Aspect-Based Sentiment Analysis Using Deep

Learning

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*Abstract*—Aspect-Based Sentiment Analysis (ABSA) focuses on extracting opinions tied to specific attributes of products or services, particularly in movie reviews. This study leverages Long Short-Term Memory (LSTM) networks to analyze sentiments by considering key aspects such as storyline, performances, direction, and cinematography. The approach involves preprocessing text data to remove noise and standardize inputs. Following this, reviews undergo tokenization and are transformed into word embeddings to capture semantic associations. LSTM is employed due to its ability to retain contextual meaning and manage long-term dependencies, making it well-suited for sentiment classification. The model is trained on an annotated dataset where each review is labeled with aspect-specific sentiments (positive, negative, neutral). A multi-class classification strategy is implemented to discern attitudes related to different aspects within a single review. Performance is assessed using evaluation metrics such as accuracy, precision, recall, and F1-score. Results demonstrate that the LSTM model effectively identifies nuanced sentiments across various dimensions, offering deeper insights into audience opinions. This research enhances sentiment analysis by refining the granularity and interpretability of insights derived from movie reviews.

*Index Terms—LSTM, Sentiment classification, Text preprocessing, Tokenization, Semantic relationships, Multi-class classification, Performance metrics, Precision, Recall.*

## I. INTRODUCTION

The growth of digital platforms for sharing opinions and reviews has significantly reshaped how audiences engage with the entertainment industry, especially in the film domain. Movie reviews, often containing detailed descriptions, provide meaningful insights into various aspects such as narrative structure, acting, direction, and cinematography. These reviews not only influence audience preferences but also mirror the general satisfaction of viewers. However, interpreting the subtle sentiments expressed in these reviews is challenging, as a single review may offer conflicting views about different elements of a film. To tackle this issue, the present study utilizes Aspect-Based Sentiment Analysis (ABSA), a method designed to extract and evaluate sentiments related to specific movie features. By employing Long Short-Term Memory (LSTM) networks, this research seeks to capture the contextual relationships within the text, enabling more accurate sentiment classification and offering a deeper understanding of audience feedback.

Sentiment analysis, a prevalent technique, is used to assess whether a text conveys a positive, negative, or neutral sentiment. It is a key tool for gauging public opinion on a variety of subjects, products, or services by examining the language used. This approach is widely applied in several fields, such as market research, where businesses analyze consumer perceptions; social media analysis, which helps brands manage their public image; political research, where sentiment data offers insights into voter behavior; and customer service, where sentiment analysis helps companies prioritize customer interactions. Methods for sentiment analysis include lexiconbased systems that use predefined word lists, rule-based algorithms, and machine learning models trained on labeled datasets. Advanced techniques, like deep learning models with LSTM networks, improve sentiment classification by considering contextual meanings and long-term dependencies in text. Despite the advancements, challenges remain, including detecting sarcasm, interpreting context-specific expressions, and handling domain-specific language variations. Nevertheless, sentiment analysis continues to be an essential tool for gaining valuable insights into public sentiment, supporting decisionmaking processes across various sectors.

## II. LITERATURE REVIEW

1. *Sentiment Analysis of IMDb Movie Reviews Using LongShort-Term Memory*

In a 2020 study, Saeed Mian Qaisar investigates sentiment analysis of IMDb movie reviews using an LSTM model. The process involves converting text data into vectors via Doc2Vec, followed by dataset preprocessing and LSTM classifier training. The model, evaluated on 50,000 reviews, achieved an accuracy of 89.9% based on metrics such as the confusion matrix. The approach combines Doc2Vec for text vectorization with careful preprocessing of the IMDb dataset, enhancing the LSTM’s predictive capabilities. Future improvements include optimizing data preprocessing and exploring ensemble classifiers to further boost model performance.

1. *Sentiment Analysis on Product Reviews*

A 2019 study by Rahul, Vasundhara Raj, and Monika examines sentiment analysis on product reviews using machine learning and lexical methods. Various classifiers, including Support Vector Machine (SVM), Na¨ıve Bayes, and Neural Networks, were evaluated, with SVM achieving 71.80% precision. This analysis was based on reviews from platforms such as Amazon and Flipkart, with performance assessed through accuracy, precision, and F1-score. The study highlights challenges like sparse data and sarcasm detection, and suggests future work could focus on image data integration and improving sparse text analysis.

1. *Comprehensive Study on Sentiment Analysis: Types, Ap-proaches, Recent Applications, Tools and APIs*

In 2020, Ms. Binju Saju, Ms. Siji Jose, and Mr. Amal Antony provide a thorough overview of sentiment analysis, including its types, methodologies, and tools. They employ techniques such as Bag-of-Words and word embeddings, utilizing classifiers like Naive Bayes and SVM to achieve high accuracy. The study applies sentiment analysis to social media, reviews, and customer feedback, assessing performance based on accuracy, precision, and recall. While it offers valuable insights for improving customer service and brand management, the paper also identifies the need for expanding machine learning techniques in future research, particularly addressing the limitations of RNNs, which are resolved by GRU and LSTM architectures.

1. *Sentiment Analysis of Movie Reviews: A Novel Feature-based Heuristic for Aspect-level Sentiment Classification*

In their 2013 research, V.K. Singh, R. Piryani, A. Uddin, and P. Waila introduce a feature-based heuristic for aspect-level sentiment analysis of movie reviews. They focus on extracting features like adjectives, adverbs, verbs, and n-grams, using a SentiWordNet-based approach. The methodology, tested on 1000 IMDb reviews, achieved 78.7% accuracy with a 0.773 Fmeasure. This aspect-level approach provides a more granular sentiment profile compared to traditional document-level analysis, though it is domain-specific and relies on aspect vectors. The authors suggest future research could adapt this method to other domains with minimal modifications.

1. *Sentiment Analysis on Customer Reviews using Convolu-tional Neural Network*

In a 2020 study, Mr. Srikanth Tammina and Mr. Sunil Annareddy investigate sentiment analysis using a Convolutional Neural Network (CNN) and pre-trained word vectors (Word2Vec). Applied to Amazon product and IMDb movie reviews, the CNN model achieved accuracies of 68% and 74%, respectively. The CNN outperforms traditional machine learning methods but requires significant computational resources. Future research could enhance the model through hyperparameter tuning and by exploring other deep learning models, such as RNNs and LSTMs, for improved sentiment classification.

1. *Importance Evaluation of Movie Aspects: Aspect-BasedSentiment Analysis*

Yanqing Wang, Liangyu Hu, and Gufeng Shen’s 2020 study examines aspect-based sentiment analysis to evaluate movie components. They use a lexicon-based method with VADER and classifiers like SVM, Na¨ıve Bayes, K-NN, and Random Forest, analyzing over 19,000 IMDb reviews. The highest accuracy was achieved for the plot (84%), followed by actors (83%) and music (77%). While the study provides valuable insights into movie features, it faces limitations related to VADER’s performance and manual labeling. The authors suggest future improvements could involve incorporating critics’ opinions and utilizing multilingual lexicons.

1. *A Word Vector-based Review Vector Technique for Senti-ment Analysis of Movie Reviews*

The 2018 study by Yin Fulian, Wang Yanyan, Pan Xingyi, and Su Pei proposes a word vector-based method for sentiment analysis of movie reviews. By applying word embeddings to generate n-dimensional vectors, the authors preprocess text and create review vectors by averaging the word vectors. Tested across six datasets, including both English and Chinese movie reviews, the approach achieves an accuracy of 86.18%. Although efficient and simple, the method’s limitations stem from the dimensionality of word vectors. Future work could involve incorporating deep learning techniques, such as Long Short-Term Memory (LSTM).

1. *Movie Success Prediction Utilizing Machine Learning Al-gorithms and Their Comparison*

In a 2018 study, Rijul Dhir and Anand Raj explore predicting movie success using machine learning algorithms. They examine parameters such as IMDb scores, director, budget, user votes, and social media activity, using the IMDb 5000 Movie Dataset from Kaggle. Algorithms like Random Forest, SVM, and AdaBoost were employed, with Random Forest yielding the highest accuracy. This research provides valuable insights for predicting movie success, aiding marketing and advertising strategies prior to release.

1. *Weakly Supervised Framework for Aspect-based SentimentAnalysis on Student Reviews of MOOC*

Zenun Kastrati, Ali Shariq Imran, and Arianit Kurti’s 2020 study presents a weakly supervised framework for aspectbased sentiment analysis of student reviews on MOOCs. Using pre-trained embeddings from Word2Vec, GloVe, and FastText, the system utilizes CNN and LSTM networks to analyze 105,000 Coursera reviews with minimal labeled data.

The CNN model achieved a macro-F1 score of 82.10% and a micro-F1 score of 86.13% for aspect identification. This framework reduces the need for extensive manual labeling, making it efficient for large-scale analysis across various domains.

1. *Analysis Sentiment Based on IMDb Characteristics fromMovie Reviews Using SVM*

The 2022 study by Nur Ghaniaviyanto Ramadhan and Teguh Ikhlas Ramadhan investigates sentiment based on IMDb characteristics from movie reviews, focusing on the series ”Squid Game.” They use a Support Vector Machine (SVM) with a linear kernel, employing TF-IDF for feature extraction and preprocessing steps like tokenization, stopword removal, and stemming. The SVM model achieves high accuracy and recall, demonstrating its efficacy for text classification. However, the precision value may vary, indicating the need for future research to consider additional aspects such as film genre to strengthen the analysis.

1. *Sentiment Analysis Utilizing Machine Learning and DeepLearning*

Yogesh Chandra and Antoreep Jana’s 2020 study examines sentiment analysis by integrating machine learning and deep learning methods. Multiple feature extraction techniques, such as Bag-of-Words (BoW), TF-IDF, and word embeddings, were employed. Although specific methodology and dataset details were not provided, the study emphasizes the typical stages of text preprocessing, classifier training, and performance evaluation. While performance metrics such as accuracy, precision, recall, and F1-score are commonly used in sentiment analysis, the study did not disclose exact results. The combination of machine learning and deep learning techniques is expected to enhance accuracy beyond traditional methods.

1. *Implementation of Sentiment Classification of Movie Re-views by Supervised Machine Learning Approaches*

The 2019 work by Tejaswini M. Untawale and Prof. G. Choudhari focuses on sentiment classification of movie reviews using supervised machine learning techniques like Na¨ıve Bayes (NB) and Random Forest (RF). Several feature types, including syntactic, semantic, link-based, and stylistic features, are utilized, with reviews from platforms such as Times of India and Rotten Tomatoes. The results indicate that RF outperforms NB in terms of memory usage and execution time, showcasing RF’s efficiency. However, NB requires more resources, highlighting the trade-offs involved in model selection.

1. *Sentiment Analysis of IMDb Movie Reviews Using LSTM*

Saeed Mian Qaisar’s 2022 study on sentiment analysis of IMDb movie reviews examines various methods, including lexicon-based approaches, machine learning algorithms like BERT and VADER, and deep learning architectures such as LSTM. The research utilizes existing IMDb datasets, assessing performance using criteria such as accuracy, precision, recall, and F1-score. Results show that complex models like BERT lead to improvements in sentiment prediction accuracy, though they come with higher computational demands.

1. *Predicting IMDb Movie Rating Using Deep Learning*

The 2020 research by Saikiran Gogineni and Anjusha Pimpalshende investigates predicting IMDb movie ratings using deep learning algorithms. Traditional methods like BoW and TF-IDF are employed for text representation, and classifiers like Na¨ıve Bayes, SVM, Random Forest, KNN, RNN, LSTM, and GRU are evaluated. The study outlines text preprocessing techniques, including case conversion, tokenization, stopword removal, stemming, and lemmatization, using the IMDb Movie Review Dataset from Kaggle. Performance is assessed with accuracy, precision, recall, True Positive rate, False Positive rate, and AUC.

1. *Hierarchical Clustering and Regression Classification Based Review Analysis on Movie-Based Applications*

Manjunath D R and Basavaraj S Hadimani’s 2019 study proposes a hierarchical clustering approach for sentiment analysis of movie reviews. After preprocessing the data, hierarchical clustering groups similar reviews, which are then classified as positive or negative using logistic regression. The method, applied to reviews from platforms like IMDb and Paytm, achieved an impressive 89.5% accuracy, far exceeding a decision tree algorithm, which achieved only 59.6%.

1. *Sentiment Analysis of Movie Reviews Using Lexicon Ap-proach*

Sentiment analysis using a lexicon-based approach evaluates text by referencing predefined sentiment lexicons. This method relies on the idea that specific words evoke distinct emotional responses, enabling sentiment measurement based on the frequency of these terms in reviews. For instance, adjectives like ”fantastic” or ”horrible” are mapped to positive or negative sentiment scores. Preprocessing steps such as tokenization, stemming, and stop word removal are crucial to ensure a clean dataset for analysis.

1. *Systematic Review on Implicit and Explicit Aspect Extrac-tion in Sentiment Analysis*

Jaafar Zubairu Maitama et al.’s 2020 systematic review evaluates implicit and explicit aspect extraction approaches in sentiment analysis. They categorize methods into supervised, semi-supervised, and unsupervised techniques, with unsupervised methods most commonly used for extracting explicit aspects. The review identifies challenges in extracting implicit aspects and recommends future research into semantic understanding to improve sentiment analysis capabilities.

1. *Analysis of Various Sentiment Analysis Techniques of NLP*

In their 2021 study, Dr. Satyen M. Parikh and Mitali K.

Shah analyze various sentiment analysis techniques within NLP, focusing on N-Gram feature extraction. Using the KNearest Neighbor (KNN) algorithm, they classify sentiment from Twitter data obtained via the Twitter API. Despite showing good performance, they highlight challenges related to managing large datasets and inefficiencies in older data. Future research could involve creating hybrid strategies and advanced feature extraction methods to improve performance on larger datasets.

1. *Collaborative Deep Learning Techniques for SentimentAnalysis on IMDb Dataset*

The 2018 study by Savitha Mathapati et al. explores the use of collaborative deep learning techniques for sentiment analysis on the IMDb dataset. The authors combine LSTM and CNN to capture long-term dependencies and classify reviews using max pooling. The model achieved 89.29% accuracy in 166 seconds with CNN, while the hybrid LSTM-CNN model reached 88.32% accuracy. The study shows that combining LSTM and CNN enhances sentiment analysis, though it increases computational time.

1. *Sentiment Analysis of Movie Reviews: A Comparative StudyBetween the Naive-Bayes Classifier and a Rule-based Approach*

In a 2021 study, Vihaan Nama et al. compare sentiment analysis techniques using the Naive-Bayes classifier and a rulebased approach with the AFINN-111 dataset. The Naive-Bayes classifier outperformed the rule-based method with 80.10% accuracy, but faced challenges with complex sentences and mixed sentiments. The paper suggests future improvements, including handling nuanced sentiments and incorporating new lexicon-based strategies to boost performance.

## III. METHODOLOGY

*A. Data Collection*

a) Users will have the option to either upload their own review data or specify platforms like IMDb, Rotten Tomatoes, or social media from which the system will automatically retrieve reviews. This may involve scraping or leveraging APIs to gather reviews related to movies or web series. By offering both manual and automatic data input options, the system provides flexibility for both casual users and more experienced analysts with pre-existing datasets. The system will standardize various review formats for seamless analysis.

*B. Aspect Identification*

b) Once the reviews are collected, the system will automatically extract key aspects associated with movies or web series, including elements such as “acting,” “storyline,” “direction,” and “visual effects.” This extraction process is crucial because it enables users to focus on specific components of a review rather than just the overall sentiment. Additionally, users can define custom aspects of interest, such as “dialogue” or “special effects,” allowing for a tailored analysis that aligns with their unique research goals.

*C. Sentiment Analysis*

c) After identifying the aspects, the system will employ machine learning models, such as LSTM or BERT, to classify the sentiment for each identified component. The sentiments will be categorized into positive, negative, or neutral classes, and these results will be shown for each aspect individually. This granular approach to sentiment classification helps users gain a deeper understanding of how different features of the movie or web series are perceived. For example, “acting” might receive a positive sentiment, while “storyline” could be associated with negative sentiment.

*D. Genre Selection*

d) Users will have the option to refine their analysis by selecting a specific genre, such as action, drama, or comedy. The system will filter reviews based on the chosen genre and analyze sentiment trends accordingly. This genre-based breakdown is particularly useful for understanding how different types of content are received. For example, users might examine whether “special effects” are more highly rated in action films than in drama, or if “acting” is more frequently praised in comedies compared to thrillers.

*E. Visualization and Results*

e) Following sentiment analysis, the system will present the results through visual aids such as bar graphs, pie charts, or line plots. These visualizations will help users quickly assess the data and identify sentiment patterns. Users will be able to see which aspects consistently receive favorable or unfavorable sentiment and observe how sentiment fluctuates over time. By providing a clear and interactive view of the data, the system improves the user experience and enables the extraction of actionable insights.

*F. Search and Filtering*

f) To further enhance the analysis process, users can search for specific reviews or apply filters based on criteria like sentiment (positive, negative, neutral), aspects, genre, or the title of the movie or web series. This feature allows users to focus on particular types of reviews or sentiments that meet their exact specifications, making it easier to spot trends. For instance, a user might wish to review only negative feedback for action films to understand the common criticisms within that genre.

*G. Report Generation*

g) Users can generate comprehensive reports based on the sentiment analysis results. These reports will offer detailed insights into sentiment by aspect, genre, and time period, helping users better understand audience sentiment. The generated reports can be downloaded in various formats, such as PDF or Excel, for easy sharing with stakeholders or use in further research. The report generation tool ensures that users have access to a thorough analysis tailored to their specific needs.

*H. User Feedback and Adjustments*

h) The system will allow users to provide feedback regarding the accuracy of the sentiment analysis. If users believe the classification of sentiment is incorrect, they can submit corrections, and the system can use this feedback to improve future analyses or retrain the model. Furthermore, users will be able to adjust the sentiment threshold, for example, by considering mildly negative reviews as neutral, to better align with their analytical goals. This feedback mechanism ensures that the system remains adaptable, continuously improving based on user input.

## IV. RESULTS AND DISCUSSION

To evaluate the performance of the proposed aspect-based sentiment analysis system, the model was tested on a dataset containing 27,135 movie reviews annotated with sentiment labels: *Positive*, *Neutral*, and *Negative*. The predictions were analyzed using standard classification metrics including accuracy, precision, recall, F1-score, and a confusion matrix.

*A. Model Performance Metrics*

The LSTM-based model demonstrated consistently strong performance across all evaluation metrics, as shown in Table I. All metrics were balanced around 89.87%, reflecting the model’s robustness in handling multi-class sentiment classification.

## TABLE I

PERFORMANCE METRICS ON TEST DATASET

|  |  |
| --- | --- |
| Metric | Value (%) |
| Accuracy | 89.87 |
| Precision | 89.87 |
| Recall | 89.87 |
| F1-Score | 89.87 |

*B. Confusion Matrix Analysis*

The confusion matrix in Table II highlights the classification breakdown of actual vs predicted sentiment labels. The model correctly classified a high majority of instances in each sentiment class, with minimal misclassifications between similar sentiment classes such as *Neutral* and *Positive*.

## TABLE II

CONFUSION MATRIX

|  |  |  |  |
| --- | --- | --- | --- |
| Actual *\*Predicted | Positive | Neutral | Negative |
| Positive | 8175 | 486 | 439 |
| Neutral | 478 | 8172 | 432 |
| Negative | 450 | 464 | 8039 |

*C. Classification Report Summary*

The model’s per-class metrics are summarized in Table III. Each class achieved an F1-score near or above 90%, indicating the model’s balanced sensitivity and precision across all sentiment types.

## TABLE III

PER-CLASS CLASSIFICATION REPORT

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Class | Precision | Recall | F1-Score | Support |
| Positive | 90% | 91% | 90% | 8953 |
| Neutral | 90% | 90% | 90% | 9082 |
| Negative | 90% | 88% | 90% | 9100 |

*D. Discussion*

The results demonstrate that the LSTM model is highly effective for aspect-based sentiment analysis. The model is capable of differentiating nuanced expressions of sentiment, even when multiple aspects are discussed within a single review. Slight confusion between similar sentiments (e.g., *Neutral* vs *Positive*) is observed, which is typical in subjective text interpretation. However, the overall performance metrics affirm the reliability of the model in extracting valuable insights from opinion-rich movie reviews.

## V. CONCLUSION

This sentiment analysis system for web series and movie reviews, powered by LSTM and other machine learning algorithms, offers an effective and intuitive platform for extracting meaningful insights from user feedback. By performing aspect-based analysis (e.g., acting, storyline, direction) and classifying sentiment into categories such as positive, negative, or neutral, the system allows users to understand how various aspects of movies or series are perceived across different genres.

The project not only empowers users to visualize sentiment trends and generate detailed reports but also provides flexibility in training and tailoring the model. Users can train the system on specific genres or customize it to meet their unique requirements. Furthermore, the system’s ability to incorporate user feedback enables ongoing improvements to the model, ensuring its accuracy and reliability over time.

With its scalable and efficient design, the system satisfies both functional and non-functional requirements, ensuring strong performance, ease of use, security, and precision. The application is adaptable to various data sources and user preferences, making it a highly flexible solution for diverse use cases. Its modular design guarantees that the system can evolve and expand as new data and advanced analytical methods become available.

In conclusion, this approach offers significant value to content creators, marketers, and analysts, enabling them to make informed, data-driven decisions based on audience sentiment. By providing a comprehensive understanding of how audiences perceive content, it empowers users to refine their content strategies, enhance marketing campaigns, and influence the future creation of web series and movies.

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