Neuro-Symbolic Sentiment Analysis: Integrating Lexicon Features with Deep Learning Models

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Abstract. Sentiment analysis is critical for extracting views and emotions from textual data, with applications including consumer feedback and social media insights. This paper shows a mixed system that combines Neuro-Symbolic Sentiment Analysis (using deep learning models to combine symbolic lexicon features) and Topic-Driven Sentiment Analysis (using techniques for latent variables). By combining symbolic thinking and current machine learning, we improve both interpretability and classification accuracy. The framework uses a number of methods for binary and multiclass sentiment categorization, including Logistic Regression, Naive Bayes, SVM, Random Forests, and Fully Connected Neural Networks (FCNN). To ensure reliability, we use k-fold cross-validation for model evaluation. The use of latent variable modeling reveals underlying thematic implications on sentiment classification.Experimental validation on a real-world sentiment dataset reveals the usefulness of our strategy, which achieves high accuracy while remaining comprehensible. This study demonstrates the utility of neurosymbolic and topic-driven modeling in enhancing understandable sentiment analysis.

Keywords: Sentiment Analysis · Neuro-Symbolic Approach · Machine Learning · Deep Learning.

1 Introduction

The extensive use of social media platforms, particularly Twitter, has increased the importance of sentiment analysis in natural language processing (NLP). Social media is an invaluable resource for understanding public ideas and feelings, particularly in businesses such as aviation, where customer feedback is essential. However, the unstructured and informal nature of social media data, which includes slang, abbreviations, multilingual phrases, and sarcasm, presents hurdles for classic sentiment analysis techniques. In this study, we concentrate on airline sentiment analysis, using hybrid methodologies that mix symbolic and data-driven techniques to achieve interpretability and high classification accuracy. Our proposed system combines Neuro-Symbolic Sentiment Analysis, which blends symbolic lexicon-based features with deep learning models, and Topic-Driven Sentiment Analysis, which employs latent variable techniques to reveal thematic implications on sentiment classification. To validate the framework, we used a variety of machine learning methods for binary and multiclass sentiment categorization, including Logistic Regression, Naive Bayes, Support Vector Machines (SVM), Random Forests, and Fully Connected Neural Networks (FCNN). K-fold cross-validation was used to ensure robustness and dependability by methodically evaluating performance using five different models. Experimental validation on airline sentiment datasets reveals the approach's usefulness, with excellent accuracy and explainability.

We organize the rest of this paper as follows: Section II reviews related works, Section III outlines the proposed methodology, Section IV presents the results, and Section V concludes the study with future research directions.

2 Literature Review

In [1], a way to separate sentiment features was suggested by putting together neural network models with dependency relations. The study tackled the challenge of determining sentiment polarity in complex phrases by creating a dependency weighting mechanism. This method enhanced sentiment feature extraction by explicitly considering syntactic dependencies, which are often critical for understanding the sentiment of particular aspect words in sentences. The authors suggested that leveraging these dependency relations can improve the accuracy of sentiment analysis models, especially in text with intricate syntactic structures. A multi-level graph neural network (MLGNN) was created to solve the problems with traditional graph neural networks (GNNs), which only look at local context. MLGNN integrates both local and global variables, making it more efficient at capturing nuanced sentiment patterns that span beyond immediate word-level connections. The MLGNN model did better at sentiment analysis tasks than other models on public datasets by using a scaled dot-product attention mechanism and multi-size node connection windows. This breakthrough suggested that, for better sentiment analysis, it is critical to account for both micro- and macro-level textual relationships. A paper by [2] described a fine-grained sentiment analysis model that used a heterogeneous graph neural network to understand the complex connections between words and aspect terms. This model was designed to process complex sentence structures and various sentiment nuances, making it particularly effective in dealing with aspect-based sentiment analysis (ABSA), where the goal is to identify the sentiment related to specific features or aspects of a product or service. The study highlighted the importance of creating flexible and adaptable graph-based models for fine-grained sentiment analysis. For real-time sentiment analysis on Twitter data, the authors in reference [4] developed a transformer-based approach leveraging RoBERTa. The model was specifically tailored for Twitter, a platform known for its noisy and informal text. Using transformer architectures, especially RoBERTa, helped the model deal with noisy data and still do well in tasks that required figuring out how people felt about something. The study indicated that the model could adapt to continuously changing topics and language patterns, which is vital for analyzing social media data in real time. Building on these findings, Smith et al. (2023) introduced a method for sentiment drift analysis of trending topics on Twitter. They used transformer-based models to analyze how sentiment changes in real time as public discussions around topics evolve. This method proved effective in detecting sentiment shifts and trends, providing valuable insights for understanding public opinion on ongoing events. It highlighted the importance of real-time data processing and adaptability in social media sentiment analysis. To further advance sentiment analysis on social media platforms, [14] presented a multi-layered network approach for emotion analysis. This method incorporated a graphical representation of tweets, enhancing sentiment classification by modeling both the emotional content of the text and the relationships between different users and posts. The study emphasized the need for deep integration of user behavior and emotional context in sentiment analysis models. The work in [19] tackled sentiment analysis using an attentional graph neural network (AGNN) that combined text and social graph information for better prediction. By considering both the textual content and the social network connections between users, AGNN improved sentiment prediction accuracy. This approach is particularly valuable in understanding sentiment dynamics in social media environments, where interactions and connections often influence the emotional tone of messages. In [9], the authors looked into ways to make sentiment analysis more accurate by fixing data imbalances with SMOTE (Synthetic Minority Oversampling Technique) and boosting methods. They combined K-Nearest Neighbors with these techniques to enhance the model's ability to classify sentiment accurately, even in datasets where certain sentiment categories were underrepresented. This method proved effective in improving the performance of sentiment analysis models on imbalanced datasets. Lastly, [6] examined the professional quality of life among healthcare providers and its related factors. While not directly related to sentiment analysis in text, this study provided insights into how sentiment, particularly emotional experiences, can impact professional behavior. The work emphasized the significance of emotional analysis in healthcare settings, where understanding the sentiment of staff could contribute to improved workplace environments and outcomes. Some of the techniques presented in [18, 8, 7, 12, 13, 15, 17, 10, 11, 20, 16, 4, 3] may also be useful for such kinds of studies.

3 Methodology

In this section, we have presented our proposed frameworks as depicted in Fig. 1. A sentiment dataset is taken from Kaggle; this data consists of labels used for training [5]. The dataset consists of 14,640 tweets labeled as favorable, neutral, or negative. The data was thoroughly preprocessed to ensure reliability and consistency. This comprised text cleaning (removing special characters, URLs, and stop words), tokenization, lemmatization, and feature extraction with TF-IDF and pre-trained word embeddings, such as GloVe embeddings. The dataset was then split into 80% training and 20% testing using stratified sampling to main-

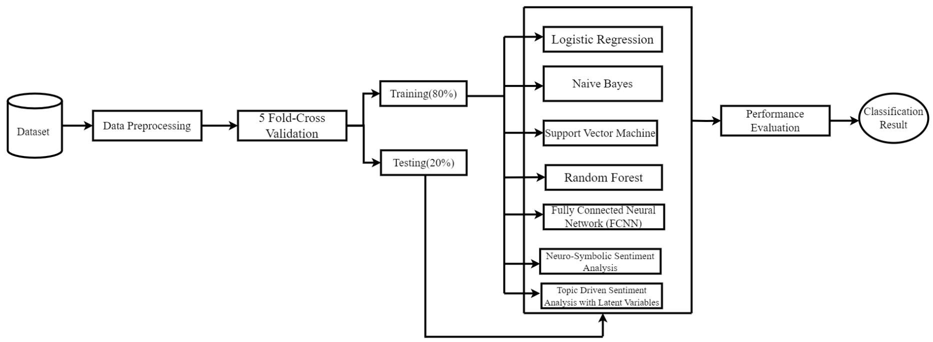

Fig. 1: Neuro-Symbolic Sentiment Analysis.

tain balanced sentiment distribution.

To guarantee effectiveness, our methodology combines traditional machine learning models with advanced deep learning techniques to enhance sentiment analysis performance. It uses Neuro-Symbolic Sentiment Analysis, which blends symbolic lexicon features (e.g., VADER, AFINN) with BERT-based deep contextual embeddings to capture both rule-based and contextual sentiment patterns. Additionally, topic-driven sentiment analysis uses latent Dirichlet allocation (LDA) to select important themes (for example, customer service, delays) and include them as features to improve sentiment prediction, particularly for ambiguous tweets. We thoroughly test the models using 5-fold cross-validation, producing performance measures such as accuracy, precision, recall, and F1-score for each fold.

Because of its ease of use and interpretability, Logistic Regression was used as the baseline model. It used tokenized text embeddings and a logistic function to predict the likelihood of sentiment classes (positive, negative, and neutral). In a similar manner, relationships within the dataset were captured using Gaussian Naïve Bayes in conjunction with Node2Vec embeddings, and dimensionality reduction was achieved using Principal Component Analysis (PCA). Decision boundaries were optimized using Support Vector Machines (SVMs), which use both linear and Radial Basis Function (RBF) kernels. The RBF kernel handled complicated, non-linear connections, while the linear kernel handled separable data. An ensemble learning method called Random Forest combined many decision trees and used randomized feature selection to reduce overfitting. To guarantee toughness, 5-fold cross-validation was applied to all models, splitting the dataset into five subsets, four of which were utilized for training and one for testing in each cycle. Accuracy, precision, recall, and F1-score were used in the performance evaluation to guarantee generalizability and consistency.

In addition to classification, other methods were used to improve model efficacy and interpretability. Naïve Bayes used Bayes' theorem to find the most likely sentiment class, while SVMs optimized hyperplanes to maximize the margin between sentiment classes. This made separation better, especially in high-dimensional spaces. Random Forest's feature importance analysis offered insights into key attributes influencing sentiment classification. Together, these models helped provide a thorough framework for sentiment analysis by striking a balance between conventional and cutting-edge techniques to improve interpretability and prediction.

Fully Connected Neural Networks (FCNN): We used TensorFlow/Keras's Fully Connected Neural Networks (FCNN) to model sentiment from text characteristics. Numerous layers of neurons, each completely coupled to the others, make up the network. A softmax function was employed in the output layer for multi-class classification, while ReLU activation functions were used in the hidden layers to introduce non-linearity. We employed dropout layers and batch normalization to reduce overfitting. 5-fold cross-validation was used to test the FCNN model in order to make sure it was robust and generalizable. For every fold, performance metrics including F1-score, recall, accuracy, and precision were computed.

4 Results and Discussion

In this paper, we propose a neuro-symbolic sentiment analysis that blends symbolic lexicon-based features with deep learning models and a topic-driven sentiment analysis that employs latent variable techniques to reveal thematic implications for sentiment classification. This method tries to improve sentiment analysis using social media data. Table 1 shows the performance metrics used to evaluate the model using accuracy, precision, recall, F1 score, and support. The correlation matrix demonstrates weak correlations among attributes, with the strongest correlation (0.603) found between airline_sentiment_confidence and negative reason_confidence. Other features, such as retweet_count, have low correlations with the others, indicating that there are only limited linear relationships across variables (see Fig. 2). Sentiment appears to have little effect on tweet properties such as length and retweet count, implying that these aspects are essentially independent.

5 Conclusion

In this paper, we used the Airline Sentiment Dataset to present a comprehensive framework for sentiment analysis. Our methodology tackled the issues of sentiment categorization by combining classic machine learning methods with sophisticated deep learning methodologies. Several models were used and tested thoroughly with 5-fold cross-validation. These models included logistic regression, naive Bayes, support vector machines, random forests, fully connected neural

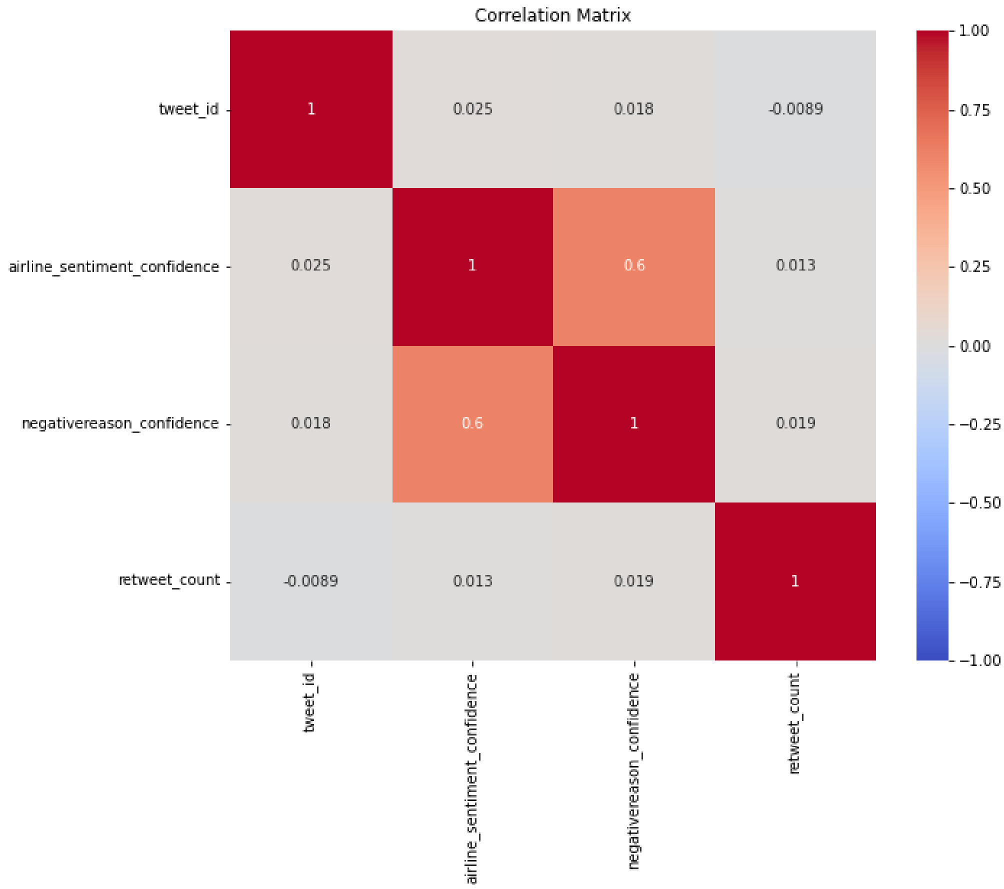

Fig. 2: Correlation Matrix of Dataset Variables

networks, neuro-symbolic sentiment analysis, and topic-driven sentiment analysis. The outcomes achieved strong performance metrics and reliable generalization to previously unexplored data. Neuro-Symbolic Sentiment Analysis used both explicit and nuanced sentiment patterns because it combined symbolic lexicon features with pre-trained embeddings. Topic-Driven Sentiment Analysis, on the other hand, used theme context to make better predictions. Our research showed that using smart preprocessing and feature engineering along with hybrid and ensemble techniques makes sentiment classification a lot more accurate. This work presents a scalable and interpretable sentiment analysis approach that may be used in domains apart from the airline sector. Future studies could look into combining multimodal data or expanding the framework to handle more difficult sentiment tasks, such as emotion detection or sarcasm analysis.

Table 1: Performance Metrics of Sentiment Analysis Models

Model	Precision	Recall	F1-Score	Accuracy	K-Fold Accuracy
Neuro-Symbolic	0.69	0.70	0.69	76.50	71.90
Topic-Driven Sentiment Analysis (TDSA)	0.60	0.56	0.57	70.49	68.80
Logistic Regression	0.59	0.52	0.55	69.26	67.12
Naive Bayes	0.41	0.39	0.36	66.22	63.90
Support Vector Machine (SVM)	0.22	0.33	0.26	64.52	62.75
Random Forest	0.60	0.55	0.57	70.59	68.44
Fully Connected Neural Network (FCNN)	0.46	0.47	0.43	46.50	54.00

References

1. AlBadani, B., Shi, R., Dong, J., Al-Sabri, R., Moctard, O.B.: Transformer-based graph convolutional network for sentiment analysis. Applied Sciences **12**(3), 1316 (2022)
2. Bai, X., Fei, R., Liu, Z., Chen, X.: Fine-grained sentiment analysis based on heterogeneous graph neural network. In: 2022 6th Asian Conference on Artificial Intelligence Technology (ACAIT). pp. 1–6. IEEE (2022)
3. Chaitanya Datta, M., Venkaiah Chowdary, B., Senapati, R.: Multi disease prediction using ensembling of distinct machine learning and deep learning classifiers. In: Patel, K.K., Santosh, K., Patel, A., Ghosh, A. (eds.) Soft Computing and Its Engineering Applications. pp. 245–257. Springer Nature Switzerland, Cham (2024)
4. Chowdary B, V., Datta M, C., Senapati, R.: An improved cardiovascular disease prediction model using ensembling of diverse machine learning classifiers. In: 2023 OITS International Conference on Information Technology (OCIT). pp. 329–333 (2023). https://doi.org/10.1109/OCIT59427.2023.10430692
5. Kaggle: Crowdflower. twitter airline sentiment dataset. https://www.kaggle.com/datasets/crowdflower/twitter-airline-sentiment (2015)
6. Keshavarz, Z., Gorji, M., Houshyar, Z., Tamajani, Z.T., Martin, J.: The professional quality of life among health-care providers and its related factors. Asian Journal of Social Health and Behavior **2**(1), 32–38 (2019)
7. Kommineni, S., Muddana, S., Senapati, R.: Explainable artificial intelligence based ml models for heart disease prediction. In: 2024 3rd International Conference on Computational Modelling, Simulation and Optimization (ICCMSO). pp. 160–164. IEEE (2024)
8. Kommineni, S., Muddana, S., Senapati, R.: Impact of temperature on power consumption-a machine learning approach. In: 2024 IEEE International Conference on Smart Power Control and Renewable Energy (ICSPCRE). pp. 1–6. IEEE (2024)
9. Lubis, A., Irawan, Y., Junadhi, J., Defit, S.: Leveraging k-nearest neighbors with smote and boosting techniques for data imbalance and accuracy improvement. Journal of Applied Data Sciences **5**(4), 1625–1638 (2024)
10. Maddukuri, C.D., Senapati, R.: Hybrid clustering-based fast support vector machine model for heart disease prediction. In: International Conference on Machine Learning, IoT and Big Data. pp. 269–278. Springer (2023)
11. Manda, S.C., Muttineni, S., Venkatachalam, G., Kongara, B.C., Senapati, R.: Image stitching using ransac and bayesian refinement. In: 2023 3rd International Conference on Intelligent Technologies (CONIT). pp. 1–5 (2023). https://doi.org/10.1109/CONIT59222.2023.10205634

12. Masana, S.N.D.S., Rudrapati, G.S., Gudiseva, K., Palutla, D.V., Gogineni, T.K., Senapati, R.: Temporal data mining on the highseas: Ais insights from bigdataocean. In: International Conference on Machine Intelligence, Tools, and Applications. pp. 394–402. Springer (2024)
13. Muttineni, S., Yerramneni, S., Kongara, B.C., Venkatachalam, G., Senapati, R.: An interactive interface for patient diagnosis using machine learning model. In: 2022 2nd International conference on emerging frontiers in electrical and electronic technologies (ICEFEET). pp. 1–5. IEEE (2022)
14. Nguyen, A., Longa, A., Luca, M., Kaul, J., Lopez, G.: Emotion analysis using multilayered networks for graphical representation of tweets. IEEE Access **10**, 99467–99478 (2022)
15. Sahoo, A., Senapati, R.: A parallel approach to partition-based frequent pattern mining algorithm. In: Intelligent Systems: Proceedings of ICMIB 2021, pp. 93–102. Springer (2022)
16. Samudrala, K., Kolisetty, J., Chakravadhanula, A.S., Preetham, B., Senapati, R.: Novel distributed architecture for frequent pattern mining using spark framework. In: 2023 3rd International Conference on Intelligent Technologies (CONIT). pp. 1–5 (2023). https://doi.org/10.1109/CONIT59222.2023.10205903
17. Senapati, R.: A novel classification-based parallel frequent pattern discovery model for decision making and strategic planning in retailing. International Journal of Business Intelligence and Data Mining **23**(2), 184–200 (2023)
18. Singh, D., Pandey, N.K., Gupta, V., Prajapati, M., Senapati, R.: Beyond textual analysis: Framework for csat score prediction with speech and text emotion features. In: 2024 IEEE International Conference on Computer Vision and Machine Intelligence (CVMI). pp. 1–6. IEEE (2024)
19. Wang, M., Hu, G.: A novel method for twitter sentiment analysis based on attentional-graph neural network. Information **11**(2), 92 (2020)
20. Yerramneni, S., Vara Nitya, K.S., Nalluri, S., Senapati, R.: A generalized grayscale image processing framework for retinal fundus images. In: 2023 3rd International Conference on Intelligent Technologies (CONIT). pp. 1–6 (2023). https://doi.org/10.1109/CONIT59222.2023.10205834