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Sentiment Based Model for Recommender Systems

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Abstract: Recommender systems have proven to be a valuable way for online users to cope with the issues of information overload. They have become one of the most powerful and popular tools in electronic commerce as illustrated by Amazon.com, YouTube, Netflix, Yahoo, and IMDb. While recommender systems have shown significant contribution, they still suffer from the long-standing problems related to cold-start users and data-sparsity. This is due to the fact that recommendation algorithms mostly rely on users' rating to make prediction of items. Such ratings are usually insufficient and very limited. On the other hand, sentiment ratings of items which can be derived from online news services, blogs, social media or even from the recommender systems themselves are seen capable of providing better recommendations to user as opposed to tags alone. Sentiment based model has been exploited in recommender systems to overcome the data-sparsity problem that exists in conventional recommender systems. Hence, embedding sentiment in recommender systems may significantly enhance the recommendation quality of recommender systems. Among the aims of this research is to integrate sentiment analysis in recommender systems particular to those items with no associated rating that commonly contribute to the problem of data-sparsity.

1.INTRODUCTION

Product recommendation systems are commonly used in various industries, including e commerce, streaming services, and online content platforms. A product recommendation system is designed to suggest relevant items or products to users based on their preferences, behaviour, or other relevant factors. It leverages algorithms and data analysis techniques to analyse user data and make personalized recommendations. A sentiment-based recommendation system considers user preferences along with sentiment or opinion expressed by users towards products or services. It utilizes natural language processing (NLP) techniques to extract sentiment-related features from user reviews, ratings, or feedback. Analyses of sentiment, such as positive, negative, or neutral, the system can generate recommendations that align with users' sentiment towards products. This approach helps to personalize recommendations based on users' emotional responses, leading to a more tailored and satisfying user experience. Current ecommerce websites can fine tune their strategies to improve customer satisfaction using sentiment based recommendations. These innovations help to create a more customized and fulfilling user experience by tailoring recommendations based onusers' emotional reactions.

This method goes into the psychological and emotional aspects of user behaviour and choice, going beyond simple algorithmic recommendations. This research holds significance in ecommerce and other industries as it can enable organizations to improve customer satisfaction. E-commerce websites can improve user engagement and loyalty by adjusting their methods to better match customers' emotional responses by utilizing the power of sentiment-based suggestions. The primary objective of this research is to create, assess, and improve a sentiment-based product recommendation system that uses natural language processing (NLP) techniques to extract sentiment-related data and provide tailored suggestions. By conducting a thorough assessment, this research seeks to determine how well the system works to enhance user experience and customer happiness in the context of e-commerce, offering useful information and workable solutions to companies operating in this industry.

2. LITERATURE SURVEY

Integrating Collaborative Filtering and Sentiment Analysis: A Rating Inference Approach", F. Peleja, P. Dias and F. Martins, 2013. The activity of Social-TV viewers has grown considerably in the last few years—viewers are no longer passive elements. The Web has socially empowered the viewers in many new different ways, for example, viewers can now rate TV programs, comment them, and suggest TV shows to friends through Web sites. Some innovations have been exploring these new activities of viewers but we are still far from realizing the full potential of this new setting. For example, social interactions on the Web, such as comments and ratings in online forums, create valuable feedback about the targeted TV entertainment shows. In this paper, we address this last setting: a media recommendation algorithm that suggests recommendations based on users' ratings and unrated comments. In contrast to similar approaches that are only ratings-based, we propose the inclusion of sentiment knowledge in recommendations. This approach computes new media recommendations by merging media ratings and comments written by users about specific entertainment shows. This contrasts with existing recommendation methods that explore ratings and metadata but do not analyse what users have to say about particular media programs. In this paper, we argue that text comments are excellent indicators of user satisfaction. Sentiment analysis algorithms offer an analysis of the users' preferences in which the comments may not be associated with an explicit rating.

Thus, this analysis will also have animpact on the popularity of a given media show. Thus, the recommendation algorithm—based on matrix factorization by Singular Value Decomposition—will consider both explicit ratings and the output of sentiment analysis algorithms to compute new recommendations. The implemented recommendation framework can be integrated on a Web TV system where users can view and comment entertainment media from a video-on-demand service. The recommendation framework was evaluated on two datasets from IMDb with 53,112 reviews (50 % unrated) and Amazon entertainment media with 698,210 reviews (26 % unrated). Recommendation results with ratings and the inferred preferences—based on the sentiment analysis algorithms—exhibited an improvement over the ratings only based recommendations. This result illustrates the potential of sentiment analysis of user comments in recommendation systems.

"Recommender Systems" D. Jannach, M. Zanker, A. Felfernig and G. Friedrich, 2010.

Recommender systems assist and augment this natural social process. In a typical recommender system people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients. In some cases the primary transformation is in the aggregation; in others the system's value lies in its ability to make good matches between the recommenders and those seeking recommendations. The developers of the first recommender system, Tapestry, coined the phrase "collaborative filtering" and several others have adopted it. We prefer the more general term "recommender system" for two reasons. First, recommenders may not explicitly collaborate with recipients, who may be unknown to each other. Second, recommendations may suggest particularly interesting items, in addition to indicating those that should be filtered out. This special section includes descriptions of five recommender systems. A sixth article analyses incentives for provision of recommendations.

"Toward the Next Generation of Recommender Systems: A Survey of the State-of the-Art and Possible Extensions", G. Adomavicius and A. Tuzhilin, 2005.

This paper presents an overview of the field of recommender systems and describes the current generation of recommendation methods that are usually classified into the following three main categories: content-based, collaborative, and hybrid recommendation approaches. This paper also describes various limitations of current recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications. These extensions include, among others, an improvement of understanding of users and items, incorporation of the contextual information into the recommendation process, support for multicriteria ratings, and a provision of more flexible and less intrusive types of recommendations.

"Multiple Aspect Ranking using the Good Grief Algorithm", B. Snyder and R. Barzilay, 2007.

We address the problem of analysing multiple related opinions in a text. For instance, in a restaurant review such opinions may include food, ambience and service. We formulate this task as a multiple aspect ranking problem, where the goal is to produce a set of numerical scores, one for each aspect. We present an algorithm that jointly learns ranking models for individual aspects by modelling the dependencies between assigned ranks.Thisalgorithm guides the prediction of individual rankers by analysing meta-relations between opinions, such as agreement and contrast. We prove that our agreement based joint model is more expressive than individual ranking models. Our empirical results further confirm the strength of the model: the algorithm provides significant improvement over both individual rankers and a state-of-the-art joint ranking model.

"Sentiment Analysis Using Common-Sense and Context Information", B Agarwal, N Mittal , P Bansal, S Garg, 2015.

Sentiment analysis research has been increasing tremendously in recent times due to the wide range of business and social applications. Sentiment analysis from unstructured natural language text has recently received considerable attention from the research community. In this paper, we propose a novel sentiment analysis model based on common sense knowledge extracted from Concept Net based ontology and context information. Concept Net based ontology is used to determine the domain specific concepts which in turn produced the domain specific important features. Further, the polarities of the extracted concepts are determined using the contextual polarity lexicon which we developed by considering the context information of a word. Finally, semantic orientations of domain specific features of the review document are aggregated based on the importance of a feature with respect to the domain. The importance of the feature is determined by the depth of the feature in the ontology. Experimental results show the effectiveness of the proposed methods.

"Pessimists and optimists: Improving collaborative filtering through sentiment analysis", Miguel A. García-Cumbreras, Arturo Montejo-Ráez and Manuel C. Diaz-Galiano, 2013.

This work presents a novel application of Sentiment Analysis in Recommender Systems by categorizing users according to the average polarity of their comments. These categories are used as attributes in Collaborative Filtering algorithms. To test this solution a new corpus of opinions on movies obtained from the Internet Movie Database (IMDb) has been generated, so both ratings and comments are available. The experiments stress the informative value of comments. By applying Sentiment Analysis approaches some Collaborative Filtering algorithms can be improved in rating prediction tasks. The results indicate that we obtain a more reliable prediction considering only the opinion text (RMSE of 1.868), than when apply similarities over the entire user community (RMSE of 2.134) and sentiment analysis can be advantageous to recommender systems.

"Using tags for measuring the semantic similarity of users to enhance collaborative filtering recommender systems", A. S. Ghaayen and S. A. M. Noah, 2017.

Recent years have seen a significant growth in social tagging systems, which allow users to use their own generated tags to organize, categorize, describe and search digital content on social media. The growing popularity of tagging systems is leading to an increasing need for automatic generation of recommended items for users. Much previous research focuses on incorporating recommender techniques in social tagging systems to support the suggestion of suitable tags for annotating related items. Collaborative filtering is one such technique. The most critical task in collaborative filtering is finding related users with similar preferences, i.e., “liked-minded” users. Despite the popularity of collaborative filtering, it still suffers from certain limitations in relation to “cold-start” users, for example, where often there are insufficient preferences to make recommendations. Moreover, there is the data-sparsity problem, where there is limited user feedback data to identify similarities in users’ interests because there is no intersection between users’ transactional data a situation which also results in degraded recommendation quality. For this reason, in this paper, we present a new collaborative filtering approach based on users’ semantic tags, which calculates the similarity between users by discovering the semantic spaces in their posted tags. We believe that this approach better reflects the semantic similarity between users according to their tagging perspectives and consequently improves recommendations through the identification of semantically related items for each user. Our experiment on a real-life dataset shows that the proposed approach outperforms the traditional user-based collaborative filtering approach in terms of improving the quality of recommendations.

3. PROPOSED METHODOLOGY

This proposed methodology is used to address the limitations of traditional recommendation systems, the proposed methodology integrates **comment sentiments along with ratings** to improve recommendation accuracy and relevance. Instead of relying solely on numerical ratings, the system incorporates **Natural Language Processing (NLP) techniques** to analyze user-generated comments and extract sentiment-related features.

The proposed methodology typically includes the following key components:

Sentiment-Based Approach:

- The system **extracts and processes textual comments** from various sources like YouTube, e-commerce platforms, and review websites.
- Sentiments are categorized into five levels (Negative, Neutral, Positive, Happy, Extremely Happy) to determine user preferences more effectively.
- Unlike traditional methods that suffer from **cold-start and data sparsity issues**, this approach enables the model to generate recommendations even when rating data is limited.

Implementation of Convolutional Neural Networks (CNN2D):

- A **deep learning-based CNN model** is trained to classify comments based on sentiment intensity.
- The CNN model undergoes multiple training iterations to **learn from past user interactions**, allowing it to adapt and refine its prediction capabilities.
- The extracted sentiments are then **mapped to relevant items**, enhancing the recommendation system’s decision-making process.

Performance Evaluation and Optimization:

- The effectiveness of the model is assessed using **Root Mean Square Error (RMSE)**, ensuring that prediction errors are minimized.
- The dataset is dynamically split into training and testing sets, allowing the model to **self-optimize over multiple runs**.
- Additional fine-tuning techniques, such as **hyperparameter tuning and dropout layers**, are implemented to prevent overfitting and improve generalization.

Integration with User Interface:

- Users can interact with the system through an intuitive GUI, where they can input their comments or browse through personalized recommendations.

- The system also allows for **real-time sentiment analysis**, where users can enter custom reviews and get immediate predictions on recommended items.

Applications:

The Sentiment-Based Recommender System utilizing deep learning (CNN2D) and sentiment analysis can be applied across various industries to enhance user experience and decision-making. Some key applications include:

- E-commerce Platforms(Better Customer Engagement).
- Healthcare & Mental Health Applications (personalized health tips and doctor recommendations).
- Educational Platforms & E-Learning (Course Recommendations).

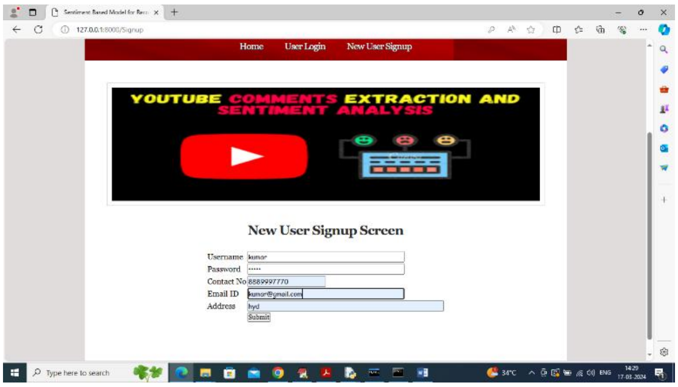
Advantages:

The Sentiment-Based Recommender System incorporating deep learning (CNN2D) and sentiment analysis offers several advantages over traditional recommendation models. Below is an in-depth explanation of its benefits:

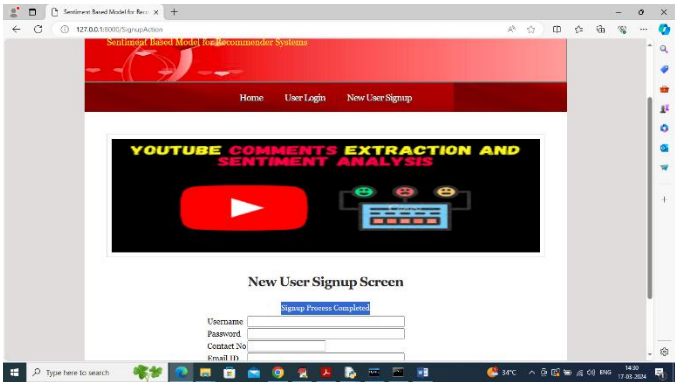
- Higher Accuracy in Recommendations: By incorporating text-based sentiment analysis, the system can extract valuable insights from user comments.The CNN model classifies sentiments into multiple categories, providing a more nuanced understanding of user preferences.This reduces misleading recommendations that arise due to sparsely rated items.
- Improved Recommendation Quality:By analyzing both explicit ratings and implicit user sentiments, it matches products, movies, or services more precisely to user preferences.Sentiment-based recommendations ensure that users receive suggestions that align with their emotional reactions, leading to higher satisfaction and engagement.
- Addresses Cold-Start Problem:Instead of waiting for numerical ratings to accumulate, the system leverages user comments and sentiment analysis to make early-stage recommendations.Even if an item has zero ratings, it can still be recommended based on the sentiments extracted from textual feedback.
- Scalability and Adaptability: The CNN-based model can process massive volumes of text data, making it scalable for large platforms. It continuously learns from new data, allowing it to adapt to trending topics, products, and changing user preferences.
- Robust Performance Evaluation (RMSE-Based Optimization): The model uses Root Mean Square Error (RMSE) as an evaluation metric to continuously fine-tune prediction accuracy. Lower RMSE values indicate that the system is making precise predictions with minimal errors.The CNN model is trained using dynamic dataset splitting, ensuring that it optimizes itself over multiple iterations.
- Enhanced User Engagement and Satisfaction: By aligning recommendations with user emotions, it improves engagement and reduces bounce rates. It creates a feedback loop where users are encouraged to leave more comments, further refining the system.
- Versatility Across Multiple Domains: The sentiment-based approach can be integrated into multiple industries, including e-commerce, entertainment, healthcare, finance, and education. The deep learning model can be retrained with domain-specific datasets to suit different applications.

4. EXPERIMENTAL ANALYSIS

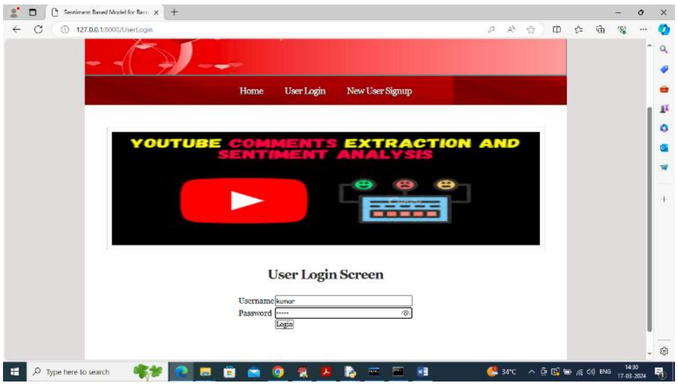
In above screen click on 'User Sign up' link to get below page



In above screen user is entering sign up details and then press button to get below page

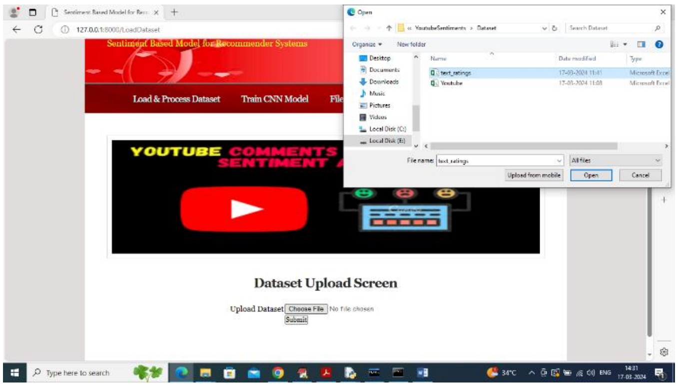


In above screen user sign up completed and now click on ‘User Login’ link to get below page

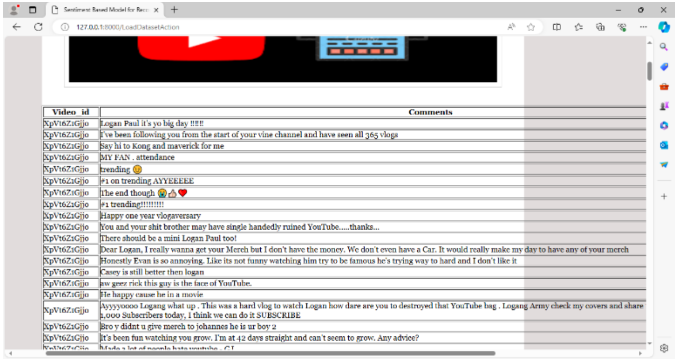


In above screen user is login and after login will get below page

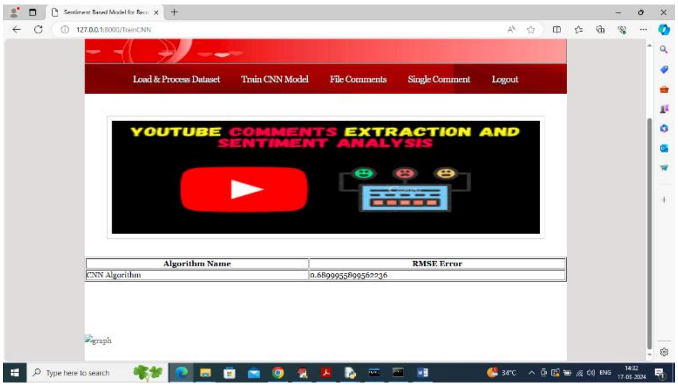
In above screen click on ‘Load & Process Dataset’ link to get below page



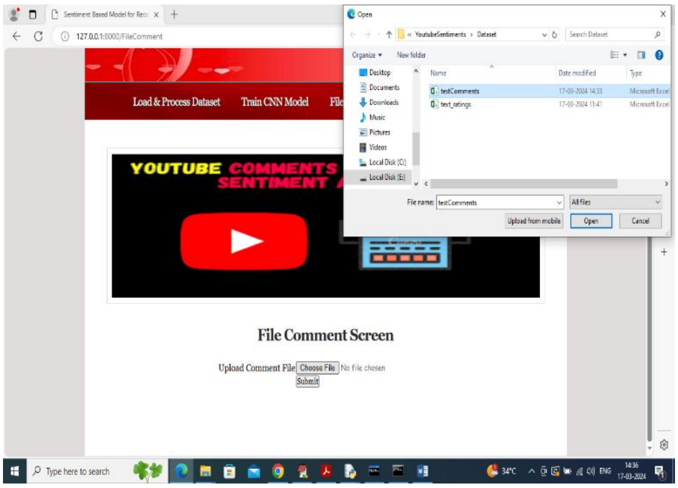
In above screen selecting and uploading ‘text_ratings.csv’ file and then click on ‘Open’ button to load dataset and get below page



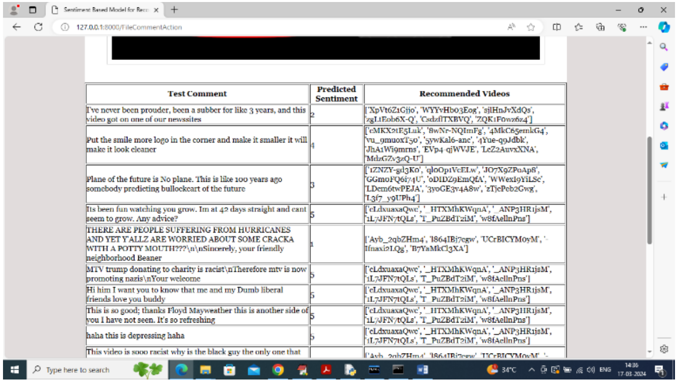
In above screen dataset loaded and now click on ‘Train CNN’ link to train algorithm and get below page



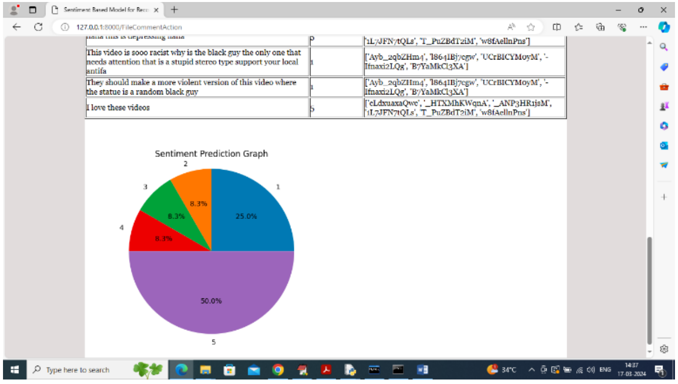
In above screen CNN training completed and got RMSE error as 0.68% and now click on ‘File Comments’ link to get below page



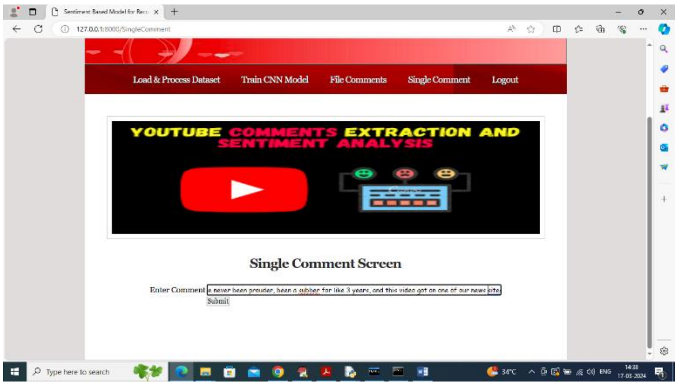
In above screen selecting and uploading ‘test comment.csv’ file and then click on ‘Open’ and ‘Submit’ button to get below page



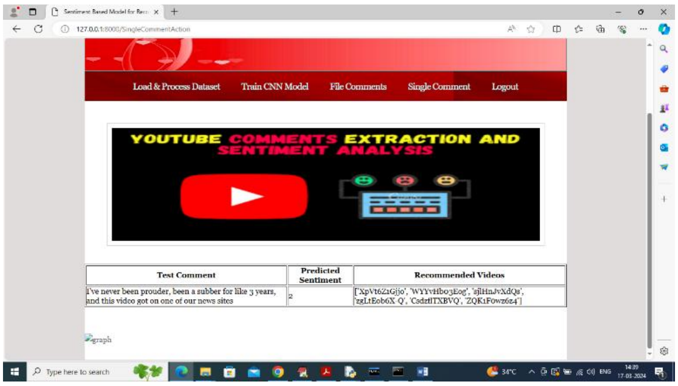
In above screen in first column can see Test Comment Text and in second column can see predicted sentiments from range 1 to 5 and then based on predicted sentiments displaying top 10 recommended videos and in below is predicted sentiments graph



In above graph can see percentage of different sentiments and now click on 'Single Comment Analysis' link to get below page



In above screen entered single comments and then press button to get belowoutput



In above screen can see test single comment text and then can see predicted sentiment and list of recommended videos.

5. CONCLUSION

In this work, the CatBoost classifier demonstrated superior performance for sentiment classification, while the userbased recommendation model proved to be the best for product recommendations. Finetuning recommendations using the CatBoost classifier improved sentiment prediction for each recommended product. The sentiment-based product recommendation system was evaluated using real-time data and successfully deployed as a web application using Streamlit and Ngrok to enhance product recommendations and drive customer satisfaction and engagement. In summary, this research emphasizes how well CatBoost performs in sentiment classification and how useful the userbased recommendation model is for making product recommendations. Sentiment predictions for suggested products were further enhanced by fine-tuning using the CatBoost classifier. When used as a web application, the sentiment-based recommendation system improves user engagement and satisfaction. The future scope of this project includes integrating deep learning algorithms for more accurate sentiment analysis, incorporating SEO techniques to optimize website content and attract more traffic, and integrating chatbots for realtime support and personalized recommendations based on customer emotions and preferences. These advancements will further enhance the recommendation system, improving customer satisfaction and loyalty. Chatbots and SEO strategies will optimize content and offer real time support, while deep learning algorithms will improve sentiment analysis accuracy. All of these developments will eventually increase customer satisfaction and loyalty.

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