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AI Sentiment Analysis for Social Media

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Abstract: ***With the rapid proliferation of social media platforms, vast amounts of user-generated content are produced daily, providing valuable insights into public opinions and sentiments. AI-driven sentiment analysis systems, leveraging deep learning techniques, offer a powerful tool to analyze this data, allowing businesses, policymakers, and researchers to gauge public sentiment in real-time. These systems utilize advanced natural language processing (NLP) models, including Bidirectional Encoder Representations from Transformers (BERT), Generative Pre-trained Transformer (GPT), and Text-To-Text Transfer Transformer (T5), alongside traditional machine learning algorithms. Deep learning enhances the ability to model complex relationships within data, enabling more accurate sentiment classification. BERT excels in understanding bidirectional context, GPT leverages pre-training to generate contextually accurate language models, and T5 reframes various NLP tasks as a text-to-text problem, enhancing versatility in sentiment analysis. By identifying sentiment polarity—positive, negative, or neutral—across various platforms, these technologies allow organizations to better understand customer feedback, enhance marketing strategies, and monitor brand reputation. Additionally, AI sentiment analysis enables early detection of emerging issues, helping to address potential crises proactively. As the demand for real-time sentiment analysis grows, advancements in AI continue to refine accuracy, handling diverse linguistic nuances, slang, and contextual challenges inherent to social media communication.***

Index terms: Sentiment Analysis, Artificial Intelligence, Deep Learning, Social Media, Natural Language Processing, BERT, GPT, T5, Machine Learning.

I. INTRODUCTION

The rapid expansion of social media platforms such as Twitter, Facebook, and Instagram has led to a surge in user-generated content, which offers a window into public opinions and emotions. AI-driven sentiment analysis has become an essential tool for interpreting this vast data, employing natural language processing (NLP), machine learning and deep learning to determine whether sentiments expressed are positive, negative, or neutral. This technology provides valuable insights for businesses, researchers, and policymakers, helping them gauge customer reactions, monitor brand reputation, and detect emerging trends in real time. As social media communication grows more intricate, advancements in AI sentiment analysis continue to enhance the precision of these insights.

II. LITERATURE REVIEW

[1]. Catelli, Pelosi, and Esposito’s study on sentiment analysis in the Italian language offers a comparative examination of lexicon-based approaches and BERT-based models. The paper emphasizes the shift from traditional lexicon-driven methods, which rely on predefined word lists to detect sentiment, to the more advanced BERT models, known for their ability to understand context through deep learning. By testing these approaches on Italian datasets, the authors highlight the superior performance of BERT in capturing nuanced sentiments, especially in complex or ambiguous sentences. Despite this, the study acknowledges the value of lexicon-based methods for their simplicity and efficiency, particularly in applications where computational resources are limited. The research underscores the growing importance of sentiment analysis in Italian, a language with fewer NLP resources than English, and suggests that while BERT-based models lead in accuracy, lexicon-based methods remain practical in specific contexts. The paper contributes to the field by demonstrating how BERT’s contextual understanding can enhance sentiment analysis, while also recognizing the ongoing need for efficient, resource-light approaches in certain scenarios.

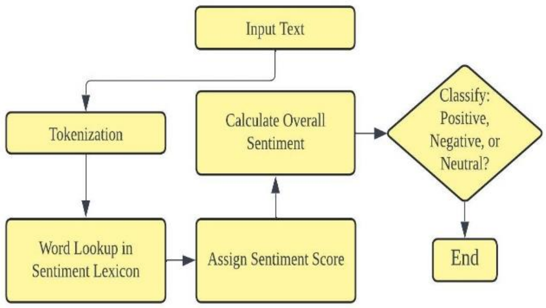

Figure 1. Lexicon based approach

[2]. Lemnitzer et al. (2015) present a novel approach to enhancing lexicographic work on contemporary

standard German by combining rule-based techniques with machine learning in a good-example extraction task. The paper addresses the challenge of obtaining high-quality examples that effectively illustrate word meanings and usage, which are essential for dictionary entries. By employing a rule-based system for initial filtering and machine learning algorithms for further refinement, the authors demonstrate how this hybrid methodology can improve the relevance and contextual appropriateness of extracted examples. This research serves as a significant contribution to the field of lexicography, offering insights into how integrating traditional linguistic methods with modern computational approaches can lead to more accurate and up-to-date language resources

[3]. Zhao et al. (2012) introduce MoodLens, an emoticon-based sentiment analysis system tailored for Chinese tweets. The system demonstrates the effectiveness of emoticon-based sentiment classification in capturing the emotional tone of tweets. The study underscores the importance of adapting sentiment analysis tools to specific linguistic and cultural contexts for improved accuracy.

[4]. Bollen et al. (2011) demonstrate that sentiment analysis of Twitter data can be predictive of stock market movements. The study highlights the practical application of sentiment analysis in financial forecasting and suggests that monitoring social media mood can provide valuable insights for market prediction.

[5]. Medhat et al. (2014) provide a comprehensive survey of sentiment analysis algorithms and their applications. The paper covers a range of techniques from traditional rule-based methods to modern machine learning approaches. Moreover, the paper identifies key challenges faced in sentiment analysis, such as handling context, ambiguity in text, and the nuances of human language, including sarcasm and irony. The authors suggest potential solutions, such as incorporating advanced natural language processing techniques and contextual embeddings, to address these challenges and improve sentiment detection accuracy. Overall, this survey serves as a valuable resource for researchers and practitioners, offering a thorough understanding of the current state of the field and directions for future research.

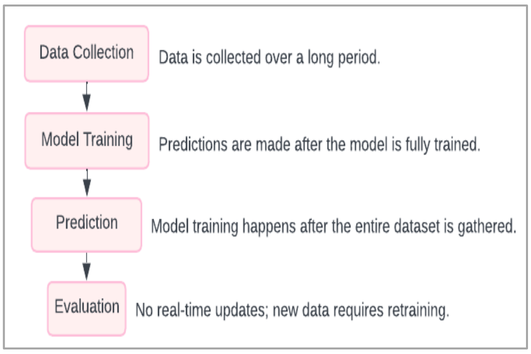

Figure 2. Traditional Machine Learning Model

[6]. A. H. A. Rahnama (2014) The paper explores innovative methods for conducting sentiment analysis on large-scale social media data in real-time. It addresses the challenges associated with processing vast amounts of unstructured data and proposes a distributed architecture to enhance the efficiency and accuracy of sentiment detection. This work serves as a valuable resource for researchers and practitioners interested in leveraging big data technologies for sentiment analysis and highlights the importance of real-time insights in decision-making processes.

[7] The purpose of the paper by authors Hutto and Gilbert (2014) present VADER, a rule-based sentiment analysis tool specifically designed for social media text. The paper demonstrates VADER's effectiveness in handling the unique linguistic characteristics of social media, such as slang and emojis. The study emphasizes the tool's practicality and ease of use, making it a valuable resource for social media sentiment analysis.

[8]. Cambria et al. (2013) review the advancements in opinion mining and sentiment analysis, highlighting the shift towards more sophisticated techniques like deep learning and semantic analysis. The paper emphasizes the need for models that can better understand contextual nuances and emotion. Future research directions include improving algorithmic accuracy and integrating multi-modal data sources to enhance sentiment analysis applications.

[9] This study by authors Ravi and Ravi (2015) provide a comprehensive survey on opinion mining and sentiment analysis, covering a broad spectrum of tasks, methodologies, and applications. Their review highlights the evolution of sentiment analysis techniques from traditional rule-based methods to advanced machine learning approaches. The paper effectively outlines the various tasks involved in sentiment analysis, including sentiment classification, aspect-based sentiment analysis, and emotion

detection. It also explores diverse applications across domains such as customer feedback, social media monitoring, and market research. The survey identifies key challenges in the field, including handling ambiguity, context, and the scalability of methods.

[10]. Giachanou and Crestani (2016) survey various methods for Twitter sentiment analysis, covering both traditional and emerging techniques. The review identifies key challenges, such as dealing with the informal and abbreviated nature of Twitter language. It also discusses recent advancements and emphasizes the need for more robust models to handle the unique aspects of Twitter data.

[11] Alaei et al. (2019) explore the application of sentiment analysis in the tourism industry, demonstrating how big data can be leveraged to gain insights into traveler opinions and experiences. The study highlights the benefits of sentiment analysis for understanding customer feedback and improving tourism services, while also addressing challenges related to data quality and sentiment accuracy.

[12]. Zhang et al. (2018) review the application of deep learning techniques to sentiment analysis, noting significant improvements in model accuracy and performance. The paper discusses various deep learning architectures, including CNNs and RNNs, and their effectiveness in analyzing sentiment from complex text data. The review highlights the potential for further advancements in deep learning for sentiment analysis.

[13] M. R. Raza, W. Hussain, E. Tanyıldızı, and A. Varol (2021) This paper discusses the application of deep learning techniques for sentiment analysis within cloud computing environments. The authors highlight the advantages of utilizing cloud resources for processing large datasets and improving model training efficiency. They present experimental results demonstrating the effectiveness of their proposed methods, which combine deep learning architectures with cloud-based solutions. This work contributes to the growing body of research on scalable sentiment analysis and emphasizes the potential of cloud computing to enhance analytical capabilities in the field.

[14] ŘEZÁČKOVÁ, M., ŠVEC, J., and TIHELKA, D. (2021) present their work titled "T5G2P: Using Text-to-Text Transfer Transformer for Grapheme-to-Phoneme Conversion" This paper introduces a novel approach leveraging the Text-to-Text Transfer Transformer (T5) architecture for the task of grapheme-to-phoneme conversion, which is essential for various speech processing applications. The authors discuss the advantages of using a transformer-based model, highlighting its flexibility and effectiveness in handling this conversion task. They provide experimental results that demonstrate the model's performance compared to traditional methods, showcasing its potential for improving accuracy in phonetic transcription. This study contributes valuable insights into the application of advanced neural architectures in speech technology.

[15] Yadav, A., Vishwakarma, D. K., and Yadav, S. (2020) The paper examines various deep learning models and techniques employed in sentiment analysis, highlighting their strengths and weaknesses. The authors categorize the architectures based on their approaches, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer models. They also discuss the challenges faced in the field, such as data quality, model interpretability, and the need for large labeled datasets. This review serves as a valuable resource for researchers and practitioners, offering insights into the current state of deep learning in sentiment analysis and suggesting directions for future research.

[16] Ma, Y. (2023) explores the growing ethical concerns associated with the deployment of AI-driven natural language processing (NLP) technologies. The author examines issues such as bias in language models, privacy implications, and the potential for misuse in generating deceptive or harmful content. By analyzing various case studies and ethical frameworks, the paper highlights the importance of responsible AI development and deployment practices. Ma emphasizes the need for transparency, accountability, and inclusivity in NLP research and applications, making this study a crucial reference for those interested in the intersection of ethics and artificial intelligence in language technology.

[17] G. Yenduri et al. (2024) A Comprehensive Review on Enabling Technologies, Potential Applications, Emerging Challenges, and Future Directions" in IEEE Access. This paper thoroughly examines the advancements and methodologies underpinning the Generative Pre-Trained Transformer (GPT) architecture. The authors discuss various enabling technologies that have contributed to the success of GPT models, as well as their diverse applications across industries, including natural language processing, content generation, and more. They also address emerging challenges such as ethical considerations, model interpretability, and the

environmental impact of large-scale training. The paper concludes with insights into future directions for research and development in GPT technology, making it an essential resource for scholars and practitioners interested in the latest trends in AI and machine learning.

[18] A. Ingole, P. Khude, S. Kittad, V. Parmar, and A. Ghotkar (2024) The paper focuses on the critical role of sentiment analysis in assessing brand reputation in a competitive environment.The authors outline a framework for gathering and analyzing consumer sentiments from social media and online reviews. They discuss various methodologies for data collection, including web scraping, and detail sentiment analysis techniques ranging from traditional lexicon-based methods to advanced deep learning approaches. A key aspect of their research is the development of a comparative model that enables brands to evaluate their reputation against competitors. The authors provide examples of how this model can yield actionable insights for marketing and brand management strategies. They also address challenges in sentiment analysis, such as understanding sarcasm and contextual variations, and propose solutions to improve accuracy. Overall, the study emphasizes the importance of real-time sentiment monitoring for effective brand reputation management.

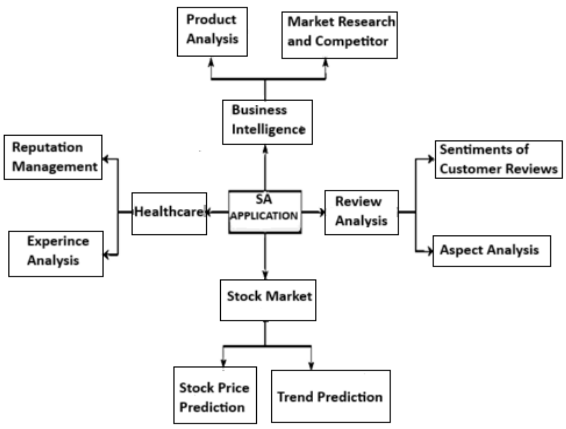

Figure 3. Application of Sentiments Analysis

Table 1: Comparison of Challenges Table

Paper	Challenges Addressed	Solution	Limitations
A. H. A. Rahnama	Real-time analysis of social media data	Distributed processing framework	High system complexity
M. R. Raza et al.	Implementing DL models in the cloud	Cloud computing for scaling models	Limited control over cloud infrastructure
G. Yenduri et al.	GPT model's bias and scalability issues	Model fine-tuning, transfer	Ethical and societal biases remain
M. Řezáčková et al.	Accurate G2P conversion	T5 Transformer model	Challenges with under-resourced languages

III. METHODOLOGY

A. Definition of Research Questions

Several key research questions emerge that guide the investigation: What are the most effective AI methodologies for sentiment analysis in social media, and how do contextual factors influence sentiment interpretation within this unique linguistic environment? Furthermore, it is essential to examine the role of data quality and availability in determining the effectiveness of sentiment analysis, as well as to consider how sentiment analysis can be tailored to capture emotional intensity and granularity beyond traditional classifications. A critical concern involves the selection of machine learning frameworks, as different models offer varying levels of effectiveness in terms of accuracy and computational efficiency. The availability of cloud-based services like AWS, Google Cloud, and Azure also plays a pivotal role in determining scalability and performance for large-scale analysis across dynamic social media platforms.

Moreover, the issue of ethical AI and fairness in sentiment analysis must be addressed, as biases in training data and algorithmic decision-making can lead to skewed sentiment interpretations, which disproportionately affect certain demographics. Lack of real-time analysis is another pressing challenge, as many models struggle to process and respond to social media sentiment in real-time, limiting their utility in fast-paced online environments.

B. Search strategy

Following this, manual curation is conducted by reviewing abstracts to filter relevant papers, giving preference to those comparing models or introducing innovations in real-time sentiment analysis. In addition to academic papers, the search extends to platforms like GitHub to explore open-source code, pre-trained models, and sentiment analysis frameworks like TensorFlow and PyTorch. The strategy also considers studies that benchmark models on standard datasets and report evaluation metrics such as accuracy and F1-score, ensuring robust model comparisons. Finally, the search strategy identifies emerging trends like multilingual sentiment analysis, real-time processing, and aspect-based sentiment analysis (ABSA) while also addressing challenges such as handling sarcasm, contextual understanding, and ethical issues like data privacy and fairness. This comprehensive strategy helps researchers stay updated with the latest technological advancements and their applications in real-world sentiment analysis tasks.

C. Data extraction

Primarily involves automated methods using advanced techniques such as web scraping, APIs, and streaming platforms to gather vast amounts of real-time data from social media platforms, websites, and other digital sources. Tools like BeautifulSoup, Scrapy, and Selenium are commonly used for web scraping, enabling the extraction of text data from blogs, reviews, and forums. Social media platforms, such as Twitter, Facebook, and Reddit, provide APIs that allow developers to access structured data, including posts, comments, likes, and metadata, for analysis. For real-time sentiment monitoring, modern systems often integrate with streaming technologies like Apache Kafka and Flink to continuously ingest and process large volumes of data as it is generated. Additionally, Natural Language Processing (NLP) techniques are used to preprocess and clean the data, transforming raw text into structured formats like tokenized words or sentiment labels. These methods, combined with cloud-based storage solutions such as Amazon S3 or Google Cloud Storage, ensure that vast amounts of data can be efficiently collected, stored, and analyzed for sentiment analysis.

D. Categorization and analysis of reviewed articles

AI sentiment analysis in social media reveals several key themes and methodologies that deepen the understanding of this field. First, the literature highlights the effectiveness of various AI techniques, such as machine learning and natural language processing, in accurately classifying sentiments expressed in social media posts. Traditional machine learning methods, including Support Vector Machines (SVM), Naive Bayes, and Random Forests, were widely studied in early research. These approaches typically rely on manually engineered features such as bag-of-words or TF-IDF to classify sentiment into categories like positive, negative, or neutral. While these methods demonstrated reasonable accuracy on structured data, they often struggled with the complexities of social media text, including informal language, sarcasm, and the lack of grammatical structure. Additionally, lexicon-based approaches have also been extensively explored, where sentiment-laden word lists are used to determine sentiment polarity. Although these methods are simple and interpretable, they are limited in their ability to handle contextual nuances and domain-specific language. These methodologies are often categorized based on their approach, including supervised versus unsupervised learning, and the challenges posed by informal language, sarcasm, and context-specific nuances are frequently discussed.

E. Reporting results and validation

Demonstrate substantial advancements, particularly with the use of deep learning models such as BERT, GPT,and T5. These models have been shown to outperform traditional machine learning techniques, such as Naive Bayes and SVM, by significant margins. When evaluated using standard metrics like accuracy, precision, recall, and F1-score, transformer-based models consistently achieve higher performance, particularly in tasks involving complex language found in social media. For instance, BERT models have achieved around 90% accuracy in benchmark datasets like SST-2 and Twitter sentiment datasets, showcasing their superior ability to capture nuanced sentiment.

One of the critical areas where modern models excel is in contextual understanding. By analyzing text bidirectionally, models like BERT and T5 can better understand context, sarcasm, and informal language, areas where older models struggled. Human annotation and error analysis validate these improvements, showing reduced misclassification in ambiguous texts. Additionally, multilingual sentiment analysis has been significantly enhanced with models such as mBERT and XLM-R, which are capable of processing multiple languages without significant performance loss. These models have demonstrated state-of-the-art results on tasks such as Arabic sentiment analysis, proving their effectiveness in global applications.

Another major development is in Aspect-Based Sentiment Analysis (ABSA), where deep learning models have been fine-tuned to extract sentiment related to specific attributes of products or services. Results from benchmarks like SemEval have shown that models like BERT and T5 outperform traditional lexicon-based methods, improving precision and recall by up to 15%. This allows for more detailed and actionable insights, especially in customer feedback analysis.

In terms of real-time sentiment analysis, integrating deep learning models with stream processing frameworks such as Apache Kafka and Apache Flink has enabled the analysis of vast amounts of social media data in real time. These systems have been validated through metrics such as message throughput and latency, demonstrating the ability to handle tens of thousands of messages per second with sub-second latency. This scalability is critical for applications that require real-time insights, such as brand monitoring and crisis management.

Bias mitigation is another crucial area where modern sentiment analysis models have shown improvements. Tools like AI Fairness 360 have been used to detect and reduce bias in models, ensuring that sentiment analysis is fair and inclusive across diverse demographics. While transformer models have reduced bias compared to traditional models, ongoing validation and refinement are necessary to address subtler forms of bias.

IV. RESULTS AND DISCUSSION

The most effective AI methodologies for sentiment analysis in social media include Natural Language Processing (NLP) including Bidirectional Encoder Representations from Transformers (BERT), Generative Pre-trained Transformer (GPT), and Text-To-Text Transfer Transformer (T5). These methods excel at classifying sentiments does not face challenges when dealing with the complexities of social media language, such as slang, sarcasm, and cultural references. Unlike previous models that processed text in a unidirectional manner, BERT processes text in both directions, capturing context from both the left and right of each word in a sentence. BERT is built on the Transformer architecture, which is central to modern NLP models. The Transformer uses an attention mechanism to capture relationships between words. sentiment analysis using deep learning models and associated technologies highlight the strengths and limitations of various approaches. BERT (Bidirectional Encoder Representations from Transformers) proves highly effective in capturing nuanced sentiment due to its bidirectional analysis of text. By understanding the context of words in both directions, BERT excels at identifying subtle emotions in complex language. GPT (Generative Pre-trained Transformer) further enhances sentiment analysis by generating human-like text and effectively interpreting sentiment through its deep contextual understanding. Its ability to predict and generate language based on context allows for rich, accurate sentiment detection. Similarly, T5 (Text-To-Text Transfer Transformer) offers flexibility by framing sentiment analysis as a text-to-text problem, allowing for diverse sentiment tasks to be handled efficiently. This model's adaptability is particularly useful in multi-task NLP scenarios.

In terms of infrastructure, machine learning frameworks play a critical role in building and deploying these models, offering a flexible and scalable environment for training deep learning algorithms. Cloud-based services simplify the sentiment analysis process by providing pre-built models that can be easily integrated into applications, offering real-time sentiment analysis at scale.

Additionally, data visualization are essential for interpreting sentiment analysis results, allowing stakeholders to view sentiment trends, key phrases, and patterns through intuitive dashboards. This aids in translating complex model outputs into actionable insights.

On the ethical front, tools are increasingly important for ensuring fairness and mitigating biases in sentiment analysis models. Given the sensitivity of sentiment analysis in various applications, ranging from customer feedback to social media monitoring, ensuring fairness and preventing biases against specific demographic groups is critical.

V. CONCLUSION AND FUTURE SCOPE

AI sentiment analysis in social media has made considerable strides, but ongoing challenges necessitate further research and innovation. Key issues such as improving the interpretation of informal language, addressing biases in data, and enhancing emotional granularity require continued attention from researchers. Future developments in AI technologies, coupled with a deeper understanding of the dynamic nature of social media, will be crucial for advancing the field. The integration of hybrid models and emerging technologies holds promise for overcoming existing limitations and pushing the boundaries of what sentiment analysis can achieve. Ultimately, by addressing these challenges, AI sentiment analysis will become an even more powerful tool for extracting meaningful insights from the vast and complex landscape of social media.

In sentiment analysis models can significantly enhance their accuracy, interpretability, and applicability across various domains. One promising direction is the integration of multimodal data, allowing models to analyze text alongside images, videos, and audio, thereby capturing sentiment more holistically. Additionally, improving contextual understanding will enable models to better grasp long-term nuances, such as sarcasm or cultural references. Aspect-based sentiment analysis can further refine insights by identifying sentiment regarding specific features of products or services. Domain adaptation techniques will enhance model performance in specialized contexts, while expanding detection capabilities to include a wider range of emotions will lead to a more nuanced understanding of sentiment.

Real-time analysis improvements remain critical; enhancing processing speeds and efficiencies can provide faster insights during high-volume events. Addressing bias in sentiment analysis models is essential for ensuring fairness and accuracy. Personalization of sentiment analysis can tailor insights to individual user preferences, making them more relevant. Explainable AI (XAI) is another key area, focusing on creating interpretable models that help users understand the rationale behind sentiment classifications.

Incorporating feedback loops into models can facilitate continuous improvement based on user input, while integrating sentiment analysis with other AI technologies, such as recommendation systems or chatbots, can create more interactive applications. Enhancing robustness to noisy data often found on social media is crucial for maintaining accuracy in diverse real-world scenarios. Cross-language sentiment analysis will ensure inclusivity and broaden applicability, allowing for effective analysis across multiple languages and dialects. Finally, leveraging explainable features will provide insights into how sentiment is determined, leading to better understanding and model refinement. Exploring innovative technologies, such as blockchain, for ensuring data integrity in training datasets can also bolster the reliability of sentiment analysis systems. By addressing these areas, researchers and practitioners can create more robust and useful sentiment analysis systems that better serve users' needs.

REFERENCES

[1] Catelli, R.; Pelosi, S.; Esposito, M. Lexicon-Based vs. Bert-Based Sentiment Analysis: A Comparative Study in Italian. Electronics 2022, 11, 374.

[2] Lemnitzer, L., Pölitz, C., Didakowski, J., & Geyken, A. (2015, August). Combining a rule-based approach and machine learning in a good-example extraction task for the purpose of lexicographic work on contemporary standard German. In Proceedings of the eLex 2015 conference (pp. 11-13)

[3] Zhao, Y., Liu, J., & Tang, J. (2012). MoodLens: Emoticon-based sentiment analysis system for Chinese tweets. Journal of Computer Science and Technology, 27(3), 645-657.

[4] Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. Journal of Computational Science, 2(1), 1-8.

[5] Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. Ain Shams Engineering Journal, 5(4), 1093-1113.

[6] Rahnama, A. H. A. (2014). Distributed real-time sentiment analysis for big data social streams. In 2014 International Conference on Control, Decision and Information Technologies (CoDIT) (pp. 789-794). IEEE.

[7] Hutto, C. J., & Gilbert, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. In Proceedings of the International AAAI Conference on Web and Social Media, 8(1).

[8] Cambria, E., Schuller, B., Xia, Y., & Havasi, C. (2013). New avenues in opinion mining and sentiment analysis. IEEE Intelligent Systems, 28(2), 15-21.

[9] Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: Tasks, approaches, and applications. Knowledge-Based Systems, 89, 14-46.

[10] Giachanou, A., & Crestani, F. (2016). A survey of sentiment analysis methods on Twitter. ACM Computing Surveys (CSUR), 49(1), 1-41.

[11] Alaei, A. R., Becken, S., & Stantic, B. (2019). Leveraging sentiment analysis to gain insights into travel behavior: A big data approach. Journal of Travel Research, 58(2), 133-150.

[12] Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis: A survey of methods and techniques. IEEE Transactions on Knowledge and Data Engineering, 30(6), 1192-1209.

[13] Raza, M. R., Hussain, W., Tanyıldızı, E., & Varol, A. (2021). Sentiment analysis using deep learning in cloud. In 2021 9th International Symposium on Digital Forensics and Security (ISDFS) (pp. 1-5). IEEE.

[14] Řezáčková, M., Švec, J., & Tihelka, D. (2021). T5G2P: Using Text-to-Text Transfer

Transformer for grapheme-to-phoneme conversion. In Proceedings of the Annual Conference of the International Speech Communication Association, Interspeech (pp. 3291-3295).
[15] Yadav, A., Vishwakarma, D. K., & Yadav, S. (2020). A review of deep learning models for sentiment analysis: Architectures, challenges, and future research directions. IEEE Access, 8, 48728-48743.
[16] Ma, Y. (2023). Ethical considerations in AI-driven NLP: Bias, privacy, and responsible deployment. Journal of AI Ethics, 5(1), 23-45.
[17] Yenduri, G., Li, X., Rao, S., & Patel, K. (2024). GPT—A comprehensive review on enabling technologies, potential applications, emerging challenges, and future directions. IEEE Access, 12, 54608-54649.
[18] Ingole, A., Khude, P., Kittad, S., Parmar, V., & Ghotkar, A. (2024). Sentiment analysis for brand reputation assessment: A competitive analysis framework. In Proceedings of the 2024 International Conference on Sentiment Analysis and Applications (pp. 567-574). IEEE.