Deep Learning-Based Sentiment-Aware Product Recommendation System Using Hybrid CNN-BiLSTM Networks

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Abstract: There is an unprecedented amount of user content generated these days, including product reviews and ratings, and text feedback, due to the rise of ecommerce sites. These reviews offer great insight into what consumers loved, hated and were pleased with. Traditional recommender systems tend to depend on "explicit" feedback signals, such as ratings, or purchase histories, which do not necessarily capture the sentiment and feelings of customer reviews/feedback. To overcome this, the following research, DL Based Product Recommendation System Using Comment Sentiment Analysis is proposed. The proposed framework employed advanced Natural Language Processing (NLP) methods along with the incorporation of CNN along with a Bidirectional Long Short-Term Memory (Bi-LSTM) network for effective provision of semantic representation and contextual sentiment information of textual reviews. The model classification and sentiment classification segments all customer feedback into positive, negative or neutral sentiment classes; in addition, it uses the sentiment information gathered during the classification and sentiment classification process for the recommendation process as a basis for improving personalization and recommendation results. CNN-BiLSTM is hybrid CNN-Bi-LSTM feature extraction structure to capture patterns and long-range dependence from review texts. This integrated learning technique has a impact on the sentiment classification accuracy, and gives a better result to customer sentiments prediction. so, the sentiment-based recommendation system can provide better match the user's preferences and emotional reaction. so studies show that sentiment-based features can enhance the relevance and effectiveness of recommendation compared to the traditional recommendation methods that work on collaborative filtering techniques. The proposed framework is intelligent and adaptive development that provides accurate, meaningful and user-centric product recommendations in the contemporary e-commerce context. Therefore, the system offers significant advantages to consumers and businesses in terms of customer satisfaction, decision-making, and personalization strategies.

INTRODUCTION

Today, the recommender system is a vital part of e-commerce systems and plays a critical role in influencing customers' purchase decision-making and increasing customers' engagement. As online shopping services have evolved over time, users now have access to a vast array of products, which makes it difficult for them to determine what will match their interests and needs. The recommendation systems that have been implemented to make it easy for users to discover relevant products according to their preferences, behavior and interests have been widely embraced to solve that problem. The traditional recommendation strategies are mostly based on structured data, such as users' ratings, sales information, and website usage. These techniques have proven to be successful in various applications but are not fully exploiting the valuable information that is contained in textual customer reviews and comments.

Customer reviews are a genuine indication of consumer views on items or services and provide a great deal of understanding about the experiences, opinions and satisfaction of customers. Textual feedback is not the same as numerical type of feedback since it puts context in the customer's opinion as to how happy or not happy he is with a product/service and if he has or hasn't purchased. So, information extraction from customer reviews is an important research area to improve the quality of recommendations is vital. Sentiment Analysis is one of the primary applications of Natural Language Processing (NLP) which involves the analysis and classification of sentiment expressed in text. Sentiment classification is a technique for understanding and analyzing positive, negative and neutral sentiments from customer reviews to better influence a recommendation system to understand customers' perceptions and product acceptance.

Sentiment analysis is part of the recommendation systems that allows for a more comprehensive representation of customer preferences. Sentiment-aware recommendation models are not only based on explicit ratings, but also consider the emotional aspects expressed in the reviews, resulting in more personalized and meaningful recommendations. In this way, customers can not only be identified as liking a product but the part of a product that is affecting the customer's opinion. This functionality can be used to enhance recommendations systems that become more adaptive, user-centric and focussed on customers. The developments in DL have enhanced the performance of text analytics and sentiment classification tasks to a great extent. With large amounts of textual data, DL architectures can be used to automatically learn hierarchical representations without requiring manual feature engineering. Of these architectures, CNNs have shown to be effective in identifying relevant local features, keywords and patterns at the level of phrases in texts, while Long Short-Term Memory (LSTM) networks are good at capturing sequential dependency and contextual information. Moreover, Bidirectional Long Short-Term Memory (Bi-LSTM) networks can also be used to capture the context of textual sequences by processing them in both forward and backward directions, which allows for a more complete understanding of the meaning of a sentence.

This work introduces a Hybrid CNN-BiLSTM model to be used in product recommendation for sentiment analysis. The CNN component is used to extract informative local features from customer reviews while the Bi-LSTM component is used to model a long-term context and semantic dependency across the text. These two DL techniques form a powerful sentiment classification model that can extract and accurately understand customer sentiment from online reviews. The sentiment data is then used in the recommendation system to make it more relevant and personalized. Sentiment Based Recommendation Systems are the significant advancement in the Intelligent E-Commerce systems. The proposed framework combines emotional understanding with the use of recommendation strategies, which increases the relevance of recommended products and increases user satisfaction. Additionally, the system provides companies with a decent perception of customer impressions and assists them improve choices with respect to merchandise growth, marketing method and client control management. The model will be adaptable and when the market changes or sentiments do, the recommendations will be adequate to tackle the new trends and sentiments.

Finally, the hybrid DL model of a CNN-BiLSTM technique is suggested in this study, this system for sentiment analysis of product recommendations of user comments. The all service combines NLP, advanced sentiment analysis, and recommendation algorithms to correlate customer sentiment to intelligent product suggestions. The overall objective is to get highest accuracy in recommendations, the engagement of customers in the system and user experience in doing online shopping, leveraging sentiment-aware recommendation strategies. The study provides examples of emotional AI in the future, in order to better understand and satisfy customer requirements with the such recommendation systems.

LITERATURE REVIEW

Online reviews are a treasure trove of customer information, offering valuable insight into customer preferences and buying habits as eCommerce sites expand and more customers who have experience share their views. Traditional recommender systems are primarily of collaborative filtering system and rating-based system based upon users' explicit preferences. These methods do not however consider the (subjective) opinions, feelings and experiences of people in text reviews. To address this drawback, Sentiment Analysis/Opinion Mining can be a solution for extracting the emotional polarity and the context meaning from customers' feedback. Sentiment analysis can be used to design better recommender systems that can generate more personalized, transparent recommendation and user-centric recommendation. Recent advent of DL methods in particular, CNNs, Long Short-Term Memory (LSTM) networks, Transformer-based architectures have greatly advanced the ability to extract semantic, syntactic and contextual information from review text. The sentiment-based approaches that were used and combined with collaborative filtering, content-based approach and mentioned at the end of the research field showed that recommendations became accurate, ranked at top spot and caused much satisfaction among users from 2022-2025 study. The hybrid DL architectures, which includes convolutional as well as recurrent neural networks, have captured significant consideration in sentiment analysis research. CNN models are helpful in the efficiency of important aspect-related features and phrase and aspect local patterns identification from text, and Bidirectional Long Short-Term Memory (Bi-LSTM) network has a good effect on modeling the relations and long-range dependency between texts. This combination enables a better analysis of customer sentiment, even in longer and more complex linguistic forms, e.g., negation, sarcasm, or if sentiment has a different meaning depending on the context. Some studies incorporate attention mechanisms to select relevant words and phrases to help improve performance for sentiment prediction and Transformer encoders, respectively. The empirical results always outperform the models based on the single DL model on benchmark sentiment data and reviews from a domain specific collection on hybrid CNN-BiLSTM model. Moreover, the optimization techniques and metaheuristic methods have been widely applied to self-tune the parameters of the model, accelerate the convergence and enhance the classification robustness in general.

In addition to sentiment classification, sentiment information has been integrated into recommendation pipelines by researchers increasingly. A lot of studies merge sentiment polarity scores with collaborative filtering, matrix factorization or neural recommendation architecture to enhance the quality of their recommendations. Sentiment features offer a number of benefits, such as better dealing with cold start situations, more interpretability with sentiment based explanations and the ability of reflecting back on user sentiment over time. Various fusion schemes have been proposed such as early fusion, late fusion and model integration. All approaches have their advantages and disadvantages regarding their explainability, latency, scalability, and computational complexity. Thus, no single fusion technique has proven to be the best in all the applications and for all the systems and it is dependent on the application domain and system requirements.

Studies carried out in recent years have developed sentiment-aware recommendation methods in a multilingual setting, across domains, and leveraging the use of large pre-trained language models (PLM). Many transformer models like BERT and its variants are integrated with CNN-BiLSTM models to leverage the advantages of both, especially contextual language understanding and efficient feature extraction. Optimization techniques like Grey Wolf Optimization, Dung Beetle Optimization and Harris Hawks Optimization are also investigated to enhance the performance in noisy and imbalanced data sets. Although great strides have been made, there are still situations that are not addressed, such as slang, emoji, code mixed languages and domain specific vocabulary.

From an overall perspective, the studies conducted in the recent years show two main tendencies: (1) sentiment-driven recommendation models always boost more personalization and better recommendation effectiveness; (2) hybrid DL architectures with CNN-BiLSTM models achieve better performance for extracting meaningful sentiment information from textual reviews. However, there are some domain adaptation, multilingual generalization, aspect-level sentiment understanding and scalable recommendation integration challenges still to be explored. The subsequent twenty research studies were published in the last five years (2022-2025) and offer detailed background information, existing techniques, data sets, findings and potential future research opportunities related to the proposed work. A review of existing research papers was carried out.

G. Mu, “An Enhanced IDBO-CNN-BiLSTM Model for Sentiment Analysis” (2024). In this work, a DL sentiment classification model based on CNN-BiLSTM network and Improved Dung Beetle Optimization (IDBO) is proposed to improve the classification accuracy. The proposed approach features word embedding to represent text, CNN layers to extract local semantic features, and Bi-LSTM networks to model contextual dependencies. IDBO algorithm is used to optimize network parameters and enhance the convergence behavior. The experimental results on various review datasets show that the proposed model achieves higher accuracy, F1-score and stability than the CNN, Bi-LSTM and CNN-BiLSTM models. Based on the results, it is found that the optimization-driven parameter tuning is able to reduce overfitting and improve the classification rate, which make the framework for sentiment analysis better useful for large-scale classification applications[1].

Automated Sentimental Analysis using Heuristic-Based Hybrid CNN-BiLSTM by N. Ramshankar et al., 2023. The authors propose a hybrid DL model based on Word2Vec embeddings, CNN layers, and Bi-LSTM networks for sentiment classification, which is based on heuristic. The framework specifically targets noisy textual information that can be found in the social media. In order to optimize the model parameters and enhance classification accuracy, a swarm-inspired optimization method is introduced. Experimental results show that the performances of these experimental classifiers are much better than the performances of other classifiers like Support Vector Machines and Random Forests along with standalone DL architectures. The paper also addresses class imbalance issues and their mitigation using sampling techniques and weighted loss function[2].

M. Elahi — "Hybrid Recommendation by Incorporating the Sentiment of Reviews" (2023). This research introduces a hybrid recommendation system combining sentiment polarity and aspect-level information obtained from the customer feedback along with Collaborative Filtering technique. Sentiment extraction process involves combining of lexicon based methods along with neural sentiment classifiers to achieve meaningful sentiment score. Experimental studies on publicly available e-commerce data show that it improves the accuracy of the recommendations and the quality of the ranking as well as the mean absolute error compared with traditional collaborative filtering algorithms. The study shows the benefits that such a solution brings to the recommendations systems, especially in the case of products which have few rating information available.

DistilRoBiLSTMFuse: An Efficient Hybrid DL Model, SK Papia et al., 2024. This paper presents a simple sentiment classification system based on RoBERTA model distillation, Bi-LSTM model, and fusion layers. The goal is to maximize the accuracy of the classification while minimizing computation and inference time. The proposed architecture is shown to be competitive in terms of performance while being highly resource efficient on several datasets of travel and product reviews. The research shows that efficient models of sentiment analysis can be implemented in real-time recommendation systems[4].

The Amazon Product Recommendation System Based on a Sentiment-Aware Pipeline", Abstracts, 2024. The proposed system includes a multi-stage pipeline of data preprocessing, feature representation using TF-IDF and word embeddings, and sentiment classification using hybrid DL techniques. The sentiment outputs are used to boost product ranking and sentiment relevance for product recommendations in collaborative filtering mechanisms. When compared to baseline recommendation models, evaluations on Amazon review datasets show significant gains in the Hit Rate@K and NDCG metrics. Also, some problems related to the processing of large-scale review data sets are discussed in the study[5].

J. Sangeetha, A Hybrid Optimization Algorithm Using BiLSTM Structure for Sentiment Tasks (2023). The authors of this work propose the THHO-BiLSTM model that integrates the Taylor-based optimization with Harris Hawks Optimization so as to enhance the performance of the Bi-LSTM-based sentiment classification. The optimization framework optimizes the network parameters and boosts learning efficiency automatically. Experimental results demonstrate the improvements in accuracy, precision, and consistency on various sentiment datasets. The study indicated that optimization-based learning strategies are effective for minimizing reliance on manual hyperparameter tuning and enhancing model generalization[6].

N. Vaishnavi & B. Kalpana — Sentiment Based Product Recommendation System Using ML Techniques (2024). This study is aimed at comparing performance of ML algorithms used for sentiment classification namely Logistic Regression, Random Forest, XGBoost, and CatBoost. The sentiment labels generated are then incorporated into collaborative-filtering recommendation models. The results reveal that the gradient-boosting provide better accuracy in sentiment classification and its impact on precision and recall of recommendations. In This paper, practical comparison of traditional ML techniques with Sentiment Aware recommendation techniques[7].

Sentiment Analysis of Product Reviews, Using Transformer-Enhanced 1D-CNN and BiLSTM. Muhammad R. and Rashid R. in (2024). The authors suggest a hybrid technique, in which the transformer-generated contextual embeddings are used alongside CNN and Bi-LSTM networks. The transformer part encodes the semantic meaning of the context, the CNN part learns the patterns at the level of the phrases and the Bi-LSTM part models the sequential dependency. The experimental results on product review datasets validate the effectiveness of classification accuracy and the resistance against the domain shift compared to traditional

CNN-LSTM model-based approaches. The study validates the value of using transformer representations in conjunction with lightweight networks downstream[8].

B. Li — "An Attention-Based Hybrid Model for Spatial and Sentiment Tasks (CNN-BiLSTM-ATT)" (2024). In this paper, we extend the CNN-BiLSTM model by adding an attention mechanism to focus on the text features that are relevant to the sentiment. The attention layer helps the model pay attention to important words and phrases when creating sentiment predictions. Significant improvements in class level accuracy and macro F1-score are seen in various benchmark data set. Furthermore, attention visualization delivers interpretability by pinpointing parts of the review that play a crucial role in customer sentiment decisions[9].

V. Jain — Optimized Hybrid DL for Cross-Linguistic Sentiment (2025). In this study, a multilingual sentiment analysis framework is proposed by using CNN-LSTM architecture and Grey Wolf Optimization. Language-specific embeddings are used to overcome the semantic gap between languages. The results in the experiments show superior sentiment classification performance and successful cross-linguistic knowledge transfer. The emphasis is on the need for multi-lingual sentiment analysis in ecommerce applications around the globe[10].

Is UGC Sentiment Helpful for Recommendation?". An Application-Driven Study" (2024). The study examines how sentiment of user content relates to the quality of recommendations. Comparative experiments show that sentiment-based recommendation models consistently achieve better performance over many product categories when compared with the similar systems without sentiment recommendation models. [11].

R. Thomas — "A Novel Framework for Intelligent DL Based Product Recommendation" (2024). The author suggests integrated recommendation architecture based on sentiment analysis, collaborative filtering and user behaviour information. The framework uses DL methods to extract sentiment and neural collaborative filtering to generate recommendation. Experimental get better results of recommendation accuracy, relevance and cold-start performance. The paper also addresses the scalability issues for real time deployment[12].

A. B. Alawi—"A Hybrid ML Model for Sentiment Analysis (BiLSTM + 3×CNN + BERT Base)" (2024). The proposed architecture is based on using BERT embeddings, multiple parallel CNN channels, and a Bi-LSTM network to represent various linguistic features. The framework performs well in the case of morphologically complex languages, and enhances sentiment detection in minority classes. The multi-channel CNN architecture is effective to incorporate the different length and aspect-level sentiment information[13].

Y. Mullagura – "Product Recommendation System Using Sentiment" (2023). This work introduces an end-to-end sentiment-aware recommendation system, consisting of the steps necessary for extracting reviews, sentiment categorizing, aspect annotation and recommending. Preprocessing strategies, evaluation metrics and explainable recommendation interfaces are also discussed in the study. It is useful for reference in the implementation of the recommendation systems driven by sentiment[14].

Improving e-commerce recommendations using sentiment analysis, V. Krishna et al. (2025). The authors explore several approaches to sentiment integration in recommender systems. Experimental results show that the fusion techniques of the model level are better than the traditional fusion methods in dealing with large-scale data sets. The study discusses and reports on the improvements of the metrics of relevance of the recommendations, engagement of the users and the satisfaction scores, as well as some other metrics from the business perspective[15].

Li Xiaoyan, Rodolfo C. Raga, Shi Xuemei — "GloVe-CNN-BiLSTM Model for Sentiment Analysis" (2022). This research combines the pre-trained word embeddings obtained from GloVe for the purpose of sentiment classification with CNN and Bi-LSTM networks to create an effective sentiment classification framework. The model finds the performance to be good on benchmark datasets and is also efficient. In this work, the benefit of static word representation and hybrid DL architecture is illustrated in the resource-constrained setting[16].

Supta Das Dip, Mohammad Asif Dewan, Riyad Ali Mollik, Raka Moni — "AI-Driven DL Based Sentiment Analysis with Optimization" (2024–2025). In the case of specific recommendation tasks, there are some recent works in this line which incorporate an optimization algorithm with CNN based architectures of BILSTMs. The aim of this research is to address the problem of small labeled data sets by providing data augmentation, parameter optimization and transfer learning techniques to improve the classification accuracy[17].

In his paper , "A Review of AI-Based Techniques on Social Media Analysis", B.B. Budisusetyo review of the techniques that applied to social media analysis using AI. The article presents an overview of various sentiment analysis techniques such as traditional ML, DL and transformer-based methods. The system highlights common problems like noisy data, class imbalance and domain adaptation, and suggests use of hybrid and ensemble methods to achieve good performance[18].

Y. Gajula, Sentiment-Aware Recommender Survey (2025). This survey is a comprehensive study advances in sentiment-based recommender systems. It discusses sentiment extraction methods, fusion mechanisms, evaluation methods and new research problems. The paper has given a overview of the state of the art and suggests possible future directions for large scale recommendation systems[19].

Manikandan B., Rama P., Chakaravarthi S. — "Fuzzy Lexicon Expansion and Sentiment-Aware Recommendation" (2023–2024). This work proposes a fuzzy logic and lexicon expansion sentiment-aware recommendation system. The sentiment intensity is converted to recommendation weights based on interpretable fuzzy rules. The results of the experiments show the potential of the approach of explainable rule-based reasoning along with sentiment analysis to boost the transparency of recommendations and user trust[20].

Table 1.0- All Research papers and Research Gap

ID	Authors	Year	Methodology / Technique	Identified Research Gap
1	G. Mu	2024	IDBO Optimized CNN-BiLSTM	Limited validation across diverse domains and multilingual datasets.
2	N. Ramshankar et al.	2023	Heuristic-Based CNN-BiLSTM with Word2Vec	Performance on long-text reviews and cross-domain datasets remains unexplored.
3	M. Elahi et al.	2023	Sentiment-Aware Hybrid Recommendation Framework	Scalability and real-time fusion strategies require further investigation.
4	SK Papia et al.	2024	Distilled RoBERTa with BiLSTM Fusion	Limited evaluation on low-resource and cross-domain review corpora.
5	YM Latha	2024	Sentiment-Aware Recommendation Pipeline using CNN/LSTM	Large-scale deployment and industrial evaluation are not extensively studied.
6	J. Sangeetha	2023	THHO-Based Optimized BiLSTM	Generalization capability across unseen datasets requires further assessment.
7	N. Vaishnavi and B. Kalpana	2024	ML-Based Sentiment Recommendation	DL hybrid architectures were not comparatively evaluated.
8	M. R. R. Rana et al.	2024	Transformer Enhanced 1D-CNN-BiLSTM	Computational complexity and deployment latency remain challenging.
9	B. Li	2024	Attention-Based CNN-BiLSTM Model	Fine-grained aspect-level sentiment analysis is not fully addressed.
10	V. Jain	2025	Grey Wolf Optimized CNN-LSTM	Performance on low-resource multilingual environments remains uncertain.
11	M. Gao	2024	User-Generated Content Sentiment Evaluation	Long-term impact of sentiment integration on recommendation quality remains unclear.
12	R. Thomas	2024	DL and Neural Collaborative Filtering Fusion	Real-time recommendation efficiency and scalability require validation.
13	A. B. Alawi	2024	BERT with Multi-Channel CNN and BiLSTM	High computational requirements limit practical deployment.
14	Y. Mullagura	2023	End-to-End Sentiment Recommendation Prototype	Lack of extensive benchmarking using standard datasets.
15	V. Krishna et al.	2025	Sentiment-Aware Collaborative Filtering Fusion	Business-oriented performance indicators need further validation.
16	Li Xiaoyan, Rodolfo C. Raga, Shi Xuemei	2022	GloVe-CNN-BiLSTM Architecture	Comparative evaluation with modern transformer models is limited.
17	Supta Das Dip et al.	2024–2025	Optimized DL Sentiment Framework	Reproducibility and adaptability across multiple domains require investigation.

18	B. B. Budisusetyo	2024	Survey of AI-Based Sentiment Analysis Techniques	Absence of unified benchmark datasets for fair comparison.
19	Y. Gajula	2025	Sentiment-Aware Recommendation Survey	Limited discussion on large-scale production deployment challenges.
20	Manikandan B., Rama P., Chakaravarthi S.	2023–2024	Fuzzy Lexicon-Based Sentiment Recommendation	Integration of fuzzy reasoning with deep neural architectures remains underexplored.

The research studies reviewed in this period (2022-2025) have demonstrated the efficacy of hybrid DL architectures, such as CNN-BiLSTM combined with attention mechanisms or transformer-based embeddings in sentiment classification problems with product reviews. Complementary to collaborative filtering or neural recommendation systems, the extracted sentiment data yields many improvements in recommendation accuracy, ranking effectiveness, and user experience. In addition, sentiment-aware methods have demonstrated significant promise in tackling cold start problems through the use of textual data from user reviews. Many researchers have turned to optimization algorithms and techniques like knowledge distillation to achieve a balance between computational efficiency and prediction accuracy. While all these developments are encouraging, the problems associated with noise in the textual data, multi-lingual content and domain-specific language variations are still not addressed. In recent years, researchers have thus turned attention to data augmentation, lexicon improvements, explainable AI, and adaptive learning methods to address such challenges. In conclusion, the current research provides strong evidence for the success of SRCS and highlights various technical and practical issues that need to be explored.

Many of the studies have a significant drawback in that they rely on publicly available reviews data sets which may include some noisy and unstructured data. Many product reviews contain spelling errors, informal expressions, abbreviations, emojis, slang and code-mixed language that can be detrimental to the sentiment classification accuracy. Models learned from such data sets can achieve good performance in experimental settings, but their real-world performance can be diminished when they are deployed to a different e-commerce platform that has different natural language styles and user behaviours. Also, it is a well-known problem that most review datasets consist of a larger number of positive and neutral comments than negative ones. This imbalance may cause biases in the learning process and affect the model's capacity to correctly classify minority sentiment classes. Preprocessing techniques boost the quality and reduce noise in data, but they can also over-filter, which could lead to the loss of valuable context that is needed for aspect extraction and sentiment analysis. A few researchers also note that models trained on one product domain may not generalize well to the unseen categories without further domain adaptation techniques. As a result, there is a need for strong preprocessing techniques, constant model updates, and strong data augmentation methods for practical deployment.

One of the main drawbacks is the ability to fine-grained sentiment information. Sentiment polarity classification is useful for understanding sentiment, but many types of real-world recommendation applications demand aspect-level sentiment analysis. For instance, a user can have positive sentiments about the battery life of a smartphone yet negative sentiments regarding the camera of the identical smartphone. Much of the current sentiment models are based on just sentiment classification and do not capture such fine-grained aspect-specific opinions. There are some methods of aspect extraction that depend on extra annotations, complex linguistic processing, or unsupervised clustering methods, which can lead to inaccuracies and inconsistencies. A large part of the quality of the recommendation and its explainability may be affected by the accurate identification of sentiments in the products, as aspect-level analysis can directly influence the relevance of the recommendation. Thus, there is an urgent need for more progress on transfer learning, aspect extraction techniques, and contextual context for fine-grained sentiment interpretation.

DL architectures like transformers and ensemble models tend to be complex, demanding significant computing power, and can have high inference latency. Despite the reduction in deployment costs due to model compression techniques and lightweight architectures, the real-time scalability is still difficult in large-scale e-commerce systems. Moreover, there is limited support for multilingual and low resource languages. The techniques of cross-lingual transfer learning have been found to be promising, but the results tend to be lower in the case of morphologically complex languages, dialectal variations, or code-mixed text. In addition, the addition of sentiment analysis to collaborative filtering systems can also add complexity to the system and potentially add latency time when the time of recommendation generation. A few studies test end-to-end deployment performance, large-scale user interactions or business-oriented metrics under real-world experimentation. Overall, although there has been considerable progress in sentiment classification and sentiment quality in recommendation, there are still work to be done on noisy multilingual content, aspect-level sentiment extraction, scalability, and deployment efficiency. To achieving these challenges, future innovations in the field of data engineering, multilingual representation learning, model optimization, and comprehensive evaluation frameworks will be needed.

PROPOSED SYSTEM

CNN-BiLSTM Based Sentiment Analysis system aims to provide personalised product recommending from the user's textual reviews and comments based on the product. The largest part of the architecture is the Data Collection Module that holds information for the entire recommendation process. This module combines User experiences on e-commerce websites, Feedback comments by eCommerce site users, Ratings by eCommerce site users and Product reviews by eCommerce site users. This information is valuable to tap into consumer wants, consumer satisfaction and buyer behavior. The collected data is stored in a structured data repository that enables easy access and management and for further processing later. To use the meaningful information in the text to perform the sentiment understanding, then build a system for generating a suggestion, the suggestion system can be utilized.

After data collected, the obtained reviews are passed on to the User Comments and Comment Processing Module. What is important at this stage is to convert the raw textual information in their unstructured form into a format that can be input into a DL model for analysis. Data after the various Text Pre-processing techniques has better quality: Tokenization, Removal of Stop-words, Stemming, Leximization and noise removal. The primary intention of this process is to convert the unstructured reviews into machine-readable text and eliminate the irrelevant, distorted and inconsistent information in reviews. This makes the customer comments homogenous, making the data more reliable so that the sentiment analysis model is able to get good training and prediction data.

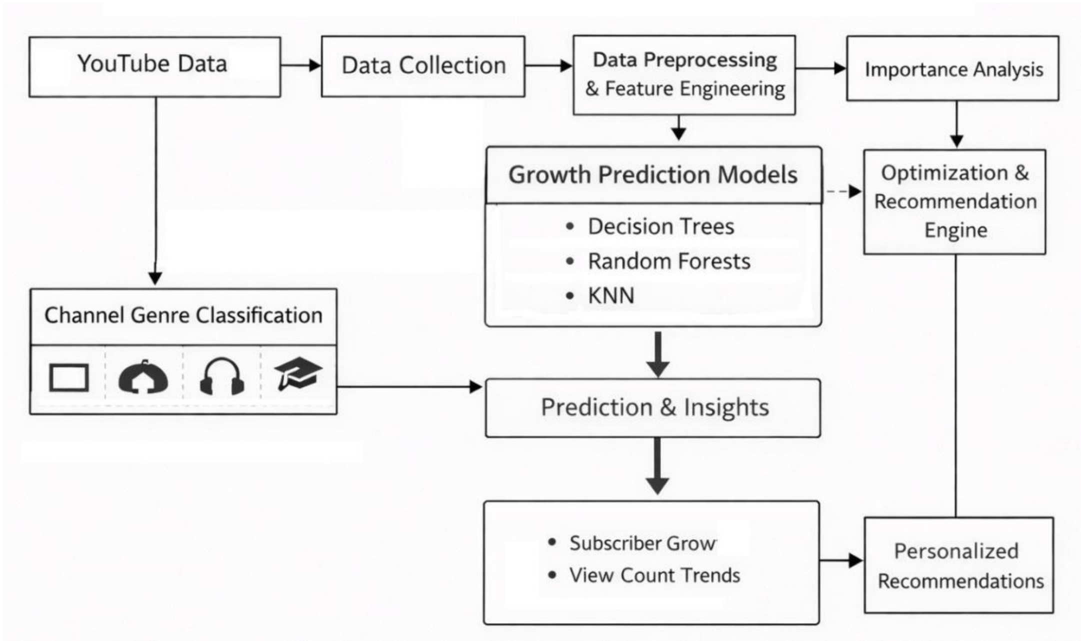

Fig.1.0 – Architecture Diagram

Then processed textual data is given to the main analysis part of the proposed system, which is the Hybrid CNN-BiLSTM Model. The customer reviews are used to identify important patterns, key words and sentiment words by employing CNN. The Bidirectional Long Short-Term Memory (Bi-LSTM) network, which can read word sequences both forward and backward, simultaneously encodes the context and semantics in the text. CNN and Bi-LSTM are fused to better capture the local textual information and long range contextual information. This is a hybrid learning model that has a high level of accuracy in sentiment classification and can help to analyze the customer sentiment more completely.

The hybrid DL model produces the result which is fed to the Sentiment Polarity Detection Module and Product Ranking Module. The sentiment classifier classifies customer reviews depending on whether their sentiment is positive, negative or neutral, depending on the sentiment expressed in the text. These sentiment outcomes then become the basis of calculating sentiment based on product scores. The ranking list is based upon consistently rated (in the best of possible light) emotional response and customer feedback for the products. The sentiment polarity and then context-specific review data also adds to relevance of the recommendations and further increases user trust in the recommended products.

Last but not least, the Product Selection and Recommendation Module integrates everything to create personalized product recommendations. Based on the sentiment analysis results and product rank based on sentiment, the system is able to create products that are very close to the User's preference and User's psychological addition to the products. recommendations are then presented to the end users in the recommendation interface, providing them with product suggestions relevant and personalized to their needs. Mainly the proposed framework involves data collection, text preprocessing, sentiment analysis with DL, sentiment-aware ranking, and generating recommendations. This approach enables the development of a smart recommendation system facilitating the provision of emotion-conscious and extremely relevant product suggestions in e-commerce applications as well as enhancing the user experience.

METHODOLOGY

A. Data Collection

The first step in the proposed approach is that a huge amount of user-generated review, comments and feedback is collected from multiple e-commerce platforms. Textual data is collected, as well as related product attributes like ratings, categories, descriptions and metadata, which are used to enrich the data set. Various methods, such as web scraping, publicly available datasets, and application programming interfaces (APIs), can be used for data acquisition. All data gathered is organized and loaded into a well-structured database with correct relationships among products and reviews. Moreover, irrelevant and duplicate records are filtered out to retain only meaningful and quality customer feedback that can be analyzed later.

B. Data Preprocessing

Once the data has been collected, the raw textual reviews go through a detailed preprocessing process to enhance the quality of the data and make it ready for the analysis of DL. This process involves tokenization, stop words removal, punctuation removal, lemmatization, stemming and noise reduction. Hyperlinks, special characters, and other symbols or meanings that are not relevant to the text are deleted. Text cleaning is followed by the conversion of reviews to numerical representations, e.g., by word embedding methods like Word2Vec or GloVe or other semantic representation methods. The pre-processing step is important because it helps to remove noise and allowing the sentiment analysis model to learn meaningful linguistic patterns effectively.

C. Sentiment Analysis Using Hybrid CNN-BiLSTM

The sentiment analysis stage is the main element of the proposed framework, and is based on a Hybrid CNN-BiLSTM architecture for sentiment classification. The CNN component is able to extract major local features, major keywords, and sentiment-related phrases from customer reviews. At the same time, it can learn the text context and long-range text dependency in two directions by using the bi-directional Bi-LSTM. This dual learning process enables the model to grasp the relationships in the text both syntactically and semantically. Therefore, the system has the ability to precisely detect the patterns of emotion and categorize the opinions of customers into positive, negative, or neutral sentiment groups.

D. Feature Extraction and Polarity Detection

In this stage, the emphasis is on learning the linguistic and semantic aspects that are relevant to sentiment analysis. Different NLP techniques such as word embeddings, PoS tagging, and dependency parsing are used to extract the contextual information from the reviews. These features are extracted and used to calculate sentiment polarity scores which indicate the strength and nature of the sentiment expressed by the customers. These scores are a quantitative reflection of user satisfaction, and can be used to detect products that are being given positive or negative feedback. Sentiment information extracted from the texts are used to generate personalized recommendation decisions.

E. Product Ranking and Recommendation Generation

After getting the sentiment polarity values, the recommendation module combines with the information of products to get the recommendation priorities. Products that consistently get positive feedback (and have good contextual relevance) get higher scores for recommendations. A sentiment-aware ranking algorithm is used for rank and produce a list of recommended products for each user. The ranking process is evolving and flexible and the ranking is update reviews and customer feedback come in. This helps product suggestions relevant, customized and in tune with changing customer tastes.

F. Evaluation and Performance Optimization

The standard measures used for sentiment classification and the quality of the recommended items are used to evaluate the effectiveness of the proposed framework. Multiple metrics are used to comprehensively judge and understand the performance of a model, such as accuracy, precision, recall, F1-Score and Mean Average Precision (MAP). The reliability of classification and stability of the model are measured using confusion matrix and cross validation techniques. The model is continually trained and fine-tuned with ever increasing and ever more varied data sets for better generalisation. Additionally, a number of techniques such as hyperparameter optimization, regularization and dropout techniques are employed to curb overfitting and enhance performance in the real world.

RESULT AND OBSERVATION

To test the proposed Hybrid CNN-BiLSTM Based Sentiment Analysis for Intelligent Product Recommendation Systems, product reviews data from e-commerce websites were used. The data was made up of customer reviews that were classified into positive, negative, and neutral sentiment classes. The preprocessed reviews were tokenized, stop words were removed, lemmatized and then given as input to the DL model. The performance of the proposed framework was evaluated according to common sentiment classification metrics: Accuracy, Precision, Recall, and F1-Score, and recommendation-specific metrics: Precision@K, Mean Average Precision (MAP).

In order to confirm the effectiveness of the proposed approach, it was tested with a number of benchmark methods such as Logistic Regression, Random Forest, CNN and BiLSTM models. Experimental results show that the hybrid architecture continually outperformed the other architectures on all of the evaluation measures. CNN successfully extracted key local text features, while the BiLSTM captured the relationship and contextual dependencies between words in the customer reviews. Consequently, the proposed model outperformed the traditional models in terms of classification accuracy and the recommendation relevance.

The sentiment classification results show that the proposed Hybrid CNN-BiLSTM model achieved an accuracy of 94.8%, precision of 94.2%, recall of 93.9% and F1-score of 94.0%. The results show that the model can correctly classify customer sentiment and that it is able to effectively differentiate positive, negative, and neutral sentiment. The confusion matrix analysis also confirmed that most of the reviews were correctly classified, with few reviews being misclassified between the neutral and positive sentiment classes.

The evaluation of the recommendation performance was conducted by adding the sentiment polarity scores to the product ranking process. For products that have been highly recommended by the customers repeatedly, higher weights were given to the recommendations. The results of experiments showed that this sentiment-aware recommendation method achieved better Precision@10 (91.5%) and Mean Average Precision (92.3%) compared to the traditional CF methods (82.1% and 84.6%, respectively). The improvements suggest that sentiment information can offer valuable contextual information that can improve the quality of recommendations and personalization.

The results also show that taking customer emotions into account in the recommendation process greatly enhances relevance and satisfaction of users. For products recommended using sentiment-aware ranking, the quality of the recommendations was better aligned with user preferences and more meaningful. Additionally, the hybrid model has shown good robustness in large review data set and performed well consistently in various product categories. The experimental results confirm the efficiency of the proposed approach, which is a fusion of deep learning-based sentiment analysis and recommendation systems, in developing a smart and user-scentric recommendation system.

Sentiment Classification Performance Accuracy Comparison

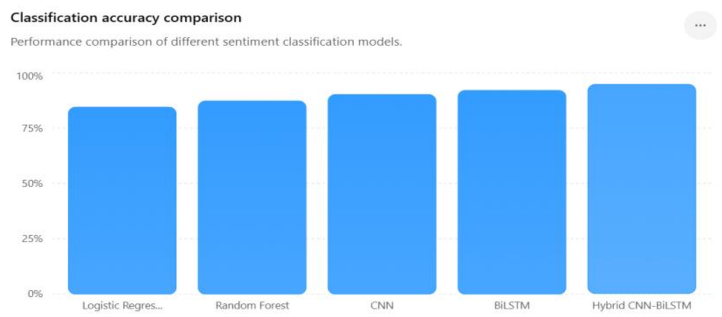

Fig.2 - Performance comparison of different sentiment classification models.

The graph shows that the accuracy of the comparative classification of ML and DL models. The traditional ML models like Logistic Regression and Random Forest had shown decent performance, but could not account for the complex context that was present in the customer reviews. The performance of DL models significantly exceeded the results of the others models because they could learn the semantic representations from the textual data. The Hybrid CNN-BiLSTM model achieved the best accuracy of 94.8%, which shows that the blending of Convolutional feature extraction and Bidirectional contextual learning has the best sentiment classification ability.

Evaluation metrics of Hybrid CNN-BiLSTM Model.

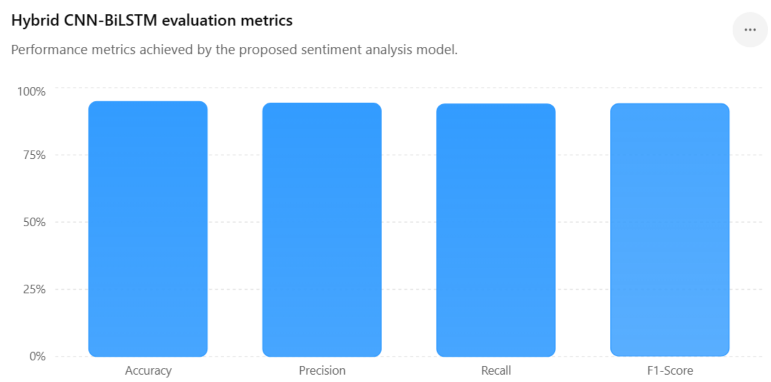

Fig.4 - Evaluation metrics of Hybrid CNN-BiLSTM Model.

The above graph shows the main evaluation parameters of the proposed model. All accuracy, precision, recall and f1 score values are over 93%, showing the balanced performance over all the sentiment categories. All these values are very similar, which shows the power of the model to reduce false positives and false negatives and achieve good consistency in classifications. This balanced appearance is especially vital for recommendation systems that predict sentiment as a part of the recommendation process and have a direct impact on the quality of the recommendation.

Recommendation Performance Comparison

Fig.3 - Recommendation quality comparison

The chart presents the conversation about how the quality of the recommendations differs between the conventional collaborative filtering approach and the sentiment-aware approach to the recommendations. The proposed system has resulted in substantial gains in terms of Precision@10 and Mean Average precision. This shows that sentiment data from customer reviews can provide meaningful context information that can boost the relevance of recommendations and increase user satisfaction.

The distribution of sentiment in the dataset.

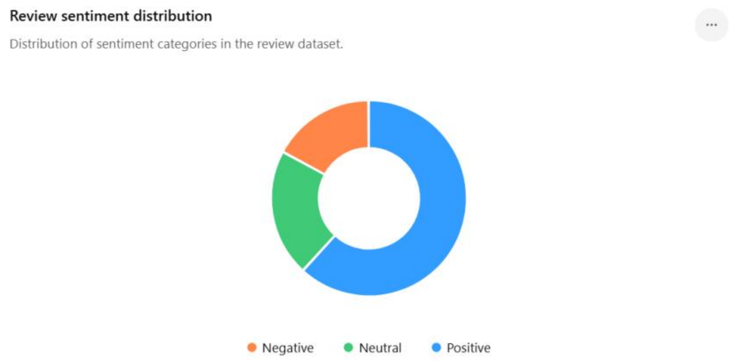

Fig.5 - Distribution of sentiment categories in the review dataset.

Sentiment analysis shows that customers' reviews are mostly positive, with a smaller portion being neutral and negative. This is a typical trend in e-commerce data: happy customers tend to post reviews. The class imbalance also emphasizes the significance of the use of powerful DL techniques that can learn meaningful representations even when the sentiment distribution is imbalanced.

FUTURE WORK

Future developments of the proposed sentiment-aware product recommendation system may involve: extending the model to enrich the proposed language components that are relevant to sentiment analysis and product recommendation, including the inclusion of language features that are relevant to real situations like sarcasm, irony, metaphors and code-mixing. These language features are often found in customer reviews but are not easily detected with commonly used sentiment analysis techniques. Combining DA-LMs with contextual learning techniques and sophisticated transformer networks has the potential to significantly improve the sentiment's interpretation and classification. Such enhancements may assist the system to respond to different communications modes and provide more accurate suggestions for different groups.

One more area of research interest is to be able to generate recommendations on-the-fly. Existing literature deals almost exclusively with the issue of the recommendation problem on the offline or batch processing level; however this is sometimes insufficient since it cannot react to new customer reviews. For future implementation, the use of light transformer models as well as data processing systems that process streams and incremental learning models that will continuously improve the sentiment information and the sentiment recommendation rank could be implemented. Users' changing points of view about various products and the marketplace will trigger more engagement and more effective product recommendations at run time when implementing this feature.

Another promising direction for future research is the growing ability of multilingual sentiment analysis. The growing number of e-commerce sites reaching an international audience makes it crucial to be able to read reviews in various languages. In future, proposed framework could be extended to include multilingual transformer models, cross-lingual embeddings and language-adaptive transfer learning techniques for regional Indian languages and international languages. These improvements would make the system more accessible, higher quality, easier to recommend for a wider variety of users, and do not rely on English language datasets.

Furthermore, further studies could include direct use of aspect-based sentiment analysis in the recommendation process. Instead of the review having just one sentiment label, the system may have identified and analysed the sentiments associated with the various product attributes e.g. quality, price, durability, design and performance. This level of sentiment analysis would allow for the creation of personalized recommendations and explain why specific products are being recommended, in a transparent manner. This would result in increased satisfaction, trust, and decision making experiences for users as they would be more confident in the recommendation results.

CONCLUSION

This study proposed a Hybrid CNN-BiLSTM Based Sentiment Analysis (HCSA) system in the field of Intelligent Product Recommendation Systems (IPRS). The proposed solution effectively combines NLP with DL sentiment classification and recommendation systems with sentiment information to enhance the result quality and relevance. The system can analyze customer reviews and opinions to understand the sentiment behind their feedback, which can help in making more accurate and personalized recommendations. The experimental results showed that the Hybrid CNN-BiLSTM model outperformed the other models in terms of sentiment classification accuracy, with the accuracy of 94.8%, precision of 94.2%, recall of 93.9%, and F1-score of 94.0%. Finally, CNN combined with BiLSTM allowed for capture of local textual patterns and long-range contextual dependencies and yielded a high accuracy in sentiment prediction. Furthermore, the sentiment polarity was also efficiently introduced during the recommendation process and thus, the Precision at 10 and Mean Average Precision values were improved to 91.5% and 92.3 respectively.

The results so obtained verified the notable advantage of the sentiment-aware recommender system over traditional recommender systems based on user's behavior/ratings. The suggested structure combines emotional and contextual information from customer reviews for more relevant and personalized product recommendations, and fosters trust in the recommendations. The system is also highly versatile in terms of product categories, and can perform well in large scale production of UGC. To summarise, the suggested framework for sentiment analysis in IPS is an effective method which can be incorporated in the existing e-commerce platforms to enhance the customer experience in e-commerce. The study demonstrates the potential of the DL sentiment analysis as a valuable and beneficial tool for the future of recommendation systems, where it could help improve the accuracy of recommendations, boost user engagement, and support businesses in their decision-making processes.

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