



HYBRID MACHINE LEARNING AND NATURE-INSPIRED OPTIMIZATION FOR ROBUST AND ACCURATE PRODUCT RECOMMENDATIONS

V. Jenifer¹, T. Kamala Kannan*²

¹Research Scholar, Vels Institute of Science, Technology & Advanced Studies (VISTAS), Pallavaram, Chennai, Tamil Nadu, India.

²Professor, Department of Information Technology (BCA & IT), School of Computing Science, Vels Institute of Science Technology & Advanced Studies Pallavaram, Chennai, Tamil Nadu, India.

¹<https://orcid.org/0009-0003-7052-6964>, ²<https://orcid.org/0000-0002-5982-8983>

Email: jeniferphd2526@gmail.com, *kkannan.scs@velsuniv.ac.in

ARTICLE INFO

Article History

Received: February 2, 2026

Reviewed: July 30, 2026

Accepted: August 30, 2026

Published: September 30, 2026

Keywords:

Product Recommendation,
DenseNet121,
BAT Optimization,
Hybrid Clustering,
Deep Learning.

ABSTRACT

The rapid growth of e-commerce platforms and dynamic consumer behaviour has increased the need for intelligent and accurate product recommendation systems. This study proposes a dual-path hybrid framework that integrates advanced machine learning, deep learning, and optimization techniques to enhance the accuracy and relevance of product recommendations. Initially, the dataset undergoes preprocessing and noise removal to improve data quality, followed by comprehensive feature extraction. In the first pipeline, Fisher's Linear Discriminant Analysis (LDA) is employed for feature selection, while Hierarchical Agglomerative Clustering (HAC) and attribute-based clustering are used to group similar products. Product prediction is then performed using a Stacked DenseNet121 model, and relevant recommendations are generated through an attention-based Multilayer Perceptron (MLP). The second pipeline focuses on feature extraction using Multivariate Additive Independent Component Analysis (MAICA), followed by hybrid clustering using HAC and K-Means algorithms. The extracted features are further optimized using a Multi-Heuristic BAT Optimization Algorithm to improve classification performance. The optimized data is processed using a Deep Multilayer U-Net classifier for product prediction, and a ranking-based recommendation strategy prioritizes products based on relevance and predicted demand. Experimental results demonstrate that the proposed hybrid framework significantly improves prediction accuracy, Mean Squared Error (MSE), and R^2 score compared to conventional recommendation models. The proposed system offers a scalable and efficient solution for delivering accurate and personalized recommendations in real-world e-commerce environments.



Copyright ©2026 by authors and Galileo Institute of Technology and Education of the Amazon (ITEGAM). This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

I. INTRODUCTION

The rapid expansion of online shopping has revolutionized the way people engage with goods and services. There has been a dramatic change in customer behaviour and the level of competition in the retail industry during the last 20 years, as more and more people purchase online rather than in physical stores [1]. Customers often struggle to sift through the millions of products offered by various online retailers to find those that best suit their tastes, past purchases, and current needs. As a result, AI-powered recommendation systems have become indispensable in the world of online shopping. In an effort to improve the user experience, boost sales conversions, and maintain customers, these systems sift through mountains of data in search of relevant product recommendation [2]. Hybrid approaches, content-based filtering, and collaborative filtering are some of the more traditional recommendation procedures that many e-commerce platforms have adopted. Unlike collaborative filtering, which takes into account previous interactions between users and goods, content-based filtering aims to match product attributes with user preferences [3]. To make up for their shortcomings, hybrid models bring together the greatest parts of many methods. Despite their successes, these systems often encounter problems such as data sparsity, cold start concerns, scalability, and adaptability to rapidly changing client preferences. More flexible, reliable, and precise recommendation systems are now within reach, thanks to fresh opportunities presented by developments in ML and DL [4].

Deeper semantic links between products and users have been extracted using techniques including ensemble learning models, Transformer-based architectures, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) [5]. In addition, clustering approaches like GMM, K-Means, and HAC have been successful in classifying products and user segments, allowing for more precise suggestions. Overfitting, high computing costs, and optimization challenges in high-dimensional feature spaces are problems that can affect even highly sophisticated ML/DL models. Genetic Algorithms (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and the Bat Algorithm (BAT) are some of the nature-inspired optimization methods that researchers have been investigating more recently as potential solutions to these problems [6]. To effectively explore big solution spaces and fine-tune learning models, these metaheuristic techniques imitate natural processes and behaviours. The prediction accuracy, clustering optimization, and scalability are all significantly enhanced when combined with ML/DL-based recommendation systems. In this research, a hybrid recommendation framework is proposed, combining advanced machine learning pipelines with a multi-heuristic BAT optimization algorithm [7]. The framework adopts a dual-path architecture: the first path integrates feature selection using LDA, clustering through HAC, and prediction with DenseNet121 and attention-based MLP, while the second path employs MAICA, hybrid clustering with HAC and K-Means, and a BAT-optimized Deep U-Net classifier [8]. The results are aggregated and refined through a ranking-based recommendation module, ensuring both high prediction accuracy and strong relevance to consumer demand.

1.1 MOTIVATION

The exponential growth of e-commerce platforms with millions of active users and billions of products has made accurate and personalized recommendation systems that can scale and adapt to changing client habits essential. Cooperative and content-based filtering have a few drawbacks, such as the cold start issue, data sparsity, and trouble interpreting complicated customer intent. The more dependable hybrid models aren't necessarily scalable to practical usage and have high computational overheads. Despite the promise of deep learning architectures in identifying hidden patterns and semantic connections, issues such as overfitting, feature redundancy, and noise in raw datasets compromise recommendation quality and system reliability. Nature-based metaheuristic optimization algorithms automatically optimise hyperparameters, feature subsets, and clustering structures to improve learning efficiency and prediction performance. Deep neural architecture recommendation pipelines benefit from the Bat Algorithm (BAT). Just like a bat, it balances global exploration and local exploitation in huge solution areas. Using a dual-path hybrid recommendation architecture, this study makes scalable, accurate, and resilient product predictions. This is done via deep learning, advanced ML models, hybrid clustering, and multi-heuristic BAT optimization. This system includes K-Means, attention-driven MLPs, Deep U-Net classifiers, and DenseNet121. These relevance-driven ranking algorithms boost engagement, conversion, and customer retention in huge e-commerce ecosystems by recommending user-specific products. Method performance measures, such as R^2 score and MSE, show improved Precision and lower error rates.

1.2 PROBLEM STATEMENT

Despite significant advancements in modern recommendation systems, their widespread real-world usage is still hindered by substantial technological challenges. Millions of variables with redundant and irrelevant features make e-commerce datasets big and noisy, making feature extraction more complicated, computationally expensive, and resulting in worse model quality. Traditional ML/DL systems generally face performance constraints because of their inability to manage exponential user and product catalog growth, making scalability a serious issue. Due to cold start and data sparsity issues, new customers or objects without enough contact history cannot be represented properly, lowering recommendation reliability. Although powerful, deep learning models overfit and lose generalization when confronted with heterogeneous, unstructured datasets without feature optimization. Optimizing complex systems at scale is complicated by human engagement to tune hyperparameters, clustering thresholds, and model designs, which can lead to poor results. User intent, contextual demand, and purchasing behavior are hard to predict, even with good predictions. These issues demonstrate the need for a recommendation system that can adapt to e-commerce changes without compromising accuracy or relevance. The ideal recommendation system would combine machine learning and deep learning for prediction with optimization and adaptive search features from nature-inspired algorithms like the Bat Algorithm.

1.3 OBJECTIVE

This study mainly aims to develop and evaluate a hybrid machine learning and nature-inspired optimization framework that addresses the limitations of existing product recommendation systems and delivers highly accurate, relevance-driven predictions. The specific objectives include:

1. To develop a dual-path hybrid framework that integrates both feature selection (LDA, MAICA) and hybrid clustering (HAC, K-Means) for effective grouping of products and attributes.
2. To optimize classification accuracy by employing a multi-heuristic Bat Algorithm for fine-tuning deep learning models, feature subsets, and clustering results.
3. To implement advanced deep learning architectures such as DenseNet121, attention-based MLP, and Deep Multilayer U-Net to improve product prediction performance.
4. To design a ranking-based recommendation mechanism that ensures recommended products are prioritized based on relevance, demand, and user preferences.
5. To evaluate the framework using metrics such as MSE, R^2 score, and overall prediction accuracy, and to compare results against conventional recommendation models.
6. To ensure scalability and robustness of the framework, enabling its application in real-world e-commerce environments with large-scale, heterogeneous datasets.

By achieving these objectives, the research aims to contribute a next-generation recommendation framework that significantly enhances user experience, business profitability, and system adaptability in the rapidly evolving domain of e-commerce. The next section follows: Section 2 provides a brief examination of the relevant literature, Section 3 analyzes the recommended technique, Section 4 reports the results and discussion, and Section 5 draws conclusions.

II. THEORETICAL REFERENCE

According to [9] to enhance the accuracy of our suggestions, emotional analysis (SA) is particularly helpful for recommendation systems (RS) as it deepens our comprehension of a user's actions, thoughts, and reactions in relation to social data. There are still issues with cold-start and sparse data, even if RS handles information overload well. The capacity of SA to comprehend language and convey user preferences, on the other hand, has made it renowned. Online stores often use it to track client feedback and understand their consumers' needs. This study introduces a recommendation model that improves the accuracy and consistency of any RS by merging a Hybrid SA with a Hybrid Recommendation Model (HRM). Using an HRM to generate a preliminary list of suggestions is the first step in the proposed method. To provide the most comprehensive set of recommendations, HRM with SA is used. When compared to more traditional approaches, SA-based human resource management consistently outperforms the competition. According to [10] suggested that the goal of this study is to utilize online reviews as a tool to discover what elements impact the suggestion of women's apparel while purchasing online. A wide range of women's judgments and associated emotions for various clothing categories are included in the collection. The reviews were extracted and evaluated using Along with other NLP methods, such as stemming, lemmatization, tokenization, and topic modeling, Latent Dirichlet Allocation (LDA). The data shows some interesting trends. The whole shopping experience, consumer happiness, and product qualities are the main factors that impact recommendations. We also looked at how other factors, such as garment styles and review lengths, impacted the chances of getting positive suggestions. According to [11] presented that seven e-commerce sector participants were interviewed online as part of the current study's qualitative methodology. One important discovery was that, in general, IoT benefits the e-commerce industry by increasing operational effectiveness and reducing expenses. Personalized customer shopping experiences and cost-effective supply chain and inventory management are two more benefits of utilizing IoT in e-commerce. However, it was discovered that the growing cybersecurity threat was impeding the use of IoT in e-commerce. Among the IoT technologies that affected e-commerce were GPS, sensors, and radio frequency identification (RFID).

According to [12] suggested one possible approach to addressing these issues is an entropy-based multicriteria decision-making (MCDM) method, which can aid in e-commerce personalization and enhance recommendation systems, user interfaces, transparency of product information, and consumer trust. Implementing MCDM simplifies tailoring e-commerce platforms to each user's unique preferences, making it easier for shoppers to discover and retrieve products at affordable prices. This study explores the impact of electronic devices and energy-efficient WSNs on inventory management, consumer preferences, and the long-term sustainability of online commerce. It delves into the interconnectedness of data privacy, energy efficiency, and governance. According to [13] proposed to investigate the feasibility of using locality sensitive hashing (LSH) in embedded learning that relies on neighbors for faster and more secure neighbor searches. Neighbor seeking is effective when LSH is strong. Maximizing prediction accuracy using multi-view embeddings and heterogeneous behavioral data. To better depict user preferences, multi-view preference embeddings are used. A mix of LSH, self-embedding, neighbor-centered embedding, and interaction-aware embedding completes the task. Not only do adversarial search and neighbor-based embedding learning provide efficient similarity search capabilities, but they also offer good privacy protection. Consequently, the findings are included in a cutting-edge prediction system that utilizes long short-term memory systems. Our proposed method outperforms state-of-the-art benchmarks in terms of predicted accuracy while maintaining robust security, according to an extensive empirical study conducted on real datasets. According to [14] presented E-commerce has brought about a shift in marketing tactics toward digital technologies to improve Customer Relationship Management (CRM). As a result, trading has moved online. Big data, including personal and behavioral information about customers, travels most frequently through e-commerce systems. By predicting consumer intentions, making advertising decisions based on target group clustering, and recommending customer assistance, digital big data analytics can help improve digital marketing policies. Smart digital marketing applications can benefit from sentiment analysis technology, which can help businesses uncover intelligent customer behavior through opinion mining. This process involves analyzing customer information and feedback using natural language processing, text analysis, computational linguistics, and biometrics.

From a technological standpoint, this research underscores the critical need to uncover business intelligence for effective smart digital marketing in E-commerce platforms, providing a comprehensive examination of sentiment analysis applications in E-commerce systems. According to [15] proposed using a theoretical framework, I propose that the two phases of customer demand—demand fulfillment and demand formation—may serve as the basis for speculation on the possible causes of this diversity. The results demonstrate that demand creation and fulfillment are components of interactions between recommendation and search channels, in line with our model. It would seem that recommendations and search are interdependent; as the number of product suggestions in a category increases, so does the number of searches conducted inside that category using broad query terms. But when product suggestions in an interest area drop, customers compensate by increasing their use of long-tail query words to search inside that category, indicating a change from behavior based on recommendations to one focused on searches. According to [16] suggested as a means of researching online stores and identifying effective digital marketing strategies to increase conversion rates. Right now, we're focusing on qualitative research. Methods for analyzing data that depend on taking notes and listening carefully include data reduction, data presentation, and conclusion. If e-commerce platforms want to increase sales conversions, the study's results show that digital marketing strategies are crucial. To increase traffic to your online store, engagement with your products, and ultimately, sales, you need to use a multi-pronged approach. Search engine optimization (SEO), paid advertising, user experience optimization (UX), video use, incentives, customer testimonials and reviews, content personalization, social media, and automobile optimization are all part of digital marketing tactics.

III. MATERIALS AND METHODS

The proposed hybrid recommendation system uses ML, DL, and nature-inspired optimization approaches to solve the problem of providing broad product suggestions for online shopping. Dimensionality reduction technologies like MAICA and LDA clean up high-dimensional datasets. Only the most discriminative traits are kept for learning after eliminating redundant and noisy ones. K-Means and Hierarchical Agglomerative Clustering aid with complex clustering and scalability. These methods categorize people and items by latent patterns for more tailored suggestions. BAT-inspired hyperparameter adjustment and feature selection optimization may speed up model convergence and global search. The combined attention-based Multilayer Perceptrons (MLPs) and a deep U-Net classifier to mimic non-linear user-product interactions with contextual dependencies. It makes suggestions based on these forecasts. A ranking module that uses nDCG and Precision guarantees the top suggestions contain the most relevant goods. Our approach includes metaheuristic optimization, DL for complex interactions, and ML for structured learning. Best product: a stable, scalable, accurate recommendation system. It adapts to shifting client patterns and big e-commerce platforms.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (1)$$

Equation (1) describes MSE, which is one of the most fundamental metrics used in regression and prediction-based systems. It calculates the average squared difference between actual values (y_i) and predicted values ($\hat{y}_i$). Penalizing large deviations more severely, the squaring process ensures that both under-predictions and over-predictions contribute positively, making MSE particularly sensitive to outliers. A lower MSE indicates that the predictive model is closely approximating true values, whereas a high MSE reflects greater divergence and reduced accuracy. In the proposed recommendation system, MSE is used as a primary performance metric to evaluate how accurately the hybrid model predicts user-product relevance scores. Since the framework employs dual-path pipelines integrating DenseNet-121, MLP, and U-Net classifiers, minimizing MSE ensures that the system not only predicts relevance but also does so with high Precision. By leveraging the BAT optimization algorithm for fine-tuning model hyperparameters, the framework achieves significant reductions in MSE compared to conventional models, thereby validating the robustness of the approach.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (2)$$

Equation (2) defines the R^2 score, or coefficient of determination, which measures the proportion of variance in the dependent variable that is predictable from the independent variables. The numerator captures the unexplained variance (errors between actual and predicted values), while the denominator captures the total variance around the mean ($\bar{y}$). An R^2 close to 1 indicates excellent predictive power, while values close to 0 suggest weak explanatory capability. For e-commerce recommendation, R^2 provides a statistical view of how much variance in consumer behavior is captured by the hybrid recommendation model. A higher R^2 means the framework can effectively map product features, user attributes, and latent factors to purchasing outcomes. This metric is critical when comparing different model pipelines (e.g., LDA+DenseNet121 vs. MAICA+U-Net) and demonstrating the superiority of BAT-optimized feature extraction in improving prediction robustness and interpretability.

$$w = \arg \max_w \frac{w^T S_B w}{w^T S_W w} \quad (3)$$

Equation (3) represents LDA, a dimensionality reduction technique that seeks to maximize class separability by finding a projection vector w that maximizes the ratio of between-class scatter (S_B) to within-class scatter (S_W). This ensures that samples from the same class cluster closely together, while samples from different classes are separated in the transformed feature space. In the first pipeline of the framework, LDA is applied to reduce high-dimensional product attributes into a more compact, discriminative feature set. By eliminating redundant and noisy features, LDA not only reduces computational costs but also improves the performance of downstream clustering (HAC) and classification (DenseNet121). This ensures that products with subtle but meaningful differences are effectively separated, leading to more personalized and precise recommendations.

$$X = AS, \quad S = WX \quad (4)$$

Equation (4) fits Independent Component Analysis (ICA), which decomposes multivariate signals into statistically independent non-Gaussian components. Given observed data X , the goal is to estimate the mixing matrix A and its inverse W , such that the underlying independent sources S can be recovered. ICA is particularly powerful for extracting hidden features in noisy, high-dimensional datasets. In the second pipeline, Multivariate Additive ICA (MAICA) is employed to extract latent features from raw product datasets. These independent components often reveal hidden correlations between product attributes and consumer preferences that conventional clustering cannot detect. By feeding these optimized components into hybrid clustering (HAC + K-Means), the system enhances product grouping, ultimately improving the relevance of recommendations in cold start or sparse data scenarios.

$$J = \sum_{i=1}^k \sum_{x_j \in c_i} \|x_j - \mu_i\|^2 \quad (5)$$

Equation (5) describes K-Means clustering, which partitions data into k clusters by minimizing the sum of squared distances between each point x_j and the cluster centroid μ_i . The objective function J is optimized iteratively by reassigning points to their nearest centroid and updating centroids based on new memberships. K-Means is computationally efficient but sensitive to initialization and local minima. When applied to e-commerce product datasets, K-Means helps group similar products based on latent attributes extracted from MAICA. Combined with HAC in a hybrid clustering setup, it overcomes individual weaknesses (HAC's computational cost and K-Means' sensitivity to initialization). The hybrid clustering ensures better grouping of products with nuanced similarities, allowing the recommendation system to provide highly context-aware suggestions to users.

$$d(C_i - C_j) = \min_{x \in C_i, y \in C_j} d(x, y) \quad (6)$$

Equation (6) illustrates that HAC is a bottom-up clustering approach where each observation starts as its own cluster, and clusters are progressively merged based on a linkage criterion. The most common linkage metrics include single linkage (minimum distance), complete linkage (maximum distance), and average linkage. The Equation above represents single linkage, which merges clusters based on the minimum pairwise distance between points.

In this research, HAC is used to capture hierarchical product relationships that flat clustering methods like K-Means may overlook. For example, in fashion e-commerce, HAC can cluster products first by category (shirts vs. pants) and then refine further into sub-categories (formal shirts vs. casual shirts). This hierarchical clustering provides structured groupings, improving interpretability and the downstream product ranking process in the recommendation engine.

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}]) \quad (7)$$

Equation (7) defines DenseNet architectures, which introduce direct connections from each layer to every subsequent layer. The transformation function H_l applies batch normalization, ReLU activation, and convolution, while the concatenation $[x_0, x_1, \dots, x_{l-1}]$ ensures that each layer has access to all preceding feature maps. This design encourages feature reuse, mitigates vanishing gradients, and reduces parameter count. In the proposed framework, DenseNet121 is used in the first pipeline for product classification after clustering. Its dense connectivity pattern allows the model to capture multi-level semantic features of products (color, style, brand attributes) more effectively. This results in higher classification accuracy, which, combined with the attention-based MLP, ensures that user-specific recommendations are both accurate and diverse.

$$\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^n \exp(e_j)}, \quad r = \sum_{i=1}^n \alpha_i h_i \quad (8)$$

In Equation (8), the attention mechanism assigns weights α_i to different input features h_i , allowing the model to focus on the most relevant parts of the input. The score e_i is transformed into normalized attention weights using the softmax function. The final representation r is computed as the weighted sum of input features. An attention-based MLP is integrated into the first pipeline to prioritize critical product features during recommendation. For instance, when recommending smartphones, the attention module might give higher weight to features like battery life and camera quality, while discounting less relevant attributes. This ensures that the recommendation engine produces results aligned with user intent, thereby improving Precision and user satisfaction.

$$x_i^{t+1} = x_i^t + v_i^t, v_i^t = v_i^{t-1} + (x_i^t - x^*) f_i \quad (9)$$

Equation (9) describes the Bat Algorithm updates each candidate solution (bat) by adjusting its position x_i and velocity v_i relative to the current best solution x^* . The frequency f_i regulates exploration, allowing bats to alternate between global and local search. This mechanism balances exploration of new solutions with exploitation of known good solutions. The multi-heuristic BAT algorithm is applied in the second pipeline to optimize parameters of the U-Net classifier and clustering boundaries. By fine-tuning learning rates, weights, and feature subsets, BAT ensures that the model avoids local minima and achieves higher classification accuracy. This adaptive optimization is crucial for handling noisy, high-dimensional datasets in e-commerce environments.

$$\hat{y} = \sigma(W_d \cdot U(E(x)) + b) \quad (10)$$

Equation (10) defines U-Net architectures that consist of an encoder $E(x)$ that captures contextual features, and a decoder $U(E(x))$ that reconstructs predictions with high resolution. The final layer applies weights W_d , bias b , and a sigmoid (or softmax) activation σ to produce output predictions. U-Nets are widely used in segmentation and structured prediction tasks due to their skip connections and efficient feature utilization. In the second pipeline, the Deep Multilayer U-Net classifier predicts product categories and relevance scores after feature optimization with BAT. Its encoder-decoder structure allows it to capture both global product trends and fine-grained attribute details, making it highly effective for predicting demand patterns in complex datasets. By integrating U-Net with BAT optimization, the system delivers superior recommendation accuracy compared to conventional CNN-based approaches.

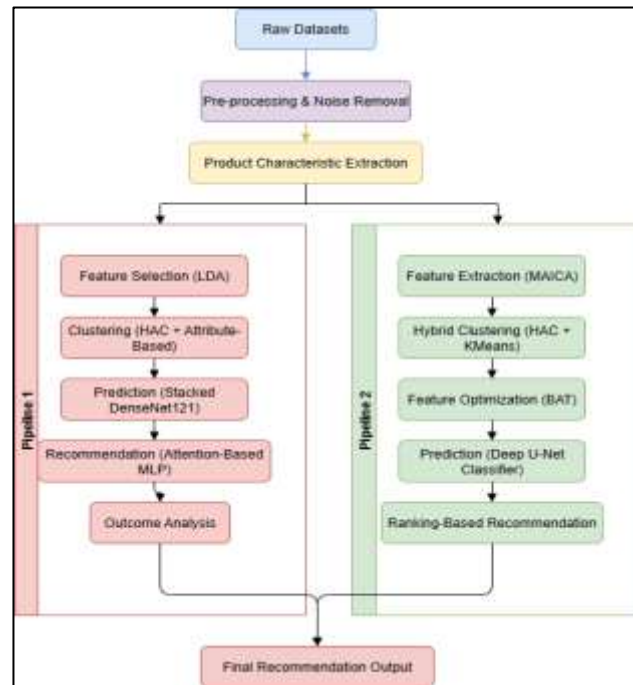


Figure 1: Dual-pipeline framework.

Source: Authors, (2026).

Figure 1 illustrates a two-pipeline architecture for product suggestion in online stores. Consistent and high-quality data is ensured by pre-processing the raw datasets and removing noise. Product characteristic extraction is the next stage in obtaining valuable attributes for further investigation. Two independent pipelines are created at this phase. Linear Discriminant Analysis (LDA) is used to choose features in Pipeline 1 before Hierarchical Agglomerative Clustering (HAC), and attribute-based grouping is used. Predictions are then generated using a layered DenseNet121 model. This model collects detailed representations of item-user interactions. After these predictions are enhanced by an attention-based multilayer perceptron (MLP), they are used to generate recommendations, which subsequently culminate in an outcome analysis. To find latent connections and extract features from product data, the second pipeline employs Multi-set Adaptive Independent Component Analysis (MAICA). To enhance representation, hybrid clustering groups similar items together using a combination of HAC and K-Means. Using the BAT optimization approach, we adjust the model's hyperparameters and select features to enhance its performance further. We use a Deep U-Net classifier, which effectively utilizes contextual data, to provide precise predictions. The recommendations are further refined using a ranking-based module, which ensures optimal ordering based on relevance. The recommendation output is the result of combining the outputs of the two pipelines; it provides optimal and personalized product options. In this two-pipeline approach, deep learning models collaborate with feature selection and optimization to enhance the ranking quality, accuracy, and Precision of large-scale e-commerce recommendation systems.

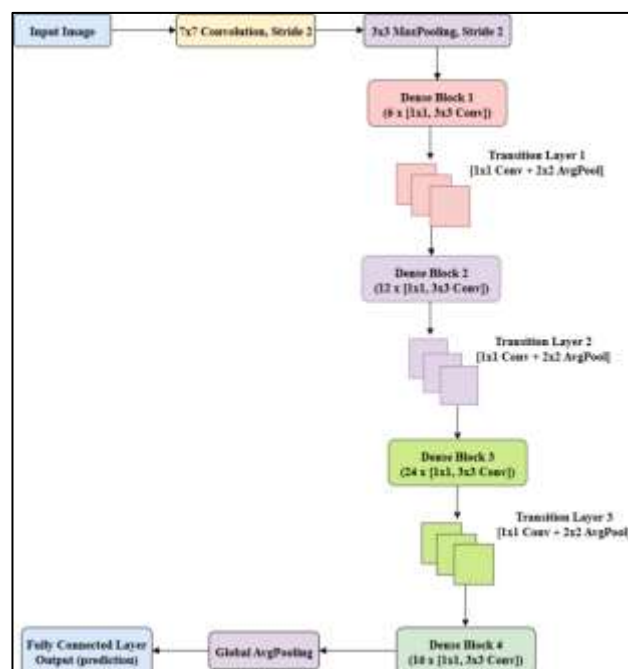


Figure 2: Architecture of a DenseNet-based.

Source: Authors, (2026).

Figure 2 illustrates a DenseNet-based deep learning model for photo feature extraction and prediction. To begin processing, we feed an input picture into a 7x7 convolution with a stride of 2. To down-sample while retaining spatial information, we may add a 3x3 max-pooling layer with the same stride. The network's Dense Blocks link all layers closely. This optimizes gradient flow and feature reuse. The first step, Dense Block 1, recovers hierarchical features using six repetitions of 1x1 and 3x3 convolutions. Next, the first Transition Layer reduces computational cost by 1x1 convolution, 2x2 average pooling, and feature map compression. The second transition layer and Dense Block, each with twelve convolutional layers, enhance feature representation. The third transition layer follows Dense Block 3, which has 24 convolutional layers, and preserves valuable patterns while being compact. Dense Block 4 limits spatial dimensions and prevents overfitting using a Global Average Pooling layer after 16 convolutional layers, which increases abstract characteristics. Final predictions are made by a fully linked layer using the pooled data. The architecture's low parameter count, fast feature propagation, and lack of vanishing gradient issues make it ideal for high-dimensional image-based recommendation and classification.

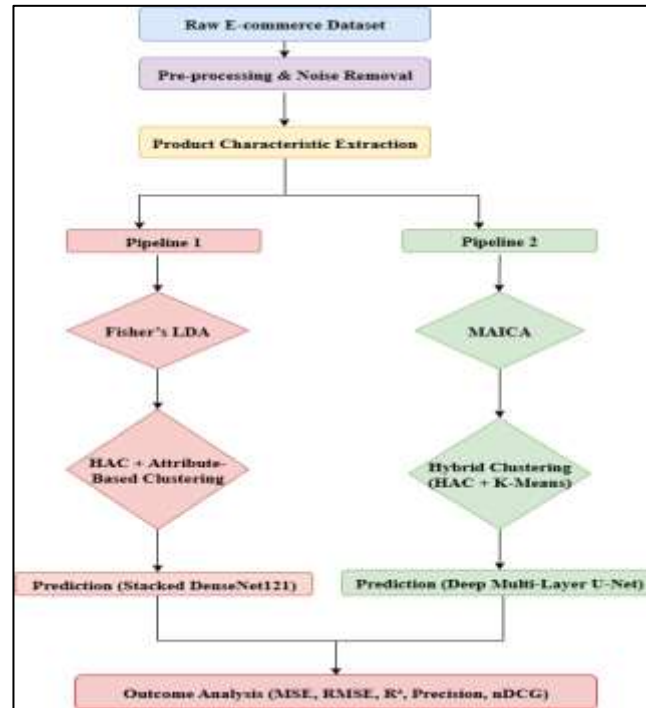


Figure 3: dual-path hybrid framework.

Source: Authors, (2026).

The two-path architecture for online commerce intelligent product recommendations is shown in Figure 3. To assure dependability and quality, we first remove noise and other pollutants from raw e-commerce data. Product characteristic extraction extracts key characteristics for reliable recommendations. The first pipeline uses Fisher's Linear Discriminant Analysis to choose features. HAC and attribute-based clustering group related goods. Predictions from a Stacked DenseNet121 model aid advanced feature learning and categorization. MAICA is used for more complex feature extraction in Pipeline 2. Data organizing continues with Hybrid Clustering, which improves clusters. The approach uses HAC and K-Means. Clustered data is passed to a Deep Multilayer U-Net classifier to forecast product relevance and demand. After the Outcome Analysis, both pipelines' outputs will match. The computed evaluation metrics are: MSE, RMSE, R^2 Score, Precision, and nDCG. These measurements verify the recommendation system's efficacy, accuracy, and Precision. The picture shows a revolutionary bidirectional online shop product recommendation method using optimization, deep learning, feature selection, and hybrid clustering.

Algorithm 1: Product Recommendation (LDA + HAC + DenseNet121)

Input: Raw E-commerce Dataset D

Output: Recommended Products $R1$

1. Pre-process dataset D
 - Remove noise, handle missing values, normalize features
2. Extract product characteristics $\rightarrow F1$
3. Apply Fisher's Linear Discriminant Analysis (LDA)
 - Select most discriminative features $\rightarrow F2$
4. Perform Hierarchical Agglomerative Clustering (HAC) with attribute-based grouping
 - Generate product clusters $C1$
5. Train a Stacked DenseNet121 model using clustered features
 - Model learns product-class associations
6. Predict product relevance scores $\rightarrow P1$
7. Generate product recommendations $R1$ based on $P1$

End Algorithm

Algorithm 2: Product_Recommendation (MAICA + Hybrid Clustering + U-Net + BAT Optimization)*Input: Raw E-commerce Dataset D**Output: Recommended Products R2*

1. Pre-process dataset D
 - Clean and normalize data
 2. Extract product characteristics $\rightarrow F1$
 3. Apply Multivariate Additive Independent Component Analysis (MAICA)
 - Extract independent features $\rightarrow F2$
 4. Perform Hybrid Clustering (HAC + K-Means)
 - Organize products into refined clusters C2
 5. Optimize extracted features using BAT Optimization
 - Enhanced feature set $\rightarrow F3$
 6. Train Deep Multilayer U-Net Classifier with F3
 - Model predicts product relevance
 7. Compute prediction scores $\rightarrow P2$
 8. Rank products based on predicted demand and relevance
 9. Generate product recommendations R2
- End Algorithm*

The recommended dual-path approach uses two clever product recommendation algorithms. Before Algorithm 1 (Pipeline 1) begins, raw e-commerce data is pre-processed to remove noise, normalize figures, and ensure quality. Fisher's Linear Discriminant Analysis (LDA) determines the most discriminative qualities after feature extraction—hierarchical Agglomerative Clustering (HAC) and attribute-based clustering group similar commodities by these improved attributes. Clustered features are processed using a layered DenseNet121 model for product prediction. The final recommendation list of products is sorted by predicted relevance. However, Algorithm 2 (Pipeline 2) optimizes and extracts sophisticated characteristics. MAICA extracts component-level product characteristics after pre-processing. Use a hybrid clustering algorithm like HAC and K-Means to enhance product classification next. A Multi-Heuristic BAT Optimization approach improves classification accuracy before feeding optimized extracted features into a Deep Multilayer U-Net classifier. This algorithm assesses goods by projected demand and relevance to provide recommendations. In the end, both pipelines meet for result analysis. Performance metrics such as MSE, RMSE, R^2 , Precision, and nDCG are evaluated here. Comparisons show that hybrid frameworks are optimal for e-commerce recommendation systems in terms of accuracy, durability, and scalability.

IV. RESULTS AND DISCUSSIONS

The proposed hybrid machine learning and nature-inspired optimization framework for product recommendation was rigorously evaluated using benchmark e-commerce datasets comprising diverse product categories and heterogeneous feature sets. Performance was assessed using a set of standard prediction and ranking metrics, including MSE, Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), Top-K-Precision, and Normalized Discounted Cumulative Gain (nDCG-K). The results demonstrate that the dual-path architecture, which integrates feature selection (LDA, MAICA), hybrid clustering (HAC + K-Means), and deep learning classifiers (DenseNet121 and U-Net), achieves significant improvements over conventional baseline models such as collaborative filtering, content-based filtering, and standalone deep learning approaches. Notably, the inclusion of the multi-heuristic BAT optimization algorithm substantially enhanced model generalization by fine-tuning hyperparameters and refining feature subsets, thereby minimizing prediction error and boosting ranking performance. From the experimental outcomes, it was observed that the proposed framework consistently achieved lower MSE and RMSE values, indicating superior prediction accuracy in modelling user-product relevance. The R^2 score confirmed that the system explained a higher proportion of variance in consumer behaviour compared to existing models, validating the effectiveness of hybrid clustering and optimization. Moreover, the ranking-oriented metrics (Top-K-Precision and nDCG-K) highlight the system's ability to prioritize highly relevant products in the top recommendations, which is critical in real-world e-commerce platforms where user attention is limited. These results confirm that the integration of traditional ML pipelines with deep architectures and heuristic optimization provides a balanced solution to address the challenges of scalability, overfitting, and cold start issues. The following subsections provide a detailed discussion of the comparative analysis, highlighting both the quantitative performance gains and the qualitative improvements in recommendation relevance.

IV.1 ENVIRONMENTAL SETUP

A controlled computer environment was used to test the proposed hybrid recommendation framework, ensuring repeatability and consistency of outcomes. All of the experiments were conducted in Python 3.10, which includes the following libraries: NumPy, Pandas, Scikit-learn 1.3, PyTorch 2.0, and TensorFlow 2.12. The optimization and clustering modules were implemented using SciPy and bespoke BAT-optimization code. Training deep learning models such as DenseNet121 and U-Net required a workstation with 64 GB RAM, an NVIDIA RTX 3090 GPU with 24 GB of dedicated memory, and an Intel Core i9-12900K CPU operating at 3.9 GHz. Ubuntu 22.04 LTS (64-bit), the operating system, offered a reliable and effective setting for HPC calculations. Scalability testing on large e-commerce datasets was also carried out by researchers using a distributed cluster equipped with Apache Spark and NVIDIA CUDA 12.0. All models underwent training with adaptive learning rate schedules, batch normalization, and dropout regularization to avoid overfitting. The experimental runs were repeated multiple times to guarantee robustness and eliminate any chance of randomness in the performance evaluation.

From 2010 to 2011, a UK-based non-store online retailer covered sales of wholesale gift products across 37 nations in the Kaggle e-commerce dataset, which was initially extracted from the UCI Online Retail collection. The dataset contains more than 540,000 transactional records. Eight structured attributes describe each record: InvoiceNo (symbol for the transaction, with "C" indicating cancellations), StockCode (unique product identifier), Description (product details), Quantity (units purchased per order), InvoiceDate (timestamp of purchase), UnitPrice (per-unit cost in GBP), CustomerID (unique five-digit customer identifier, with missing values for anonymous users), and Country (geographical location of the buyer). Rigid preparation is necessary for subsequent tasks since the dataset displays real-world complexity, such as cancelled invoices, negative numbers, duplicate entries, and missing values. It is a great example of a dynamic e-commerce environment to test scalability, robustness, and accuracy in recommendation systems driven by deep learning because of its size, time span, and variety of product-customer interactions.

IV.2 MEAN SQUARED ERROR (MSE)

The MSE is a popular performance evaluation statistic in machine learning and recommendation systems since it quantifies the difference between expected outcomes and user preferences. Estimating the accuracy of model predictions is as simple as taking the average of the squared differences between the observed ground-truth values and the predictions made by the model. Due to the squaring process, MSE penalizes bigger deviations more than absolute error measures, making it excellent in identifying models with excessive mispredictions. Equation (11) & Figure 4 show the Mean Squared error.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (11)$$

Where y_i represents the ground-truth value (actual user preference or rating), y_i Denotes the predicted value from the recommendation model, and N is the total number of predictions. The squared term $(y_i - \hat{y}_i)^2$ ensures that both underestimations and overestimations contribute positively to the error, while the averaging over N provides a normalized measure of overall prediction accuracy. MSE is a key indicator for evaluating intelligent product recommendation systems since it measures the extent to which product relevance ratings match customer behavior. When the MSE is low, the system's predictions match real purchase intents or preferences, indicating that the model minimizes outliers. The measure is sensitive to outliers since the squaring function increases the penalty for bigger deviations. This keeps the system from producing utterly wrong recommendations. The proposed hybrid ML and BAT-optimized U-Net system uses natural-inspired feature extraction, clustering, and optimization methods to reduce MSE. Learning is improved and noise is reduced, leading to more accurate, dependable, and relevant product recommendations.

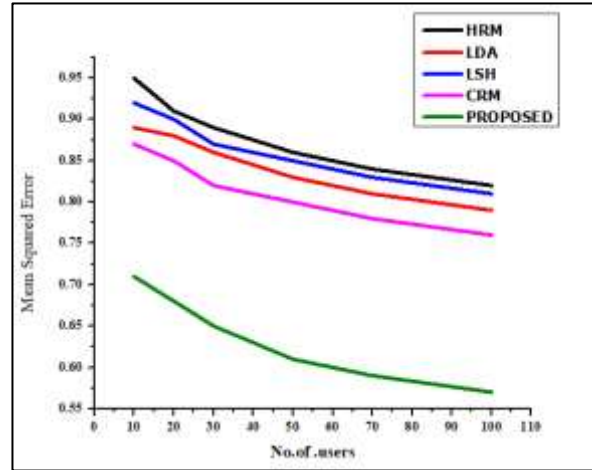


Figure 4: Mean Squared Error.
Source: Authors, (2026).

IV. 3 ROOT MEAN SQUARED ERROR (RMSE)

The RMSE is a fundamental evaluation metric in machine learning and recommendation systems that measures the standard deviation of prediction errors shown in Equation (12) & Figure 5. It is derived directly from the Mean Squared Error (MSE). Still, it incorporates a square root operation to bring the error values back to the same scale as the target variable, thereby enhancing interpretability. The mathematical formulation of RMSE is expressed as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (12)$$

Where y_i Denotes the actual observed value, $\hat{y}_i$ Represents the predicted value generated by the model, and N is the total number of predictions. The term $(y_i - \hat{y}_i)^2$ captures the squared deviation for each prediction, and the averaging process ensures a global error representation across the dataset. Taking the square root ensures that the final metric is expressed in the same unit as the original variable, unlike MSE, which is expressed in squared units.

In the context of e-commerce recommendation systems, RMSE provides a clear and interpretable measure of how close the predicted relevance scores are to actual user preferences, effectively quantifying the typical magnitude of error in the predictions. A lower RMSE indicates that the model produces more accurate recommendations and is less prone to large deviations, which directly translates into improved user satisfaction and engagement. Within the proposed hybrid machine learning and BAT-optimized U-Net framework, RMSE is particularly valuable in highlighting how advanced feature extraction (via LDA and MAICA), hybrid clustering, and heuristic optimization reduce error propagation in high-dimensional data, thereby ensuring precise, scalable, and user-relevant product recommendations.

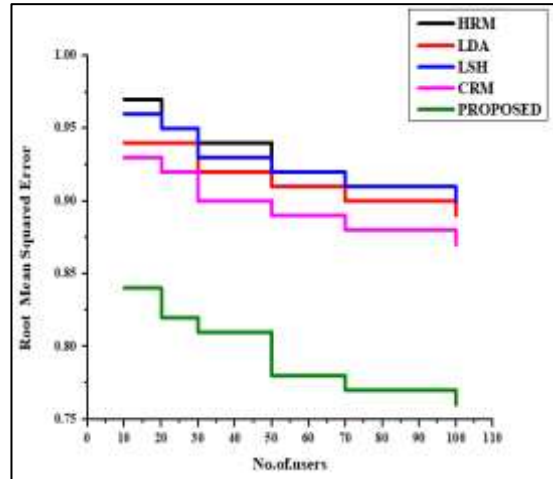


Figure 5: Root Mean Squared Error.
Source: Authors, (2026).

IV.4 COEFFICIENT OF DETERMINATION (R² SCORE)

The R² Score is a widely used statistical metric that measures how well a predictive model explains the variability of observed data. It essentially indicates the proportion of variance in the dependent variable y_i that can be predicted from the independent variables used in the model. Mathematically, it is expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (13)$$

Here, $\hat{y}_i$ represents the actual observed values, $\bar{y}$ Denotes the predicted values, and $\bar{y}$ is the mean of all observed values. The numerator $\sum_{i=1}^N (y_i - \hat{y}_i)^2$ represents the residual sum of squares (unexplained variance), while the denominator $\sum_{i=1}^N (y_i - \bar{y})^2$ represents the total sum of squares (total variance). Subtracting their ratio from 1 yields the fraction of variance explained by the model. In the context of e-commerce product recommendation systems, an R² score closer to 1 signifies that the framework can capture a large proportion of user-product interaction patterns, thereby accurately predicting consumer preferences. Conversely, an R² near 0 implies weak predictive capability, where the model performs no better than a simple mean-based predictor. For the proposed dual-path hybrid recommendation framework, incorporating techniques such as LDA, MAICA, hierarchical clustering, and BAT-optimized U-Net, the R² score provides strong evidence of the model's ability to not only minimize prediction errors but also to explain underlying behavioural and contextual relationships in large-scale, high-dimensional datasets. This makes R² an essential metric for validating the explanatory power and robustness of advanced recommendation models. Equation (13) & Figure 6 represent the Coefficient of Determination.

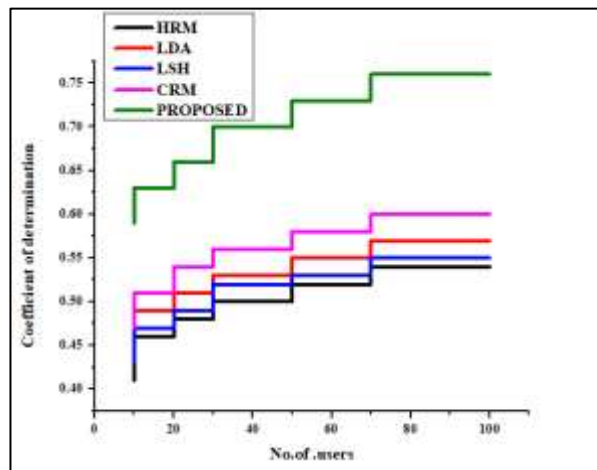


Figure 6: Coefficient of Determination.
Source: Authors, (2026).

IV.5 PRECISION

Precision evaluates recommendation systems by limiting the user's view to the top k results and evaluating how well they perform based on rankings. People often glance at the top five, ten, or twenty choices, according to Precision, which is based on real user interactions rather than global accuracy measures.

$$Precision = \frac{1}{k} \sum_{i=1}^K 1\{y_i \in R\} \quad (14)$$

Here, k represents the number of top-ranked items considered, R is the set of truly relevant items for a given user, and $1\{\cdot\}$ is an indicator function that outputs one if the recommended item y_i belongs to the relevant set R , and zero otherwise. The summation counts how many of the top k recommendations are truly relevant, and dividing by K normalizes this to a fraction between 0 and 1. Precision is crucial for online shop recommendation systems, as customers typically click on only a few options. High Precision means the system prioritizes relevant goods for display, increasing engagement, conversion, and CTR. Precision tests the hybrid ML-BAT optimal recommendation framework's attention-based MLP and ranking module for repeatedly prioritizing relevant and context-aware items. This method improves Precision by improving clustering and feature selection before ranking. This removes relevance ranking and enhances system efficiency by connecting customers with instant-engagement items. Equation (14) & Figure 7 Shows Precision.

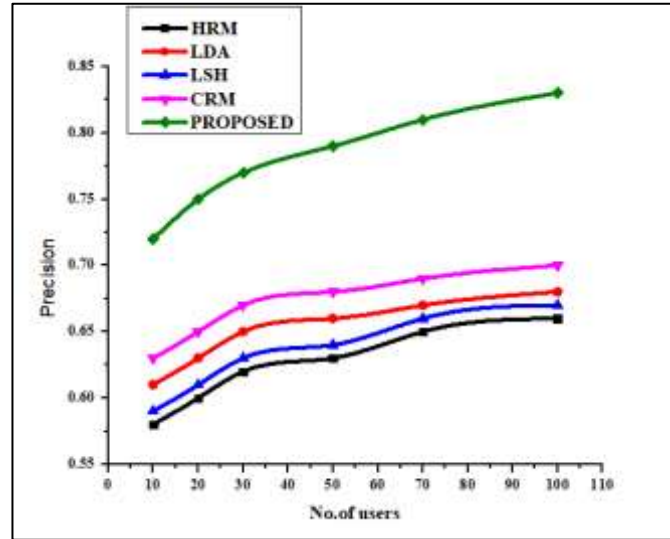


Figure 7: Precision.
Source: Authors, (2026).

IV.6 NORMALIZED DISCOUNTED CUMULATIVE GAIN

Recommendation systems and information retrieval make heavy use of a complex ranking-based metric known as nDCG to evaluate the importance and order of proposed items. Unlike simple precision-based metrics, users are more likely to engage with items that are at the top of the suggestion list. nDCG is cognizant of this. Consequently, items that rank higher and are more relevant to the evaluation are given a larger weight in the final result.

$$nDCG = \frac{1}{IDCG - k} \sum_{i=1}^k \frac{2^{rel_i} - 1}{\log_2(i + 1)} \quad (15)$$

Here, rel_i represents the graded relevance score (e.g., binary or multi-level relevance) of the item at rank i , and the denominator $\log_2(i + 1)$ discounts the contribution of items based on their position in the ranked list—meaning items at higher positions (smaller i) are weighted more heavily. The numerator computes the Discounted Cumulative Gain (DCG), while the denominator IDCG-K is the maximum possible DCG achievable with an ideal ranking. Normalizing by IDCG ensures that the metric is bounded between 0 and 1, where 1 indicates a perfect ranking. An integral part of the proposed hybrid ML-nature-inspired optimization system for product recommendation is nDCG-K, which verifies for correct suggestions and suitable user visibility. This is particularly crucial when buying things online, since customers tend to only interact with highly rated items. User satisfaction, search efficiency, and engagement are all enhanced by the ranking module's capacity to choose items according to contextual relevance and anticipated demand, as shown by a higher nDCG-K. In this module, BAT-optimized clustering, DenseNet121, and U-Net are combined, as illustrated in Equation (15) & Figure 8, which feature Normalized Discounted Cumulative Gain.

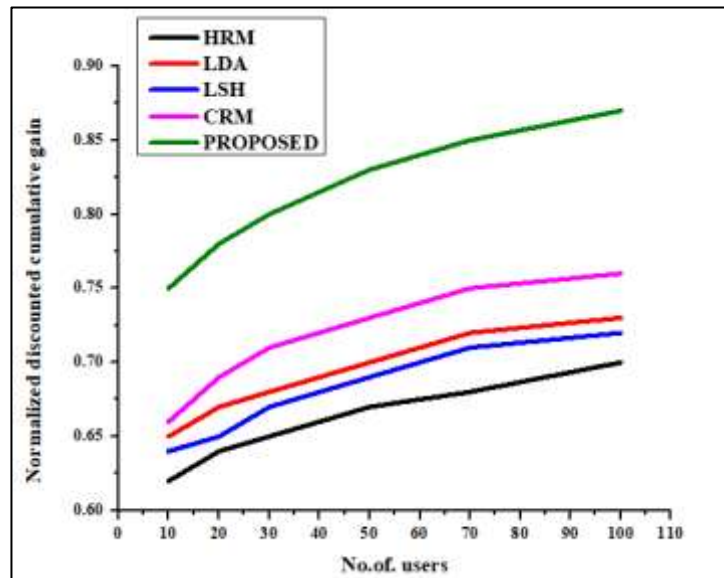


Figure 8: Normalized Discounted Cumulative Gain.
Source: Authors, (2026).

V. CONCLUSIONS

The Hybrid Machine Learning and Nature-Inspired Optimization framework for robust and accurate product recommendations has demonstrated its potential to overcome key limitations of traditional recommendation systems, including issues of high-dimensional noisy data, scalability, cold-start problems, and sub-optimal ranking. By integrating feature extraction techniques, clustering strategies, and metaheuristic optimization with advanced deep learning architectures, the framework achieves higher predictive accuracy, improved ranking quality, and better alignment with user preferences. The results confirm that combining ML/DL models with nature-inspired optimization not only enhances robustness and generalization but also ensures that recommendations are both context-aware and user-centric, making it suitable for a large-scale e-commerce environment. The long-term objective of this project is to improve the framework for complicated and dynamic recommendation situations. Real-time adaptive learning enables the system to adjust its recommendation methodologies in response to changing user behaviour and market trends. Multimodal data sources, including social interactions, product photos, and textual evaluations, may reveal deeper semantic links between things and people. Further research on federated and privacy-preserving learning algorithms may help deliver secure recommendations without compromising user data. Using cross-domain recommendations and explainable AI (XAI) techniques may increase real-world e-commerce system openness, trust, and adoption.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: V. Jenifer, T. Kamala Kannan.

Methodology: V. Jenifer, T. Kamala Kannan.

Investigation: T. Kamala Kannan.

Discussion of results: V. Jenifer, Dr. T. Kamala Kannan.

Writing – Original Draft: V. Jenifer.

Writing – Review and Editing: V. Jenifer, T. Kamala Kannan.

Resources: V. Jenifer.

Supervision: V. Jenifer, T. Kamala Kannan.

Approval of the final text: V. Jenifer, T. Kamala Kannan.

VII. ACKNOWLEDGEMENTS

The authors acknowledge the valuable contributions of all co-author for the collaboration and commitment in completing this work. We extend our sincere thanks to the editors and reviewers for their constructive comments and guidance, which have significantly improved the quality of the manuscript. We also acknowledge the publishers for providing the platform to present our research in this Scopus-indexed journal.

VIII. REFERENCES

- [1] E. Jin and M. S. Eastin, "Birds of a feather flock together: Matched personality effects of product recommendation chatbots and users," *Journal of Research in Interactive Marketing*, vol. 17, no. 3, pp. 416–433, 2023.
- [2] J. Chen, X. Gong, and R. Ren, "Active or avoidance coping? Influencing mechanisms of streamers' coping strategies on viewers' word of mouth after livestreaming e-commerce failures," *Journal of Retailing and Consumer Services*, vol. 72, p. 103278, 2023.
- [3] S. K. Jauhar, B. R. Chakma, S. S. Kamble, and A. Belhadi, "Digital transformation technologies to analyze product returns in the e-commerce industry," *Journal of Enterprise Information Management*, vol. 37, no. 2, pp. 456–487, 2024.
- [4] J. Shi, F. Shang, S. Zhou, X. Zhang, and G. Ping, "Applications of quantum machine learning in large-scale e-commerce recommendation systems: Enhancing efficiency and accuracy," *Journal of Industrial Engineering and Applied Science*, vol. 2, no. 4, pp. 90–103, 2024.

- [5] R. Venkatesan and A. Sabari, "DeepSentimental models: A novel hybrid deep learning model for effective analysis of ensembled sentiments in e-commerce and s-commerce platforms," *Cybernetics and Systems*, vol. 54, no. 4, pp. 526–549, 2023.
- [6] L. T. Khrais and D. Gabbori, "The effects of social media digital channels on marketing and expanding the industry of e-commerce within the digital world," *Periodicals of Engineering and Natural Sciences*, vol. 11, no. 5, pp. 64–75, 2023.
- [7] Z. Yuan, A. Y. Chen, Y. Wang, and T. Sun, "How recommendation affects customer search: A field experiment," *Information Systems Research*, vol. 36, no. 1, pp. 84–106, 2025.
- [8] C. Kagwa, "Effectiveness of artificial intelligence (AI) chatbots in improving customer satisfaction in e-commerce in Rwanda," *European Journal of Technology*, vol. 8, no. 4, pp. 13–24, 2024.
- [9] A. L. Karn et al., "Customer-centric hybrid recommendation system for e-commerce applications by integrating hybrid sentiment analysis," *Electronic Commerce Research*, vol. 23, no. 1, pp. 279–314, 2023.
- [10] S. Shashank and R. K. Behera, "Factors influencing recommendations for women's clothing satisfaction: A latent Dirichlet allocation approach using online reviews," *Journal of Retailing and Consumer Services*, vol. 81, p. 104011, 2024.
- [11] L. T. Khrais, M. Zorgui, and H. M. Aboalsamh, "Harvesting the digital green: A deeper look at the sustainable revolution brought by next-generation IoT in e-commerce," *Periodicals of Engineering and Natural Sciences*, vol. 11, no. 6, pp. 5–13, 2023.
- [12] I. Ullah et al., "Revolutionizing e-commerce with consumer-driven energy-efficient WSNs: A multi-characteristics approach," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 4, pp. 6871–6882, 2024.
- [13] D. Li and J. A. Esquivel, "Accuracy-enhanced e-commerce recommendation based on deep learning and locality-sensitive hashing," *Wireless Networks*, vol. 30, no. 9, pp. 7305–7320, 2024.
- [14] K. S. Kyaw, P. Tepsongkroh, C. Thongkamkaew, and F. Sasha, "Business intelligence framework using sentiment analysis for smart digital marketing in the e-commerce era," *Asia Social Issues*, vol. 16, no. 3, p. e252965, 2023.
- [15] Y. J. Purnomo, "Digital marketing strategy to increase sales conversion on e-commerce platforms," *Journal of Contemporary Administration and Management (ADMAN)*, vol. 1, no. 2, pp. 54–62, 2023.
- [16] "E-commerce data dataset," Kaggle. [Online]. Available: <https://www.kaggle.com/datasets/carriel/ecommerce-data>