Aspect-Based Sentiment Analysis Using Deep

Learning

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*Abstract*—Aspect-Based Sentiment Analysis (ABSA) deals with sentiment extraction of thoughts related to certain aspects of products or services, mainly movie reviews. The current research finds out the efficiency of various deep learning models such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Deep Neural Networks (DNN) to analyze the sentiment based on major aspects like storyline, performances, direction, and cinematography. The method includes text data preparation to eliminate noise and normalize inputs. Subsequently, reviews are tokenized and converted into word embeddings to identify semantic relationships. Each model is trained on an annotated dataset in which reviews are tagged with aspect-specific sentiments (positive, negative, neutral), and a multi-class classification method is used to identify attitudes associated with individual features within a single review. Performance is evaluated employing universal metrics such as accuracy, precision, recall, and F1-score. Results identify that although the performance of all models is adequate in detecting weak emotions, classification accuracy is maximized by RNN and CNN models. This work pushes sentiment analysis in that it compared several deep-learning algorithms and adds to the fineness and interpretablity of conclusions derived from movie reviews.

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

## I. INTRODUCTION

The way people interact with the entertainment industry, especially in the movie industry, has greatly transformed due to the development of online forums for reviewing and commenting. Film reviews, which typically provide detailed explanations, provide meaningful information on diverse topics such as acting, cinematography, director, and plot structure. Apart from affecting the preference of the audience, reviews also express overall satisfaction among viewers. It is possible to find it difficult to grasp the subtle specifics offered in such reviews, however, since a single review may offer differing viewpoints regarding different movie aspects.

Aspect-Based Sentiment Analysis (ABSA), an approach developed in order to collect and analyze feelings regarding specific elements of a movie, is utilized in this paper in order to bypass this issue. By associating attitudes with certain features of the content, ABSA offers more informative insights than general sentiment analysis, which measures the tone in total. In this research, some deep learning models—Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Deep Neural Networks (DNN)—are applied comparatively. Each of the varieties has several advantages: CNN performs well at recognizing local patterns and significant features in sentence patterns, DNN employs dense layers to discover complicated semantic representations, and LSTM and RNN are good at learning sequential and contextual dependencies in text. The framework seeks to enhance sentiment classification precision and flexibility in dealing with different review formats through the combination of these architectures.

One common technique for determining whether a text has a positive, negative, or neutral tone is sentiment analysis. Analyzing the words used is an important method of measuring public opinion about many subjects, products, or services. This approach is commonly employed in a wide range of fields, such as political studies, where sentiment information offers information about voter behavior; social media analysis, which helps brands to handle their public perception; market studies, where companies study consumer opinion; and customer care, where sentiment analysis helps companies to rank customer interactions. Lexicon-based approaches utilizing pre-established word lists, rule-based systems, and machine learning models learned on labeled data are few methods of sentiment analysis. Through the use of contextual semantics, spatial signals, and deep semantic relationships in text, advanced approaches like deep learning models such as LSTM, CNN, RNN, and DNN enhance sentiment classification.

Despite the advances, there are still challenges, including the recognition of sarcasm, comprehension of expressions unique to a particular context, and handling domain-specific variations in language. Sentiment analysis is still an essential tool for generating valuable insights into public opinion, facilitating decision-making in numerous fields.

## II. LITERATURE REVIEW

### A. Sentiment Analysis of IMDb Movie Reviews Based on Long Short-Term Memory

Saeed Mian Qaisar discusses sentiment analysis of IMDb movie reviews using an LSTM model in his 2020 study. The process includes converting text to vectors using Doc2Vec, preprocessing the dataset, and training an LSTM classifier. Tested on 50,000 reviews, the model achieved an 89.9% accuracy using performance metrics like the confusion matrix. The integration of Doc2Vec with deep preprocessing boosted the model’s accuracy. Future improvements suggest optimizing data preparation and exploring ensemble classifiers.

### B. Sentiment Analysis on Product Reviews

In 2019, Rahul, Vasundhara Raj, and Monika examined sentiment analysis on product reviews using machine learning and lexical methods. They tested various classifiers—SVM, Na¨ıve Bayes, and Neural Networks—with SVM achieving the best precision at 71.80%. Evaluations were based on Amazon and Flipkart reviews. Key challenges noted include handling sparse text and sarcasm. Future directions include integrating image data and enhancing sparse text handling.

### C. Overall Review of Sentiment Analysis: Types, Approaches, Applications, and Tools

In 2020, Binju Saju, Siji Jose, and Amal Antony provided a comprehensive review of sentiment analysis methodologies. They utilized Bag-of-Words and word embeddings, evaluated with Na¨ıve Bayes and SVM. The study covered sentiment applications in social media and customer feedback. It emphasized the need to address the limitations of RNNs through GRU and LSTM for better contextual understanding.

### D. Feature-based Heuristic for Aspect-level Sentiment Classification

V.K. Singh et al. (2013) proposed a heuristic approach for aspect-level sentiment analysis of movie reviews. They extracted features like adjectives, adverbs, verbs, and n-grams using SentiWordNet. Evaluated on 1000 IMDb reviews, the approach achieved 78.7% accuracy. While offering granularity, the method was domain-specific. The authors recommended adapting the technique across domains with minimal changes.

### E. Sentiment Analysis Using Convolutional Neural Network

In a 2020 study, Srikanth Tammina and Sunil Annareddy used a CNN with pre-trained Word2Vec embeddings to classify sentiment in Amazon and IMDb reviews. The CNN model achieved 68% accuracy on Amazon and 74% on IMDb. It outperformed traditional ML methods but required more computational power. Future work could include hyperparameter tuning and comparing CNN with RNN and LSTM.

### F. Aspect-Based Sentiment Analysis of Movie Features

Yanqing Wang, Liangyu Hu, and Gufeng Shen (2020) conducted aspect-based sentiment analysis on over 19,000 IMDb reviews using VADER and ML models like SVM, KNN, and Random Forest. The plot aspect had the highest accuracy (84%), followed by actors (83%) and music (77%). Limitations included VADER’s performance and reliance on manual labeling. Future work suggested including critic reviews and multilingual lexicons.

### G. Word Vector-based Sentiment Analysis of Movie Reviews

Yin Fulian et al. (2018) introduced a word embedding-based method for movie review sentiment analysis. By averaging ndimensional word vectors, their method achieved 86.18% accuracy across English and Chinese datasets. Though efficient, it was limited by vector dimensionality. Future improvements suggested using deep learning models like LSTM.

### H. Movie Success Prediction Using Machine Learning

Rijul Dhir and Anand Raj (2018) explored predicting movie success using algorithms like Random Forest, SVM, and AdaBoost. Factors like IMDb score, director, budget, and social activity were analyzed using the IMDb 5000 Movie Dataset. Random Forest showed the best accuracy. The study supports ML for pre-release predictions.

### I. Weakly Supervised Aspect-Based Sentiment Analysis on MOOC Reviews

Zenun Kastrati et al. (2020) introduced a weakly supervised framework for aspect-based sentiment analysis on MOOC reviews. Using CNN and LSTM with Word2Vec, GloVe, and FastText embeddings, the model achieved a macro-F1 of 82.10% and micro-F1 of 86.13% on 105,000 Coursera reviews. It reduced manual labeling and demonstrated high domain adaptability.

### J. Sentiment Classification Based on IMDb Features Using SVM

Nur Ghaniaviyanto Ramadhan and Teguh Ikhlas Ramadhan

(2022) applied SVM with TF-IDF to analyze sentiment in “Squid Game” reviews. After preprocessing (tokenization, stemming, stopword removal), the SVM showed strong recall and precision. The study noted precision fluctuations and suggested incorporating genre-based features.

### K. ML and DL-Based Sentiment Analysis

In 2020, Yogesh Chandra and Antoreep Jana explored hybrid sentiment analysis using ML and DL approaches with BoW, TF-IDF, and embeddings. While the exact dataset and results were not reported, the study emphasized combining DL and ML for better accuracy and performance metrics like F1-score and recall.

### L. Sentiment Classification Using Supervised Learning

Tejaswini M. Untawale and Prof. G. Choudhari (2019) compared Na¨ıve Bayes and Random Forest for movie review sentiment analysis. Using datasets from Rotten Tomatoes and Times of India, they found Random Forest outperformed Na¨ıve Bayes in memory usage and speed.

### M. IMDb Movie Reviews Using LSTM and BERT

Saeed Mian Qaisar (2022) explored sentiment analysis using LSTM and BERT on IMDb data. The study noted improved performance with BERT but highlighted increased computational demands. Performance was assessed using accuracy, precision, recall, and F1-score.

### N. Deep Learning for IMDb Movie Rating Prediction

Saikiran Gogineni and Anjusha Pimpalshende (2020) predicted IMDb ratings using deep learning classifiers like RNN, LSTM, GRU, and traditional ML models. Text preprocessing included lemmatization, stemming, and tokenization. The IMDb dataset was used for training and evaluated using accuracy, recall, precision, and AUC.

### O. Hierarchical Clustering for Review Classification

Manjunath D R and Basavaraj S Hadimani (2019) proposed using hierarchical clustering followed by logistic regression to classify IMDb and Paytm reviews. Their approach reached

89.5% accuracy—much higher than decision trees (59.6%).

### P. Lexicon-Based Sentiment Analysis

Lexicon-based approaches score sentiment using predefined word dictionaries. Adjectives like “fantastic” or “terrible” are mapped to sentiment values. Preprocessing includes stopword removal, stemming, and tokenization.

### Q. Implicit vs. Explicit Aspect Extraction Techniques

Jaafar Zubairu Maitama et al. (2020) reviewed techniques for extracting implicit and explicit aspects. They categorized supervised, semi-supervised, and unsupervised methods. Future research should focus on semantic understanding to improve implicit aspect extraction.

### R. Comparing Sentiment Techniques in NLP

Dr. Satyen M. Parikh and Mitali K. Shah (2021) analyzed NLP sentiment methods using N-grams and KNN on Twitter data. They found good performance but noted issues with large datasets and outdated data handling.

### S. Collaborative Deep Learning Techniques for Sentiment Analysis

Savitha Mathapati et al. (2018) evaluated collaborative DL methods by combining LSTM and CNN. Their CNN model achieved 89.29% accuracy, while the hybrid LSTM-CNN reached 88.32%. The hybrid model showed better pattern detection but required more processing time.

### T. Na¨ıve Bayes vs. Rule-Based Sentiment Classifier

Vihaan Nama et al. (2021) compared Na¨ıve Bayes and rule-based methods using the AFINN-111 dataset. Na¨ıve Bayes achieved 80.10% accuracy, outperforming the rulebased approach. However, it struggled with complex or mixed sentiments. Future improvements include implicit sentiment resolution and lexicon expansion.

### Literature Review Summary

The surveyed literature shows that deep learning models—especially \*\*LSTM\*\*, \*\*CNN\*\*, and hybrid techniques—are widely used for sentiment analysis due to their ability to understand contextual and structural nuances in text. While \*\*CNN\*\* excels at identifying local patterns and \*\*LSTM/RNN\*\* at learning long-term dependencies, \*\*DNNs\*\* are less explored but offer lightweight and efficient alternatives. Very few studies evaluate multiple models sideby-side for \*\*aspect-level sentiment analysis\*\*, which limits comparative insights. Our research fills this gap by implementing and evaluating \*\*LSTM, CNN, RNN, and DNN\*\* models under a unified framework, using the same dataset and preprocessing pipeline. By combining aspect detection, clause segmentation, and user feedback, we aim to provide a more flexible and robust sentiment analysis solution.

## III. METHODOLOGY

### A. Data Collection

Users have the option to either input their own review data or allow the system to obtain reviews automatically from networks such as IMDb, Rotten Tomatoes, or social media utilising scraping or APIs. This dual-input approach accommodates both casual users and researchers with preexisting datasets. All reviews are standardized into a common format to assist consistent processing throughout analysis.

### B. Aspect Identification

The method uses a rule-based keyword mapping strategy to automatically detect particular qualities inside each review, such as acting, narrative, directing, graphics, sound, and thriller. This identification is increased through clause segmentation, where the review is separated into smaller phrases for better precision in aspect mapping. If a keyword associated to a supported aspect appears in a clause, that clause is assigned to the appropriate aspect. Users can also define specific elements based on their study needs.

### C. Sentiment Analysis

After identifying significant aspects, the algorithm classifies the sentiment for each using four deep learning models:

* LSTM (Long Short-Term Memory) for capturing longterm dependencies,
* CNN (Convolutional Neural Network) for finding local patterns in text,
* RNN (Recurrent Neural Network) for processing sequential data, and
* DNN (Deep Neural Network) for learning dense feature representations.

These models were trained on a curated and annotated dataset containing 27,135 reviews categorised as positive, neutral, or negative. Users can choose the model to employ for inference using a dropdown interface in the application. Sentiment prediction is conducted exclusively on the clauses relevant to the specified aspect, ensuring that multi-aspect reviews are understood appropriately. If no relevant aspect is discovered in a review, the system politely returns a fallback message or prediction is skipped.

### D. Genre Selection

The technology enables users to select a genre filter such as action, comedy, or drama. Once selected, the model restricts review analysis to that genre only. This enables for genre-wise emotion comparison—for instance, distinguishing if action movies garner more love for visuals, while comedies are liked for acting.

### E. Visualization and Results

Results are displayed visually via interactive bar charts, pie graphs, and sentiment timelines. Users can see sentiment distributions per facet, per model, and per genre. Sentiment patterns can also be exhibited over time for dynamic insights into audience preferences.

### F. Search and Filtering

The portal features powerful filtering capabilities that allow users to search reviews by keywords, attributes, genres, or sentiment categories. This granular control enables researchers to isolate and examine specific patterns, such as discovering frequent unfavourable comments about direction in thriller films.

### G. Report Generation

The technology enables users to generate downloadable reports in PDF or Excel format. These reports offer thorough insights on aspect-wise sentiment trends, comparative model performance, and genre-based sentiment segmentation, enabling further decision-making or academic presentation.

### H. User Feedback and Adjustments

The technology incorporates a feedback loop where users can flag inaccurate sentiment predictions. These corrections are retained for future retraining. Additionally, users can change sentiment thresholds—such as considering mildly negative evaluations as neutral—to better correspond with specific use cases or personal bias preferences.

## IV. RESULTS AND DISCUSSION

To compare the performance of the suggested aspect-based sentiment analysis system, we experimented with it on a collection of 27,135 labeled movie reviews. Each review was labeled with one of three sentiment labels: *Positive*, *Neutral*, or *Negative*. Our strategy was to identify attitudes regarding different attributes of a review—e.g., *acting*, *director*, *storyline*, *graphics*, *sound*, and *thriller*—by identifying aspect-related keywords and dividing the review into related clauses.

We compared the performance of four deep learning models: Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Deep Neural Network (DNN). All four models were trained on the same data using the same preparation steps: lowercasing, tokenization, stop-word removal, and clausebased segmentation for aspect-level prediction. Sentiment was predicted only for clauses expressing the chosen aspect.

### A. Model Performance Metrics

All the models were compared based on common metrics for classification: Accuracy, Precision, Recall, and F1-Score. The results are shown in Table I.

#### TABLE I

PERFORMANCE METRICS OF ALL MODELS ON TEST DATASET

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
| LSTM | 89.87 | 89.87 | 89.87 | 89.87 |
| CNN | 93.12 | 93.25 | 92.95 | 93.10 |
| RNN | 94.01 | 94.05 | 93.89 | 93.97 |
| DNN | 91.34 | 91.40 | 91.28 | 91.34 |

The RNN model performed the best in terms of accuracy and F1-score, indicating better handling of sequential data for sentiment tagging. CNN was ranked second with strong ability for spatial pattern identification in clause-level text. LSTM demonstrated consistent and well-balanced performance across all metrics. The DNN model, though slightly behind in accuracy, was lighter in architecture and computationally less intensive.

### B. Confusion Matrix Analysis

A confusion matrix of the LSTM model indicated correct classification into each of the three sentiments. Most misclassifications were between *Neutral* and *Positive*, which are close in tone and more difficult to separate in subjective film reviews. The confusion matrix is provided in Table II.

#### TABLE II

CONFUSION MATRIX FOR LSTM MODEL

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

### C. Classification Report Summary

The classification report for the LSTM model is presented in Table III. The results confirm that the LSTM model is equally effective for each sentiment class with relatively higher precision and recall for the *Positive* and *Neutral* categories.

#### TABLE III

PER-CLASS CLASSIFICATION REPORT FOR LSTM

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

### D. Discussion

All four models performed effectively on review segments that were pre-filtered using clause segmentation and keywordbased aspect identification. The use of clauses ensured that the models could capture attitudes toward specific movie features, even in reviews covering multiple aspects.

The RNN model delivered the highest accuracy and F1score, making it the top performer overall. The CNN model was efficient in learning spatial patterns, while LSTM remained a reliable and balanced model. Although the DNN model trailed in terms of accuracy, it remained a practical choice due to its simplicity and faster training time.

The system’s flexibility allows users to select their preferred model depending on performance requirements or hardware constraints. These findings validate the effectiveness of a multi-model framework for achieving robust and adaptable aspect-based sentiment analysis.

## V. CONCLUSION

Using deep learning algorithms like LSTM, CNN, RNN, and DNN, the sentiment analysis model for web series and movie reviews proposed here presents an effortless and highly effective approach to extracting meaningful information from consumer opinions. The model categorizes sentiment into positive, negative, or neutral categories according to aspectbased sentiment analysis, which is aspect-oriented like acting, plot, direction, visuals, sound, and suspense. This enables the users to realize how the masses perceive specific things about a movie or a web series from different genres.

To discriminate and compare sentiments at a fine level, the system employs clause segmentation and aspect keyword mapping. It supports four advanced deep learning architectures: Long-term textual dependencies can be represented by LSTM.

CNN for identifying textual spatial patterns,

RNN for effectively modeling sequence-based data

DNN for feature representation as the minimum complexity of abstractions in learning.

The users can select dynamically which model to use for prediction based on their respective performance or accuracy requirements. All models were trained and tested on a chosen dataset with more than 27,000 labeled reviews. The advantage of using a multi-model system was demonstrated by the highest accuracy ( 94.01

Apart from that, users are also offered functionality to generate downloadable reports, graph sentiment trends, and even customize the system for domain-specific requirements. Apart from that, there is also an internal feedback system that offers users the feature of giving feedbacks, which may be used for threshold tuning or model retraining so that it can be improved in real-time.

Excellent usability, security, reliability, and performance are ensured by the scalability, flexibility, and modularity of the system, meeting functional as well as non-functional needs. The system can be applied to a very large number of use cases with high variety, e.g., business-level sentiment monitoring and scientific research.

In short, content creators, analysts, and marketers can gain much from this end-to-end sentiment analysis platform. It enables more informed, improved decisions through actionable insights into the sentiment of audiences regarding various content elements. The platform gives stakeholders tools for influencing future entertainment products based on audience sentiment, whatever the application is used to fuel in the interest of optimizing advertising campaigns, script maximization, or production decision-making.

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