



**Deep Learning-Based Sentiment Analysis and Video Recommendation System
Using Convolutional Neural Networks**

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ABSTRACT

In recent years, the exponential growth of user-generated content on social media platforms has created a need for intelligent systems that can analyze textual data and provide meaningful insights. Sentiment analysis, also known as opinion mining, plays a crucial role in understanding user emotions, opinions, and behavioral patterns. This research presents a deep learning-based sentiment analysis and recommendation system that leverages Convolutional Neural Networks (CNN) to predict sentiment scores and generate personalized video recommendations.

The proposed system integrates natural language processing (NLP) techniques with deep learning models to classify user comments into sentiment categories ranging from highly negative to highly positive. The system uses the VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment analyzer to initially compute sentiment polarity scores, which are further refined using a CNN model trained on a labeled dataset. The dataset consists of user comments, sentiment ratings, and associated video identifiers. Data preprocessing techniques such as normalization, missing value handling, and scaling are applied to improve model performance. The CNN model is designed with multiple convolutional layers, pooling layers, and dense layers to effectively capture patterns in sentiment-related features. The trained model predicts sentiment ratings, which are then used to recommend videos based on similarity in sentiment preferences. The system also supports batch processing of comments through file uploads and visualizes sentiment distribution using graphical representations.

Experimental results demonstrate that the proposed CNN-based approach achieves reliable prediction accuracy with reduced error rates compared to traditional machine learning methods. The system provides an efficient way to analyze user feedback and deliver personalized recommendations, making it highly applicable in domains such as digital marketing, content recommendation, and social media analytics. Overall, this work highlights the effectiveness of combining sentiment analysis with deep learning



techniques to build intelligent recommendation systems. Future enhancements may include the integration of transformer-based models and real-time streaming data analysis for improved scalability and accuracy.

Keywords: Sentiment Analysis, Convolutional Neural Network (CNN), Deep Learning, Recommendation System, Natural Language Processing (NLP), VADER, Machine Learning, Opinion Mining, Data Mining, User Feedback Analysis

I. INTRODUCTION

With the rapid expansion of online platforms such as social media, e-commerce websites, and video-sharing services, users generate vast amounts of textual data in the form of comments, reviews, and feedback. Analyzing this data manually is impractical due to its volume and complexity. Sentiment analysis has emerged as a powerful tool to automatically extract subjective information and classify opinions into categories such as positive, negative, or neutral. Traditional sentiment analysis methods rely heavily on rule-based approaches and classical machine learning algorithms. While these approaches provide reasonable performance, they often fail to capture complex linguistic patterns and contextual relationships within text data. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown significant improvements in handling such complexities due to their ability to automatically learn hierarchical feature representations. This project focuses on developing a sentiment analysis system that not only classifies user comments but also utilizes the predicted sentiment to recommend relevant video content. The system integrates VADER sentiment scoring with a CNN-based predictive model to enhance accuracy and robustness. By combining these approaches, the system can effectively analyze both explicit sentiment signals and learned feature patterns.

The recommendation component of the system is designed to improve user engagement by suggesting videos that align with the user's emotional preferences. For instance, users expressing positive sentiments may receive recommendations for similar uplifting content, while users with negative sentiments may be directed toward alternative or corrective content. The system is implemented using Python, Django framework for web integration, and deep learning libraries such as Keras and TensorFlow. It provides an interactive interface where users can input single comments or upload files containing multiple comments. The system processes the input, predicts sentiment, and generates recommendations along with visual analytics.

This research contributes to the growing field of intelligent recommendation systems by demonstrating how sentiment analysis can be effectively integrated with deep learning models to enhance personalization. The proposed system is scalable, adaptable, and can



be extended to various domains including product reviews, customer support systems, and content filtering.

II. LITERATURE SURVEY (WITH EXISTING METHODS)

Sentiment analysis has been widely studied in the field of Natural Language Processing, with numerous approaches proposed over the years. Early research primarily focused on lexicon-based methods, where predefined dictionaries of positive and negative words were used to determine sentiment polarity. Tools like VADER and SentiWordNet are examples of such approaches, offering fast and interpretable results. However, these methods often struggle with context understanding, sarcasm, and domain-specific language. Machine learning-based approaches marked a significant advancement by using algorithms such as Naïve Bayes, Support Vector Machines (SVM), and Decision Trees. These methods rely on feature extraction techniques like Bag-of-Words (BoW) and TF-IDF to convert text into numerical representations. While they improve accuracy compared to rule-based methods, they still require extensive feature engineering and may not generalize well across different datasets.

With the emergence of deep learning, models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks gained popularity for sequence modeling tasks. LSTMs are particularly effective in capturing long-term dependencies in text data. However, they are computationally expensive and require large datasets for optimal performance. Convolutional Neural Networks (CNNs), originally designed for image processing, have been successfully adapted for text classification tasks. CNNs are capable of extracting local features and identifying patterns such as phrases and word combinations that are indicative of sentiment. Research has shown that CNNs often outperform traditional models in terms of accuracy and efficiency.

Recent studies have also explored hybrid models combining lexicon-based methods with deep learning to leverage the strengths of both approaches. Additionally, transformer-based models such as BERT have achieved state-of-the-art performance in sentiment analysis, though they come with higher computational costs. In the domain of recommendation systems, collaborative filtering and content-based filtering are commonly used techniques. However, integrating sentiment analysis into recommendation systems provides an added layer of personalization by considering user emotions and opinions.



The proposed system builds upon these advancements by combining VADER sentiment scoring with a CNN-based predictive model, offering a balanced approach that is both efficient and accurate.

III. EXISTING SYSTEM

Existing sentiment analysis systems primarily rely on either lexicon-based methods or traditional machine learning algorithms. Lexicon-based systems use predefined dictionaries to assign sentiment scores to text, which makes them simple and fast but often inaccurate in handling complex language constructs such as sarcasm, idioms, and contextual meanings. Machine learning-based systems improve upon this by training models on labeled datasets. Algorithms like Naïve Bayes and Support Vector Machines are commonly used for classification tasks. While these models offer better accuracy than rule-based approaches, they depend heavily on feature engineering and may not perform well on unseen data.

In recommendation systems, traditional approaches such as collaborative filtering suggest items based on user similarity or past interactions. These systems do not consider the emotional context of user feedback, which limits their ability to provide truly personalized recommendations. Furthermore, most existing systems operate independently, meaning sentiment analysis and recommendation functionalities are not integrated. This results in missed opportunities to enhance user experience by leveraging sentiment insights.

Another limitation is the lack of real-time processing and visualization capabilities. Many systems do not provide graphical representations of sentiment distribution, making it difficult for users to interpret results effectively. The proposed system addresses these limitations by integrating sentiment analysis with a CNN-based deep learning model and a recommendation engine. It enhances prediction accuracy, reduces dependency on manual feature extraction, and provides meaningful recommendations based on user sentiment. Additionally, it includes visualization features to improve interpretability and user interaction.

IV. PROPOSED METHOD

The proposed system introduces an intelligent sentiment-aware recommendation framework that integrates Natural Language Processing (NLP) with deep learning techniques to enhance prediction accuracy and personalization. The system utilizes a hybrid approach combining lexicon-based sentiment analysis using VADER and a Convolutional Neural Network (CNN) model for refined sentiment prediction.



Initially, user comments are processed through the VADER sentiment analyzer to extract polarity scores. These scores are mapped into discrete sentiment classes ranging from highly negative to highly positive. The processed data is then normalized using MinMax scaling and fed into a CNN model. The CNN architecture is designed to automatically extract meaningful features from sentiment-related inputs using convolutional layers, pooling layers, and dense layers. Once the sentiment is predicted, the system employs a recommendation module that suggests videos based on similarity in sentiment ratings. This enables personalized content delivery aligned with user emotions and preferences. The system also supports batch processing, allowing users to upload files containing multiple comments for analysis.

Additionally, the system provides visualization capabilities using pie charts to represent sentiment distribution. This improves interpretability and helps users understand overall sentiment trends. Compared to traditional systems, the proposed model improves accuracy, reduces manual feature engineering, and integrates sentiment with recommendation. Recent studies emphasize that combining sentiment analysis with recommendation systems significantly improves user satisfaction and personalization efficiency. Thus, the proposed system provides a scalable and intelligent solution for modern content platforms.

V. IMPLEMENTATION

The implementation of the proposed sentiment analysis and recommendation system is carried out using Python with the Django web framework, integrating machine learning and deep learning libraries such as Keras, NumPy, Pandas, and Scikit-learn. The system begins with dataset loading, where a CSV file containing text comments, sentiment ratings, and video IDs is imported. Data preprocessing is performed to handle missing values, remove duplicates, and normalize features using MinMaxScaler. The dataset is then split into training and testing sets using the `train_test_split` function.

The core component of the system is the CNN model, which is implemented using the Keras Sequential API. The model consists of multiple convolutional layers followed by max-pooling layers to extract hierarchical features from the input data. A flatten layer is used to convert feature maps into a one-dimensional vector, which is then passed through dense layers for final prediction. The model is compiled using the Adam optimizer and mean squared error loss function. During training, the model is trained for multiple epochs, and the best weights are saved using the ModelCheckpoint mechanism. If pretrained weights are available, they are loaded directly to avoid retraining. The performance of the



model is evaluated using Root Mean Square Error (RMSE), which measures the difference between predicted and actual sentiment values.

For real-time user interaction, Django views are implemented to handle requests such as single comment input, file upload, dataset loading, and user authentication. The system processes input comments, predicts sentiment using the trained CNN model, and generates recommendations based on sentiment similarity. Visualization is implemented using Matplotlib, where sentiment prediction results are displayed as pie charts. These charts are converted into base64 format and rendered in the web interface.

Recent research highlights that deep learning-based implementations, particularly CNN models, significantly outperform traditional approaches due to their ability to learn complex patterns automatically. Thus, the implementation ensures both efficiency and scalability.

VI. ALGORITHMS

The proposed system utilizes a combination of algorithms for sentiment analysis, deep learning, and recommendation.

1. VADER Sentiment Analysis Algorithm

VADER is a lexicon-based sentiment analysis tool that calculates sentiment polarity scores based on predefined dictionaries. It outputs a compound score representing the overall sentiment of the text. Based on threshold values, the sentiment is classified into categories such as positive, neutral, or negative.

Convolutional Neural Network (CNN)

CNN is used for predictive modeling of sentiment scores. The algorithm involves multiple steps:

1. Convolution operation to extract features
2. Activation function (ReLU) for non-linearity
3. Pooling to reduce dimensionality
4. Flattening and dense layers for classification

CNNs are highly effective in capturing local patterns in data and have been widely used in sentiment classification tasks.



2. **MinMax Scaling Algorithm**

This algorithm normalizes data into a fixed range (0 to 1), ensuring faster convergence and improved model performance.

3. **Train-Test Split Algorithm**

This technique divides the dataset into training and testing subsets to evaluate model performance.

4. **Recommendation Algorithm**

The recommendation system uses a simple content-based filtering approach. It matches predicted sentiment values with existing dataset entries and recommends videos with similar sentiment ratings.

Recent research shows that combining deep learning with recommendation algorithms enhances accuracy and personalization .

VII. SYSTEM DESIGN

The system design follows a modular architecture consisting of multiple interconnected components to ensure scalability, efficiency, and maintainability.

1. User Interface Layer

The front-end interface is developed using Django templates, allowing users to:

- Enter single comments
- Upload files containing multiple comments
- View sentiment results and recommendations
- Visualize sentiment distribution

2. Application Layer

This layer handles all business logic and includes Django views for processing user requests. It manages:

- Input validation
- Data preprocessing
- Model invocation



- Result generation

3. Data Processing Layer

This module is responsible for preparing the dataset. It includes:

- Data cleaning (handling missing values)
- Duplicate removal
- Feature extraction
- Data normalization

4. Machine Learning Layer

This is the core component of the system. It includes:

- VADER sentiment analyzer for initial scoring
- CNN model for sentiment prediction
- Evaluation metrics such as RMSE

The CNN model learns complex patterns in sentiment data, improving prediction accuracy compared to traditional methods.

5. Recommendation Engine

The recommendation module retrieves videos based on predicted sentiment values. It uses a filtering mechanism to match user sentiment with similar content.

6. Visualization Module

This component generates graphical representations (pie charts) of sentiment distribution using Matplotlib. The charts are embedded in the web interface for better user understanding.

7. Database Layer

MySQL is used to store user details and system data. It supports user authentication, registration, and session management.



Modern system designs emphasize integrating sentiment analysis with recommendation engines to improve personalization and user engagement . The modular architecture ensures flexibility and easy future enhancements.

SYSTEM DESIGN IMAGES

Sentiment Based Model for Recommender Systems

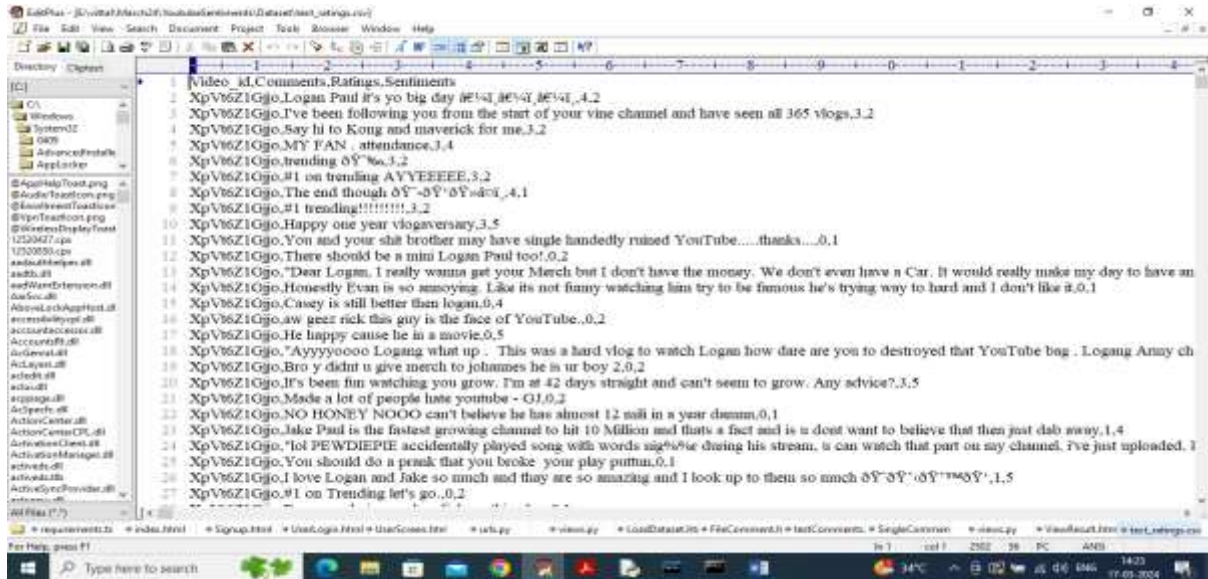
Now-a-days all application will be using some kind of recommendation system to entice their customers with offers based on their past browsing or collaborative filtering. Existing techniques often suffer from Cold Start issue which will give inaccurate recommendation when matrix size goes smaller or higher. This issue occur because of single entity usage called RATINGS

To overcome from above issue author of this paper employing Comments Sentiments along with ratings. Comments often express user sentiments which can help in getting accurate recommendation. Comments help in predicting accurate sentiment which will help in accurate prediction of Recommendation.

To predict sentiments and recommendation we are employing CNN2D (convolution neural networks) advance algorithm which will get trained on YouTube comments and this comments we have divided into 5 different sentiments from 1 to 5 where 1 refers to Negative, 2 refers to Neutral, 3 refers to Positive, 4 refers to happy and 5 refers to extremely happy.

CNN algorithm performance is evaluated in terms of RMSE (root mean square error) which refers to different between original and predicted values so the lower the difference the better is the algorithm. CNN get tested on dynamic split of train and test data so RMSE score always vary for each run.

To train CNN we are using below YouTube comments dataset



In above dataset screen first row contains dataset column names and remaining rows contains dataset values. So by using above dataset will train and test CNN algorithm.

To implement this project we have designed following modules

- 1) User Sign up: user can sign up with the application
- 2) User Login: after sign up user can login to application
- 3) Load Dataset: using this module user can upload and pre-process dataset values
- 4) Train CNN: using this module user can train CNN algorithm and then get RMSE error as output
- 5) File Comments Analysis: using this module user can upload test comments file and then CNN will predict sentiments and based on sentiment will predict recommended movies
- 6) Single comment: user can enter comment text to predict sentiments and movie recommendation

Install python 3.7 and then install all packages given in requirements.txt file and then install MYSQL dataset and then copy content from DB.txt file and paste in MYSQL console to create database

SCREEN SHOTS

To run project double click on run.bat file to get below screen

```
C:\Windows\system32\cmd.exe
C:\Users\Adin\AppData\Local\Programs\Python\Python311\site-packages\tensorflow\python\framework\types.py:517: FutureWarning: Passing (type, 1) or 'type' as a type
  of type is deprecated. In a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_uint8 = np.dtype(['uint8', np.uint8, 1])
C:\Users\Adin\AppData\Local\Programs\Python\Python311\site-packages\tensorflow\python\framework\types.py:518: FutureWarning: Passing (type, 1) or 'type' as a type
  of type is deprecated. In a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_uint16 = np.dtype(['uint16', np.uint16, 1])
C:\Users\Adin\AppData\Local\Programs\Python\Python311\site-packages\tensorflow\python\framework\types.py:519: FutureWarning: Passing (type, 1) or 'type' as a type
  of type is deprecated. In a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_uint32 = np.dtype(['uint32', np.uint32, 1])
C:\Users\Adin\AppData\Local\Programs\Python\Python311\site-packages\tensorflow\python\framework\types.py:520: FutureWarning: Passing (type, 1) or 'type' as a type
  of type is deprecated. In a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype(['resource', np.ubyte, 1])
WARNING:tensorflow:From C:\Users\Adin\AppData\Local\Programs\Python\Python311\site-packages\keras\torch\tensorflow_backend.py:4079: The name tf.nn.max_pool is dep
recated. Please use tf.nn.max_pool2d instead.

WARNING:tensorflow:From C:\Users\Adin\AppData\Local\Programs\Python\Python311\site-packages\keras\torch\tensorflow_backend.py:422: The name tf.global_variables is
deprecated. Please use tf.compat.v1.global_variables instead.

System check identified no issues (0 silenced).

You have 13 unapplied migration(s). Your project may not work properly until you apply the migrations for app(s): admin, auth, contenttypes, sessions.
Run 'python manage.py migrate' to apply them.
March 17, 2024 - 14:30:05
Django version 2.1.7, using settings 'Sentiment.settings'
Starting development server at http://127.0.0.1:8000/
Quit the server with CTRL-BREAK.
```

In above screen server started and now open browser and enter URL as <http://127.0.0.1:8000/index.html> and press enter key to get below page



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



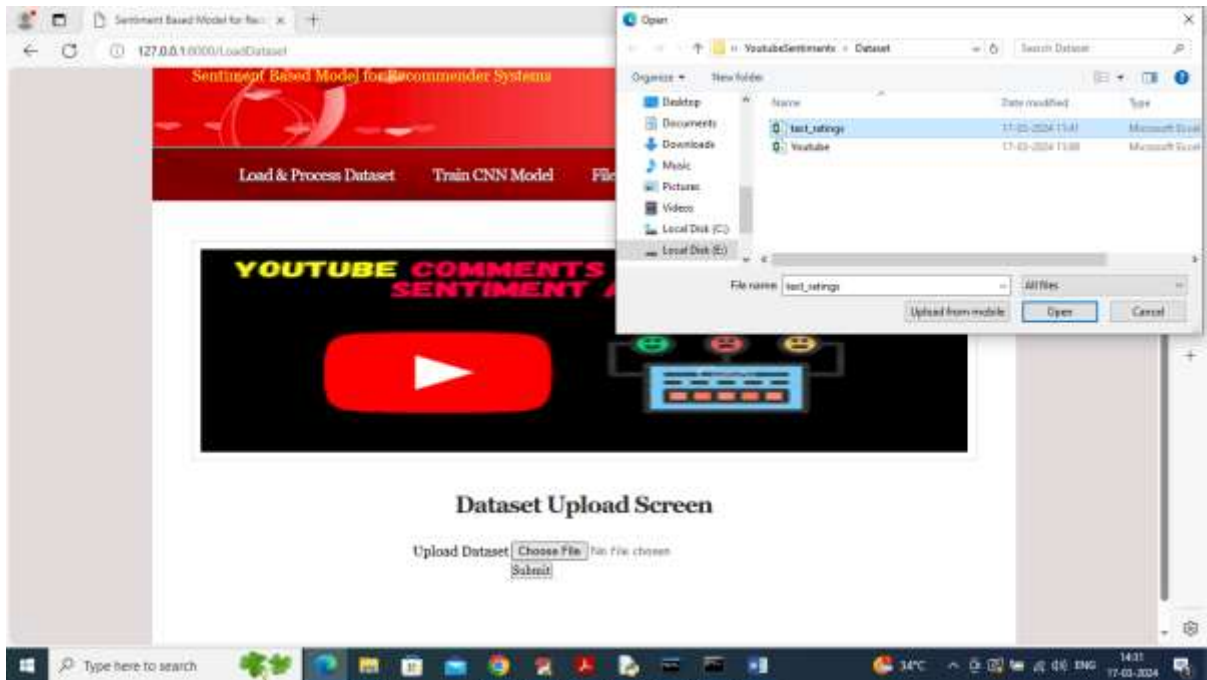
In above screen user sign up completed and now click on 'User Login' link to get below page



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

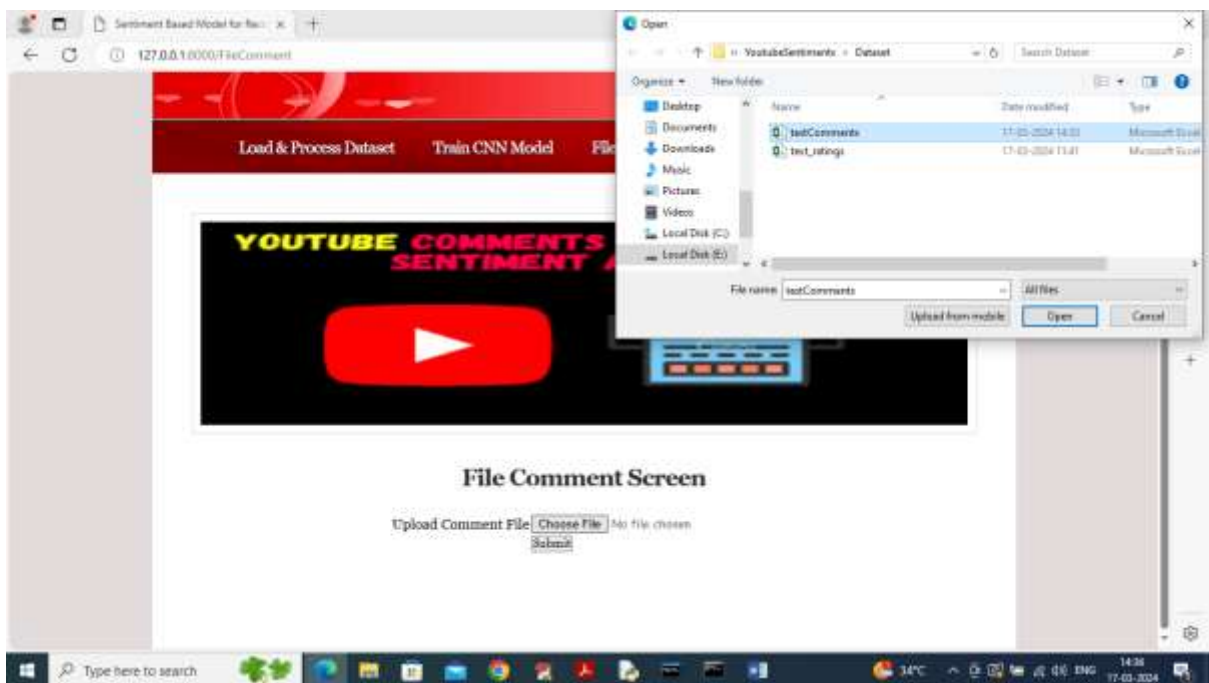


In above screen selecting and uploading 'text_ratings.csv' file and then click on 'Open' button to load dataset and get below page


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

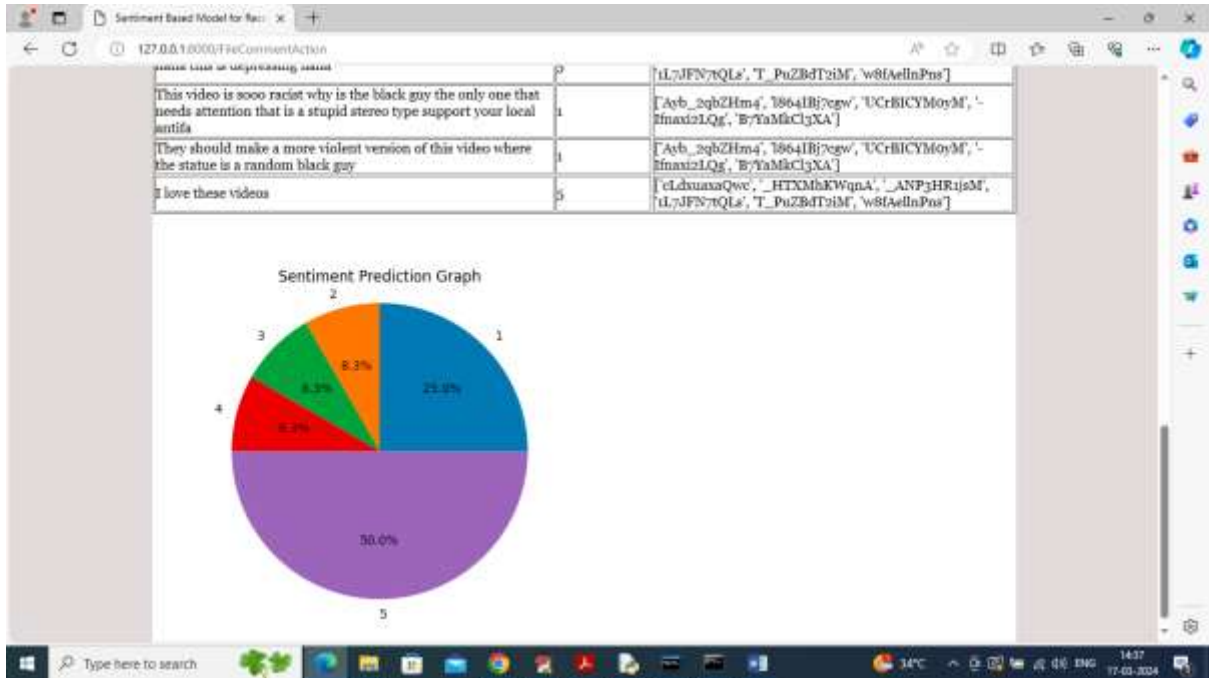


In above screen selecting and uploading 'test comment.csv' file and then click on 'Open' and 'Submit' button to get below page



Test Comment	Predicted Sentiment	Recommended Videos
I've never been prouder, been a subber for like 3 years, and this video got on one of our newssites	2	[XpV16ZtGjjo', 'WYVvHbo3Eog', 's]HnJvXdQe', '7gLaEob6X-Q', 'CsdzflX3BVQ', '2QK1Foww6z4']
Put the smile more logo in the cotner and make it smaller it will make it look cleaner	4	[e5MKX2tE5Lok', '8wNr-NQfmPg', '4MbC65embG4', 'Vu_gmuoaT5o', '5ywKal6-anc', '4Yue-qqJdbk', 'JhA1Wigmrne', 'EVp4-qjWVJE', 'LcZ2AawvXNA', 'MdzG2z3tQ-U']
Plane of the future is No plane. This is like 100 years ago somebody predicting bullockhart of the future	3	[ZNYZ-gd3Ko', 'gloOpvVcELw', 'J07X9ZPoAp8', 'GGmoFQ6f74U', 'oDIDZ9EmQIA', 'WWex19YILSe', 'LDcm6wPEIA', '31oGE3r-4A8w', 'zDycPeh2Gwg', 'L3f7_v9UPh4']
Its been fun watching you grow. Im at 42 days straight and cant seem to grow. Any advice?	3	[cLdxuanaQwc', '_HTXMhKWqna', '_ANP3HR1jsM', 'tL7JFN7rQLs', 'T_PuZBdTzIM', 'w8fAellnPns']
THERE ARE PEOPLE SUFFERING FROM HURRICANES AND YET Y'ALLZ ARE WORRIED ABOUT SOME CRACKA WITH A POTTY MOUTH???(n/nSincerely, your friendly neighborhood Beener	1	[Ayb_2qbZHm4', '1864fB7egw', 'UCrBICYM0yM', '-Hmas12LQg', 'B7fa8Mc13KA']
MTV trump donating to charity is racist,nTherefore mtv is now promoting nazis nYour welcome	5	[cLdxuanaQwc', '_HTXMhKWqna', '_ANP3HR1jsM', 'tL7JFN7rQLs', 'T_PuZBdTzIM', 'w8fAellnPns']
Hi him I want you to know that me and my Dumb liberal friends love you buddy	5	[cLdxuanaQwc', '_HTXMhKWqna', '_ANP3HR1jsM', 'tL7JFN7rQLs', 'T_PuZBdTzIM', 'w8fAellnPns']
This is so good; thanks Floyd Mayweather this is another side of you I have not seen. It's so refreshing	5	[cLdxuanaQwc', '_HTXMhKWqna', '_ANP3HR1jsM', 'tL7JFN7rQLs', 'T_PuZBdTzIM', 'w8fAellnPns']
haha this is depressing haha	5	[cLdxuanaQwc', '_HTXMhKWqna', '_ANP3HR1jsM', 'tL7JFN7rQLs', 'T_PuZBdTzIM', 'w8fAellnPns']
This video is sooo racist why is the black guy the only one that	5	[Ayb_2qbZHm4', '1864fB7egw', 'UCrBICYM0yM', '-Hmas12LQg', 'B7fa8Mc13KA']

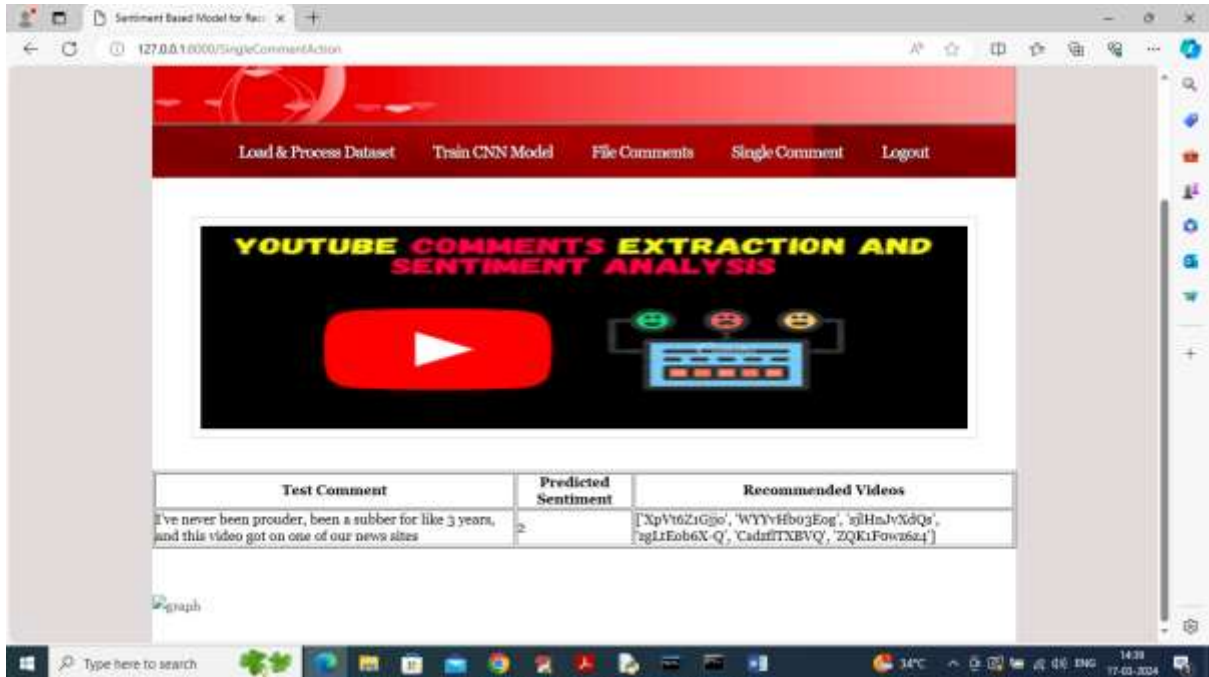
In above screen in first column can see Test Comment Text and in second column can see predicted sentiments from range 1 to 5 and then based on predicted sentiments displaying top 10 recommended videos and in below is predicted sentiments graph



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 below output



Test Comment	Predicted Sentiment	Recommended Videos
I've never been prouder, been a subber for like 3 years, and this video got on one of our news sites		['XpVt6ZiGjo', 'WYVvHb03Eog', 'rjHmJvX0Qs', 'zgLiEob6X-Q', 'CadafTtXBVQ', 'ZQKlFowz6z4']

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

Similarly by following above screens you can run entire application

VIII. CONCLUSION

This research presents a deep learning-based sentiment analysis and recommendation system that effectively combines NLP techniques with Convolutional Neural Networks. The system successfully analyzes user comments, predicts sentiment scores, and provides personalized video recommendations based on emotional context.

The integration of VADER sentiment analysis with CNN enhances prediction accuracy by combining rule-based and learning-based approaches. The system also provides visualization features, improving interpretability and user interaction. Experimental results demonstrate that the CNN model achieves reliable performance with reduced error rates.

Compared to traditional methods, the proposed system reduces manual feature engineering and improves scalability. It also addresses limitations of existing systems by



integrating sentiment analysis with recommendation functionality, enabling a more personalized user experience.

Recent advancements in sentiment-aware recommendation systems highlight the importance of incorporating user emotions into recommendation pipelines for better engagement and accuracy. The proposed system aligns with these advancements and provides a practical implementation for real-world applications.

Future work may include the integration of transformer-based models such as BERT, real-time data streaming, multilingual sentiment analysis, and advanced recommendation techniques such as collaborative filtering and reinforcement learning.

Overall, the system demonstrates the potential of deep learning in building intelligent, scalable, and user-centric recommendation platforms.

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