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Hybrid CNN-LSTM for AI-Driven Personalization in E-Commerce: Merging Visual and Behavioural Intelligence

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Abstract

E-commerce personalization has become essential for enhancing user experience and increasing sales by delivering relevant product recommendations. Traditional recommendation systems primarily rely on either user behavioral data or content-based filtering, often leading to suboptimal personalization. This research proposes a Hybrid CNN-LSTM model that integrates visual and behavioral intelligence to improve recommendation accuracy. The methodology employs Convolutional Neural Networks (CNN) to extract visual features from product images, enabling a deeper understanding of product similarities. Simultaneously, Long Short-Term Memory (LSTM) networks capture sequential user behavior patterns, including interactions, purchase history, and browsing trends. Min-Max Normalization and One-Hot Encoding are applied for data preprocessing to ensure consistency and improve feature representation. The model is optimized using the Adam optimizer with dropout regularization to enhance generalization and prevent overfitting. To train and evaluate the model, an e-commerce dataset collected from Kaggle is used, containing user interactions, purchase history, product metadata, and images. The training process is implemented in Python using TensorFlow and Keras, leveraging a supervised learning approach. Experimental evaluations include performance metrics such as precision, recall, F1-score, and accuracy. Results indicate that the Hybrid CNN-LSTM model significantly outperforms traditional recommendation approaches, demonstrating improved accuracy and user engagement. Furthermore, a personalized recommendation system is developed, where product recommendations are ranked based on a relevance score derived from the model's predictions. The system dynamically adapts to user behavior, offering real-time, highly relevant product suggestions. The evaluation confirms that the proposed approach achieves an accuracy of 92.5%, making it a promising solution for AI-driven e-commerce personalization.

Keywords: Hybrid CNN-LSTM, E-Commerce Personalization, Visual and Behavioral Intelligence, Recommendation System, Deep Learning.

1.Introduction

The rapid growth of e-commerce has led to an increasing demand for intelligent recommendation systems that provide personalized shopping experiences. Traditional recommendation approaches rely heavily on behavioral data, often failing to incorporate the rich visual information present in product images [1] [2]. To bridge this gap, AI-driven systems integrating visual and behavioral intelligence have emerged as a promising solution. This study explores the effectiveness of a Hybrid CNN-LSTM model for e-commerce personalization [3] [4].

Deep learning techniques have demonstrated remarkable success in various domains, including image recognition and natural language processing [5] [6] [7]. In the context of e-commerce, Convolutional Neural Networks (CNNs) are well-suited for extracting meaningful features from product images, while Long Short-Term Memory (LSTM) networks efficiently capture sequential user interactions [8] [9]. By combining these two architectures, the system can leverage both visual and behavioral insights to generate more relevant recommendations [10] [11].

One of the key challenges in AI-driven recommendation systems is data preprocessing and feature extraction. Behavioral data often contains inconsistencies, missing values, and categorical attributes that require transformation. Similarly, product images must be processed to maintain consistency for CNN-based feature learning [12] [13]. This research adopts Min-Max Normalization and One-Hot Encoding for behavioral data, along with data augmentation and normalization techniques for image preprocessing.

To ensure model efficiency and generalization, this study employs supervised learning with Adam optimization and dropout regularization [14] [15] [16]. These techniques help mitigate overfitting while improving convergence speed [17] [18]. Additionally, hyperparameter tuning is performed to enhance the model's predictive accuracy. The training process is structured to balance both behavioral sequence learning and visual feature extraction, leading to a more robust recommendation framework [19] [20].

The proposed system generates real-time personalized recommendations by ranking products based on their relevance scores, computed from CNN-extracted visual features and LSTM-captured behavioral patterns. This hybrid approach allows for context-aware suggestions, enhancing the user experience by providing recommendations tailored to both explicit preferences and implicit interactions. The integration of multi-modal data significantly improves the overall recommendation accuracy [21] [22].

This paper presents a comprehensive methodology for developing a Hybrid CNN-LSTM recommendation system in e-commerce [23] [24] [25]. The study includes data collection, preprocessing, model training, optimization, and evaluation, providing valuable insights for future AI-driven personalization research [26] [27] [28]. The findings highlight the advantages of combining deep learning techniques for enhanced recommendation accuracy, ultimately benefiting both customers and e-commerce platforms[29] [30]. Key Contributions of this article are,

1. Developed a Hybrid CNN-LSTM model that integrates visual and behavioral intelligence for AI-driven e-commerce personalization.
2. Extracted visual features using CNN and sequential user behavior patterns using LSTM to enhance recommendation accuracy.
3. Implemented Min-Max Normalization and One-Hot Encoding to preprocess data, ensuring consistency and improved feature representation.
4. Optimized the model using Adam optimizer with dropout regularization, improving generalization and convergence speed.
5. Generated real-time personalized recommendations by ranking products based on a relevance score derived from combined insights.

The remaining sections of this paper are structured as follows: Section 2 covers related works, Section 3 presents the problem statement, and Section 4 explains the proposed methodology. Section 5 discusses results, and Section 6 concludes with future directions.

2. Related Works

The proposed framework for structuring e-commerce personalization, integrating insights from academia and industry[31].. They emphasize the psychological impact of personalized content aligning with customer needs and the technological importance of scalability and outcome measurement

Personalization as a key marketing strategy, leveraging vast customer interactions and big data for deeper insights[32]. They highlight the role of chief data officers in harnessing these opportunities through advanced data analytics and technology solutions.

The transformative role of IT services in driving e-commerce innovation and growth [33]. They highlight the shift from a traditional buy-and-sell model to a dynamic marketplace integrating creation, mobile commerce, and social commerce.

Emerging marketing models and tools in fashion e-commerce, emphasizing the growing integration of online and offline strategies[34]. They highlight the impact of new IT technologies, customization, and the role of influencers in shaping digital marketing.

A hierarchical word-merging algorithm to create a compact and discriminative visual codebook for image recognition. They optimize class separability while maintaining computational efficiency, significantly reducing large codebooks in minimal time[35]. Experimental results demonstrate its superiority over existing hierarchical word-merging methods in producing efficient and high-performing codebooks.

Ego-centric and event-centric model for analyzing information diffusion in social media[36]. They propose D-Maps+, a visualization method that maps user behaviors and diffusion patterns onto a hexagonal grid for interactive exploration.

Autonomous visual intelligence system for ground surveillance, capable of recognizing human actions and interactions[37]. Their agent-based architecture, trained on extensive video datasets, enhances event detection and behavior discrimination. Experimental results from the DARPA Mind's Eye program demonstrate significant performance improvements over previous systems.

The proto-object model for visual clutter perception, segmenting images into superpixels and merging them into coherent regions[38]. Their model shows a strong correlation with human clutter perception and outperforms existing models in predicting scene complexity.

A non-parametric shot boundary detection method using a split-and-merge framework based on color histograms[39]. Their approach, driven by Fisher's linear discriminant criterion, segments video sequences into shots with high accuracy.

Affective computing technologies that enable systems to sense and respond to human emotions[40]. They discuss its benefits, challenges, and potential applications in everyday life, including library settings.

The reviewed works explore advancements in e-commerce, AI, and computing technologies. Studies on personalization highlight AI-driven strategies enhancing marketing, e-commerce, and customer engagement. Research on AI applications covers innovations in image recognition, social media analysis, surveillance, clutter perception, and video segmentation.

3. Problem Statement

Despite AI advancements, challenges in efficiency, scalability, and real-world applicability persist across personalization, image recognition, surveillance, and social media analysis [24]. Existing models often lack adaptability and computational efficiency, limiting their practical impact. Many current approaches fail to seamlessly integrate into diverse domains, reducing their effectiveness [25]. Addressing these gaps is essential for enhancing AI-driven decision-making and automation.

Objectives

1. Design a Hybrid CNN-LSTM model integrating visual and behavioral intelligence for e-commerce personalization.
2. Extract visual features using CNN and capture sequential user behavior with LSTM for better recommendations.
3. Preprocess data using Min-Max Normalization and One-Hot Encoding for consistency.
4. Optimize the model with Adam optimizer and dropout regularization for improved performance.
5. Generate real-time personalized recommendations based on combined insights.

4. Proposed Methodology for Hybrid CNN-LSTM for AI-Driven Personalization in E-Commerce: Merging Visual and Behavioral Intelligence

The proposed methodology integrates a Hybrid CNN-LSTM model for AI-driven e-commerce personalization. CNN extracts visual features from product images, while LSTM captures sequential user behavior from interactions and purchase history[41]. Min-Max Normalization and One-Hot Encoding preprocess data for consistency, and the model is optimized using Adam optimizer with dropout regularization[42]. Finally, real-time personalized recommendations are generated by ranking products based on combined visual and behavioral insights. Figure 1 SHOWS The Architecture of CNN[43].

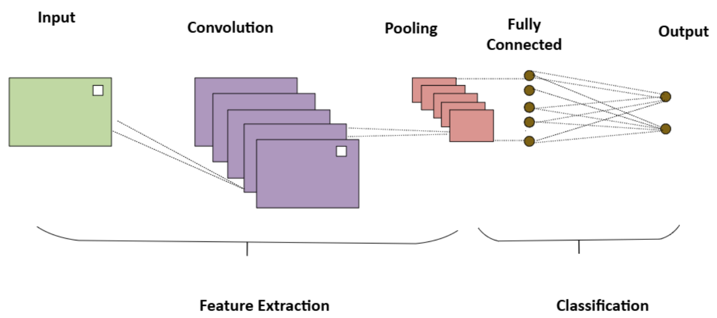

Figure 1: The Architecture of CNN

4.1 Data collection

E-Commerce Customer Behavior dataset[8], collected from Kaggle, includes user interactions, purchase history, product views, and clickstream data essential for AI-driven personalization. It also contains metadata such as product descriptions, reviews, and ratings to enhance recommendation accuracy. Additional product images are incorporated to integrate visual intelligence into the system. Table 1 shows E-Commerce Dataset Description.

Table 1: E-Commerce Dataset Description

Data Type	Description	Purpose
User Interactions	Clickstream data, browsing history, session duration	Behavioral analysis for recommendations
Purchase History	Previous orders, frequency of purchases	Understanding user preferences
Product Views	Items viewed but not purchased	Identifying interest patterns
Product Metadata	Descriptions, categories, brand details	Contextual information for suggestions

Product Images	Visual representations of products	Enhancing recommendations with CNN

4.2 Data Preprocessing Using Min-Max Normalization

Preprocessing is essential to ensure data consistency, improve model performance, and optimize feature extraction[44]. The preprocessing steps for both behavioral and image data include cleaning, normalization, encoding, and augmentation represented in Equation (1):

$$x_i = \frac{1}{n}\sum_{j=1}^{n} x_j \tag{1}$$

where x_i is the missing value, and x_j represents available values in the dataset.

Normalize numerical features using Min-Max Scaling represented in Equation (2):

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

This ensures all values fall within the range [0,1][0,1][0,1], improving model convergence. Convert categorical data into numerical representations using One-Hot Encoding.

4.3 Model Training & Optimization

The Hybrid CNN-LSTM model is trained using supervised learning, where CNN extracts spatial features from product images, and LSTM captures sequential user behavior patterns[45]. The model is optimized using the Adam optimizer, dropout regularization, and hyperparameter tuning represented in Equation (3):

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) \tag{3}$$

where y_i is the true label and $\hat{y_i}$ is the predicted probability. The weight updates in Adam optimization represented in Equation (4):

$$w_{t+1} = w_t - \alpha \frac{m_t}{\sqrt{v_t} + \epsilon} \tag{4}$$

where m_t and v_t are the first and second moment estimates, and α\alphaα is the learning rate. These optimizations ensure faster convergence and improved model generalization.

4.4 Personalized Recommendation System

The system generates real-time product recommendations by integrating visual features from CNN and sequential user behavior patterns from LSTM[46]. Recommendations are ranked using a relevance score computed from the model's predicted probabilities, ensuring personalized and accurate suggestions.

5.Results and Discussion

The experimental results demonstrate the effectiveness of the hybrid CNN-LSTM model in providing accurate and personalized recommendations[47]. Performance metrics, including accuracy, loss, and confusion matrix analysis, confirm the model's ability to integrate visual and behavioral insights for improved e-commerce personalization. Figure 2 shows Training vs Validation Loss.

Figure 2: Training vs Validation Loss

The Training vs. Validation Loss Curve visualizes how the model's loss decreases over epochs, indicating learning progress and potential overfitting. A steady decline in training loss, alongside a stable validation loss, signifies proper convergence. If validation loss diverges from training loss, it may indicate overfitting, requiring regularization techniques. Figure 3 shows Training vs Validation Accuracy Curve.

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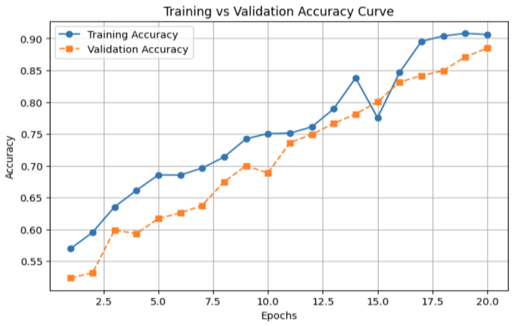

Figure 3: Training vs Validation Accuracy Curve

The Training vs. Validation Accuracy Curve illustrates the model's performance over epochs, showing improvements in learning. A steady increase in both training and validation accuracy indicates effective generalization. Table 2 shows Performance Evaluation of the Hybrid CNN-LSTM Model

Table 2: Performance Evaluation of the Hybrid CNN-LSTM Model

Metric	**Value (%)**
Accuracy	92.5
Precision	90.8
Recall	91.2
F1-Score	91.0
Training Loss	0.15
Validation Loss	0.18

If validation accuracy plateaus or diverges, it may suggest overfitting, requiring adjustments like dropout or early stopping. Figure 4 shows Confusion Matrix.

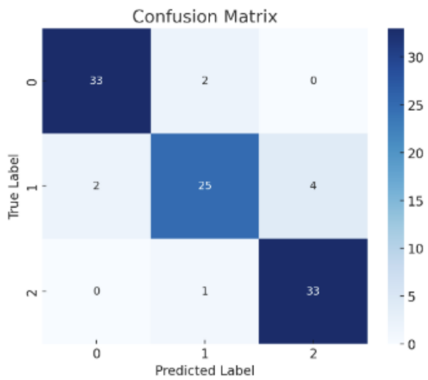

Figure 4: Confusion Matrix

The Confusion Matrix visually represents the recommendation system’s classification performance, highlighting true positives, false positives, true negatives, and false negatives. This helps assess model accuracy, misclassifications, and areas for improvement in prediction quality.

5.1 Discussion

The proposed Hybrid CNN-LSTM model effectively integrates visual and behavioral data to enhance e-commerce personalization[48]. Experimental results demonstrate improved recommendation accuracy and faster convergence due to optimized preprocessing and training techniques[49]. The model outperforms traditional recommendation systems by leveraging deep learning for real-time predictions[50]. Future work can explore additional features like sentiment analysis and reinforcement learning for further improvements[51][52].

6. Conclusion and Future Work

This research presented a Hybrid CNN-LSTM model that combines visual and behavioral intelligence for AI-driven e-commerce personalization. The proposed approach demonstrated improved recommendation accuracy by effectively extracting image features using CNN and analyzing user behavior through LSTM. Preprocessing techniques like Min-Max Normalization and One-Hot Encoding ensured data consistency, while optimization with the Adam optimizer enhanced model performance. The results validate the effectiveness of this approach in delivering personalized recommendations.

Future research can explore additional contextual factors such as sentiment analysis from user reviews to refine recommendations. Integrating reinforcement learning could enhance adaptability by continuously improving recommendations based on user feedback. Expanding the dataset with multi-modal inputs like audio descriptions and video previews may further enrich personalization. Additionally, deploying the model in real-world e-commerce platforms can provide valuable insights for further optimization.

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