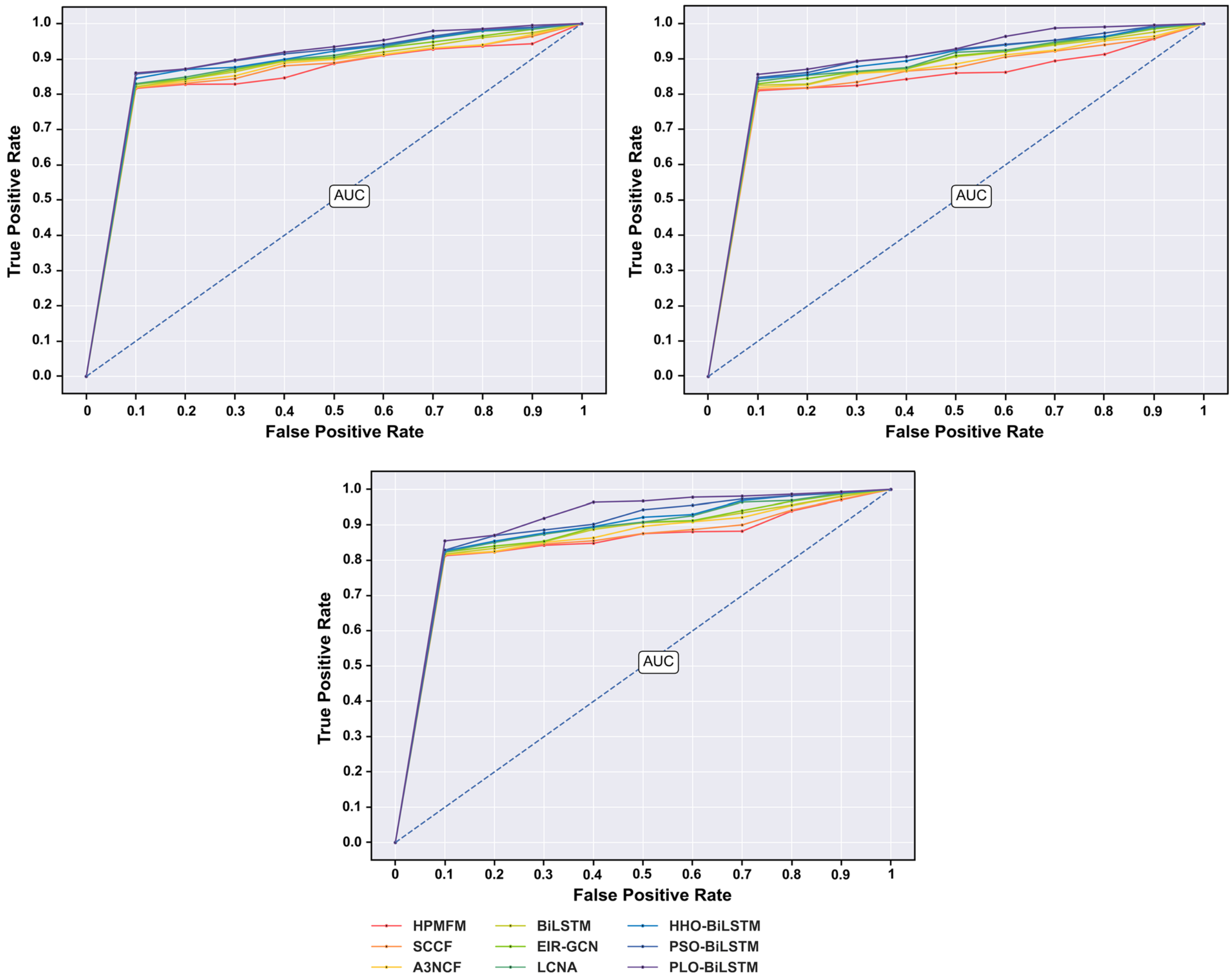


Figure 17 illustrates the ROC analysis of the proposed PLO-BiLSTM model.

5. Conclusion and Future Work

In this research, the proposed PLO-BiLSTM model significantly enhances e-commerce recommendation systems by incorporating advanced content-collaborative feature extraction techniques and a BiLSTM model with a hybrid PLO algorithm. Also, the model addresses the limitations obtained in the other existing models, such as high computation time, poor generalization, complexity with large datasets, and cold start issues. The proposed PLO-BiLSTM model handles these limitations and achieves high efficiency in e-commerce recommendation. Moreover, the proposed model achieved a high accuracy of 98.03%, F1-score of 98.03%, Precision of 98.49%, Recall of 97.57%, and minimum MSE of 1.97 based on the training percentage using the patio lawn garden dataset. Simultaneously, the model achieved a high accuracy of 97.93%, F1-score of 97.93%, Precision of 98.51%, Recall of 97.36%, and minimum MSE of 2.07 based on the K-fold value using the digital music dataset. The results not only show improved accuracy and efficiency but also reveal the model's capability to handle diverse e-commerce environments with better generalization

Figure 17
ROC analysis



and user preference. In future work, this model will be extended further by incorporating the PLO-BiLSTM with GNNs in future research for enhanced feature extraction capabilities. The model will be further utilized with diverse datasets for more efficient, real-time generalization and robustness. These kinds of hybrid approaches are going to tune up recommendation systems for a much better user experience.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The Amazon product data that support the findings of this study are openly available at https://cseweb.ucsd.edu/~jmcauley/datasets/amazon/links.html.

Author Contribution Statement

Hemn Barzan Abdalla: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Mehdi Gheisari:** Conceptualization, Software, Data curation. **Awder Ahmed:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Bahtiyar Mehmed:** Formal analysis, Investigation, Resources. **Maryam Cheraghy:** Validation, Resources, Writing – review & editing. **Yang Liu:** Validation, Investigation, Resources.

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