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Bidirectional LSTM for Electronic Product Recommendation

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Abstract: In today's retail landscape, the surge of online e-commerce platforms, especially in the electronics sector, has become ubiquitous, presenting a significant challenge of guiding customers towards relevant items. The proposed system addresses this challenge by leveraging Bidirectional LSTM neural network models, which offer more accuracy than traditional collaborative and content-based filtering methods, to deliver precise recommendations tailored to individual user preferences. Integration of speech technology enhances user interaction by vocalizing recommended products, thereby enhancing the overall user experience. The system's use of advanced algorithms such as Bidirectional LSTM for recommendation not only enables businesses to make informed decisions but also enhances their product offerings, ultimately helping them to stay competitive in the e-commerce landscape. Overall, Recommendation Systems for User Satisfaction revolutionize e-commerce by simplifying decision-making, enhancing satisfaction, and driving sales through personalized product suggestions and seamless user interaction. Having recommendation systems that are focused on user satisfaction in a way that they not only completely change the e-commerce setting but also show changes in the online business' approach to their customers is an interesting way to look at it. One of the most critical aspects of this system is that it not only caters to the user's needs but also uses advanced algorithms to get them better services, thus, the system makes it possible for us to improve our decision-making skills and better the customer experience in the quickly changing online retail.

Keywords: Recommendation System, CF,CBR, Bidirectional LSTM, Speech Technology, consumer behavior

1 Introduction

E-commerce platforms play a pivotal role in contemporary retail by granting consumers behavior access to various products. These platforms oversee the digital framework essential for facilitating online shopping experiences. They have revolutionized purchasing and selling electronic items, presenting consumers with a comprehensive range of options from diverse brands and categories [1]. The extensive array of choices available poses a significant challenge in decision-making and decreases user satisfaction. Nevertheless, e-commerce platforms play a pivotal role in contemporary retail by facilitating unparalleled access to diverse products and managing the essential digital infrastructure for online shopping. Various challenges, such as the cold start problem, sparsity, and scalability, present impediments to the efficacy of recommendation systems. Utilizing Bidirectional Long Short-Term Memory (LSTM) recurrent neural networks, along with

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deep attention layers for semantic ranking and cosine similarity for recommendation, has demonstrated remarkable accuracy compared to traditional approaches like Collaborative Filtering (CF) and Content-Based Filtering (CBF). This technology empowers businesses to make well-informed decisions, optimize pricing strategies, enhance product offerings, and ensure competitiveness in the ever-evolving e-commerce landscape. These advanced techniques involve multiple stages, from creating interactive map matrices to improving ranking using LSTM, utilizing evaluation metrics like mean absolute error (MAE), root mean square error (RMSE), and accuracy to validate the approach [2]. Overall, Recommendation Systems help users recommend interesting items, simplify decision-making by reducing options, explore the option space, find new items, and provide entertainment. For providers, it ensures unique personalized service, delivers distinctive personalized experiences, enhances user confidence and loyalty, drives up item sales, creates opportunities for promotional activities, and obtains insights into user behaviors and preferences [3]. Integrating BiLSTM technology in recommendation systems represents a significant advancement in e-commerce, offering enhanced accuracy, personalization, and user satisfaction. Businesses can tap into new growth, innovation, and success in the digital marketplace by leveraging the potential of deep learning.

Benefits for the users
Recommend items that are interesting to them.

– Simplify decision-making by reducing option.
– Explore the option space.
– Find new items.
– Provide entertainment.

Benefits for Providers
Ensure unique personalized service for the users.

– Deliver the distinctive personalized experiences for users.
– Enhance user confidence and loyalty.
– Drive up item sales.
– Opportunities for promotional activities.
– Obtain insights into user behaviors and preference

1.1 Problem Statement

In the rapidly expanding e-commerce realm, particularly within the electronics sector, traditional recommendation systems struggle with scalability, sparsity, and cold-start issues, resulting in suboptimal product suggestions and user dissatisfaction. There is a critical need for an advanced recommendation system to accurately analyze user behavior, adapt to dynamic product landscapes, and provide personalized suggestions to alleviate decision fatigue and enhance the shopping experience [4]. Developing a sophisticated recommendation system necessitates a comprehensive analysis of user behavior and the flexibility to adapt to rapid shifts in the electronics market. The proposed system seeks to leverage Bidirectional LSTM networks, renowned for their ability to capture intricate patterns in sequential data, in order to offer precise and context-aware product recommendations. Additionally, incorporating vocalization capabilities is poised to improve accessibility, thereby enhancing users' intuitiveness and engagement in the shopping experience. These enhancements not only aim to elevate user satisfaction but also to foster enduring customer loyalty. By empowering users to make informed purchasing decisions and mitigating decision fatigue, the system endeavors to drive increased conversion rates and secure a competitive advantage in online electronics retail.

2 Model Selection Process for Deployment

2.1 Algorithms Utilized:

– Collaborative Filtering(CF).
– Content-Based Filtering(CBF).
– BiLSTM (Bidirectional Long Short-Term Memory) Model.

Collaborative Filtering(CF)
Collaborative Filtering (CF), or social filtering, is a robust technique employed in recommender systems to provide personalized suggestions to users. The process encompasses three fundamental stages: data collection, neighbor selection, and prediction. Initially, the system aggregates user ratings on diverse items to establish a user-item rating matrix. Leveraging this matrix, the system identifies analogous users or items by computing similarities. In the prediction stage, the system anticipates rating scores for unrated items and ranks them accordingly, ultimately selecting the top-N items as recommendations for each user. The fundamental tenet of CF is that users with similar preferences in the past are inclined to possess akin interests in the future. CF provides recommendations by scrutinizing user preferences and discerning resemblances with other users [5]. It examines user's historical interactions with items, such as purchases or ratings, and contrasts these with the selections made by other users. Subsequently, the system forecasts items that may captivate the user based on these patterns. Fig. (1) demonstrates that when both customer A and customer B purchase a laptop and a speaker, the system identifies their shared interests. As customer B continues to shop, they will be provided with recommendations based on the preferences and shopping history of customer A. The system acknowledges familiar tastes among consumers and utilizes this information to generate product recommendations.

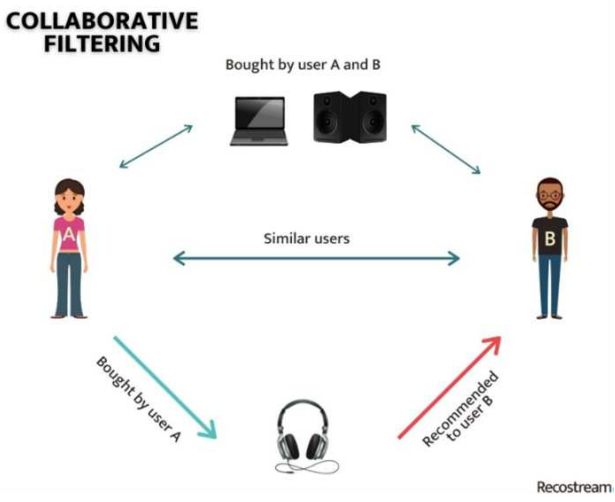

Figure 1: Collaborative Filtering.

Collaborative Filtering (CF) comprises two primary methods: item-based and user-based. Item-based systems establish connections between items using user-item matrices, while user-based systems suggest items based on similar users' preferences. CF systems are renowned for their simplicity, efficiency, and accuracy. However, they encounter challenges like cold start problems, scalability issues, and data sparsity.

a. User-Based Collaborative Filtering: This method identifies users with similar preferences and recommends items liked by those users to the target user. It measures user similarity using techniques such as Pearson correlation, cosine similarity, or Jaccard similarity.

b. Item-Based Collaborative Filtering: This approach measures similarity between items instead of users. It identifies items similar to those the user has previously interacted with and recommends them. Item-based collaborative filtering is often more scalable than user-based methods.

Benefits of Collaborative Filtering

–Simplified Implementation: Creating a recommendation system is straightforward.
–Ease of Adding New Data: New information can be incrementally added by anyone.
–Improved Prediction Performance: Accuracy of recommendations is enhanced.

Limitations of Collaborative Filtering

–An extensive dataset is essential for making precise recommendations.
–The computational capacity required by the system is substantial to effectively manage the enormous volume of data produced continuously by many devices and gadgets.
–In an online retail setting, the system's effectiveness is compromised when many items become unavailable, thereby limiting the number of rated items.

Content-Based Recommendation System (CBR): Content-based recommendation (CBR) systems leverage item descriptions and user profiles to provide personalized suggestions based on user preferences. In contrast to collaborative filtering, which relies on user interactions with items, CBR centers on item attributes and user profiles to identify similarities and propose relevant items. This methodology entails evaluating item features and user preferences to create recommendations aligned with the user's interests [6,7]. Content-Based Filtering (CBF) constitutes a recommender system approach that recommends items to users based on their preferences and attributes. It employs a user-item matrix to depict interactions and computes similarity scores between user profiles and item attributes. For example, cosine similarity is a prevalent measure utilized to quantify the similarity between two vectors representing user profiles and item features. Recommendations produced by CBF are tailored to each user's specific interests to elevate user satisfaction. However, CBF may encounter challenges when recommending diverse or novel items and heavily relies on the quality and relevance of item attributes. Despite these limitations, CBF finds widespread application in domains such as e-commerce, content streaming, and news aggregation, supplementing recommendation techniques like collaborative filtering [8].

Automatic Updating of User Profiles: These systems automatically update user profiles and make recommendations by comparing them with previously rated items by the user. They provide personalized suggestions without facing data sparsity or cold start problems. However, the effectiveness of these systems depends on the completeness and accuracy of the existing user data. Netflix and YouTube are examples of platforms that utilize content-based filtering for their recommendation systems. They analyze user interactions with videos (referred to as "items") and recommend new content based on the attributes and features of previously watched videos [9].

This approach enhances user engagement by delivering personalized content recommendations tailored to individual preferences. By concentrating on item attributes and user preferences, content-based recommendation systems contribute to a more enriched user experience across various digital platforms.

Fig. (2) demonstrates that when a viewer interacts with videos evaluating electronic gadgets, the suggested videos segment will contain additional content related to technological advancements. The content-based filtering mechanism collects data regarding the user's watched content and proposes similar-themed content based on shared characteristics.

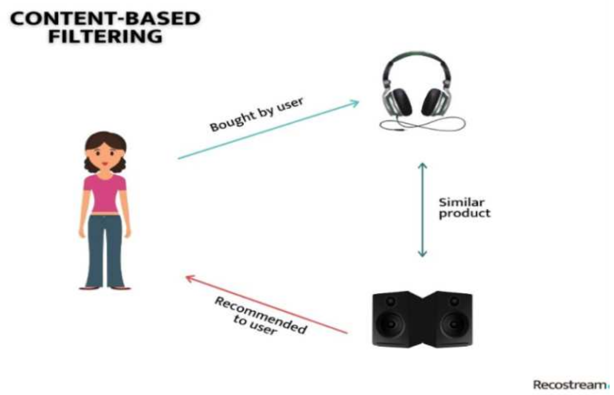

Figure 2: Content-Based Filtering.

Content-based recommendations function on the assumption that if users enjoy a specific product or content, they are likely to appreciate other items possessing similar attributes. This method examines item attributes within a dataset to align specific products with individual user preferences and interests.

Benefits of Content-based Filtering

– The model functions autonomously without relying on information about other users, emphasizing the preferences and actions of the specific user. This attribute enables the model to be scalable to a wide user base.
– Content-based filtering is particularly effective in suggesting specialized or niche items that closely match the distinct preferences of individual users, even if these preferences are not widely popular.

Limitations of Content-based Filtering

– Content-based filtering depends on manually crafted features describing item attributes, requiring substantial domain expertise for effective feature representations. Consequently, its performance is limited by the quality and appropriateness of these engineered features.
– Content-based filtering relies on manually crafted features to describe item attributes, requiring a significant domain expertise to generate valuable feature representations. Consequently, the system's efficacy is constrained by the quality and relevance of these meticulously created features.

Bidirectional LSTM The BiLSTM model, a deep learning approach, is widely utilized in recommendation systems due to its ability to comprehend sequential user behavior. In contrast to traditional models, BiLSTM analyzes data in forward and backward directions, enabling the capture of both past and future dependencies simultaneously. This capability makes it well-suited for tasks such as sequence prediction and recommendation [10]. By examining user interactions over time, BiLSTM generates tailored recommendations, effectively anticipating user preferences. Its proficiency in capturing long-range dependencies and adjusting to varying input lengths renders it adaptable for modeling complex user behaviors. Ultimately, BiLSTM enriches recommendation systems by leveraging sequential patterns to deliver precise and pertinent recommendations.

In a Bidirectional LSTM network, the input sequence is processed by two distinct LSTM layers: one handles the input sequence in its original order, while the other processes it in reverse order. These two LSTM layers' outputs are combined to produce the final output sequence [11]. This bidirectional processing enables the capture of dependencies from past time steps and future time steps, resulting in a more comprehensive understanding of the sequential data. This bidirectional approach assists the model in capturing long-term dependencies and temporal patterns in the user behavior data, leading to enhanced recommendation performance.

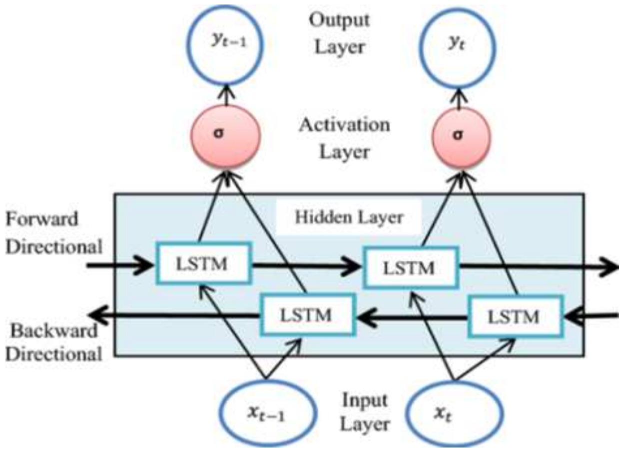

Figure 3: Bidirectional LSTM.

Fig. (3) shows the Bidirectional Long Short-Term Memory (BiLSTM) model comprises two distinct LSTM layers, one handling the input sequence's forward progression in time and the other managing the backward progression. This bidirectional approach enables the model to access information from preceding and subsequent contexts, thereby enhancing its capacity to grasp dependencies and make precise predictions [12]. The model involves input and bidirectional LSTM output layers, which can be supplemented with additional optional layers to improve its performance. By processing sequential user behavior data in a bidirectional manner, the Bidirectional LSTM model generates personalized product recommendations, thus enhancing the overall user experience within the recommendation system through its ability to make accurate predictions and capture dependencies from past and future contexts.

2.2 MODEL EVALUATION

Model evaluation is crucial to analyzing a Machine Learning model's performance in fulfilling its intended task. Evaluation metrics consist of statistical measures utilized to evaluate the performance of a model or algorithm. They offer valuable insights into the model's accuracy and root mean squared error, comprehensively assessing its effectiveness.

Accuracy: Accuracy is a widely used metric for assessing classification models, quantifying the percentage of correctly classified instances out of the total. While accuracy offers a broad assessment of the model's performance, it may not be ideal for datasets with imbalances in class distribution. Accuracy plays a role in evaluating the overall correctness of the model's recommendations in recommendation systems.

Root Mean Squared Error (RMSE): The Root Mean Square Error (RMSE) is a widely utilized metric for assessing regression models within the field. It quantifies the square root of the mean of the squared variances between forecasted and observed values [13,14]. Notably, RMSE assigns greater weight to larger errors than Mean Absolute Error (MAE), rendering it more attuned to outliers. RMSE measures the typical prediction error, with lower values indicating better model performance. In recommendation systems, RMSE can help assess the accuracy of predicted ratings or scores for recommended items, providing insights into the model's predictive capabilities.

Lower RMSE values indicate better predictive performance, enhancing user satisfaction and engagement with the recommendation platform.

Fig. (4) shows that the BiLSTM algorithm's accuracy of 89 % stands out as the preferred choice for constructing the recommendation model, surpassing Collaborative Filtering (78%) and Content-Based Filtering (80%). Additionally, Lower RMSE values, such as BiLSTM 0.31, signify better predictive precision compared to Collaborative Filtering (0.54) and Content-Based Filtering (0.49), indicating superior performance. The effectiveness of BiLSTM in capturing complex user-item interactions highlights its ability to provide highly accurate and dependable personalized recommendations tailored to individual preferences [15].

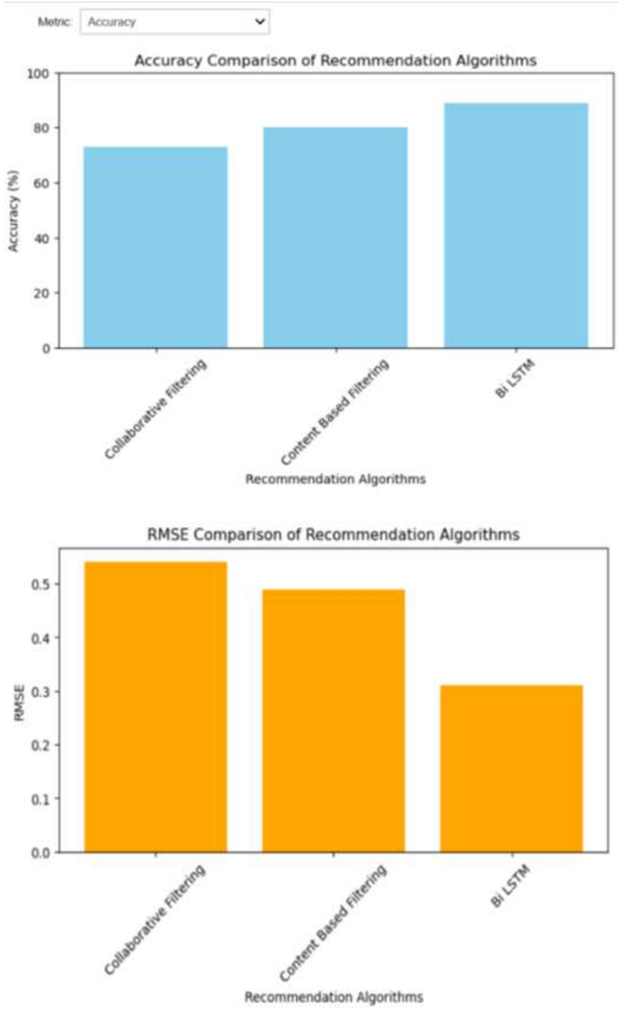

Figure 4: Metrics.

Table 1: Model Accuracy

Algorithm	Accuracy
Collaborative Filterring	78%
Content Based Filtering	80%
BiLSTM	89%

2.3 Comparison of Algorithms

Based on the comparison of it is evident that BiLSTM, boasting an impressive accuracy rate of 89%, emerges as the most fitting choice for constructing the recommendation model. BiLSTMs are adept at capturing intricate relationships within product data, thus offering more precise and tailored recommendations compared to traditional methods such as Collaborative Filtering and Content-Based Filtering. By harnessing the power of BiLSTM in the recommendation model, e-commerce platforms can elevate their recommendation performance, thereby driving increased sales and elevating customer satisfaction.

3 Feasibility Study

3.1 Dataset Preparation:

The dataset contains 2000 instances of electronic products, encompassing user interactions such as ratings, purchase history, and browsing behavior.

3.2 Dataset Division:

The dataset is segregated into training and test data. The training set is utilized to instruct the model, enabling it to comprehend known outcomes and patterns within the data. The test dataset is retained to evaluate the model's performance and functions as a standard to gauge its effectiveness in recommending products to users [16].

3.3 Bidirectional LSTM (BiLSTM)

The recommendation model Bidirectional LSTM (BiLSTM) is structured by preprocessing the dataset to extract pertinent features and encode categorical variables. The model's architecture comprises bidirectional LSTM cells to capture sequential patterns and temporal dependencies in user-product interactions from both past and future data [17].

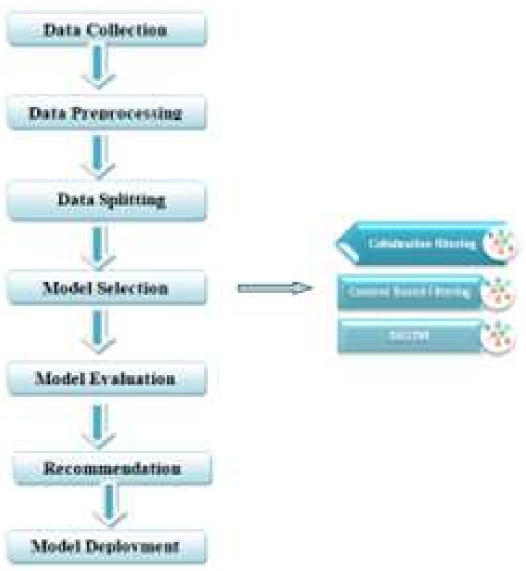

Figure 5: Process Flow.

This flow explains the procedure encompassing the acquisition of data, training of a BiLSTM algorithm using the amassed dataset, evaluating its performance, and ultimately utilizing it for product recommendation.

4 Methodology

4.1 Model Architecture:

The selection of a suitable model architecture plays a pivotal role in determining the effectiveness of the recommendation system in capturing intricate user-item interactions and generating precise recommendations. The BiLSTM model architecture is specifically crafted to efficiently capture temporal dependencies in user behavior and generate personalized recommendations [18]. This model consists of two Bidirectional LSTM layers, each comprising 64 hidden units, enabling it to process input sequences in both forward and backward directions. Such an architecture empowers the model to apprehend intricate sequential patterns in user-item interactions, amplifying its capacity to generate accurate recommendations [19]. The construction of the model encompasses:

Input Layer The initial stage in the model is the Input Layer, which is tasked with obtaining the input data. This data includes product name, category, user ID, and ratings. Prior to being transmitted to the subsequent layer, these attributes undergo encoding and preprocessing.

Bidirectional LSTM Layers The fundamental component of the model is the Bidirectional LSTM Layers, which comprise numerous stacked layers. These layers process the input sequences bidirectionally, capturing information from both past and future contexts [20,21]. They identify patterns and connections in user-product interactions, considering factors such as the product name, category, and user preferences.

Fully Connected Layer This layer consolidates information from the LSTM outputs and extricates pertinent features, thereby generating recommendations based on the acquired patterns and insights from the sequential data.

Output Layer The ultimate layer in the model is the Output Layer, which is responsible for generating predictions based on the processed sequential data. In this instance, the model makes predictions regarding the category of products that users are likely to find interesting. The output is produced using softmax activation, which produces probabilities for each product category, facilitating users' informed purchase decisions.

The Bidirectional LSTM (BiLSTM) model processes input sequences bidirectionally to capture patterns in user-product interactions. Following the Bidirectional LSTM layers, the model employs softmax multiclass classification in the output layer to generate predictions. These forecasts represent probabilities for each product category, supporting the generation of recommendations.

4.2 Training the BiLSTM Model:

The BiLSTM model undergoes training using a dataset comprising 80% of the data and encompasses historical user-item interactions. Throughout this process, it acquires insights into interaction patterns and generates recommendations based on past behavior. Furthermore, it considers the category specifics of products to customize its recommendations. The training procedure encompasses the following components: **Input Data:** The

```
# Train the model
model.fit(X_train, y_train, epochs=25, batch_size=64)
```

process involves utilizing training data that comprises users' historical interactions with items. **Epochs:** The model undergoes training over 25 epochs to iteratively adjust its parameters and enhance prediction accuracy. **Batch Size:** The training data is processed in batches to update the model's parameters efficiently.

4.3 Testing the BiLSTM Model:

Upon completing the training, the BiLSTM model undergoes evaluation using a distinct testing dataset, compromising the remaining 20% of the data, encompassing unseen user-item interactions. The testing procedure involves assessing the model's performance and predictive accuracy utilizing metrics like accuracy, root mean square, and mean absolute error. This assessment aids in gauging the model's efficacy in producing personalized recommendations and its capacity to generalize to new data.

4.4 Recommendation Generation:

Once the BiLSTM model has been trained and validated, it is deployed to produce personalized user recommendations. Utilizing users' historical interactions with items as input, the model forecasts the probability of their engagement with other items in the catalog [22,23]. The model generates a prioritized roster of recommended items customized to each user's preferences using these forecasts.

4.5 Integration with Speech Technology:

The recommendation system incorporates speech technology to vocalize recommendations, improving user experience and accessibility. This interactive functionality allows users to effortlessly receive personalized recommendations through voice commands, promoting engagement and enhancing users. The BiLSTM model employs sequential analysis of user-item interactions, including ratings, to produce personalized recommendations. By capturing patterns in both forward and backward directions, the model offers items customized to the user's preferences, as evidenced by the suggested LG Smart Hotel TV products [24]. This highlights its efficacy in delivering pertinent and personalized recommendations.

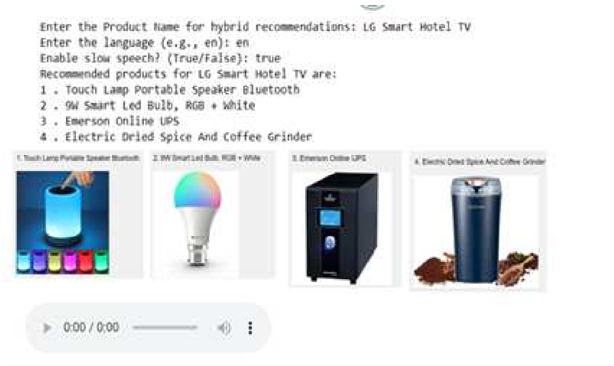

Figure 6: Recommended Products.

4.6 Model Deployment

Django Framework
The model is deployed using Django. Django is a high-level Python web framework that enables rapid application development and follows the Model-View-Template (MVT) architectural pattern [25, 26]. It simplifies web application development with features like an ORM for database modeling, views for request handling, and templates for dynamic HTML generation.

MVC Architecture: Django follows the Model-View-Controller (MVC) architectural pattern, but with slight modifications. It uses the Model-View-Template (MVT) pattern, where Django itself handles the controller's role.

Model: Models are Python classes that represent database tables. Django provides an ORM (Object-Relational Mapping) layer that allows you to define models using Python code and automatically generates the corresponding database schema.

View: Views are Python functions or classes that handle requests and return responses. They encapsulate the application's logic, fetching data from models, processing it, and passing it to templates for rendering.

Template: Templates are HTML files with embedded Django template language. They define the presentation layer of your web application and allow you to generate HTML content dynamically based on data provided by views.

URL Dispatcher: The Django framework employs a URL dispatcher to associate URLs with view functions or classes. URL patterns are specified in the project's URL configuration file, directing incoming requests to the appropriate view.

Admin Interface: Django offers a robust admin interface that automatically generates CRUD interfaces for models, facilitating data management without extra code.

Forms: Regarding data handling, Django provides forms for user input and data validation. It enables the creation of forms using built-in form classes, which automatically manage form rendering and validation error display.

Security: Django has built-in security features to safeguard against common web vulnerabilities, including SQL injection, cross-site scripting (XSS), cross-site request forgery (CSRF), and clickjacking.

Authentication and Authorization: Authentication and authorization are also strong points of Django, with robust mechanisms for user authentication and permissions access control.

Internationalization and Localization: Django further supports internationalization (i18n) and localization (l10n) for building multilingual websites, enabling the translation of text strings and formatting dates, times, and numbers according to different locales.

Scalability and Flexibility Django's scalability and flexibility empower recommendation systems to handle large volumes of data and seamlessly adapt to evolving user preferences. Its modular architecture allows for easy integration of additional features and algorithms.

Integration with Machine Learning Models: Jango seamlessly integrates with machine learning models, such as the Bidirectional Long Short-Term Memory (BiLSTM) model, to deploy and manage machine learning models within applications.

Dynamic Product Display: Django facilitates a dynamic product display interface and showcases the performance metrics of recommendation algorithms, such as accuracy, root mean square error (RMSE), and mean absolute error (MAE), to provide users with insights into the system's effectiveness and reliability.

Algorithm Performance Metrics: Django facilitates a dynamic product display interface and showcases the performance metrics of recommendation algorithms, such as accuracy, root mean square error (RMSE), and mean absolute error (MAE), to provide users with insights into the system's effectiveness and reliability.

Personalized Recommendations: Through voice-enabled interactions and user interactions on the front end, Django delivers personalized recommendations tailored to each user's preferences. It integrates advanced algorithms like BiLSTM to ensure highly relevant and accurate recommendations, thereby enhancing user engagement and satisfaction.

With Django, the recommendation system offers a dynamic product display interface. Users are presented with a list of recommended items upon selecting a product. Integrating images alongside product recommendations enhances the user experience, making it easier for individuals to visualize and explore the suggested products. Through voice-enabled interactions and user interactions on the front end, Django provides personalized recommendations tailored to each user's preferences. Integrating advanced algorithms like BiLSTM ensures that recommendations are highly relevant and accurate, thus improving user engagement and satisfaction.

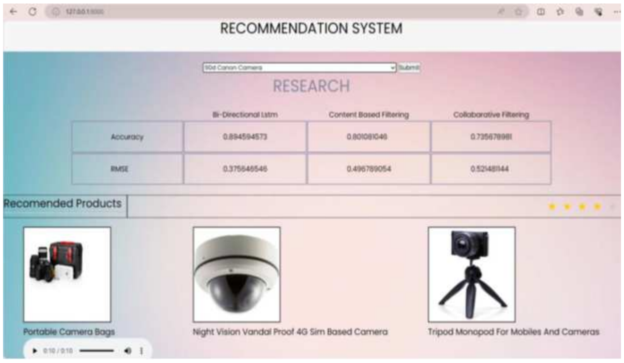

Figure 7: Model Deployed for Recommendation.

The Django-deployed model seamlessly provides recommendations for complementary products such as Portable Camera Bags, Night Vision, Vandal Proof 4G Sim-Based Camera, and Tripod Monopod for Mobiles and Cameras when a 90d Canon Camera is selected, thereby enhancing the user's shopping experience. Through voice-enabled interactions, personalized recommendations tailored to individual preferences are delivered, leveraging advanced algorithms like BiLSTM. These recommendations are supported by comprehensive metrics, demonstrating the superior performance of BiLSTM in generating relevant and accurate product suggestions.

5 Conclusion

Adopting Bidirectional Long Short-Term Memory (BiLSTM) models in recommendation systems represents a significant shift, offering exceptional capabilities in capturing sequential user interactions and providing highly personalized recommendations [27,28]. BiLSTM emerges as a crucial selection for recommendation systems owing to its enhanced capacity to capture temporal dynamics and offer customized recommendations. With an accuracy rate of 89%, BiLSTM exceeds traditional methods, such as content-based and collaborative filtering, effectively managing sparse data and learning from sequential interactions, resulting in more accurate and tailored recommendations [29,30]. Furthermore, integrating the vocalization of recommended products introduces an interactive dimension to the recommendation experience, enhancing user engagement and rendering the system more appealing. This approach optimizes product discovery, fosters a more interactive and engaging user experience, elevates customer satisfaction, and gains a competitive edge in the market, propelling continuous advancements in e-commerce platforms and revolutionizing how users interact with online recommendations. In the future, a fully voice-controlled recommendation system could enable users to interact and receive personalized recommendations seamlessly through voice commands, enhancing the user experience and convenience.

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Conflict of Interest:

The authors have no conflict of interest to declare.

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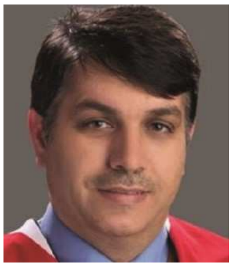

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