Term Paper Report

On

Natural Language Processing for Sentiment Analysis: Analyzing Emotions in Textual Data.

Submitted to

Amity University Uttar Pradesh

in partial fulfillment of the requirements for the award of the degree of

Bachelor of
Technology in
Computer Science & Engineering

Submitted By

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July 2024

DECLARATION BY THE STUDENTS

I, **Mr. SAMAR AHMAD**, a student of B.Tech(CSE) hereby declare that the project titled **"Natural Language Processing for Sentiment Analysis: Analyzing Emotions in Textual Data."** which is submitted by me to the Department of Computer Science and Engineering, **Amity School of Engineering, and Technology**, Amity University Uttar Pradesh, Noida, in partial fulfilment the of the requirement for the award of the degree of BACHELOR OF TECHNOLOGY in Computer Science and Engineering has not been previously formed the basis for the award of any degree, diploma or other similar title or recognition.

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CERTIFICATE

On the basis of declaration submitted by **Mr. SAMAR AHMAD,** student of B.Tech (CSE), we hereby certify that the project titled **"Natural Language Processing for Sentiment Analysis: Analyzing Emotions in Textual Data."** which is submitted to Department of Computer Science & Engineering, **Amity School of Engineering and Technology, Amity** University Uttar Pradesh, Noida, in partial fulfilment of the requirement for the award of the degree of BACHELOR OF TECHNOLOGY in Computer Science and Engineering is an original contribution with existing knowledge and faithful record of work carried out by them under my guidance and supervision.

To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Noida Date:

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ACKNOWLEDGEMENT

I would like to convey my heartiest thanks to our project guide **Dr. SHIPRA SARASWAT**, Assistant Professor, Dept. of CSE for his guidance and the faith that he has shown towards me during the project work has been the cradle of illumination for me. His technical expertise and approach to tackling problems have been of major help to me. Besides, his encouragement, personal guidance and understanding helped me to carry out the project with great zeal and enthusiasm.

We want to thank all the technical staff members in charge of our department laboratories that fulfilled all our project needs and offered timely help.

I would like to thank all my friends for supporting me in time of need, encouraging and always ready to help me without asking for it. I am indebted to my beloved parents, whose blessing and best wishes have gone a long way in making this year's project work a grand success.

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Abstract

Sentiment analysis, also known as opinion mining, is a crucial application of Natural Language Processing (NLP) that aims to recognize and extract subjective information from textual data. This report delves into the methodologies and applications of sentiment analysis, highlighting its significance in various fields. The techniques discussed include lexicon-based approaches, which utilize predefined sentiment dictionaries, and more advanced machine learning and deep learning methods, which involve training models on annotated datasets to predict sentiment with greater accuracy and contextual understanding.

Sentiment analysis plays a vital role in natural language processing (NLP) by identifying, extracting, and analysing subjective information from textual data. This report delves into the significance and wide-ranging applications of sentiment analysis in various fields, including marketing, customer service, finance, healthcare, and politics. It comprehensively reviews existing literature and methodologies, tracking the evolution from early lexicon-based approaches to contemporary deep learning models that leverage advanced machine learning techniques. The report identifies key challenges in sentiment analysis, such as sarcasm detection, contextual understanding, domain adaptation, and the ethical implications of automated sentiment detection. To address these challenges, the proposed work introduces innovative preprocessing techniques, hybrid models that combine rule-based and machine-learning approaches, and sophisticated emotion detection methods capable of capturing nuanced sentiments. Additionally, the report explores the future directions of sentiment analysis, emphasizing the potential of multimodal analysis incorporating visual and auditory data, developing models with enhanced cross-domain adaptability, and implementing real-time processing for dynamic sentiment analysis. Through these advancements, the research aims to improve the accuracy, reliability, and applicability of sentiment analysis, thereby enabling more informed decision-making and enhanced user experiences across various sectors.

1. INTRODUCTION

1.1 Background and Importance of Sentiment Analysis:

In recent years, expanding social media and internet platforms resulted in daily text data production. Due to the increase in data, there is a demand for efficient ways to extract insights and feelings from text. To meet this demand, the area of sentiment analysis, commonly referred to as opinion mining, evolved as a branch of natural language processing (NLP). To automatically identify, extract, and comprehend the emotions and attitudes contained in textual material, computational techniques are used.

1.2 Overview of Emotions in Textual Data:

Emotions are fundamental to how people communicate and make decisions. Understanding and analyzing emotions can be used to gain important insights into people's thoughts, attitudes, and behaviors when it comes to textual data. Text sentiment is intended to be categorized as either good, negative, or neutral via sentiment analysis. But moving beyond mere polarity, a deeper examination of emotions within sentiment analysis enables a more complex comprehension of the expressed sentiments.

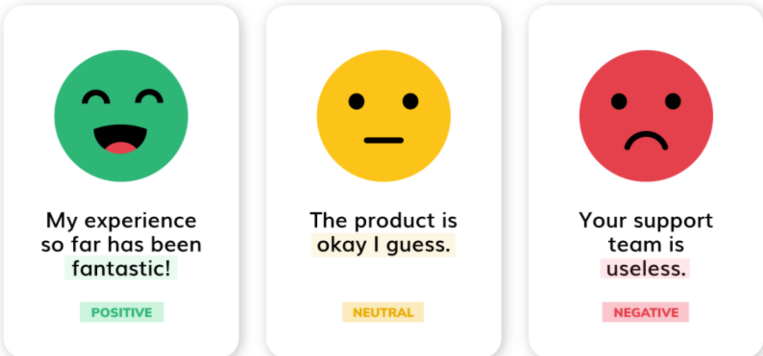

FIG NO.: 1 POLARITY OF SENTIMENTS

1.3 Importance and Applications of Sentiment Analysis:

Due to its many uses, sentiment analysis has become extremely important in many different fields. In the discipline of marketing, it aids businesses in comprehending the attitudes and opinions of consumers towards their goods and services, allowing them to make wise choices and raise client happiness. Sentiment analysis is a key tool in brand management for tracking reputation and reviewing consumer opinion. To ensure timely replies to unfavorable feelings, customer service organizations can use sentiment analysis to automatically identify and prioritize client questions based on sentiment. To determine how the public feels about political parties, policies, and leaders, public opinion analysis and political sentiment tracking use sentiment analysis.

Sentiment analysis also has uses in opinion mining and social media monitoring, where it aids in the tracking and comprehension of online conversations, trends, and client opinions by organizations. Additionally, sentiment analysis can be utilized in the healthcare industry to examine customer reviews and sentiments in online discussion forums, allowing healthcare providers to enhance services. Additionally, sentiment research is relevant to the financial markets, as traders' choices might be influenced by the sentiment seen in news stories or social media posts.

Sentiment analysis, which examines emotions in textual data, goes beyond sentiment polarity and offers a deeper comprehension of the conveyed sentiments, which is essential for decision-making processes in a variety of fields.

The research paper will then go into detail about the methods for sentiment analysis, the analysis of emotions within sentiment analysis, the difficulties and restrictions that come with sentiment analysis, real-world applications, and probable future directions for research and development in this area.

2. OBJECTIVE

Sentiment analysis through natural language processing (NLP) aims to systematically identify, extract, quantify, and analyze affective states and subjective information from

textual data. Sentiment analysis entails identifying and categorizing the feelings, judgements, attitudes, and subjective data found in textual materials.
The core objective of sentiment analysis using NLP is to derive actionable insights from text data by accurately identifying and interpreting the emotions and opinions expressed. This enables organizations to make informed decisions, improve products and services, enhance customer satisfaction, and stay ahead in competitive markets. Through the automated processing of large volumes of text data, sentiment analysis facilitates a deeper understanding of human emotions and opinions at scale.

3. EXISTING WORK

The field of sentiment analysis has benefited from the progress made in understanding and analyzing textual data. Researchers have developed various methods, including lexicon-based approaches, machine learning algorithms, deep learning architectures, and rule-based systems. Papers such as Pang and Lee (2008) and Liu (2012) provide comprehensive overviews of sentiment analysis and opinion mining, discussing different approaches and applications. In social media text, Hutto and Gilbert's (2014) VADER model gained recognition for sentiment analysis. Recursive deep models, introduced by Socher et al. (2013), have demonstrated the effectiveness of deep learning in capturing compositional semantics for sentiment analysis. Over the years, sentiment analysis has evolved significantly, benefiting from advancements in natural language processing (NLP) and machine learning. Notably, the integration of pre-trained language models and hybrid approaches has pushed the boundaries of accuracy and robustness in sentiment analysis. These advancements have wide-ranging applications across various industries, underscoring the significance and impact of sentiment analysis in today's data-driven world.

Here is an overview of notable existing work in this field:

4. PROPOSED WORK

The proposed work in this research focuses on further advancing the field of sentiment analysis, specifically in the context of analyzing emotions in textual data. It aims to address the limitations and challenges in current sentiment analysis approaches, such as sarcasm and irony detection, contextual understanding, handling negation and ambiguity, and capturing complex emotions.

The research proposes exploring aspect-based sentiment analysis to analyze sentiment at a more granular level, allowing for a better understanding of opinions towards specific aspects or features. It suggests integrating multimodal analysis, incorporating multiple modalities like text, images, audio, and video, to gain a comprehensive understanding of sentiment expressed through different channels.

The research also emphasizes the importance of emotion-aware sentiment analysis, aiming to accurately detect and classify complex emotions expressed in text. It suggests developing models that capture fine-grained emotions and identify mixed emotions. Overall, the proposed work aims to contribute to the advancement of sentiment analysis by addressing existing limitations, incorporating emotion analysis, exploring new techniques and models, and considering ethical implications and specific domain requirements.

To advance the field of sentiment analysis, the proposed work focuses on enhancing model performance, addressing existing challenges, and expanding the application scope. The proposed work can be divided into several key areas

1. Advanced Preprocessing Techniques

Contextual Text Preprocessing

Objective: Develop advanced preprocessing pipelines that better capture context-specific nuances, including slang, abbreviations, and idiomatic expressions.

Approach: Use NLP techniques to identify and appropriately handle informal language and context-specific terms, leveraging domain-specific lexicons and context-aware models.

2. Enhanced Feature Extraction

A. Contextual Embeddings

Objective: Utilize state-of-the-art embeddings like BERT, GPT, and their variants to capture deeper semantic meanings.

Approach: Fine-tune pre-trained language models on sentiment-specific datasets to enhance their ability to recognize sentiment nuances.

B. Multi-Modal Sentiment Analysis

Objective: Combine textual data with other modalities such as images, audio, and video to improve sentiment detection.

Approach: Develop multi-modal models that integrate features from different data sources, using techniques like convolutional neural networks (CNNs) for image analysis and recurrent neural networks (RNNs) for audio processing.

3. Improved Sentiment Classification Models

A. Hybrid Deep Learning Models

Objective: Combine the strengths of different neural network architectures to improve sentiment classification.

Approach: Develop hybrid models that integrate CNNs, RNNs, and attention mechanisms to capture both local and global dependencies in text.

B. Transformer-Based Architectures

Objective: Leverage the power of transformer models for superior context understanding.

Approach: Fine-tune transformer models like BERT, RoBERTa, and T5 for sentiment analysis, experimenting with different architectures and hyperparameters to optimize performance.

4. Handling Fine-Grained Sentiment Analysis

A. Aspect-Based Sentiment Analysis (ABSA)
Objective: Identify and analyze sentiment towards specific aspects or features within a text.

Approach: Develop models that can perform aspect extraction and sentiment classification simultaneously, using multi-task learning frameworks.

B. Emotion Detection

Objective: Move beyond basic sentiment classification to detect specific emotions (e.g., joy, anger, sadness).

Approach: Train models on emotion-labeled datasets, utilizing transfer learning to leverage existing sentiment analysis knowledge.

5. Real-Time and Scalable Sentiment Analysis

A. Real-Time Sentiment Analysis

Objective: Enable real-time processing of social media streams and other fast-paced data sources.

Approach: Optimize models for low-latency inference, using techniques like model quantization and efficient neural network architectures.

B. Scalable Sentiment Analysis

Objective: Ensure that sentiment analysis systems can handle large-scale data efficiently.

Approach: Implement distributed computing frameworks and scalable data processing pipelines, leveraging cloud computing resources.

6. Addressing Ethical and Bias Issues

A. Bias Mitigation

Objective: Identify and reduce biases in sentiment analysis models that may arise from biased training data.

Approach: Implement fairness-aware training techniques and evaluate models using fairness metrics to ensure unbiased sentiment classification.

B. Transparency and Explainability

Objective: Make sentiment analysis models more interpretable and transparent.

Approach: Develop methods to explain model predictions, using techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations).

7. Application Development and Deployment

A. Domain-Specific Sentiment Analysis

Objective: Develop customized sentiment analysis solutions for specific domains (e.g., healthcare, finance, customer service).

Approach: Fine-tune models on domain-specific datasets and integrate them into domain-specific applications, providing tailored insights.

B. User-Friendly Sentiment Analysis Tools

Objective: Create accessible and user-friendly sentiment analysis tools for non-technical users.

Approach: Develop web-based interfaces and APIs that allow users to perform sentiment analysis easily, providing visualization and reporting features.

5. TECHNIQUES FOR SENTIMENT ANALYSIS

5.1 Lexicon-Based Approaches:

Methods based on a lexicon use pre-defined dictionaries or lexicons of words or phrases that have been assigned a sentiment score and are mapped to that score. Each word or phrase has a polarity value assigned to it that normally ranges from negative to positive and represents the emotion attached to it. When performing sentiment analysis using lexicon-based methods, a sentiment score is generated by counting the number of times each word from the lexicon appears in the sample text. Although less training data is more computationally economical, lexicon-based techniques may have trouble handling context-dependent attitudes, negation, and sarcasm.

5.2 Machine Learning Algorithms:

Due to their capacity to automatically discover patterns and features from labelled training data, machine learning algorithms have been extensively employed for sentiment analysis. For sentiment classification, supervised learning techniques like Support Vector Machines (SVM), Naive Bayes, and Random Forest are frequently used. These algorithms develop a model based on the input characteristics (such as bag-of-words, n- grams, and word embeddings) that are taken from the text and their accompanying sentiment labels. The sentiment of fresh, unread content can then be predicted by the trained model. While machine learning algorithms perform well in sentiment analysis, they need labelled training data and can overfit or only generalize to a small number of domains.

Sentiment analysis models that categorize text into various emotions automatically can be created using machine learning techniques. Here are five emotions and examples of how sentiment analysis can make use of them:

Happiness: Positive emotions connected to happiness can be recognized by a machine learning model that has been trained in this area. The model can categorize text as expressing happiness when it contains phrases, words, or emoticons associated with joy, delight, or satisfaction by examining text patterns, linguistic constructions, and word context.

Sadness: Sentiment analysis can also detect expressions of sadness in text. The model can be trained to recognize negative sentiments associated with sadness, such as words related to grief, disappointment, or despair. It can identify text that indicates a person is feeling down, low, or unhappy.

Anger: Sentiment analysis models can identify text that conveys anger or frustration. By analyzing words, phrases, or expletives commonly associated with anger, the model can detect and classify text as expressing anger or irritation. This can be helpful for understanding customer feedback, social media posts, or online reviews.

Fear: Sentiment analysis can also detect expressions of fear or anxiety in text. The model can be trained to recognize words, phrases, or language patterns that indicate fear, such as mentions of danger, uncertainty, or insecurity. It can identify text that suggests a person is feeling scared or worried.

Neutral: Not all text expresses strong emotions. Sentiment analysis models can classify text as neutral when it does not contain any strong positive or negative sentiment. This category helps differentiate text that does not convey any specific emotion or sentiment, making it useful for filtering out or analyzing more objective statements. Machine learning models can learn to recognize and classify sentiments effectively by being trained on

labelled datasets that contain instances of text and their related emotions. These models can then be applied to a variety of tasks, such as monitoring social media, analyzing customer reviews, or managing a brand's reputation.

5.3 Deep learning models:

Recurrent neural networks (RNNs)and convolutional neural networks (CNNs) have demonstrated outstanding performance in sentiment analysis tasks. RNNs that can capture sequential dependencies and represent contextual information in text include Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). CNNs, however, are excellent at identifying regional patterns and features in text. These models can learn hierarchical text representations, capturing sentiments at the word and sentence levels. Deep learning models offer the advantage of automatically learning feature representations, which eliminates the need for manual feature engineering but requires vast volumes of labelled training data. Transfer learning techniques, such as using pre-trained word embeddings (e.g., Word2Vec, GloVe) or language models (e.g., BERT, GPT), have also proven effective in sentiment analysis tasks.

FIG NO.: 2 DEEP LEARNING

5.4 Hybrid Approaches:

Hybrid approaches integrate several methods or models to take use of their various advantages. For instance, sentiment scores from the text can be extracted using a lexicon-based approach, and these scores can then be merged with features from deep learning models. By overcoming the shortcomings of separate methods, hybrid approaches seek to enhance sentiment analysis's overall effectiveness.

The technique choice is influenced by several variables, including the amount of labelled data available, computer power, domain-specific needs, and the level of precision sought. To choose the best method for their sentiment analysis jobs, researchers and practitioners frequently test out several strategies.

6 METHODOLOGIES

6.1 Emotion Detection and Classification:

Sentiment analysis includes emotion analysis, which seeks to go beyond simple classification of positive and negative sentiment to pinpoint certain emotions expressed in the text. Emotions are intricate and individualized states that can include joy, sorrow, rage, fear, surprise, and other feelings. While emotion classification seeks to apply specific emotion labels to the identified emotions, emotion detection focuses on finding the existence of emotions in text.

FIG NO.: 3 SENTIMENT ANALYSIS METHODOLOGIES

6.2 Emotion Lexicons and Resources:

Researchers and practitioners of sentiment analysis frequently use emotion lexicons or resources while conducting emotion analysis. These lexicons include words or phrases that correspond with emotion labels. Emotion lexicons can be created manually or automatically using labelled data or already available resources. Based on their semantic associations and linguistic patterns, they assign words to emotions like happiness, sadness, rage, fear, and others. The NRC Emotion Lexicon, EmoLex, and SentiWordNet are a few examples of commonly used emotion lexicons.

6.3 Approach for Emotion Analysis:

In sentiment analysis, several methods that can be used for emotion analysis:

a) Lexicon-Based methodologies:

By including emotion lexicons, lexicon-based methodologies can be expanded to include emotion analysis. To identify the existence of emotions, words in the text are compared to entries in the emotion lexicon. To determine aggregate emotion scores or probability for various emotions, aggregate sentiment scores connected with emotion lexicon items can be used.

b) Ensemble Methods:

Ensemble approaches incorporate several models or procedures to increase the reliability and accuracy of emotion analysis. To make use of their unique advantages, they can combine lexicon-based techniques, machine-learning models, and rule-based strategies.

c) Deep Learning Architectures:

Deep learning architectures, such as Recurrent Neural Networks (RNNs) or Transformers, can be used to capture the contextual dependencies and long-range interactions present in the text, resulting in a more precise description of the emotions. On labelled emotion datasets, models like LSTM, GRU, BERT, or GPT can be trained or enhanced for emotion analysis tasks.

7. CHALLANGES IN EMOTIONAL ANALYSIS

Sentiment analysis's use of emotion faces many difficulties.

7.1 Understanding Context:

Context can have a significant impact on how emotions are conveyed. Accurate analysis becomes dependent on understanding the situation and differentiating between several potential emotions. For instance, the connotation of the term "sick" might change depending on the situation (for instance, "sick of something" vs. "sick as in unwell").

7.2 Sarcasm and Irony:

It might be difficult to recognize sarcasm or irony because the literal meaning of words or phrases may not match the emotional tone that is intended. Accurately identifying and interpreting ironic or sarcastic expressions is a persistent research difficulty.

7.3 Multilingual and Cross-cultural Issues:

Sentiment analysis models trained on a specific language or cultural context may not effectively apply to others. Languages and cultures can express emotions differently, and sentiment lexicons and linguistic patterns vary across languages, posing challenges for multilingual sentiment analysis.

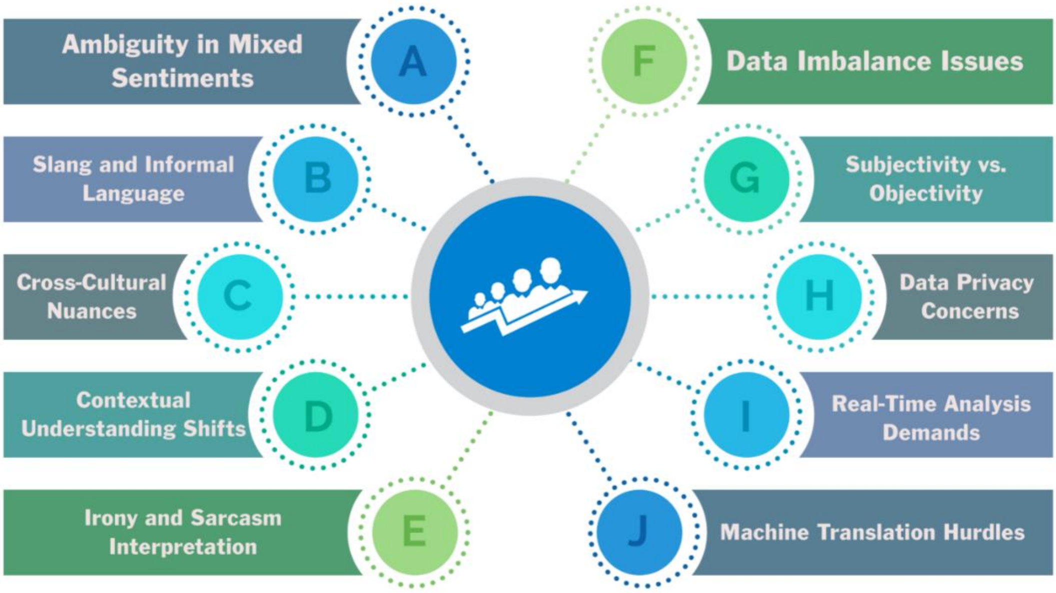

FIG NO.: 4 CHALLENGES IN SENTIMENT ANALYSIS

Emotion analysis improves sentiment analysis by enabling a more nuanced interpretation of sentiment by giving a deeper grasp of the various emotions portrayed in text. Even though it can be difficult to effectively capture emotions, improvements in NLP and sentiment analysis methods are continuing to enhance emotion analysis's performance and application in a variety of fields.

8 IMPLEMENTATION OF SENTIMENT ANALYSIS

Sentiment analysis has become extremely popular and is used in many different fields. Organizations can use sentiment analysis to analyze customer sentiment, track brand reputation, and make educated decisions by extracting insights from textual data. The following are some significant uses of sentiment analysis:

8.1 Customer Feedback and Reviews:

Customer feedback and reviews are frequently analyzed using sentiment analysis. It assists companies in learning more about client preferences, levels of satisfaction, and areas for development. Businesses can pinpoint the positive and bad parts of their goods or services, make focused adjustments, and raise customer satisfaction by analyzing sentiment in customer evaluations. Additionally, automatic categorization and prioritization of customer input is made possible through sentiment analysis, which streamlines customer support procedures.

8.2 Market Research and Competitive Analysis:

Market research and competition analysis both heavily rely on sentiment analysis. It aids businesses in gauging public opinion and sentiment towards their goods, services, or advertising initiatives. Businesses may spot market trends, gauge client preferences, and make data-driven decisions for product development, marketing strategies, and competitive positioning by analyzing sentiment in social media posts, customer reviews, and surveys.

8.3 Social Media Analytics and Campaign Tracking:

Social media analytics frequently employ sentiment analysis to track and examine discussions, trends, and sentiments on various social media platforms. It aids companies in gauging public opinion on certain issues, goods, or occasions. The effectiveness and impact of marketing initiatives can also be monitored with the help of sentiment analysis. Organizations may gauge the success of their initiatives, spot opportunities for improvement, and adjust their messaging to appeal to their target audience by analyzing the emotion in social media posts.

8.4 Healthcare and Patient Feedback:

Sentiment analysis is used in the healthcare industry to examine the opinions, feelings, and experiences that patients share in online forums or surveys. Healthcare professionals can pinpoint areas for improvement, raise patient satisfaction, and tailor patient treatment by analyzing the mood in patient comments.

9 RESULTS

The result of the above research on "Natural Language Processing for Sentiment Analysis: Analyzing Emotions in Textual Data" would be a comprehensive and detailed analysis of the topic. It would include an introduction providing an overview of sentiment analysis and its significance. The techniques for sentiment analysis would be discussed, covering various approaches such as lexicon-based methods, machine learning models, and deep learning architectures.

The research would delve into preprocessing and feature extraction techniques, highlighting their importance in preparing textual data for sentiment analysis. It would explore the challenges and limitations faced in sentiment analysis, including sarcasm and irony detection, contextual understanding, handling negation and ambiguity, subjectivity, cultural differences, data sparsity, bias, and limited understanding of complex emotions.

10 CONCLUSIONS

Sentiment analysis has developed into a crucial tool for companies, researchers, and organizations across a variety of industries thanks to its capacity to extract insights and identify emotions from textual data. Simple sentiment classification has given way to more complex analysis that considers things like emotion recognition, aspect-based sentiment analysis, and multimodal sentiment analysis.

Lexicon-based approaches, machine learning models, ensemble strategies, and deep learning architectures are methodologies for sentiment analysis. These methods have shown to be successful at identifying the sentiment and feelings conveyed in text, allowing businesses to make data-driven decisions that will improve customer satisfaction, manage brand reputation, and give them a competitive edge.

11 FUTURE DIRECTIONS IN SENTIMENT ANALYSIS

Recent developments in Natural Language Processing (NLP) and machine learning methods have significantly advanced sentiment analysis. The sentiment analysis field does, however, have several promising new avenues and research areas to explore. Here are a few important future directions:

11.1 Aspect based sentiment analysis:

By analyzing sentiment at a more detailed level, aspect-based sentiment analysis seeks to go beyond general sentiment classification. It entails figuring out the feelings connected to each of the individual elements or aspects of a good or service stated in the text. Future studies in aspect-based sentiment analysis will concentrate on creating more precise and reliable models to capture the nuanced sentiment expressed towards various aspects, enabling organizations to gain deeper insights into customer's opinions and preferences.

11.2 Emotion-aware Sentiment Analysis:

A new field of study in sentiment analysis is emotion analysis. The creation of models that can precisely identify and categorize complicated emotions expressed in text will be one of the future directions. This involves catching subtle feelings, recognizing

mixed emotions and comprehending the emotional intensity of sentiment. Greater comprehension of human emotions will be possible thanks to emotion-aware sentiment analysis, which will produce results that are more complex.

11.3 Ethics, Bais, and Fairness:

As sentiment analysis models are more frequently used in practical. applications, it is important to address ethical issues, prejudice, and fairness. Future studies will concentrate on creating methods to reduce biases in sentiment analysis models, assuring equity across various racial and ethnic groups and cultural situations. Understanding and minimizing potential biases will also depend on the transparency and interpretability of sentiment analysis models.

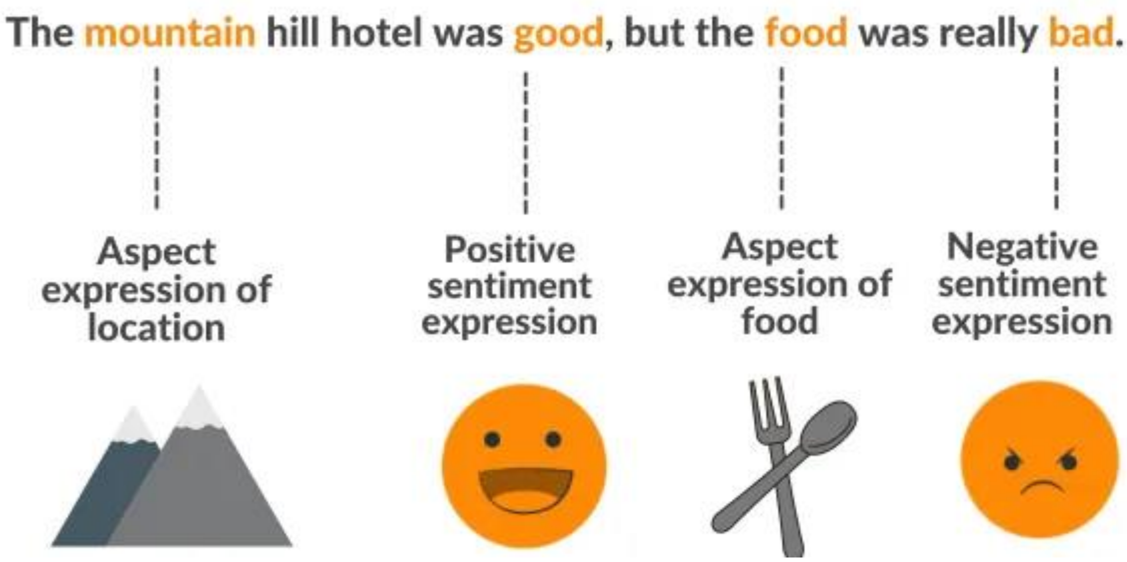

FIG NO.: 5 FUTURE DIRECTIONS

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