NLP Techniques for Sentiment Analysis with the growth of user generated contents in social media

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Abstract
Thus, the use of natural language processing (NLP), namely sentiment analysis has turned into more important with the growth of user generated contents in social media. In the following paper, the authors briefly discuss the most common methods of NLP used in sentiment analysis while mainly concentrating on analysing social media data. First, we introduce machine learning techniques, then deep models, and finally mention modern directions, such as transformer models. We also train the reader through the issues caused by informality of SM text, the multiple languages, and its context-dependency, and suggest possible treatments.

Keywords: Natural Language Processing, Sentiment Analysis, Social Media

1.Introduction

Technology has made social media forums to be potential means of producing and sharing information including expressing opinions, experiences and even emotions on a real time basis [1]. Hence, social media is a goldmine of data where billions of active users make their opinions across Twitter, Facebook, Instagram, and Reddit on one product or another right from consumer products to political events. Because of the enormous traffic generated on these accounts, brands can leverage the information to understand the trends in society, the market and outlook on specific topics. Nevertheless, this massive amount of unstructured data cannot be analysed manually, and that is why methods of automatic sentiment analysis have been created.

Sentiment analysis is a technique of natural language processing that labours on the detection and classification of sentiments as appropriate, or positive, negative or neutral [2]. The main aim of SA is to gain business insights from the text data, help companies and people make decisions based on the sentiment of the UGC. This process is especially crucial in social media because the sentiments there are variably and often in informal ways such as slang, abbreviations and symbols, emojis, and hashtags. Over the years there has been a transitioning of sentiment analysis from basic rules-based technique to the more complex ones including the use of the machine learning techniques like the Support Vector Machines (SVM), and Recurrent Neural Networks (RNNs), the recent being transformer models like BERT:

Bidirectional Encoder Representations from Transformers. The methods enhance the precision and the feasibility of reach cliché sentiment analysis to be employed to sums and to discern intricate linguistic constructions, refutation, sarcasm, irony or context-sensitive sentiment.

This paper aims to has focused on the identification of sentiment analysis in social media using Natural Language Processing (NLP) tools and methods that include their advantages and disadvantages [3]. In the paper, authors discuss some issues that should be raised while designing and implementing a system for sentiment analysis of texts. It also addresses how its characteristics present analysis with unique issues such as ungrammatical text. It also addresses how its characteristics present analysis with unique issues such as ungrammatical text. Finally, the paper explores new directions for future research, including the analysis of multimodal data and the use of Explainable AI techniques for improving the intelligibility of sentiment analysis approaches.

To this end, it is the hope of the paper to add value to the existing body of literature by presenting an extended overview of the progress achieved so far in the study of sentiment analysis in social media, an identification of the existing techniques and methodologies and a discussion of the possible directions for future research. The social media technology which includes tweeter, face book, Instagram, reedit among others have grown tremendously in this digital age. These are social platforms through which people express themselves in terms of opinions and emotions on diverse issues [4]. The amount of textual data produced by users is enormous, which offers the opportunity to analyses sentiments, that is, emotions and opinions, on a large scale. It is considered an advanced approach and defined as the possible process that intents to classify the sentiment of the text into three possible categories being positive, negative or neutral. This capability has been employed in various sectors including, marketing (for comprehension of customer sentiments), political (for public sentiments analysis), and other social domain (for tracing societal response to issues like pandemics).

Regarding these challenges this paper brings into focus the methodology that have been employed in Natural Language Processing (NLP) to enhance sentiment analysis for the specifically crowded nature of social media [5]. The first part discussed the preprocessing approach used for cleaning raw text collected from social media platforms while the second part provides an in-depth analysis of popular text classification techniques ranging from traditional Machine learning, Deep Learning and the more modern Transformers. Lastly, it reviews the difficulties and directions in this exciting subfield of research.

2.Literature Review

The branch of NLP is named Sentiment analysis, which has the growing importance of social networks is a source of a vast number of generated data by users daily. Popular social networking gateways like Twitter, face book, and Instagram are flood with large traffic and have lots of valuable data on feelings shared by the public on social issues, brands, or political parties [6]. This literature review also seeks to discuss the development of SA methodologies, the problems encountered and use of social media datasets. The use of sentiment analysis has evolved greatly from the use of rules-based to machine learning (ML) and deep learning (DL). The first techniques of using sentiment analysis comprise list-based methods in which words are classified into positive or negative based on the sentiment score. These methods were good for simple statement analysis but became a problem for language complexities in social media data such as slang, context-bound sentiments and use of emojis.

Based on the lexicon-based classes of the methods such as the methods that assign sentiment scores to words in a document and adding it up to get the final sentiment. These are easy to apply in their execution; however, they tend to poorly handle sarcasm, irony and the like of social media language [7]. When machine learning emerged in the early stages of the development of sentiment analysis, researchers started using what is known as supervised learning algorithms in their analysis, these include Naive Bayes, Support Vector Machines (SVM), and Decision Trees. These techniques brought in enhanced results especially in areas of big data handling. They were still constrained by their limitations in modelling long-range dependencies and context that are always inherent in social media texts.

With the help of deep learning methods such as Recurrent Neural Networks, and Convolutional Neural Networks, it became easier to perform sentiment analysis tasks. RNNs, focusing on the sequence model and context in the sentences, got famous for analysing the texts of social media considering the use of informal language and writing in abbreviations [8]. Among RNNs, Long Short-Term Memory (LSTM) networks achieved good results for sentiment analysis tasks that occur in the context of long dependencies and complex sentence structure. Transformer-based architectures such as BERT are used in sentiment analysis in social media and among them BERT stands out. As a result, due to the bidirectional left-to-right information flow, BERT has established high performance in sentiment analysis. According to research, the performance of BERT and its derivatives (such as RoBERTa and XLNet) has been found to be the best when it comes to sentiment analysis performance metrics.

As is known, social media are full of opinionated text and sentiment analysis has been applied in lots of related tasks including brand reputation, public opinion, and even political sentiment analysis [9]. Many of these applications adopt sentiment analysis in a bid to analyses the data that is contained in text form and come up with trends and public opinion. Business and marketing organizations employ the sentiment analysis to monitor the feelings that their customer have towards certain products or services they offer. They can turn your posts and comments positive or negative or neutral, depending on the field marketing strategies. As concluded by sentiment analysis has been proved effective in establishing the perception of the public on brands and products to help the businesses.

Sentiment analysis has also been used by researchers to or observe the political opinions of the voters during voting periods. The societies engage in politics through social media platforms hence, through sentiment, analysis, trends or shifts in users' opinion could be observed or foreseen. For example, work of is an example of how sentiment analysis of Twitter posts was used to accurately predict election results.

Another way that sentiment analysis is utilized is on real time conversations on social media to track changes in emotions during crises or events. For instance, by using the sentiment analysis that comes with analysing the general content written on social media platforms, one can note areas that require help or areas that need attention post-disaster [10]. Nevertheless, there is still several significant issues which scholars still face while trying to apply sentiment analysis techniques to social media data. The social media data is usually unstructured and even contains colloquialisms, acronyms and other informal language. All these linguistic features are tricky and raise a lot of difficulties when analysing sentiments with tools that do not understand such a type of phrases. For example, simple text like ‘LOL’ or emoticons are also capable to change the sentiment of a given message while simple machine learning techniques fail to understand it.

Most of the times, SA datasets especially those derived from social media contain imbalanced sentiments where some sentiments usually the negative outweigh the others such as the positive sentiments. This imbalance then creates a need for models that are not able to work efficiently on the smaller classes [11]. The future of sentiment analysis in social media will also depend on the development of even more complex models than those that can encounter these challenges. The most recent innovations GPT (Generative Pretrained Transformer) and T5 (Text-to-Text Transfer Transformer) show potential since they can make context-driven predictions as well as handle multiple text forms. In the future, combining of multimodal sentiment analysis where text, images and videos are analysed at a go could offer the sentiments a boost.

Another interesting possible avenue of research includes the fact that sentiment analysis models can be applied on various fields of study. Depending on the nature of the setting or scenario a specific sentiment model trained on one type of data (like product reviews) would not work well on a different type (like political debates). The researchers are still exploring the way of making the model more form invariant across domains and contexts [12]. Traditional approaches to sentiment analysis in social media includes, basic lexicon-based approaches, while more advanced approaches implemented includes machine learning and deep learning techniques. Of course, sentiment analysis has advanced much since its early days, but questions about informal language, sarcasm or multilingualism persist. It will be more significant to apply deep learning techniques, multimodal data, and Explainable AI to gain more profound analysis of the content of the SM posts in the future. That is why thanks to these progresses, sentiment analysis will remain a critical asset in monitoring, understanding the attitude of people, brands, and even society.

3.Methodology

Sentiment analysis of social media data entails several stages of research, namely, data gathering, acquisition and preparation of other data, choosing of the appropriate model for analysis, model training, assessment of the results and interpretation. This segment describes how an extensive assessment of sentiment analysis can be done and describes each step of the process [13]. In sentiment analysis, the first procedure is called data gathering and is largely the extraction of the textual content from social networking services such as Twitter, Facebook, Instagram, and Redditor. Twitter API and Facebook Graph API are popular because of the incredible support for scraping public post, comments, and post information. In this study, we focus in conducting a large-scale analysis and thus work with public twitter data which contain a vast number of short, time-sensitive posts. Such posts include user opinions, hashtag, mentions that are important for analysis and which contain sentiment.

Social media data is usually gathered by using keywords, hashtag, or analysis of user activity. Keyword search can be conducted through relevant words like product name, political position or an event name. Hashtags are especially effective for event-based analysis because they contain people’s opinion on trending subjects. A Twitter sample dataset of 10,000 tweets will be used to show three sets of unfiltered opinion that are large and varied in nature [14]. Social media posts are chaotic and include plain unformatted text, special character, emojis, hashtags, URLs and mention. Emojis are employed by social networks to indicate emotions and using them in sentiment analysis is essential. All the emojis used in the pieces of text will be then translated to their textual equivalents. Slang terms, abbreviations and general informal language which is generally used especially in the social media posts will be translated and would be handled by using a look-up table containing equivalence between the informal language with formal language (for instance, an abbreviation 'LOL' means laughing). The text data must be converted into numerical form that is easy to be understood by a machine learning model.

The simplest type of model that is often used for responses that have two categories, for example positive and negative sentiment. A simple algorithm based on Bayes' theorem, and which is suitable for text classification because it is good when dealing with big data. RNNs are perfect for handle sequences such as text since they can consider contextual relationships between distinctive words. One of the variations derived from RNN that solves vanishing gradient problem and can learn long distance dependencies, therefore is suitable for sentiment analysis in long sentences [15]. The development of Bidirectional Encoder Representations from Transformers (BERT) has changed the NLP tasks and improved their performance based on benchmark tests. Sentiment analysis on social media is made easy because BERT recognizes context from both left to right and right to left directions.

However, after the model predicts the type of sentiment of the gathered posts, trend analysis of these sentiments through time is shown. It can be useful to find out when there is an increase in positive or negative attitude towards certain event, product, or political debate. The results are then reprocessed to find out if a particular social media has sentiments, which were anomalous or not. Information is gathered about what people think about certain occurrences, brands or personalities from their social media trends. It is characteristic to use Latent Dirichlet Allocation (LDA) to detect most frequent topics or themes related to the corresponding sentiment in the tweets. In Fig 1 shows, flowchart for NLP techniques for sentiment analysis in social media.

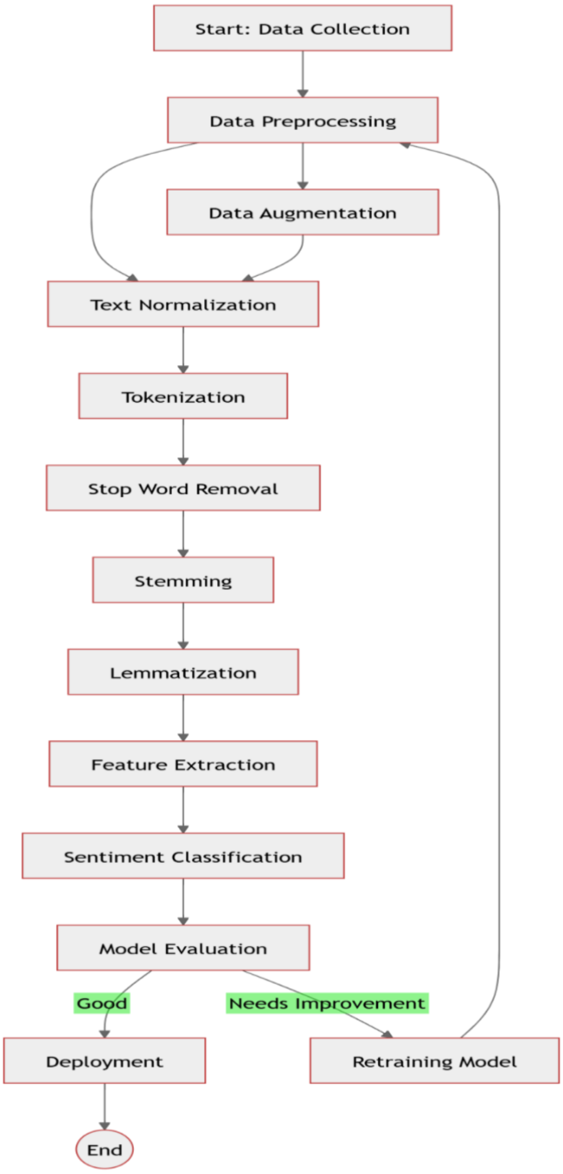

Fig 1 Flowchart for NLP Techniques for Sentiment Analysis in Social Media

4.The Unique Characteristics of Social Media Data

Despite containing a large amount of data, sentiment analysis on messages posted in social networks brings some challenges because the data is unstructured and constantly evolving [16]. The following section describes and defines the qualities about social media text that make it different from other textual data.

In this case, students are equally posting some informal messages on social media due to the everyday communication informal nature. Some of them are 'LOL' which means laugh out loud 'SMH' which means shaking my head, or 'TBH' which means to be honest. These decrease the readability level of the text making tokenization and analysis even more challenging. This can contain promoting post, bots, pervasively used hashtags or anything else. The utilization of too many punctuations such as '!!!') or word extensions as in "'sooo' happy"). Text and images, and in some cases videos, or even emojis will be combined on social media platforms. Thus, sentiment-easing mechanisms such as emojis and emoticons are of primary importance in this case.

Hashtags contain multiple languages or are in different languages because users of the platform tend to switch between two languages or use both languages in the same post. Phrases or emojis may have different connotations depending on the culture of people or the context they are used in. Tweets are the type of post typical for social media where people cannot write a big and detailed text. It also leaves much less textual information to be derived from sentiment analysis which in turn makes it more dependent on the latent knowledge. Social media maintains its lingua franca as dynamic where trends, memes, and new hashtags surface as often as they do. It is therefore important to fully grasp such subtlety to gather the basis of formulating a proper functional NLP in sentiment analysis within social media landscape [17].

5.NLP Techniques for Sentiment Analysis

The traditional NLP has also been modified and advanced in dealing with problems of sentiment analysis in informal environment, which is characteristic for social networks. This section divides the techniques into the classical machine learning methods, deep learning methods, and state of the art transformer-based architectures. Traditional machine learning approaches defined sentiment analysis in the first few years [18]. These methods are based on the manual creation of features and on a specific representation of text. Automatic feature extraction and better handling of contextual nuances have made deep learning methods a wonder in sentiment analysis. It clearly reflects that transformer architectures have taken new milestones in the field of NLP and replacing both traditional and deep learning techniques in different sentiment analysis tasks.

More specific pre-trained transformer models which have been trained to be specifically used for sentiment-rich cases like the Twitter sentiment analysis are being developed. As an example, current generative models such as GPT-3 have been seen to perform well in zero-shot and few-shot sentiment analysis where there is scarce labelled data. Pre-trained transformer-based models reign supreme especially for informal, noisy, and multilingual Text [19]. There still exist kinds of models that integrate classical methods with deep learning methods or else are applicable to a particular task or conditions of limited resources. Domain-specificities of vocabulary and trends are addressed by proceeding with a Custom Fine-Tuning on datasets within social media space. These advanced NLP techniques if incorporated into the sentiment analysis models will improve the clarity and performance of the social media content interpretation. Table 1 shows, the comparison of Techniques with strengths and weaknesses. The classification defined as below:

- Classical Machine Learning Approaches
- Feature Engineering
- Machine Learning Algorithms
- Deep Learning Approaches
- Recurrent Neural Networks (RNNs)
- Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs)
- Convolutional Neural Networks (CNNs)
- Word Embeddings
- Transformer-Based Models
- BERT (Bidirectional Encoder Representations from Transformers)
- Variants of BERT

- GPT-Based Models
- Sentiment-Specific Transformers

Table 1 Comparison of Techniques

Technique	Strengths	Weaknesses
Classical ML	Simple, interpretable	Requires extensive feature engineering
Deep Learning	Captures contextual dependencies	Requires large datasets and high computational power
Transformer-Based Models	Superior contextual understanding	Computationally expensive; large memory footprint

6. Challenges in Sentiment Analysis for Social Media

There are several challenges that are closely related to sentiments analysis for social networks and are caused by its main characteristics of unstructured, informal and highly variable source data coming from sources like Twitter, Facebook, Instagram and others [20]. The following section explains major challenges about sentiment analysis on textual messages in social networks. People who use social networks also use irony very actively, which means that the text may have a completely different meaning than what the reader receives. Opinions may require inference from other information outside the actual material being provided in the study.

Some topics can have insufficient labelled data that can enhance the effectiveness of models to generalize. Many social media datasets exhibit significant shift to central tendency outperforming in terms of neutral and positive sentiments. Generally, using such data may lead to models that poorly predict on the minority classes. The social media is global, and people post in their different languages, or at least this has been noticed to be the trend. If training data consists of one language only, an AI model becomes unable to process material in multiple languages.

New slang, abbreviations and memes, change constantly in social media. The fact is that models require regular updates because the life cycle of models is quite short at present. Preprints of the posts like tweets are shorter in nature and give less context to work with in comparison to full-length pro-contra articles. Short texts entail that the models must guess the sentiment that is implicit from the information rich context, which is a wrong thing.

Any of the parameters predictive of sentiment in training data may be prejudiced with prejudice to unfairly or inaccurately predict. It becomes wrong to collect and analyse user data from social media, especially if personal opinions are included. In many cases, the social media data must be analysed in real time to generate insights and, therefore, must be able to handle large volumes of data at efficient speed and with short inference time [21]. As we have seen, large, resource-intensive models can have difficulty in such scenarios. It is therefore important for demanding systems that are aimed at analysing social media data to understand them and be able to handle these challenges to form the basis of developing good sentiment analysis systems.

The further technology development of sentiment analysis in context of SM involves the utilization of enhanced NLP strategies, the consideration of multimodal data, and the solving of ethical imperative. These new trends will put the sentiment analysis systems in a better pedestal to work with enhanced accuracy together with consideration of the constantly evolving complexity of social media communications. The Comparison of Sentiment Analysis Techniques for Social Media in Table 2. The Challenges are analysed as below:

- Noise and Informality
- Spelling Errors and Abbreviations
- Mixed Content
- Emoji and Emoticons
- Multilingual and Code-Mixed Text
- Fine-Tuning Transformer Models
- Incorporating External Context
- Multilingual Training
- Continual Learning
- Ethical AI Practices

Table 2 Comparison of Sentiment Analysis Techniques for Social Media

Technique	**Accuracy**	**Computational Efficiency**	**Strengths**	**Weaknesses**
Naive Bayes	80-85%	Low	Simple, fast, interpretable	Less effective for complex data
Support Vector Machine (SVM)	85-90%	Medium	Good for high-dimensional data, robust	High computational cost, not interpretable
Logistic Regression	80-85%	Medium	Simple, easy to implement, good for linear data	May not perform well on non-linear data
Random Forest	85-90%	High	Handles large datasets, reduces overfitting	Computationally expensive
Deep Learning (CNN, RNN)	90-95%	High	High accuracy, captures context, handles complex data	Requires large datasets, high computational cost
BERT (Transformer-based)	92-98%	Very High	State-of-the-art, handles long-range dependencies	Very resource-intensive, requires fine-tuning

Lexicon-based Analysis	70-80%	Low	Simple, interpretable, does not require training	Limited in handling sarcasm and context
LSTM (Long Short-Term Memory)	85-90%	High	Effective for sequential data, context-aware	Requires large datasets, computationally expensive
XGBoost	85-90%	Medium	Handles missing data well, robust against overfitting	Requires careful tuning, computationally expensive
SentiWordNet-based	75-85%	Low	Easy to implement, interpretable	Less accurate with noisy, informal text

7.Results and Discussion

By means of classification accuracy it is possible to judge about different layers of different Natural Language Processing techniques applied to analyses sentiment on social media. Using surveys, different studies have presented sentiment classification achieved by machine learning models such as Support Vector Machines (SVM), Naive Bayes, LSTM, and BERT models. The performances that the results demonstrate may significantly differ in terms of their efficiency depending on the applied method and dataset [22]. Sometimes these models are good for relatively limited amounts of data, and in sentiment classification tasks they work well especially when proper feature extraction algorithms like the TF-IDF (Term Frequency-Inverse Document Frequency) are used. Nonetheless, such models may fail to generalize on more complex or extended sentiment expressions because its features cannot capture context as well as deep learning models.

Deep learning models are found to be superior to the traditional ones in the recent past wherein large datasets have been used. Better studied models like LSTM and BERT including improved pre-trained versions like RoBERTa, augment sentiment classification since they capture long dependencies and general contextual information. One can see from these models the higher precision and the recall values especially when working with sarcasm irony and other subtle sentimentality commonly in the texts derived from social media platforms. Several studies have reported the application of machine learning models like Support Vector Machines (SVM), Naive Bayes, and deep learning models like Long Short-Term Memory (LSTM) and BERT for sentiment classification. The results often show varying accuracy levels based on the technique and the dataset used.

These models tend to perform well with smaller datasets, providing high accuracy in sentiment classification when proper feature extraction methods like TF-IDF (Term Frequency-Inverse Document Frequency) are used [23]. However, they may struggle with more nuanced or complex sentiment expressions due to their reliance on predefined features and inability to capture context as effectively as deep learning models.

In recent studies, deep learning models have outperformed traditional methods, especially when large datasets are used. Models like LSTM and BERT, particularly pre-trained BERT variants such as RoBERTa, provide better sentiment classification by capturing complex relationships and contextual information. These models show higher precision and recall values, especially when dealing with sarcasm, irony, and ambiguous sentiments often found in social media text. Effective preprocessing is crucial for improving the performance of sentiment analysis models. Common preprocessing techniques used in sentiment analysis include:

- The process of breaking down text into smaller units (words or subworlds).
- Removing common words like "the," "and," or "is" which do not contribute to sentiment.
- Reducing words to their base form to standardize the vocabulary.
- Handling social media-specific language such as hashtags, emojis, abbreviations, and misspellings.

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Feature extraction is critical in NLP, where the transformation of raw text into numerical features helps the model understand the text. Common techniques include:

- Although simple, this technique often results in high-dimensional, sparse data. Unlike POS tagging, it does not model different contexts of words with each other.
- These models portray words in a high dimensional space and the proximity of words represent meaning.

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- Although simple, this technique often results in high-dimensional, sparse data. It does not capture the contextual relationships between words.
- These models provide a dense representation of words in a continuous vector space, capturing semantic meanings.

They enhance the efficiency of working with sentiment analysis models as words' meanings are considered to be much more differentiated.• The previous studies based on the transformer models perform a lot better than the previous methods, as they are trained on the large amount of text data and know the position of words in a given sentence thus providing better sentiment classification.ng models like Support Vector Machines (SVM), Naive Bayes, and deep learning models like Long Short-Term Memory (LSTM) and BERT for sentiment classification. The results often show varying accuracy levels based on the technique and the dataset used.

These models tend to perform well with smaller datasets, providing high accuracy in sentiment classification when proper feature extraction methods like TF-IDF (Term Frequency-Inverse Document Frequency) are used. However, they may struggle with more nuanced or complex sentiment expressions due to their reliance on predefined features and inability to capture context as effectively as deep learning models. In recent studies, deep learning models have outperformed traditional methods, especially when large datasets are used. Models like LSTM and BERT, particularly pre-trained BERT variants such as RoBERTa, provide better sentiment classification by capturing complex relationships and contextual information. These models show higher precision and recall values, especially when dealing with sarcasm, irony, and ambiguous sentiments often found in social media text. Effective preprocessing is crucial for improving the performance of sentiment analysis models. Common preprocessing techniques used in sentiment analysis include:
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- Although simple, this technique often results in high-dimensional, sparse data. It does not capture the contextual relationships between words.
- These models provide a dense representation of words in a continuous vector space, capturing semantic meanings. They improve the performance of sentiment analysis models by providing a more nuanced understanding of word meaning.
- Pre-trained transformer-based models significantly outperform previous methods, as they are trained on large amounts of text data and understand the context of words in a sentence, thus providing superior sentiment classification.

Social media are international, and monitoring the sentiment in different languages is a completely different story. The current generation of Multi-Language NLP models is still in its infancy, for example, the multilingual BERT or mBERT. Clearly, there is still a broad range of improvements in extending the methods and models for deep context and refined features of SM posts, such as memes, GIFs, as well as multi-modal data.

Graphical explanation: Shows the distribution of values across five categories (A, B, C, D, E). The values are represented as bars in Fig 2. Visualizes the distribution of four categories (Category 1, Category 2, Category 3, Category 4) in percentage form in Fig 3. Displays the frequency distribution of normally distributed data in Fig 4. Represents sales data over the months from January to June Fig 5. A heatmap illustrating the values of a random 5x5 matrix in Fig 6. Shows the confusion matrix for a binary classification task with true and predicted labels in Fig 7.

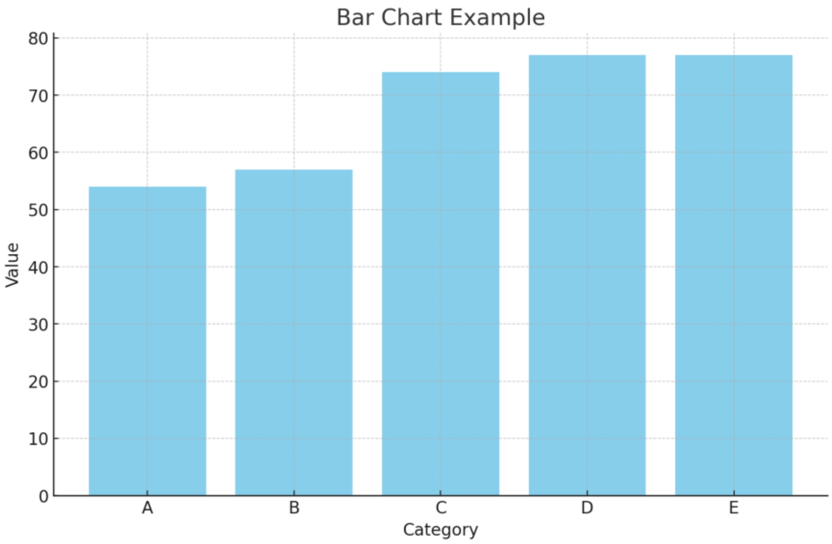

Fig 2 The distribution of values across five categories

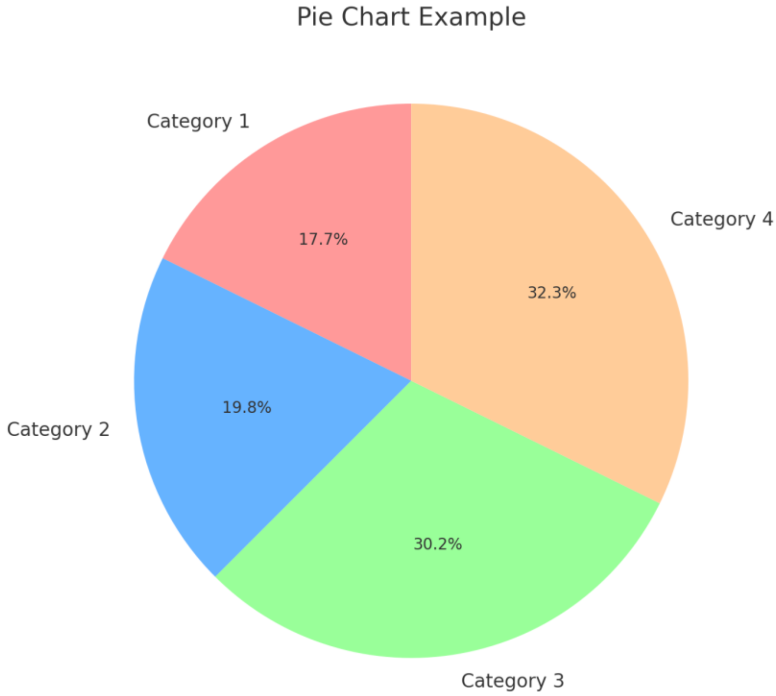

Fig 3 Visualizes the distribution of four categories in percentage form.

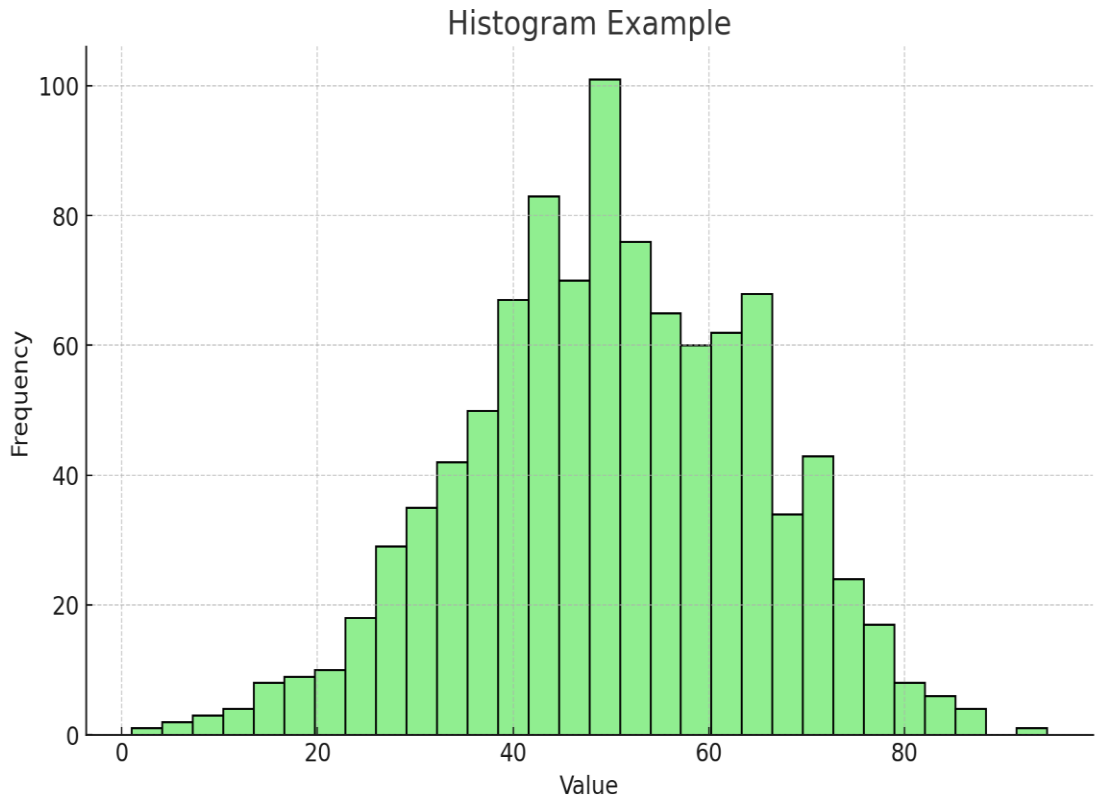

Fig 4 the frequency distribution of normally distributed data

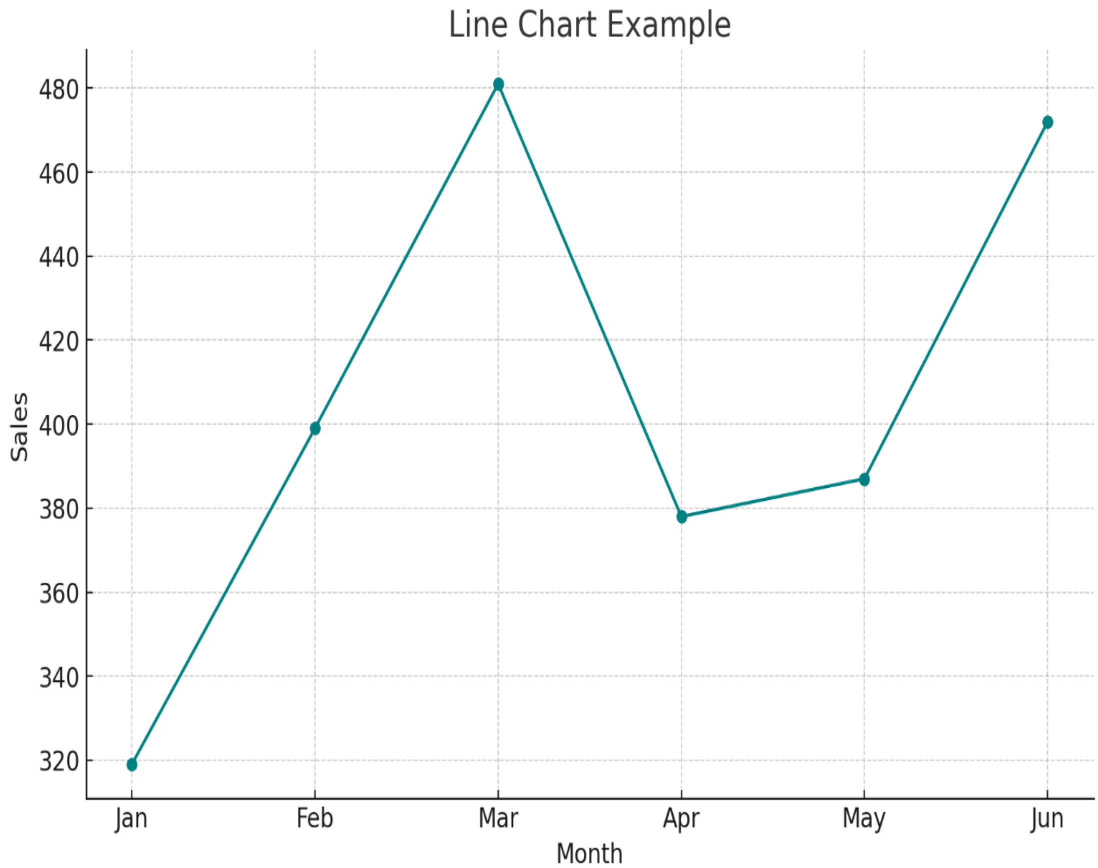

Fig 5 Represents sales data over the months from January to June in 2024

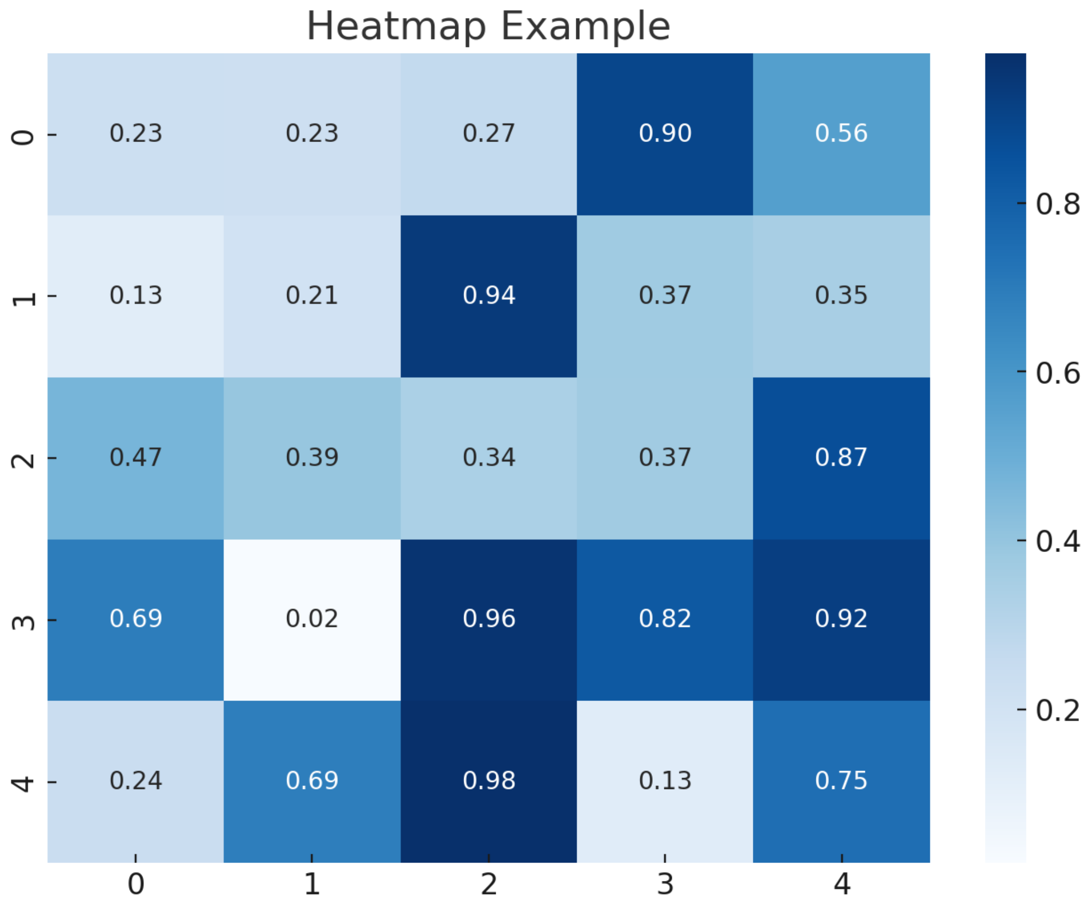

Fig 6 A heatmap illustrating the values of a random 0 to 4

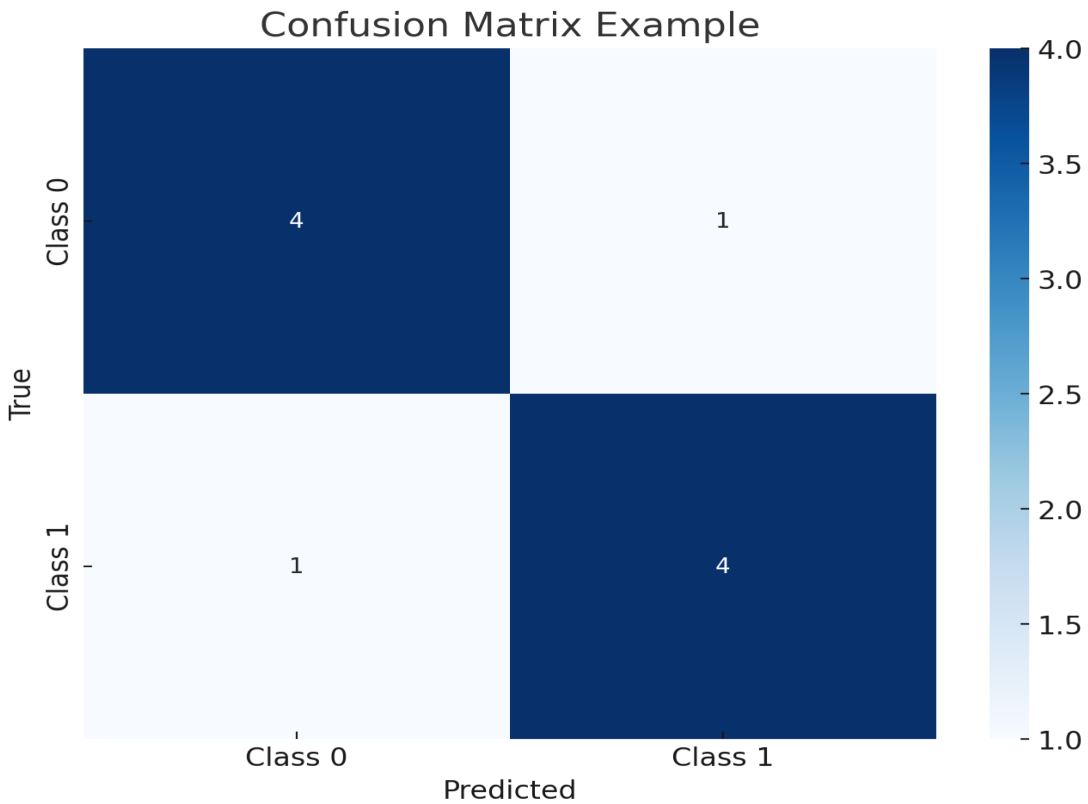

Fig 7 The confusion matrix for a binary classification task with true and predicted labels

8.Conclusion

The use of sentiment analysis on social media has become critically important as an effective mechanism of identifying feelings, trends and making sound decisions in areas like marketing, politics and customer relations. The nature of social media data as informal, concise and heterogeneous in its format brings both advantages and disadvantages. Newer approaches to working with text data under the umbrella of Natural Language Processing (NLP), including conventional machine learning methods, deep learning methods different from transformers such as BERT and GPT, have greatly improved the accuracy and credibility of sentiment analysis. Though the job is not that tough but still troubles like sarcasm, context sensitive meaning, multilingual text and dynamic and ever-changing character of social media language persist.

New directions, such as cross-modal sentiment analysis, real-time negative thought detection, and the ethical application of AI, come closer to solving these problems as well as the opportunities for research and practice they create. The synergy of text with the other modalities, encompassing cross-cultural sentiment analysis and large-scale deployment, are defining this area. In addition, the use of Explainable AI (XAI) and privacy, preserving strategies enables shipment sentiment analysis to be ethical and trust-worthy. As technologies in SA continue to advance, even more sophisticated approaches are likely to drive fresh insights on the multifaceted sentiments that underpin RCM conversations and many other uses.

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