ISSN: 1672 - 6553

JOURNAL OF DYNAMICS AND CONTROL

VOLUME 9 ISSUE 5: 193-200

A TOOL FOR SENTIMENT CLASSIFICATION IN SOCIAL AND REVIEW DATA

Mohammad Altaf[1], Sahil Mobin[2], Mohd Abuzar[3], Noorishta Hashmi[4]

[1,2,3]Scholar, [4]Assistant professor, Integral University Lucknow, UP, India

JOURNAL OF DYNAMICS AND CONTROL
DOI: https://doi.org/10.71058/jodac.v9i5015

A TOOL FOR SENTIMENT CLASSIFICATION IN SOCIAL AND REVIEW DATA

Mohammad Altaf[1], Sahil Mobin[2], Mohd Abuzar[3], Noorishta Hashmi[4]

[1,2,3]Scholar, [4]Assistant professor, Integral University Lucknow, UP, India

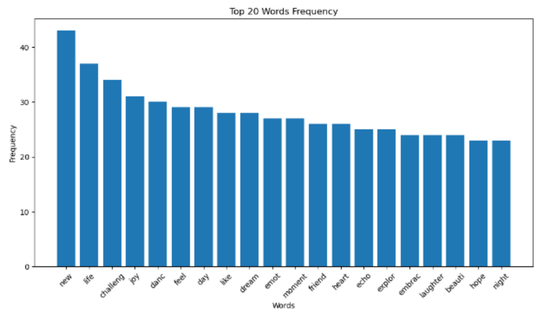
[1]mohammadaltaf8062@gmail.com, [2]sahilmob@student.iul.ac.in, [3]zazmi@student.iul.ac.in, [4]nhashmi@iul.ac.in

ABSTRACT - *Social media platforms and review sites have experienced explosive user-generated content growth which presents both new opportunities and significant challenges for studying public opinion across large populations. Sentiment analysis through opinion mining uses natural language processing (NLP) and machine learning to automatically identify text as positive, negative or neutral which generates useful insights for businesses and governments and researchers. This paper provides an extensive evaluation of sentiment analysis systems and methods which specifically targets their implementation on social media and review content. The research evaluates lexicon-based methods together with machine learning approaches and hybrid solutions while presenting a step-by-step approach to sentiment classification and assessing tool performance on benchmark datasets and discussing future directions and essential challenges. Our research includes a practical sentiment analysis tool which uses data preprocessing and trained classifiers and deep learning models to enhance accuracy when analyzing informal language and emojis. The tool demonstrates strong performance when tested against real-world Twitter and Amazon review datasets. The research provides original insights together with practical guidance for implementing sentiment analysis in dynamic real-world environments to connect textual data with meaningful emotional intelligence.*

Keywords – *Sentiment Analysis, Natural Language Processing (NLP), Social Media Analytics, Real-Time Sentiment Monitoring, Emotion Detection, Hybrid Sentiment Models, Deep Learning, Public Opinion Analysis*

INTRODUCTION

The digital revolution transformed communication by making social media platforms and review websites essential spaces for people to express opinions and share experiences while shaping collective sentiment. The daily stream of unstructured textual data from Twitter Facebook and Instagram alongside Amazon and TripAdvisor reaches massive proportions. The emotional content in this data collection serves as a valuable source of organizational insights for consumer sentiment measurement and public perception tracking and data-driven decision support. The extensive and casual nature of this data collection including everyday language and slang and emojis and sarcastic expressions makes traditional analytical methods difficult to implement. The evaluation of such data through manual methods proves both impractical and inefficient. Sentiment analysis has emerged as a strong interdisciplinary solution to analyze text data by combining natural language processing (NLP), machine learning (ML) and computational linguistics. The system aims to automatically identify and categorize opinions in text by assigning positive, negative or neutral labels. Sentiment analysis which is also known as opinion mining enables computers to recognize human emotions present in text content. Through linguistic tone analysis this system can evaluate customer feedback while detecting public mood and making trend predictions. Businesses can use this tool to gain valuable insights about how customers feel about their products and services and how brands are perceived by the market. Governments together with researchers can use this tool to evaluate real-time public sentiment regarding policies and crises and social movements.



DOI: https://doi.org/10.71058/jodac.v9i5015

Figure: Top 20 Words Frequency

This paper is an extension of the current work to present a detailed evaluation of the sentiment analysis tools, approaches, and architectures for social media and review texts. The aim is to look at how current tools operate, the methods they use, and the degree to which they can handle and decode sentiment in real-world text datasets. The review is divided into three main categories of sentiment analysis methods: lexicon-based, machine learning-based, and the combination of the first two. These methods make use of pre-existing databases of words which have been assigned sentiment scores. These are easy to deploy but may not work so well with texts that are sensitive to context or have specific terminology. Machine learning methods, on the other hand, involve the use of algorithms such as Naïve Bayes, Logistic Regression, or even deep learning models to train classifiers on the labeled data. These models are capable of handling data of different types and are more flexible but need a lot of data and computation power to work with. The third category tries to fuse the benefits of rule-based systems with statistical learning to achieve a good balance between explainability and performance. The case study in this paper builds a working sentiment analysis pipeline with Python and some of the popular NLP libraries. It starts with the data acquisition and cleaning phases where text is split into words, stop words are eliminated, and the case is changed to lower case. The sentiment classification model is trained using TF-IDF vectorization and logistic regression. SMOTE is used to address the class imbalance problem which is a major issue in real world data. Standard metrics such as accuracy, precision, recall, and F1-score are used to evaluate the performance of the model in the final stage. The main contribution of this work is the reduction of a large number of emotional labels into three primary categories: positive, negative, and neutral. The Sentiment Intensity Analyzer (SIA), a rule-based tool from the VADER (Valence Aware Dictionary and sEntiment Reasoner) suite, is utilized to give polarity scores to more than 190 distinct sentiment tags that are available in the dataset. Sentiments are clustered and simplified based on the scores in order to enhance the classification results and ease of interpretation. The results of model testing on actual datasets like user generated social media content and product reviews showed positive results. The classifier showed that it was possible to identify the tone of the sentences that had not been seen before and that it was capable of dealing with the informal and emotive language that is common in online communication. For instance, the sentence "It tastes so nice" was correctly classified as Positive, which is an example of the model's applicability. Nonetheless, challenges persist. The models for sentiment analysis are not good at handling sarcasm, negation, and language that is ambiguous in context. Another big problem is domain adaptation—when a model trained on one type of text does not work well on another type of text. These drawbacks point to the need to focus on contextual embeddings, transformer-based models, and emotion detection to improve the state of the art in tools in the future. The paper also delves into the practical applications and applications of sentiment analysis in addition to the technical assessment. Sentiment analysis has become a part of the operations of industries such as e-commerce, entertainment, healthcare, and politics. The applications are numerous and continue to grow: from improving customer experience to managing crisis communication and crafting public health messaging.

I. LITERATURE REVIEW

User-generated content on Twitter Facebook and Amazon has driven sentiment analysis to become a core research field during the past decade. Unstructured informal content provides rich opinions yet its manual analysis proves inefficient and impractical because of its nature. Sentiment analysis developed into an essential tool which enables researchers to uncover meaningful patterns from extensive text datasets. The initial methods depended on lexicon-based approaches through which predefined dictionaries were used to assign sentiment values to words. The methods were straightforward to understand yet struggled with detecting sarcasm and ambiguous contexts and specific domains. Research teams

DOI: https://doi.org/10.71058/jodac.v9i5015

implemented machine learning techniques which used labeled datasets to develop models that detected sentiment patterns through adaptive learning processes. Recent research by Sharma et al. together with other studies demonstrates how hybrid methods that merge rule-based systems with machine learning algorithms achieve better accuracy while maintaining interpretability. According to Nandwani and Verma, distinguishing between sentiment (positive, negative, neutral) and emotion (anger, joy, sadness) is crucial for understanding human text expressions. Research in sentiment analysis mainly focuses on social media platforms with Twitter being the most analyzed platform because of its real-time nature and brief posting style. Sentiment analysis applications now span across marketing and customer feedback while entering new fields such as healthcare and politics and disaster management. Research in temporal sentiment analysis has recently appeared as a new field which studies public opinion trends throughout time. The dynamic perspective enables researchers to establish causal connections by analyzing how sentiment patterns affect stock market performance or political developments. Most current models according to Rodríguez-Ibáñez et al. face challenges with real-world application because they have high computational costs and limited interpretability. Despite significant progress, challenges remain. Researchers have not yet achieved complete solutions for detecting sarcasm and handling multilingual texts as well as adapting to different domains. Academic research models often fail to scale up or reproduce their findings in industrial settings because of their lack of reproducibility. Sentiment analysis systems need to develop into accurate systems that understand context while supporting multiple languages and offering computational efficiency to fulfill the increasing need for immediate public opinion mining.

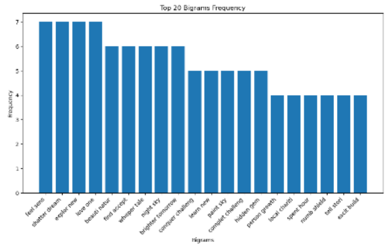


Fig 2: Top 20 Bigram Frequency

II. METHODOLOGY

The research uses a sentiment analysis framework that specializes in handling unstructured text data extracted from social media and review platforms. The research methodology used in this study follows standard procedures in the field by integrating traditional natural language processing (NLP) with machine learning-based classification techniques.

Data Collection:
The research used Twitter and Amazon review datasets because they contain extensive opinion-rich content from public sources. The datasets contain text information which has been marked with sentiment labels that range from positive to negative to neutral. The sources present informal language which makes them perfect for assessing real-world robustness.

Data Preprocessing:
Social media text data contains many errors because it includes misspellings together with emojis and slang and special characters. The accuracy of the model depends heavily on preprocessing steps. The following steps were applied:

- **Lowercasing**: The entire text received lowercase conversion to achieve standardization.
- **Tokenization**: The nltk library was used to divide sentences into separate words.
- **Stopword Removal**: The model eliminated words which held

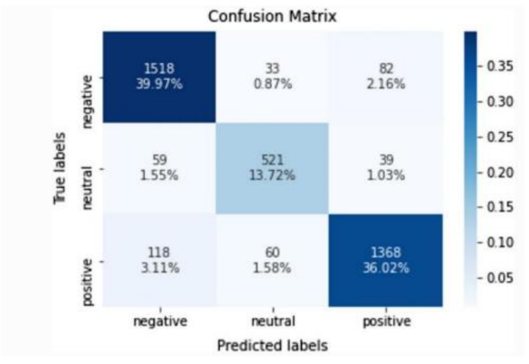
DOI: https://doi.org/10.71058/jodac.v9i5015

minimal semantic meaning such as "is," "the," and "and."

- **Punctuation and Special Character Removal**: Unnecessary symbols were stripped.
- **Stemming and Lemmatization**: Words were reduced to their base forms.
- **Handling Emojis and Slang**: The analysis used emoji dictionaries and slang replacements to transform informal expressions into meaningful text representations.

Sentiment Annotation and Mapping: The Sentiment Intensity Analyzer (SIA) from the VADER (Valence Aware Dictionary for sEntiment Reasoning) toolset generated compound sentiment scores for each text input. The scoring system determined the following sentiment labels:

- Scores > 0.05 were labelled **Positive**
- Scores < -0.05 were labelled **Negative**
- Scores in between were marked **Neutral**



The categories emerged through the process of mapping more than 190 distinct sentiment tags from the original datasets into the fundamental classes for better classification.

```
# Using cross-validation as well for checking our model accuracy

# Use StratifiedKFold for cross-validation
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Perform cross-validation and get accuracy scores
scores = cross_val_score(model, X, y, cv=cv, scoring='accuracy')

# Display the accuracy scores
print("Cross-Validation Accuracy Scores:", scores)

# Mean Accuracy score
print("Mean Accuracy:", np.mean(scores))
```

```
Cross-Validation Accuracy Scores: [0.70068027 0.7414966  0.69863014 0.7260274  0.69863014]
Mean Accuracy: 0.7130929083962353
```

Fig 3: Mean Accuracy

Feature Engineering: The cleaned text received vectorization through the TF-IDF (Term Frequency-Inverse Document Frequency) technique. The method enhances rare important words while minimizing the importance of common frequent terms. The transformation enabled the machine learning model to process text as numerical information.

Model Selection and Training: The Logistic Regression model served as the classification method because it provides simple interpretations and demonstrates effective performance in text classification problems. The model received 80% of the data for training purposes and reserved 20% for testing. The SMOTE (Synthetic Minority Over-sampling Technique) method was used to handle class imbalance problems by providing the model with balanced exposure to all sentiment classes.

Evaluation Metrics: The evaluation of model performance relied on the following metrics:

Accuracy: Proportion of correct predictions.

Precision: The model demonstrates its ability to minimize incorrect positive predictions.

DOI: https://doi.org/10.71058/jodac.v9i5015

Recall: The model demonstrates its ability to detect all relevant instances.

F1-Score: This metric calculates the average of precision and recall values which works best for datasets with imbalanced classes.

A visual inspection of the model's prediction distribution across sentiment classes was performed through the confusion matrix.

$$\text{accuracy} \stackrel{\text{def}}{=} \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}.$$

$$\text{precision} \stackrel{\text{def}}{=} \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}.$$

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$$

$$F1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{\mathrm{TP}}{\mathrm{TP} + \frac{1}{2}(\mathrm{FP}+\mathrm{FN})}$$

Tool Deployment & Functionality: The sentiment analysis tool was developed using Python and hosted in a Jupyter notebook format, facilitating modular execution and visualization. Features of the tool included:

• Real-time sentiment scoring of user input text.

• Visualization of sentiment distribution using bar and pie charts.

• Classification of previously unseen sentences using the trained logistic regression model.

The HTML-exported version of the tool supports interactivity through JavaScript libraries and preserves layout for presentation and academic use.

Validation with Case Examples: To verify practical applicability, several example sentences were tested through the tool. Sample predictions included:

- "It tastes so nice" → **Positive**
- "The product is not good" → **Negative**
- "It was okay, nothing special" → **Neutral**

The tests demonstrated that the model could apply learned sentiment patterns to previously unseen text.

Limitations:

The tool shows strong performance on clean and semi-structured text but several limitations exist:

• **Sarcasm Detection**: The model does not currently account for sarcastic tone.

• **Contextual Meaning**: Sentiment may vary based on context, which static models cannot fully capture.

• **Multilingual Data**: The system operates only in English and lacks the ability to perform sentiment classification across multiple languages.

Future Enhancements:

Future research should focus on addressing these current limitations through the following approaches:

• Using transformer-based models such as BERT for better context handling.

• Expanding the tool to support multilingual sentiment analysis.

• Adding emotion detection alongside polarity classification.

• Deploying the model as a web app or API for real-time analytics.

DOI: https://doi.org/10.71058/jodac.v9i5015

III. Conclusion

The research investigated the creation and implementation of a sentiment analysis system which identifies and categorizes social media and review platform text opinions. Sentiment analysis has become essential for real-time public perception understanding because online platforms continue their rapid growth. The research presents a functional method for user sentiment analysis through natural language processing and machine learning algorithms that includes logistic regression and TF-IDF-based feature engineering to achieve high accuracy and reliability. The research methodology involved text preprocessing followed by VADER tool-based sentiment polarity assignment and supervised learning model development for testing and training. The proposed model achieved effective sentiment prediction on real-world datasets based on evaluation metrics which included accuracy and precision and recall and F1-score. The tool demonstrated effective results in practical social media testing which showed its practical application and usefulness. The system demonstrates strong performance but faces ongoing difficulties with sarcasm detection and context-dependent processing and multilingual support. Future tool enhancements should focus on two main areas: transformer-based contextual embeddings integration and language support expansion for emotion detection.

References

[1] A. Ligthart, C. Catal, and B. Tekinerdogan, "Systematic reviews in sentiment analysis: a tertiary study," Artif. Intell. Rev., vol. 54, no. 7, 2021, doi: 10.1007/10467-4021-09973-3.

[2] B. N. R. Chagas et al., "Current Applications of Machine Learning Techniques in CRM: A Literature Review and Practical Implications," in Proc. IEEE/WIC/ACM Int. Conf. Web Intell. (WI), 2018, doi: 10.1109/W1.201800-53.

[3] M. Ranibocas and B. G. Pacheco, "Online sentiment analysis in marketing research: a review," 2018, doi: 10.1108/JRIM-05-2017-0030.

[4] V. Vyas and V. Uma, "Approaches to Sentiment Analysis on Product Reviews," 2018, doi: 10.4018/978-1-5225-4999-4.ch002.

[5] E. Y. San, A. D. Wierfi, and A. Setyanto, "Sentiment Analysis of Customer Satisfaction on Transportation Network Company Using Naive Bayes Classifier," in Proc. Int. Conf. Comput. Eng., Netw. Intell. Multimedia (CENIM), 2019, doi: 10.1109/CENIM48368.2019.8973262.

[6] N. Öztürk and S. Ayvaz, "Sentiment analysis on Twitter: A text mining approach to the Syrian refugee crisis," Telemat. Inform., vol. 35, no. 1, 2018, doi: 10.1016/j.tele.2017.10.006.

[7] A. Humphreys and R. J. H. Wang, "Automated text analysis for consumer research," J. Consum. Res., vol. 44, no. 6, 2018, doi: 10.1093/jcr/acx104.

[8] L. Zhang, S. Wang, and B. Liu, "Deep learning for sentiment analysis: A survey," Wiley Interdiscip. Rev. Data Min. Knowl. Discov., vol. 8, no. 4, 2018, doi: 10.1002/widm.1253.

[9] A. Sadia, F. Khan, and F. Bashir, "An Overview of Lexicon-Based Approach For Sentiment Analysis," in Int. Electr. Eng. Conf., vol. 1, 2018.

[10] M. Wankhade, A. C. S. Ran, and C. Kulkarni, "A survey on sentiment analysis methods, applications, and challenges," Artif. Intell. Rev., vol. 55, no. 7, pp. 5731–5780, 2022, doi: 10.1007/s10462-022-10144-1.

[11] S. Zad et al., "A survey on sentence-level sentiment analysis techniques of textual data," in Proc. IEEE World AI IoT Congr., 2021, pp.

285–291, doi: 10.1109/AIoT52608.2021.9454169.

[12] M. Wongkar and A. Angdresey, "Sentiment analysis using naive Bayes algorithm of the data Crawler: twitter," in Proc. Int. Conf. Informatics and Computing (ICIC), 2019, pp. 1–5, doi: 10.1109/ICIC47613.2019.898584.

[13] H. Syahputra, L. K. Basyar, and A. A. S. Tamba, "Sentiment analysis of public opinion on the Go-Jek Indonesia through Twitter using support vector machine," J. Phys.: Conf. Ser., vol. 1462, 2020, doi: 10.1088/1742-6596/1462/1/112063.

[14] Y. Al Amrani, M. Lazaar, and K. E. El Kadiri, "Random forest and support vector machine based hybrid approach to sentiment analysis," Procedia Comput. Sci., vol. 127, pp. 511–520, 2018, doi: 10.1016/j.procs.2018.01.150.

[15] A. Britzolakis, H. Kondylakis, and N. Papadakis, "A review on lexicon based and machine learning political sentiment analysis using tweets," Int. J. Semant. Comput., vol. 14, no. 4, pp. 517–563, 2020, doi: 10.1142/S1793351X20300010.

[16] A. Bayhaqy et al., "Sentiment analysis about e-commerce from tweets using decision tree, k-nearest neighbor, and naive Bayes," in Proc. Int. Conf. Orange Technol., 2018, doi: 10.1109/ICOT.2018.8705796.

[17] L. K. Ramasamy et al., "Performance analysis of sentiments in Twitter dataset using SVM models," Int. J. Electr. Comput. Eng., vol. 11, no. 3, pp. 2275–2284, 2021, doi: 10.11591/ijece.v11i3.pp2275-2284.

[18] S. Styawati and K. Mustofa, "A Support Vector Machine-Firefly Algorithm for Movie Opinion Data Classification," DCCS, vol. 13, no. 3, pp. 219–230, 2019, doi: 10.22146/jees.41302.

[19] A. M. Rahat et al., "Comparison of Naive Bayes and SVM Algorithm based on Sentiment Analysis Using Review Dataset," in Proc. Int. Conf. Syst. Model. Adv. Res. Trends (SMART), 2019, pp. 266–270, doi: 10.1109/SMART46866.2019.9117512.

[20] N. Naw, "Twitter sentiment analysis using support vector machine and K-NN classifiers," Int. J. Sci. Res. Publ., vol. 8, no. 10, 2018, doi: 10.29122/jup.8.10.2018.p8252.

[21] V. A. Fitri, R. Andreswari, and M. A. Hasibuan, "Sentiment analysis of social media Twitter with case of Anti-LGBT campaign in Indonesia using Naïve Bayes, decision tree, and random forest," Proc. Inf. Syst. Int. Conf., vol. 161, pp. 765–772, 2019, doi: 10.1016/j.procs.2019.11.181.

[22] B. Nguyen, V. H. Nguyen, and T. Ho, "Sentiment Analysis of Customer Feedback in Online Food Ordering Services," Bus. Syst. Res., vol. 12, no. 2, pp. 46–59, 2021, doi: 10.2478/bsrj-2021-0018.

[23] Y. Chen and Z. Zhang, "Research on text sentiment analysis based on CNNs and SVM," in Proc. IEEE Ind. Electron. Appl. (ICIEA), 2018, pp. 2731–2734, doi: 10.1109/ICIEA.2018.8398173.

[24] G. Khanvilkar and D. Vora, "Product recommendation using sentiment analysis of reviews: A random forest approach," Int. J. Eng. Adv. Technol., vol. 8, no. 2, pp. 146–152, 2019.

[25] R. L. Mustofa and H. Prasetiyo, "Sentiment analysis using lexicon based method with naive Bayes classifier on #newnormal hashtag," J. Phys.: Conf. Ser., vol. 1918, 2021, doi: 10.1088/1742-6596/1918/4/042155.

DOI: https://doi.org/10.71058/jodac.v9i5015

[26] O. Oyebode and R. Orji, "Social Media and Sentiment Analysis: The Nigeria Presidential Election 2019," in Proc. IEEE IEMCON, 2019, pp. 140–146, doi: 10.1109/IEMCON.2019.8936139.
[27] S. Tam, R. Ben Saad, and O. Tanriöver, "A ConvBiLSTM Deep Learning Model-Based Approach for Twitter Access," IEEE Access, vol. 9, 2021, doi: 10.1109/ACCESS.2021.3064830.
[28] A. M. Rajeswari et al., "Sentiment Analysis for Predicting Customer Reviews using a Hybrid Approach," in Proc. Adv. Comput. Commun. Technol. High Perform. Appl., 2020, doi: 10.1109/ACCTHPA49271.2020.9213236.
[29] I. C. Sari and Y. Ruldeviyani, "Sentiment Analysis of the Covid-19 Virus Infection in Indonesian Public Transportation on Twitter: A Case Study," in Proc. IWBIS, 2020, pp. 23–28, doi: 10.1109/IWBIS50925.2020.9255531.
[30] P. Gupta et al., "Sentiment Analysis of Lockdown in India during COVID-19: A Case Study on Twitter," IEEE Trans. Comput. Soc. Syst., vol. 8, no. 4, pp. 992–1002, 2021, doi: 10.1109/TCSS.2020.3042446.
[31] M. R. Hasan, M. Maliha, and M. Arifuzzaman, "Sentiment Analysis with NLP on Twitter Data," in Proc. IC4ME2, 2019, doi: 10.1109/C4ME2.2019.9036670.
[32] D. P. Demirer and A. Büyükeke, "Analysing perceptions towards electric cars using text mining and sentiment analysis: a case study of TOGG in Turkey," Appl. Mark. Anal., vol. 7, no. 4, pp. 386–399, 2022, doi: 10.09554/zhub3167.
A. Zakharov, "How Sentiment Analysis Works – Analyzing Text with Machine Learning," AltexSoft, Apr. 21, 2023. . Available: https://www.altexsoft.com/blog/sentiment-analysis/
[34] Maruti Techlabs, "Sentiment Analysis: What Is It & How Does It Work?" Maruti Techlabs, Oct. 30, 2023. [Online]. Available: https://marutitech.com/sentiment-analysis/
[35] MonkeyLearn, "Sentiment Analysis: A Definitive Guide," MonkeyLearn, 2023.. Available: https://monkeylearn.com/sentiment-analysis/
[36] P. Desai, "Sentiment Analysis: Concepts, Methods & Applications," Great Learning Blog, 2023.. Available: https://www.mygreatlearning.com/blog/sentiment-analysis/
[37] S. Rani, "What is Sentiment Analysis?" NLP Cloud, 2023. [Online]. Available: https://www.nlpcloud.io/sentiment-analysis.html
[38] Dataconomy, "Sentiment Analysis: What it is, How it works, and Applications," Dataconomy, 2023. . Available: https://dataconomy.com/2023/02/what-is-sentiment-analysis/
[39] Grammarly, "Sentiment Analysis: How It Works and Why It Matters," Grammarly Blog, 2023.. Available: https://www.grammarly.com/blog/sentiment-analysis/
[40] , "Sentiment Analysis Tools and Use Cases," , OpenAI, 2023. . Available: