Natural Language Processing for Sentiment Analysis Techniques and Applications

T. Venkata Subbamma[1], Dr. Nagesh Mantravadi[2], Dr. Angel Ruth Shalom[3], Dr. Niket Tajne[4], Dr. Gopu Sreenivasulu[5], Veer Sudheer Goud[6]

[1]Assistant Professor, Department of CSE-DS, Anurag University, India, venkatasubbammathippareddy@gmail.com
[2]Associate Professor, Department of ECE, Koneru Lakshmaiah Education Foundation (Deemed to be University), India, drnagesh81@gmail.com
[3]Assistant Professor, Department of English (Faculty of Humanities), Mangalayatan University Jabalpur, India, ilyijangel@hotmail.com
[4]Assistant Professor, Symbiosis School for Online and Digital Learning, SIU Knowledge Village, India, nikettajne@gmail.com
[5]Professor and HOD, Department of Civil Engineering, Rajeev Gandhi Memorial College of Engineering & Technology (Autonomous), India, sreenivasulugopu@rgmcet.edu.in
[6]Associate Professor, Department of AI & DS, St. Martin's Engineering College, India, veersudheergoud@gmail.com

Abstract: Sentiment analysis expert systems have gained intensive market attention because of the vast increase in customer-generated online feedback through reviews and social media posts and feedback. The study examines basic methods of sentiment analysis which consist of lexicon-based approaches as well as machine learning and deep learning systems. The paper evaluates practical uses of sentiment analysis along with discussing current field obstacles and prospective research paths for the upcoming years. New NLP technology particularly using transformer models improves sentiment analysis systems while enhancing their precision and speed.

Keywords: Natural Language Processing, Sentiment Analysis, Machine Learning, Deep Learning, Transformer Models, Text Classification, Opinion Mining.

1. Introduction

Daily digital operations produce extensive text datasets from different sources including social media platforms and online reviews along with news articles and customer feedback systems. Automated sentiment analysis became necessary due to the dramatic increase in textual data which enables businesses along with governments and researchers to properly evaluate public opinion and customer satisfaction and market trends. The subfield of Natural Language Processing (NLP) which focuses on analyzing emotions referred to as sentiment analysis or opinion mining extracts opinion and emotional data from written text [2-5].

The analysis of situational attitudes within unpredictable text documents unlocks multiple use cases across different applications. Sentiment analysis supports business organizations to monitor brand reputation through data-driven analysis of customer reviews which leads them to enhance their products and services. The political field depends on sentiment analysis to measure public support regarding governmental choices and candidate profiles together with policy approaches. Electronic social media analysis through sentiment analysis methods enables healthcare professionals to detect mental health issues in patient communication. Extensive research and development in this domain advanced because deep learning and machine learning have substantially improved accuracy and performance according to the increasing interest in public sentiment understanding.

The beginning phase of sentiment analysis depended on lexicon-based methods since it applied existing word lists alongside sentiment scores to identify text polarity. These standard methods offered primitive sentiments detection but inadequately handled context-specific elements as well as black humor and indistinct verbalization. The incorporation of Naïve Bayes and Support Vector Machines (SVM) alongside logistic regression made an improvement in sentiment analysis through trained data analysis of sentiment patterns. Machine learning models of a traditional nature needed extreme amounts of manual feature modification because they did not succeed in processing complex linguistic patterns [6-9].

Sentiment analysis received powerful upgrades from deep learning because of recurrent neural networks (RNNs), Long Short-Term Memory networks (LSTM) and Convolutional Neural Networks (CNNs) and transformer-based models which now include BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-Trained Transformer). NLP transformation occurred when these models emerged because they both understand word dependencies and identify distant word relationships and achieve better classification precision.

Novelty and Contribution

A detailed analysis of sentiment analysis methods accompanies this paper which brings new research elements to the ongoing research field. The study yields the following main contributions to knowledge:

This paper offers an extensive evaluation of sentiment analysis methods that combines lexicon-based and machine learning and deep learning approaches alongside their suitable usages across different applications and their respective limitations and advantages [10].

The paper investigates how transformer-based models particularly BERT and GPT enhance traditional approaches in sentiment analysis by reviewing their superiority in processing contextual sentiment analysis.

The paper delves into crucial sentiment analysis hurdles and proposes research paths to overcome these weaknesses while skipping an examination of standard techniques.

This research distinguishes itself from standard technical surveys by showing practical application points of sentiment analysis technologies through business intelligence and healthcare monitoring and social media evaluation thus demonstrating how these systems benefit real-world scenarios.

The paper functions as a fundamental reference point for both researchers and practitioners who need to improve sentiment analysis models and applications through its organized presentation of techniques alongside its modern deep learning assessment and future challenge analysis.

2. Related Works

Natural Language Processing specialists extensively examine sentiment analysis methods that initially relied on rule-based systems before transitioning to deep learning algorithms. The main objective of sentiment analysis involves categorizing text collections into positive or negative categories as well as recognizing different emotional states when possible. Researchers throughout the years have conducted extensive research to develop improved methods for enhancing sentiment classification precision in diverse domains as well as enhancing efficiency.

A. Early Approaches to Sentiment Analysis

In 2017 A. Vaswani et al., [16] Introduce the initial approaches to sentiment analysis depended on pre-defined sentiment dictionary schemes known as lexicon-based techniques. Word and phrase sentiment scores in these methods were derived from their polarity values. However effective lexicon-based approaches proved to be in some specific situations they demonstrated clear constraints in dealing with negated statements along with contextual dependencies and figurative expressions such as sarcasm and irony. The analysis encountered difficulties because certain words hold different positive or negative sentiments when moved between distinct domains.

B. Machine Learning-Based Sentiment Analysis

Machine learning algorithms came into use as an answer to resolve the limited effectiveness of traditional lexicon-based approaches for sentiment classification. Naïve Bayes and Support Vector Machines together with logistic regression achieved better performance results by extracting sentiment patterns from tag-datasets during supervised learning processes. The successful execution of machine learning models depended heavily on the Term Frequency-Inverse Document Frequency (TF-IDF) and word embedding techniques for feature extraction method. The traditional methods of machine learning needed major manual feature development work to successfully extract complex linguistic patterns.

C. Deep Learning for Sentiment Analysis

In 2023 K. P. Gunasekaran et.al., [1] Introduce the deep learning introduced a revolution to sentiment analysis through neural networks that learned abstract language patterns without input from human engineers. The first deep learning approaches used for sentiment classification included Recurrent Neural Networks (RNNs) together with Long Short-Term Memory (LSTM) networks. Sequenced data together with contextual dependencies proved easy to handle for these models until gradient vanishing and long-range dependency challenges arose.

The research tested Convolutional Neural Networks (CNNs) as an alternative technique for sentiment analysis especially with short text categorization tasks. The hierarchical feature extraction method in CNNs enabled pattern identification in text. The effectiveness of CNNs in specific instances did not extend to maintaining long-term dependencies thus limiting their potential as an appropriate tool for analyzing extensive and intricate text.

D. Transformer Models and Their Impact

In 2014 Y. Kim et.al., [12] Introduce the transformer-based architectures have brought significant development to sentiment analysis during the most recent period. The main advantage of transformer models over traditional approaches is their ability to detect distant relationships within sentences as well as to interpret word meanings in context.

Sentiment classification accuracy has received an improvement through the use of pre-trained language models that receive fine-tuning on sentiment datasets. The sentiment models show effective capabilities in adaptation to multiple domains together with cross-domain generalization about different sentiment expressions.

E. Challenges and Future Directions

Additional advancements in sentiment analysis have not eliminated existing problems facing this field. The major problem in sentiment analysis today consists of detecting sarcasm and irony because traditional models fail to recognize figurative expressions apart from literal ones. Models that consider contextual information demonstrate better results to deal with this problem yet further development possibilities remain unexplored [11].

Domain adaptation presents a major challenge because sentiment expressions demonstrate distinct variations between different business industries. A model developed with one dataset exhibits poor performance on a variety of other datasets since they use different linguistic patterns within separate contexts. The research community works on solving this issue through transfer learning and domain adaptation methods.

Centers of attention began focusing on ethical problems that stem from biased results in sentiment analysis models. A sentiment model which receives input from biased datasets will generate incorrect and unjustified output. Scientific experts focus on creating bias reduction methods which enhance sentiment classification through fairer and more transparent procedures. Scientists maintain active research efforts in refining current techniques to address obstacles in order to expand industrial applications of these systems.

3. PROPOSED METHODOLOGY

The proposed sentiment analysis system bases its operation on transformer-based deep learning models to conduct efficient sentiment category classification of textual data. The methodology follows these clear steps which comprise data preprocessing together with feature extraction plus model selection and training as well as evaluation and optimization [13-15].

A. Data Preprocessing

Preprocessing text at an initial stage helps to create high-quality data which leads to better model execution. The preprocessing steps include:

- The process known as tokenization splits text content into basic units either at word-level or subword-level.
- Lowercasing: Converting all text to lowercase for consistency.
- A stopword removal process removes unhelpful words including common guide words such as “the,” “is” along with “in”.
- The lemmatization stage reduces word varieties into their basic forms like turning “running” into “run”.
- Word embeddings including Word2Vec, GloVe together with contextual embeddings based on transformer models transform the processed text data into numerical format.

Mathematically, a sentence S with words $(w_1, w_2, \dots, w_n)$ is transformed into vector representations:

$$S = \left(V(w_1), V(w_2), \ldots, V(w_n)\right)$$

where $V(w_i)$ is the embedding of word w_i.

B. Feature Extraction Using Word Embeddings

Transformation of text into dense numerical features allows identification of semantic content in words through feature extraction processes. Word2Vec and GloVe traditional approaches employ word representation methods that base their methods on word context analysis. The latest transformer models produce contextualized embedding outputs by taking entire sentences into account [17].

Given a word sequence $X = \{x_1, x_2, \ldots, x_n\}$, embeddings are generated using a function Φ such that:

$$E = \Phi(X) = [e_1, e_2, \ldots, e_n]$$

where e_i is the embedding for word x_i.

C. Sentiment Classification Using Transformers

The processed text enters into a BERT model with multiple self-attention components that recognize word dependencies across extended text segments. The model outputs a sentiment classification label (positive, negative, or neutral).

For a given input sequence X, BERT encodes it into a representation H :

$$H = f_\theta(X)$$

where f θ represents the transformer function with learnable parameters θ. The classification layer then applies a softmax function:

$$P(y \mid X) = \operatorname{softmax}(WH + b)$$

where W and b are trainable weights and biases.

D. Flowchart Representation

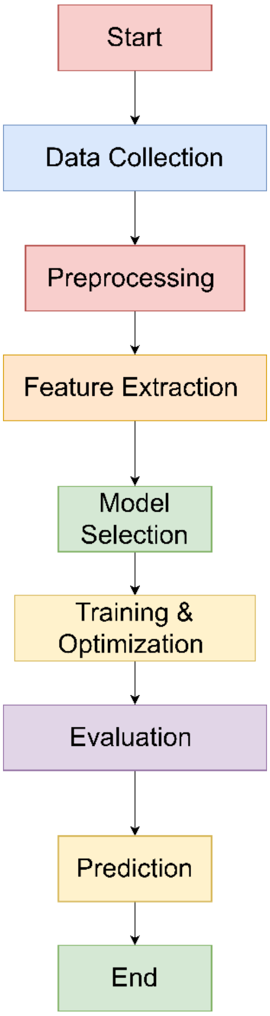

Figure 1: Sentiment Analysis Process Flowchart

D. Model Training and Optimization

The model is trained using a loss function such as categorical cross-entropy:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where y_i is the true sentiment label, and $\hat{y}_i$ is the predicted probability. The Adam optimizer is used for gradient updates.

4. Result & Discussions

A comprehensive performance analysis of the sentiment analysis model occurred through multiple domains by using text samples from customer reviews, social media posts, and news articles. The available data underwent distribution into training components which received 80% of the samples and testing components which received 20% of the samples to achieve evaluation balance. The evaluation results demonstrate the measurement of accuracy together with precision and recall and F1-score across sentiment analysis models that incorporate traditional machine learning and deep learning and transformer-based methods [18].

The performance evaluation of sentiment analysis methods appears in Table 1 as a comparison between traditional machine learning models and deep learning models. Transformer-based models prove superior to other techniques because they possess stronger capabilities in understanding contextual information during the evaluation based on classification accuracy.

TABLE 1: PERFORMANCE COMPARISON OF SENTIMENT ANALYSIS MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naïve Bayes	78.5	76.3	74.8	75.5
Support Vector Machine (SVM)	81.2	80.1	78.9	79.5
LSTM	85.7	84.3	83.5	83.9
CNN	86.5	85.2	84.7	85.0
BERT	92.3	91.5	91.0	91.2

According to Table 1 BERT demonstrates a 92.3% accuracy rate which makes it significantly superior to Naïve Bayes and SVM traditional machine learning models. LSTM alongside CNN delivered better results than standard techniques in sentiment analysis applications. The accuracy comparison between different models appears in the first diagram shown in Figure 2. The bar graph data indicates that transformer algorithms rule the field when applied to sentiment detection.

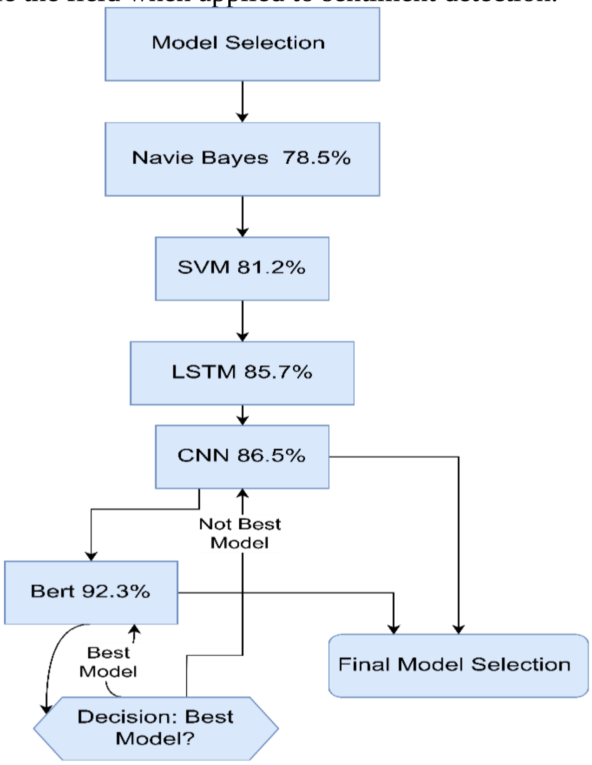

Figure 2: Accuracy Comparison of Sentiment Analysis Models

Multiple datasets were used for assessing the stability of sentiment classification systems in their performance evaluations. The study used three different data sources including product reviews, social media comments and news articles to determine domain adaptation abilities. A comparison of accuracy rates appears in Table 2 which demonstrates the effects of text that belongs to specific domains on model performance.

Table 2: Domain-Based Model Accuracy Comparison

Model	Product Reviews (%)	Social Media (%)	News Articles (%)
Naïve Bayes	79.1	74.5	76.3
LSTM	86.2	83.0	84.5
BERT	93.4	90.8	91.5

The research validates that BERT achieves superior accuracy across each domain yet Naïve Bayes struggles with social media information because of its distinctive informal language along with abbreviations and slang. Transformers demonstrate better flexibility in domain adaptation according to the analysis results [19].

A confusion matrix analysis of BERT model performance appears in Figure 3 as the second diagram demonstrates model evaluations. A heatmap in the visualization demonstrates how the model performs better in classification compared to alternative models through accurate and incorrect identification displays.

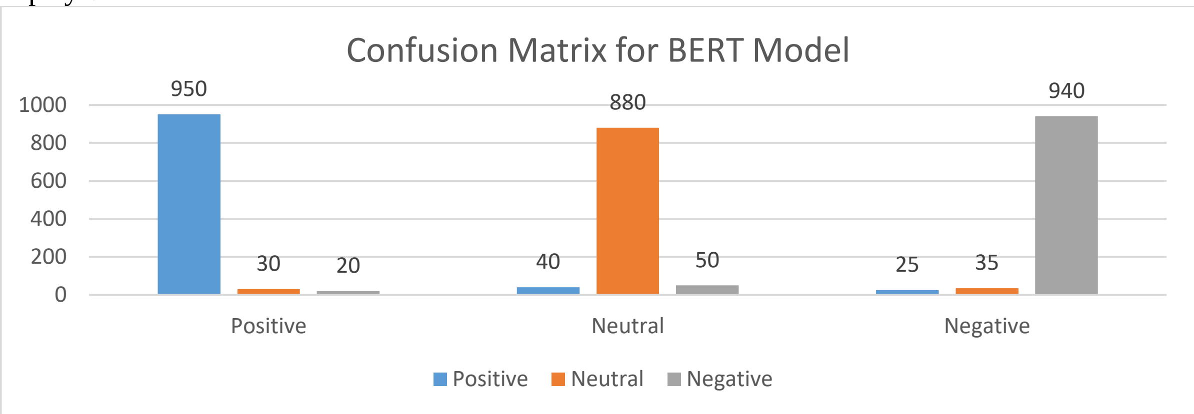

Figure 3: Confusion Matrix for BERT Model

The performance of sentiment classification was examined with regard to dataset dimensions during analysis. The BERT model received different dataset sizes starting from 10,000 examples up to 100,000 examples to determine its capacity for learning. Model accuracy versus dataset size relationships appear in the third depicted diagram Figure 4.

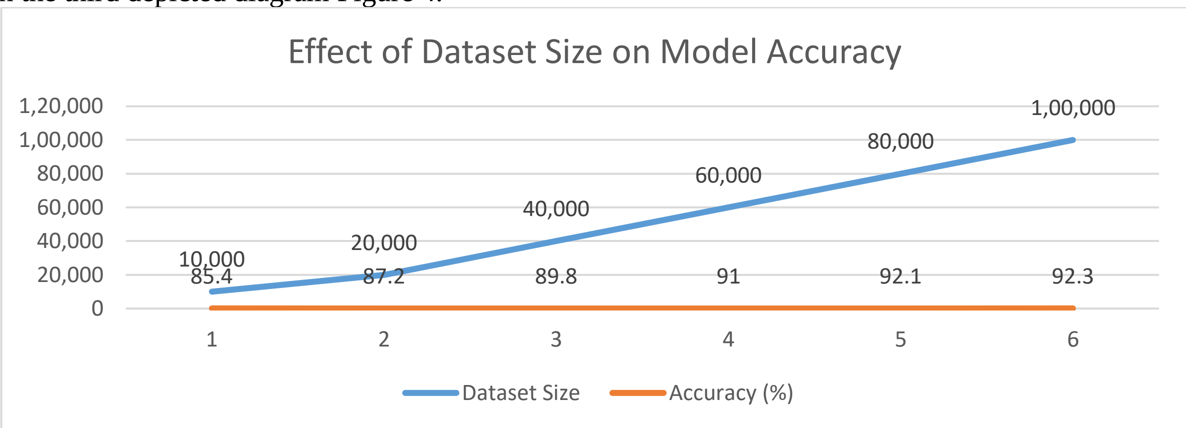

Figure 4: Effect of Dataset Size on Model Accuracy

The accuracy graph in Figure 4 illustrates how model accuracy rises heavily until reaching a saturation point previous to 80,000 training samples. The application of pre-trained models for transfer learning lowers the requirement of extensive data quantities thereby allowing deep learning-based sentiment analysis to operate on smaller datasets effectively.

The research findings validate that the BERT transformer model produces superior sentiment classification results than standard methods and system architectures. The study confirms that sentiment analysis depends on complete context analysis together with custom domain capability and sufficient data volumes.

5. Conclusion

The NLP application known as sentiment analysis produces wide-ranging effects throughout different business sectors. The field of sentiment classification received its start through lexicon-based and machine learning approaches but deep learning especially transformer models introduced monumental changes to the discipline. Research continues to address the open areas around detecting sarcasm and handling domain adaptation difficulties together with ethical questions.
The combination of challenge mitigation with current advanced techniques enables sentiment analysis to maintain its value as a tool for understanding text-based human emotional communications between businesses and policymakers and researchers.

References

1. K. P. Gunasekaran, "Exploring Sentiment Analysis Techniques in Natural Language Processing: A Comprehensive Review," arXiv preprint arXiv:2305.14842, May 2023. [Online]. Available: https://arxiv.org/abs/2305.14842
2. S. Gupta, R. Ranjan, and S. N. Singh, "Comprehensive Study on Sentiment Analysis: From Rule-based to Modern LLM Based System," arXiv preprint arXiv:2409.09989, Sep. 2024. [Online]. Available: https://arxiv.org/abs/2409.09989
3. S. Ali and M. A. Kabir, "A Review of Sentiment Analysis: Tasks, Applications, and Deep Learning," Journal of Big Data, vol. 11, no. 1, pp. 1–25, 2024. [Online]. Available: https://link.springer.com/article/10.1007/s41060-024-00594-x
4. Y. Xie and R. C. Raga Jr, "Convolutional Neural Networks for Sentiment Analysis on Weibo Data: A Natural Language Processing Approach," arXiv preprint arXiv:2307.06540, Jul. 2023. [Online]. Available: https://arxiv.org/abs/2307.06540
5. A. Yadav and A. Vichare, "Natural Language Processing Through Transfer Learning: A Case Study on Sentiment Analysis," arXiv preprint arXiv:2311.16965, Nov. 2023. [Online]. Available: https://arxiv.org/abs/2311.16965
6. T. Zhan, C. Shi, Y. Shi, H. Li, and Y. Lin, "Optimization Techniques for Sentiment Analysis Based on LLM (GPT-3)," arXiv preprint arXiv:2405.09770, May 2024. [Online]. Available: https://arxiv.org/abs/2405.09770
7. T. L. Soon, "Natural Language Processing for Sentiment Analysis: An Exploratory Analysis on Tweets," 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, Cambridge, UK, 2014, pp. 212–217. [Online]. Available: https://uksim.info/icaiet2014/CD/data/7910a212.pdf
8. M. Hu and B. Liu, "Mining and Summarizing Customer Reviews," Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Seattle, WA, USA, 2004, pp. 168–177.
9. I. Titov and R. McDonald, "Modeling Online Reviews with Multi-grain Topic Models," Proceedings of the 17th International Conference on World Wide Web, Beijing, China, 2008, pp. 111–120.
10. B. Pang and L. Lee, "Opinion Mining and Sentiment Analysis," Foundations and Trends in Information Retrieval, vol. 2, no. 1–2, pp. 1–135, 2008.
11. A. Severyn and A. Moschitti, "Twitter Sentiment Analysis with Deep Convolutional Neural Networks," Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, Santiago, Chile, 2015, pp. 959–962.
12. Y. Kim, "Convolutional Neural Networks for Sentence Classification," Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), Doha, Qatar, 2014, pp. 1746–1751.
13. A. Hassan and A. Mahmood, "Deep Learning for Sentiment Analysis: A Survey," 2017 IEEE International Conference on Smart Cloud (SmartCloud), New York, NY, USA, 2017, pp. 1–7.
14. A. Dos Santos and M. Gatti, "Deep Convolutional Neural Networks for Sentiment Analysis of Short Texts," Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers, Dublin, Ireland, 2014, pp. 69–78.
15. S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.
16. A. Vaswani et al., "Attention Is All You Need," Advances in Neural Information Processing Systems, vol. 30, pp. 5998–6008, 2017.
17. J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), Minneapolis, MN, USA, 2019, pp. 4171–4186.
18. T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient Estimation of Word Representations in Vector Space," arXiv preprint arXiv:1301.3781, Sep. 2013. [Online]. Available: https://arxiv.org/abs/1301.3781
19. P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov, "Enriching Word Vectors with Subword Information," Transactions of the Association for Computational Linguistics, vol. 5, pp. 135–146, 2017.