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An Efficient Deep Learning Framework for Real-Time Product Recommendation in E-Commerce

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Abstract

E-commerce platforms generate massive volumes of user-generated product reviews, making sentiment-aware recommendation systems essential for improving personalization and decision-making. This study aims to develop a high-performance real-time product recommendation framework by integrating sentiment analysis with deep learning techniques. The proposed method utilizes Amazon review data, which is preprocessed through feature extraction using TF-IDF, followed by class balancing using SMOTE. Accurate sentiment categorization in user evaluations is achieved by using a stacked LSTM-based DL model that captures contextual and sequential relationships. Accuracy, Precision, Recall, F1-score, and AUC-ROC measures are used for model evaluation after training using Binary Cross-Entropy loss and the Adam optimizer. Based on the experimental findings, the suggested model regularly beats more conventional ML models like Decision Tree, Logistic Regression, and Naïve Bayes, as well as other DL methods like RNN and DeepFM, with an accuracy rate of 98.42%. This study primarily contributes by enhancing the relevance of recommendations in real-time via the merging of balanced learning and sentiment-driven LSTM modeling. In conclusion, the framework provides a scalable, accurate, and robust solution for large-scale deployment in modern e-commerce systems.

Keywords: E-commerce, User Reviews, Product Recommendation, Sentiment Analysis, Deep Learning, LSTM, Amazon product review data.

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I. INTRODUCTION

In the current digital era where online shopping has become a significant aspect of our daily lives, the issue of product recommendations is critical in improving the overall shopping experience. With the wide range of products in the internet, customized recommendations assist the users in discovering new products based on their preferences and end up getting greater customer satisfaction and sales [1][2]. The significance of product recommendation systems has increased as a result of their ability to offer consumers personalized recommendations that are tailored to their preferences, purchasing behaviors, and perusing history. These technologies not only help consumers make decisions, but it also play an important role in generating income for e-commerce platforms [3]. However, creating and deploying such recommendation systems is a significant obstacle for smaller businesses entering the e-commerce market [4][5].

Traditional methods are very dependent on either explicit user ratings or similarity of items which in many cases give rise to the problems. AI, ML and NLP methods of improving the recommendation systems by allowing them to learn independently of human interactions and user behavior models [6][7]. Machine learning algorithms have been effectively applied to automate learning from user data and generate more relevant recommendations [2][8]. Deep Learning (DL) has become one of the most important developments in order to tackle these issues by providing effective means of finding intricate trends in vast amounts of data. The necessity for precise product recommendations and the rapid increase of e-commerce platforms are the reasons behind this research. Personalization is necessary due to the excessive quantity of possibilities faced by users. Collaborative filtering and item similarity are conventional recommendation algorithms that frequently encounter data sparsity and cold-start issues. The contextual significance of user evaluations is also not captured by them. Machine learning techniques make text more adaptable, but it's impossible for fully comprehend complex semantic patterns presently. When modeling sequential dependencies in evaluation data, deep learning, and LSTM networks in particular, perform better. Additionally, user evaluations include valuable sentiment data that is sometimes overlooked. As a result, there's an opportunity to enhance suggestion quality by merging deep learning with sentiment analysis. The need for more precise, personalized, individualized, and context-aware recommendation algorithms for modern e-commerce platforms have inspired the research. This paper's primary contributions are as follows:

- Introduces a sentiment-driven recommendation approach that improves personalization by leveraging user review polarity.
- Enhances recommendation accuracy by capturing contextual meaning and sequential patterns in textual feedback using deep learning.
- Improves learning from imbalanced e-commerce datasets, leading to more reliable and unbiased predictions.
- Achieves consistently superior performance compared to existing ML and DL baselines across all evaluation metrics.
- Strengthens real-time recommendation quality by directly linking user sentiment with product relevance.
- Demonstrates high scalability and robustness for deployment in large-scale e-commerce environments.

For e-commerce real-time product recommendation, the proposed strategy is innovative since it combines sentiment analysis with an LSTM-based DL model. Rather of relying on generic recommendations, it improves customization by using the emotion of user reviews. With the help of SMOTE, the model is able to handle class imbalance and accurately capture sequential textual patterns, resulting in more accurate predictions. Its better performance over conventional ML and DL approaches across all of the evaluation measures justifies its explanation. Its ability to provide scalable, accurate, and sentiment-aware product suggestions has been proven to greatly improve customer satisfaction.

A. *Structure of Paper*

The rest of the paper is organized as follows: Section II reviews the relevant literature. A thorough description of the recommended method is given in Section III. The experiments and their findings are presented in Section IV. Lastly, Section V concludes and outlines future directions.

II. Literature Review

The following sections include machine learning, product recommendation systems and a literature review on techniques and algorithms used to develop better recommendation systems.

Siddharth and Sariki, (2025) present a multimodal deep learning approach, in this study that uses a fusion-based model to merge structured attribute information with product images. To handle noisy and incomplete metadata, we apply preprocessing steps such as one-hot encoding and class balancing, while CNNs are used to extract RichVisual features. Our experiments show that the fusion model consistently outperforms image-only and attribute-only baselines, reaching 84.2% ± 2.1 test accuracy and a macro F1score of 0.87 across five folds [9].

Goranthala *et al.*, (2025) use of the GPU-YOLO Ensembled Classifier is essential in reducing the usual problems of bias and variance that older classifiers have.

The use of various models together leads to predictions being highly accurate, with a rate of up to 95.8% which is much more accurate than the other two mod- els i.e., SVM and DT. According to the study's findings, e-commerce companies may now leverage consumer input to identify and create better goods and services [10].

Gupta *et al.*, (2024) explores the submission of DNNs to enhance corresponding product references in e-commerce stages. By leveraging the Neural Collaborative Filtering (NeuMF) model, which integrates GMF and MLP, the study captures both linear and non-linear user-item connections to improve recommendation accuracy. Results show that the NeuMF model significantly improves recommendation accuracy and user satisfaction, with an AUC of 0.94 [11].

Diwu *et al.*, (2024) studies Image Recognition and Product Recommendation techniques in e-commerce platforms using CNN methods and DL as the foundation. The experimental outcomes showed that the Acc and Rec of the model in image recognition in e-commerce systems are between 95.2%-96.5% and 91%-85%, respectively. At the same time, users show a very satisfactory attitude towards product recommendation results [12].

Bagga *et al.*, (2022) suggest Afetler as a model. In Afetler, an adaptive fusion method is used to dynamically integrate suggestions from many sources, including forecasts of new arrivals, CTR predictions, and popularity predictions. On criteria like Top-K recommendation accuracy, ROC-AUC, and precision, the proposed AFETLERmodel beats some of the current recommendation models by an average of 2% to 5%. Additionally, both the MSE and the MAE have decreased by a certain percentage [13].

Shi, (2022) purpose of introducing BLSTM was to acquire textual contextual semantic information by merging the output of forward and backward hidden layers. According to the experimental results, the recommended model, BERT-BiLSTM, has the best recommendation accuracy (0.82 RMSE) when it comes to personalized e-commerce product recommendations, when compared to the benchmark models, BERT-SVM, BERT-RNN, and BERT-LSTM. Consequently, the suggested methodology is workable for tailored product suggestions in e-commerce [14].

Hamzah, Erizal and Diqi, (2022) builds an effective recommender for e-commerce items by creating a unique recommendation model utilizing a learning method. We gather a large e-commerce dataset in order to build up our model. Our results show that our method increases accuracy by 91.17% on the testing set and 91.47% on the training set. Because of this, the strategy we provide may be a useful way to address recommendation-related issues in the real-world e-commerce implementation [15].

TABLE I. COMPARATIVE ANALYSIS OF EXISTING E-COMMERCE RECOMMENDATION SYSTEM

Author	Method	Data	Findings	Limitation / Future Study
Siddharth & Sariki (2025)	Multimodal DL (CNN + Attribute Fusion)	Product images + metadata	Improved performance over single-modal models (Acc: 84.2%, F1: 0.87)	Limited handling of real-world noisy large-scale datasets; future work can explore scalability
Goranthala et al. (2025)	GPU-YOLO Ensemble Classifier	Customer reviews / e-commerce data	High accuracy (95.8%) with reduced bias and variance	Limited evaluation on diverse datasets; real-time scalability needs validation
Gupta et al. (2024)	Neural Collaborative Filtering (NeuMF)	User-item interaction data	Captures linear & non-linear relations effectively (AUC: 0.94)	Cold-start problem not addressed; future work can include hybrid approaches
Diwu et al. (2024)	CNN-based Recommendation	E-commerce image dataset	High accuracy (95%+) and good recall in image-based recommendation	Lacks integration with user behavior data; limits personalization
Bagga et al. (2022)	AFETLER (Adaptive Fusion Model)	Multi-source recommendation data	Improves recommendation metrics (2–5%) and reduces MAE/MSE	Complexity increases; real-time deployment not fully explored

Shi (2022)	BERT-BiLSTM	Text-based product data	Better semantic understanding with low RMSE (0.82)	Computationally expensive; scalability issues for large datasets
Hamzah et al. (2022)	Learning-based Recommender	Large e-commerce dataset	Achieves ~91% accuracy in recommendation tasks	Generalization across platforms not studied; needs real-world validation

Research Gap: Current literature is primarily concerned with improving the accuracy of recommendations using single or hybrid deep learning models, as summarized in Table I. Nevertheless, most solutions are based on minimal data streams like images alone or user interfaces, limiting the overall performance. Scalability, real-time deployment, and cold-start are not well-handled in most of the models. Also, there is a lack of efficient multimodal data integration. Consequently, a powerful and scalable structure is required that is capable of integrating various sources of data and has enhanced generalization and practical use in the real world.

III. METHODOLOGY

Figure 1 depicts the proposed methodology pipeline for product recommendations in real time. After being gathered, the data of Amazon reviews is preprocessed to eliminate any instances of duplication, noise, special characters, or stopwords. The text is transformed into numerical characteristics using TF-IDF. There are 75% training data points and 25% testing data points in the dataset. The classes are balanced using SMOTE. For sentiment classification, utilize an LSTM-based model that includes dense layers, embedding, and LSTM. Binary cross-entropy loss and the Adam optimizer were used to train the model. Precision, Accuracy, F1-score, and AUC-ROC are the performance measures that are used.

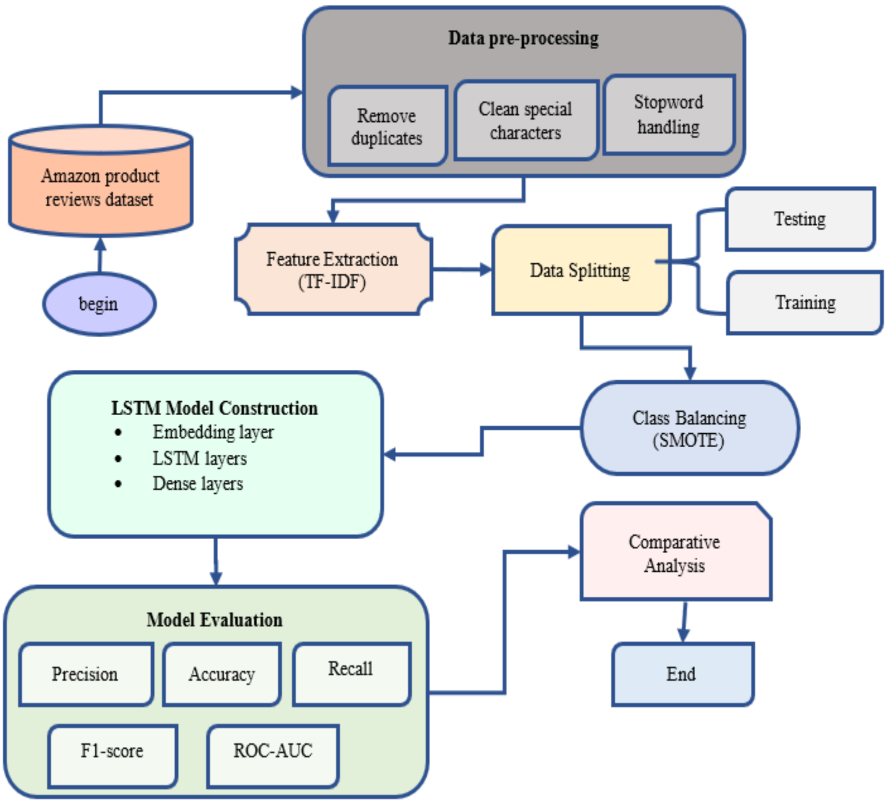

Fig. 1. Propose Flowchart for Product Recommendation in E-Commerce

The following steps of propose flowchart are describe in next section.

A. Data Collection

The Amazon product Review data is gathered from Kaggle. The dataset comprises over 30,000reviews across more than 200products. The reviews and ratings are given by more than 20,000users. The SA model can utilize only the chosen attributes for analysis. The pre-processed data visualization is shown in the figure below.

Fig. 2. Word cloud for positive sentiment

Figure 2 shows positive sentiment, with most commonly used words like great, keep, feel, and watch being the most prominent in the list, which are highly used as per user feedback. The words around these terms such as love, awesome, excellent, happy, and amazing also contribute to the positive tone and underline satisfaction, enjoyment, and positive experiences. This figure is effective in reflecting the prevailing themes of positivity displayed in the dataset.

Fig. 3.Word cloud for negative sentiment

Figure. 3 illustrates a word cloud representing negative sentiment, where frequently occurring terms such as see, use, put, back, well, and buy dominate the visualization, while smaller words like terrible, smell, break, and return highlight recurring dissatisfaction in user feedback. The visual is a good representation of the linguistic patterns of dissatisfaction, as it provides insight into shared themes influencing negative sentiment.

Figure 4 displays the distribution of user sentiment; roughly 3,000 people expressed negativity views, while almost 25,000 people indicated positive sentiments. This is a huge disparity to show that the data in question is highly skewed towards positive thoughts, with individuals expressing positive sentiments much more frequently than negative ones. The graphic captures the sentiment trend and provides an idea of the overall tone of user input.

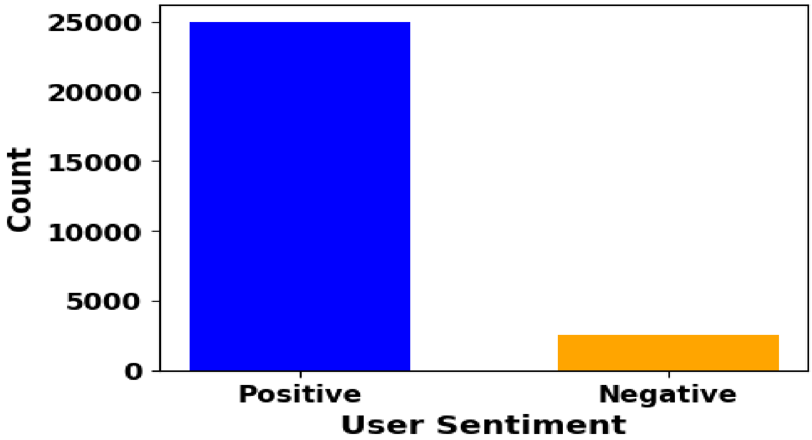

Fig. 4. Bar Graph for User Sentiment Distribution

B. Data pre-processing

Data preparation allows for the enhancement of data quality, the reduction of noise, the standardization of text and words, the correction of misspellings, the transformation of text into numerical characteristics, and the assurance that the data is ready for analysis. The following lists the several data preparation techniques used in this study:

- Duplicated: It is possible to remove duplicate values such that only unique occurrences remain. This ensures that each data point is displayed only once in the dataset.
- Remove Characters: Punctuation and special characters may be removed since they are often superfluous in text analysis. Whitespace, apostrophes, and characters other than lowercase letters may all be removed.
- Remove Stop word: Nouns, pronouns, and other frequently used words are called stop words. The usage of stopwords like "don't" with phrases like "don't buy," "don't try," and "don't like" should not be excluded.

C. Feature Extraction

The TF-IDF method is utilized to extract features from text by transforming it into numerical feature vectors. A term's significance is determined by adding its document-specific frequency (TF) to its overall corpus-wide rarity (IDF). A higher weight is given to terms that occur often in a text but are uncommon in the entire dataset. The TF-IDF vectorizer allows ML and DL models to analyze the text corpus efficiently by transforming it into a matrix representation. Each document is then represented as a vector of term weights.

D. Data Splitting

There are two sets of pre-processed data: test and train. The data is divided into two parts: 25% for testing and 75% for training.

E. SMOTE for Data Balancing

A well-liked and often used oversampling method for resolving the unbalanced classification issue is SMOTE. Sample overlap, SMOTE's handling of all minority class samples equally, and its disregard for the class information of the nearest neighbor samples all contribute to poor classification outcomes.

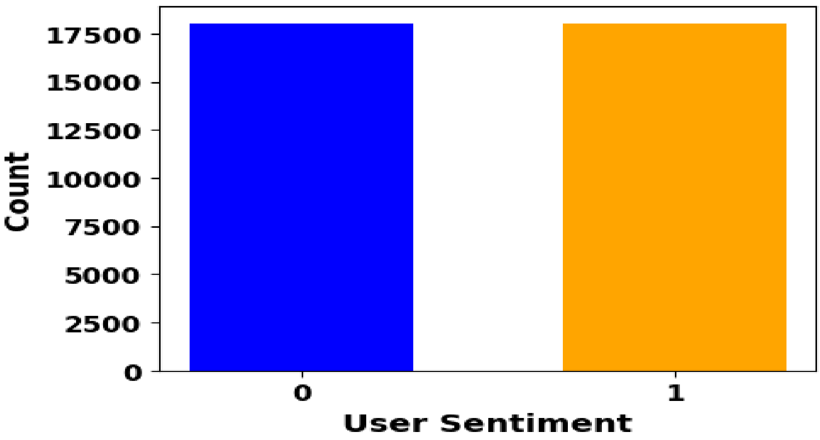

Fig. 5. Bar Graph for User Sentiment Distribution After Balancing

Figure 5 demonstrates the balanced distribution of user sentiment categories, with approximately 17,500 products in each of the two classes (0 and 1). To ensure fair training and improve the model's capacity to generalize across sentiment classes, this balanced distribution reduces the skew in the original dataset. With the balancing process stated out so clearly in the visualization, classification tasks are now more well established.

F. Neural network: deep learning LSTM model

Networks of neurons have been used to construct the model. Furthermore, a sequential model is used, which is well-suited to a basic multi-layer architecture with a single InputTensor and a single OutputTensor from each layer. It is essential that the model be informed about the expected input shape. Consequently, input shape data must be sent to the first layer of a sequential model. Sequence classification is a sort of predictive modeling that aims to classify a collection of inputs that include both spatial and temporal dimensions. A recurrent neural network known as an LSTM network employs LSTM cell blocks as opposed to the more conventional neural network layers. Every one of these cells has an input gate, a forget gate, and an output gate. A multi-LSTM, dense-layered LSTM model is necessary for proper product suggestion classification.

The first layer, known as the Embeddingayer, uses vectors of 32 lengths to represent each word.

The LSTM layer follows with 128 MemoryUnits, and the convolutional layer follows with 64.

The output is divided into two dense layers. The first Dense Layer consists of 32 Memory Units and the reLu activation function.

The output layer follows the input layer as the next dense layer. It has one neuron and is activated using a sigmoid function.

Neural networks use regular layers of neurons, which are called dense layers. A densely linked network is created when all the neurons in one layer get signals from all the neurons in the layer above it. Its components are the activations from the layer before it, a Bisector b, and a Weight Matrix W. If you want to avoid over-fitting, their recommended network architecture usually has only one or two deep layers.

There have been 80 training iterations of the model. The Binary Cross Entropy loss function has also been included, and the weights are optimized using an Adam algorithm. With a value of 0.01, the learning rate is chosen. In this case, 256 is the BatchSize. Nonetheless, 100 is the embedding size. Reducing the batch size improved the model's accuracy. The 168,769 trainable parameters make up the suggested model.

G. Performance Matrix

Additionally, we selected Precision and Recall as evaluation measures to provide a thorough assessment of the model's performance. A confusion matrix is utilized to compute the model's recall, accuracy, and precision rates. The number of samples when the real and expected outcomes are negative is represented by TN in a confusion matrix. The number of samples where the actual and projected outcomes are positive is shown by

TP. The number of samples with a positive genuine result but a negative anticipated outcome is known as FN. FP is the number of samples in which the expected result is positive but the actual result is negative. The metrics for performance is as follows:

An accuracy rate is defined as the chance of making right positive and negative class predictions over all samples, as seen in Equation (1).

$$\text{Aaccuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

The precision rate is the percentage of projected positive samples that were actually detected correctly, as given in Equation (2).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

The possibility of a sample being accurately classified as a positive sample among the real positive samples is shown by the recall rate, which is defined as Equation (3).

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

Equation (4) defines F1-score as a harmonic mean of rec and prec with a possible value between 0 and 1. With low false negative and false positive readings, this measure is created at a higher value.

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

It is the integral of the FPR times the TPR that gives the area under the ROC curve (AUC). Equation (5) is used to determine AUC.

$$AUC = \int_0^1 TPR\,(FPR) \quad (5)$$

TPR is defined as the ratio of TP to the sum of true positives and false negatives (TP + FN). The FPR is calculated by dividing the number of FP by the sum of false positives and true negatives (FP + TN). FPR is also referred to as 1-Specifcity.

IV. RESULTS AND DISCUSSION

Computational settings that allow for the replication of ML experiments are among the most important components of these studies. The components and characteristics of the computational environment are shown in Table II. As shown in Table III, the LSTM model achieved very good performance of product recommendation, with acc of 98.42%, prec of 99.29%, rec of 98.11% and F1score of 98.70%. Based on these outcomes, it is clear that the model has excellent predictive power and achieves a good balance between recall and precision across all measures.

TABLE II. SYSTEM CONFIGURATION

Component	Specification
Processor	Intel i7-9700K CPU @ 3.6GHz
GPU	NVIDIA GeForce RTX 3070
RAM	16GB DDR4
Python Version	3.9
Visualization libraries	Matplotlib
Scikit-learn Version	2.12
Scikit-learn Version	11.3

TABLE III. EXPERIMENT RESULTS OF THE LSTM MODELS FOR THE PRODUCT RECOMMNEDATION

Models	Accuracy	Precision	Recall	F1-score
LSTM	**98.42**	**99.29**	**98.11**	**98.70**

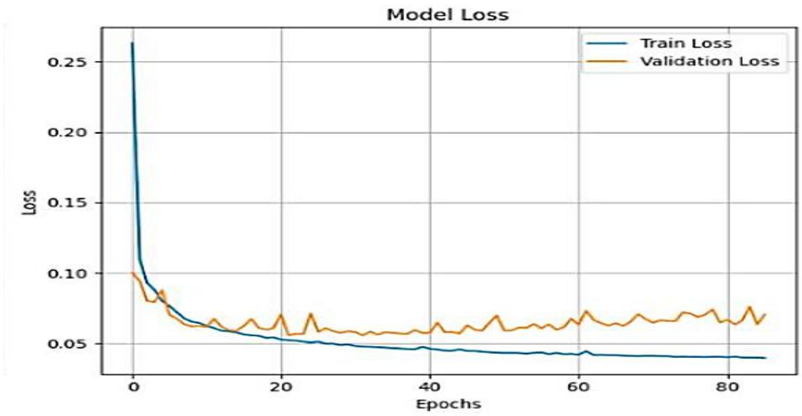

Fig. 6. Training and validation Loss of LSTM Models

Figure 6 illustrate a steady learning process with effective convergence. At first, both losses fall rapidly, which means that learning occurs fast in initial epochs. The model's ability to match the training data is shown by the training loss's steady decline and eventual leveling out at a low value. The validation loss also has a similar negative trend at the beginning but starts to fluctuate a bit after a certain number of epochs, indicating a bit of overfitting. Nevertheless, the difference between training and validation loss is comparatively small, which signifies good generalization performance. In general, the model indicates a stable convergence with minimum loss divergence, which represents a well-trained and balanced LSTM model.

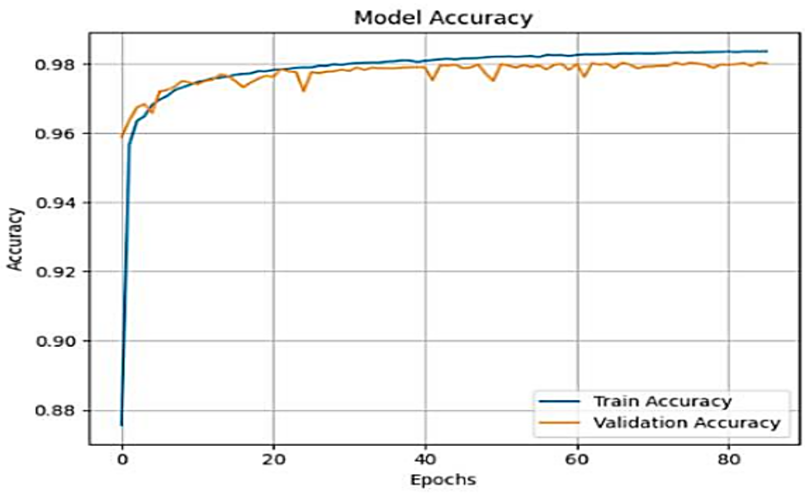

Fig. 7. Training and validation Accuracy of LSTM Models

Figure. 7. illustrate that training and validation accuracy curves of the LSTMmodel rapidly increase in the first epochs, increasing by approximately 0.88 to almost 0.98. The two curves stabilize and converge after about 10 epochs, indicating successful learning and high generalization. Consistent performance across datasets and little overfitting are outcomes of the high degree of connection between training and validation accuracy. This demonstrates the robustness of the LSTM model in achieving high accuracy and reliable convergence.

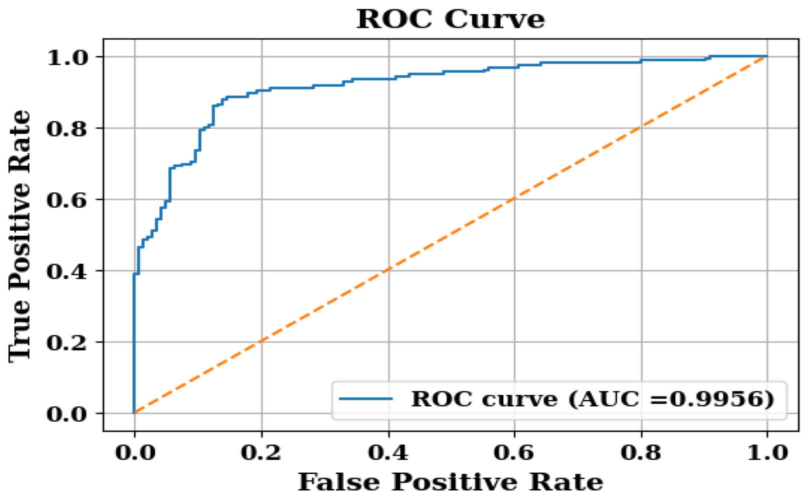

Fig. 8. Plot ROC Curve of Propose LSTM Models

Figure. 8. illustrates the ROC curve of the proposed LSTM model, where the curve rapidly increases towards the top-left corner, with an AUC of 0.9956. This almost perfect score emphasizes the capability of the model to differentiate the classes with the lowest false positives and the highest true positives. Its greater predictive ability compared to the random baseline is further highlighted in the comparison. In general, the figure shows the strength and stability of the LSTM architecture in providing highly precise classification outcomes.

TABLE IV. COMPARISON BETWEEN ML AND DL MODELS FOR PRODUCT RECOMMENDATION

Models	Accuracy	Precision	Recall	F1-score
IBNN [16]	-	56	31	31
RNN [17]	93.53	92.41	92.44	-
DT [18]	94.54	95	95	95
DeepFM [19]	73.08	-	-	74.64
LR [20]	64.14	43.93	35.97	37.68
MNB [21]	66.8	59.3	66.8	57.6
LSTM	**98.42**	**99.29**	**98.11**	**98.70**

Table IV comparison indicates that various models perform best in different evaluation measures. Decision Tree (DT) model shows good overall performance with high prec, rec, and F1score (95%). The RNN model also has good performance in terms of prec (92.41%) and rec (92.44%), but its F1-score is not reported. DeepFM, in turn, demonstrates moderate results with an F1-score of 74.64% but no reported values of precision and recall. The Logistic Regression (LR) model is characterized by relatively low recall (35.97%) and F1-score (37.68%), which implies the lower predictive ability. Likewise, Multinomial Naïve Bayes (MNB) achieves a rec of 66.8% and F1score of 57.6% with a moderate degree of effectiveness. The LSTM model is unique in that it has the highest accuracy 98.42% meaning that it is the most successful in complex recommendation patterns. In general, although certain models show good results in certain measures, LSTM is consistently better in all evaluation measures.

The suggested LSTM-based real time product recommendation system has a number of major strengths. It achieves high scores for accuracy, precision, recall, and F1-score, outperforming both competitive DL models and traditional ML in terms of predictive performance. In order to increase sentiment understanding and suggestion quality, the architecture can record long term dependencies in user review language. The TF-IDF and SMOTE also enhance the feature representation and class balance, which in turn improves the robustness of the model. Moreover, the model exhibits high convergence behavior with a little overfitting, indicating high generalization capability. The ROC-AUC score is also reflective of the good class separability. In general, the suggested solution is highly accurate, scalable and reliable in real-time personalized product recommendation in e-commerce systems.

V. CONCLUSION AND FUTURE WORK

Customers now have a wide range of alternatives due to the rapid growth of e-commerce websites. Product recommendation systems are becoming a vital resource for helping consumers navigate the vast product space.

This study proposes a new approach to e-commerce product recommendation engines by combining sentiment analysis with a LSTMmodel based on DL. The system is structured to efficiently handle large volumes of user-generated Amazon review data, using systematic preprocessing. The LSTM architecture which is comprised of embedding, stacked LSTM, and dense layers is trained on the Binary Cross-Entropy loss and the AdamOptimizer to ensure effective convergence. Experimental results show that performance is excellent, with an acc of 98.42, and F1score of 98.70, which indicate a high predictive performance and balanced classification performance. This is further indicated by the ROC-AUC score that indicates better class separability. Evaluations against both conventional ML and competing DL models demonstrate the superiority of the suggested method for extracting complicated sequential patterns from textual input. This approach is great for e-commerce systems because it improves suggestion quality by considering user sentiment, which improves customization and decision making. The proposed framework may be used in real-time recommendation systems and the creation of intelligent e-commerce apps since it is generally scalable, precise, and efficient.

The proposed model has some disadvantages even when it is doing well. It may not pick up on indicators of user activity because of its dependence on textual review data. Also, TF-IDF is ineffective in terms of the ability to extract in-depth semantic meaning. The model has high computing resource demands, which might compromise scalability in real-time. In future studies, greater contextual understanding can be realized through a combination of transformer-based models such as BERT and multi-modal information such as user behavior and product metadata. The computational cost and real-time efficiency of large-scale e-commerce platforms may be further optimized.

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