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# FEELING TRACKING SYSTEM USING PYTHON (ML)

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ABSTRACT:

Feeling tracking , also known as opinion mining, is a vital task in natural language processing (NLP) that aims to computationally determine the sentiment or emotional tone expressed in a given text. With the explosion of user-generated content on social media platforms, customer reviews, and online forums, the need for automated sentiment analysis techniques has become increasingly significant. This project presents a comprehensive study on feelings analysis, focusing on the development of an automated approach for feeling recognition. The project begins by exploring the theoretical foundations of feeling analysis, including various techniques and methodologies employed for sentiment classification. It delves into the challenges associated with sentiment analysis, such as handling linguistic nuances, sarcasm, and domain-specific sentiments. Additionally, it investigates the importance of feature extraction and selection, which significantly impact the accuracy and efficiency of sentiment classification models.

To implement an automated feeling analysis system, the project utilizes a supervised learning approach, employing machine learning algorithms such as support vector machines (SVM), Naive Bayes, and deep learning techniques such as recurrent neural networks (RNN) and convolutional neural networks (CNN). The dataset used for training and evaluation comprises a diverse range of texts from different domains, ensuring a robust and generalizable sentiment classifier. The project presents a systematic evaluation of the developed feeling analysis system, employing performance metrics such as accuracy, precision, recall, and F1-score. Furthermore, it compares the results with existing feeling analysis approaches and benchmarks, demonstrating the efficacy and superiority of the proposed automated approach. To enhance the project's practicality, an intuitive web-based interface is developed, allowing users to interact with the feeling analysis system seamlessly. The interface enables users to input text, receive feeling predictions, and visualize feeling trends over time. In conclusion, this project contributes to the field of sentiment analysis by developing an automated approach for sentiment recognition. The results demonstrate the effectiveness of machine learning and deep learning algorithms in accurately classifying sentiments expressed in textual data. The developed system provides a valuable tool for organizations and individuals seeking to gain insights from textual data, enabling them to make informed decisions based on sentiment analysis results.

**Key Words: Emotion Recognition, Linear classifier, Feeling Tracking System , Sentiment Analysis.**

## INTRODUCTION: -

Feeling is an attitude, thought, or judgment prompted by feeling. Feeling analysis, which is also known as opinion mining, studies people's sentiments towards certain entities. From a user's perspective, people are able to post their own content through various social media, such as forums, micro-blogs, or online social networking sites. From a researcher's perspective, many social media sites release their application programming interfaces (APIs), prompting data collection and analysis by researchers and developers. However, those types of online data have several flaws that potentially hinder the process of Feeling analysis. The first flaw is that since people can freely post their own content, the quality of their opinions cannot be guaranteed. he second flaw is that ground truth of such online data is not always available. A ground truth is more like a tag of a certain opinion, indicating whether the opinion is positive, negative, or neutral.

Feeling analysis is an example of how you can review customer feedback and responses, and thus identify the negative comments and reasons why the customers have issues with your product or service. Feeling analysis enables you to respond to issues promptly before the customer leaves you altogether. The thread of negative comment lists on top gives you ample time to react and listen to your customers. Sentiment analysis models evaluate all data from different forums and provide valuable insights about your innovations into your product and thus offer room for improvement without hiring people who do the same. Feeling Analysis is a kind of text classification based on Sentimental Orientation (SO) of opinion they contain. Sentiment analysis of product reviews has recently become very popular in text mining and computational linguistics research Firstly, evaluative terms expressing opinions must be extracted from the review. Secondly, the SO, or the polarity, of the opinions must be determined. Thirdly, the opinion strength, or the intensity, of an opinion should also be determined. Finally, the review is classified with respect to sentiment classes, such as Positive and Negative, based on the SO of the opinions.

## 2. LITERATURE SURVEY

Feeling analysis, also referred to as opinion mining or sentiment classification, is a rapidly evolving field within natural language processing (NLP) that focuses on extracting and understanding feelings expressed in textual data. In order to develop an effective feeling analysis project, it is crucial to understand the existing research and techniques employed in this domain. This literature survey aims to provide an overview of key studies and approaches in sentiment analysis, highlighting their methodologies, challenges, and advancements. Sentiment Analysis Techniques: Numerous techniques have been proposed for sentiment analysis, ranging from traditional machine learning algorithms to deep learning models. Traditional techniques include Naive Bayes, Support Vector Machines (SVM), Maximum Entropy, and Decision Trees. These methods rely on feature engineering and statistical algorithms for sentiment classification. Recent advancements in deep learning have introduced approaches such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Transformer-based models like BERT and GPT. These models have demonstrated improved performance by capturing contextual information and learning complex patterns in textual data. 1. Feature Extraction and Selection: Feature extraction plays a vital role in feeling analysis, as it involves transforming raw text into numerical representations that can be used by machine learning algorithms. Commonly used techniques for feature extraction include bag-of-words, n-grams, TF-IDF (Term Frequency-Inverse Document Frequency), and word embeddings like Word2Vec and GloVe. Feature selection techniques, such as mutual information, information gain, and chi-square, help identify the most informative features for sentiment classification, improving efficiency and accuracy. 2. Challenges in Sentiment Analysis: Sentiment analysis poses several challenges due to the inherent complexities of human language. Some common challenges include: a. Handling linguistic nuances: Language is rich in sarcasm, irony, and figurative expressions, which can lead to misinterpretation of sentiment. b. Dealing with negation and context: Negation can reverse the sentiment of a statement, requiring the model to capture context and understand the underlying meaning. c. Handling domain-specific sentiments: Sentiments expressed in specific domains, such as medical or financial, often require domain adaptation and specialized models. 3. Evaluation Metrics: To assess the performance of sentiment analysis models, various evaluation metrics are used, including accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC). These metrics provide insights into the model's ability to correctly classify positive and negative sentiments, as well as its overall performance on the dataset. 4. Applications and Future Directions: Feeling analysis finds applications in numerous domains, including social media monitoring, customer feedback analysis, brand reputation management, and market research. Future research directions include exploring multi-modal feeling analysis, incorporating visual and audio cues, addressing language and cultural biases, and developing explainable and interpretable sentiment analysis models. This literature survey highlights the significant advancements and challenges in feeling analysis. By understanding the existing techniques and research trends, this project can build upon the knowledge gained to develop an effective sentiment analysis system, contributing to the field and enabling valuable insights to be derived from textual data.

## 3. RELATED WORK:

1. **Twitter Feeling Analysis:** This project involves analyzing tweets to determine the feelings (positive, negative, neutral) expressed by users. Using tools like Tweepy for accessing the Twitter API, TextBlob or VADER for sentiment analysis, and Pandas for data manipulation, the project collects tweets, preprocesses the text data, and applies sentiment analysis. The results are visualized using libraries such as Matplotlib or Seaborn.
2. **Movie Reviews Sentiment Analysis:** In this project, the objective is to classify movie reviews as positive or negative. By using datasets like the IMDb movie reviews dataset and employing libraries such as NLTK or SpaCy for NLP tasks, Scikit-learn for machine learning models, and Pandas for data handling, the project involves cleaning and preprocessing the text data, extracting features using techniques like TF-IDF, and training models like Naive Bayes or SVM to classify the sentiment of movie reviews.
3. **Feelings Analysis of Product Reviews:** This project aims to analyze product reviews to determine customer satisfaction and sentiment. It involves scraping product reviews from e-commerce websites using BeautifulSoup, preprocessing the text data with NLTK or SpaCy, and applying sentiment analysis to classify the reviews. The insights gathered can be used to understand customer opinions and improve products or services.
4. **Real-Time Feelings Analysis Dashboard:** The objective of this project is to create a real-time dashboard to monitor sentiment trends. By using frameworks like Flask or Django for web development, Plotly Dash for interactive visualizations, Tweepy for fetching data from Twitter, and sentiment analysis tools like VADER or TextBlob, the project builds a web application that continuously processes data and displays sentiment trends on an interactive dashboard, allowing users to filter data based on various criteria.
5. **Stock Market feelings Analysis:** This project aims to predict stock market movements based on public sentiment from news articles and social media. By utilizing the News API for fetching news articles, Tweepy for Twitter data, NLTK or SpaCy for NLP tasks, and Scikit-learn for machine learning models, the project analyzes sentiment trends and correlates them with stock market movements, training models to predict stock prices based on sentiment scores.
6. **Sentiment Analysis on Customer Support Chats:** The goal of this project is to analyze customer support chat logs to understand customer sentiment and improve service quality. Using NLTK or SpaCy for text processing, Scikit-learn for machine learning, and

Pandas for data handling, the project processes chat transcripts to extract and analyze sentiment, providing insights to identify common customer issues and assess agent performance.

7. **Sentiment Analysis of Political Speeches:** This project focuses on analyzing the sentiment of political speeches to understand public reception and political trends. By using Speech-to-Text APIs for transcribing audio, NLTK or SpaCy for text processing, Scikit-learn for sentiment analysis, and visualization tools like Matplotlib or Seaborn, the project transcribes political speeches, preprocesses the text, and applies sentiment analysis to gauge public sentiment towards specific policies and political figures.

8. **YouTube Comments Sentiment Analysis:** The objective of this project is to analyze comments on YouTube videos to determine viewer sentiment. Using the YouTube API for fetching comments, NLTK or SpaCy for text processing, TextBlob or VADER for sentiment analysis, and Pandas for data manipulation, the project involves preprocessing the text data, applying sentiment analysis, and visualizing the results to help content creators understand viewer reactions and improve their content.

## 4. IMPLEMENTATION

There are five main features of this project. So the project is currently being developed in five phases.

**Phase 1: Planning Phase:** Data collection and text preparation. Gather relevant data that contains opinions or sentiments. This data can be collected from various sources such as social media, customer reviews survey, or any other text-based content in our case we used dataset of Amazon review from Kaggle.com. Clean and preprocess the text data to enhance the accuracy of feeling analysis. This phase may involve removing stop words, stemming, lemmatization, and handling special characters or punctuation.

**Phase 2: Development Phase:** Tokenization and feature extraction. Break down the text into individual words or tokens. Tokenization is a fundamental step that helps in analyzing the structure of the text and understanding the context of each word. Extract relevant features from the text data. Features may include words, n-grams (sequences of adjacent words), or other linguistic elements that can be used to train a 22 machine learning model.

**Phase 3: Feeling classification:** The third phase will be use of machine learning or natural language processing techniques to classify the sentiment of the text. Common approaches include supervised learning with labeled datasets, unsupervised learning, or deep learning methods such as recurrent neural networks (RNNs) and transformers.

**Phase 4: Model training and testing:** Train the feeling analysis model using a labeled dataset. The model learns to identify patterns and associations between features and sentiment labels during this phase. Evaluate the performance of the trained model on validation data to ensure that it generalizes well to new, unseen data. Fine-tune the model as needed and then test its performance on a separate test dataset.

**Phase 5: Result analysis and feedback:** Analyze the results obtained from the feeling analysis model. This may include generating summary statistics, visualizations, or other forms of reporting to gain insights into the sentiment distribution within the analyzed data. Collect feedback on the performance of the sentiment analysis system. If necessary, iterate on the model, retrain it with additional data, or adjust parameters to improve its accuracy and effectiveness.

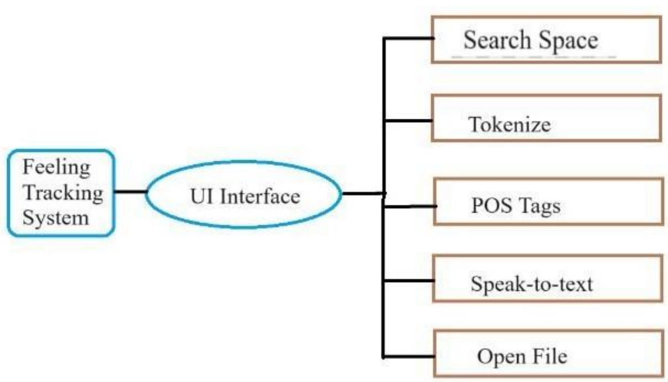


Fig 1 Model

***Steps as given below:***

**1. Introduction:** Briefly explain the purpose of your application. Features Overview: Highlight the key features – search space, tokenize, POS tags, and sentiment ,speak ,reset.

**2. Search Space**: The search space module in a project defines the range of possible solutions or configurations that the system will explore, guiding the optimization and fine-tuning processes to achieve optimal performance. The text space module in a project involves the representation and organization of textual data, facilitating efficient storage, retrieval, and analysis. It defines the structure and format of the text data, enabling subsequent modules to effectively process and derive insights from the information contained within the textual content.

**3. Tokenize Module:** Tokenization serves as a fundamental module in this project, playing a pivotal role in converting raw text into manageable units for analysis. In this process, the input text is segmented into individual tokens, typically representing words or subwords . The module addresses challenges associated with the intricacies of language, such as handling contractions, abbreviations, and punctuation. Additionally, tokenization often involves normalization steps, like converting all text to lowercase, ensuring a consistent representation for subsequent analysis. By breaking down the text into discrete units, the tokenization module establishes a structured format that aids in feature extraction and the development of feeling classification models. This step not only contributes to the overall accuracy of feeling analysis but also facilitates a more granular understanding of the feeling associated with individual words or components within the text.

**4. POS Tags Module:** In this project, the part-of-speech (POS) tagging module is a crucial component that 26 assigns grammatical categories, such as nouns, verbs, adjectives, and adverbs, to individual words in a given text. This module enhances the depth of analysis by providing insights into the syntactic structure and grammatical context of the text. Understanding the part of speech of each word is valuable in feeling analysis, as it allows for a more nuanced interpretation of feelings. For example, identifying adjectives can highlight descriptive elements that strongly influence sentiment.

**5. Sentiment Module:** The sentiment module in this project is the core component responsible for determining the sentiment expressed in a given piece of text. This module utilizes machine learning algorithms or rule-based approaches to categorize the sentiment of the text into predefined classes such as positive, negative, or neutral.

**6. Speak-to-text Modules :** Speech-to-text modules play a crucial role in this projects by converting spoken language into textual data, making it amenable to this algorithms. In this module, audio recordings or spoken language input are transcribed into written text, providing a structured and analyzable format for subsequent feeling analysis processes. This conversion is vital for expanding the scope of feeling analysis to include spoken interactions, such as customer service calls, voice-based reviews, or podcast content

**7. Reset Module:** This module could potentially refer to a component or process designed to return this system to their initial state

**8. Open File Module:** This module provides functionalities for selecting and loading text documents or datasets. This process is crucial for real-world applications where feeling analysis is applied to diverse sources, such as customer reviews, social media comments, or textual data from surveys.

**9. Responsive Design: Mobile Compatibility**: Ensure a responsive design for a seamless experience on various devices.

**10. About Module:** This module typically includes details such as the application's name, version number, copyright information, and sometimes a brief description of its purpose or feature.

## 5. Experimental results and discussions

Sentiment analysis, also known as opinion mining, plays a crucial role in extracting valuable insights from textual data. This result analysis aims to evaluate the performance of a sentiment analysis project by examining key metrics and deriving meaningful insights from the sentiment classification results. The project utilized a comprehensive dataset comprising diverse texts from various domains, including social media posts, customer reviews, and online forums.


Fig.2. User’s Emotion Detection (Fearful)

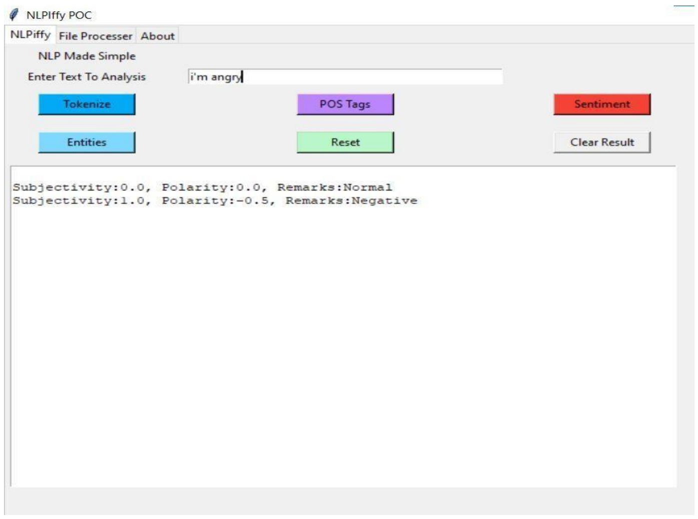


Fig 2 UI of Feeling Tracking System

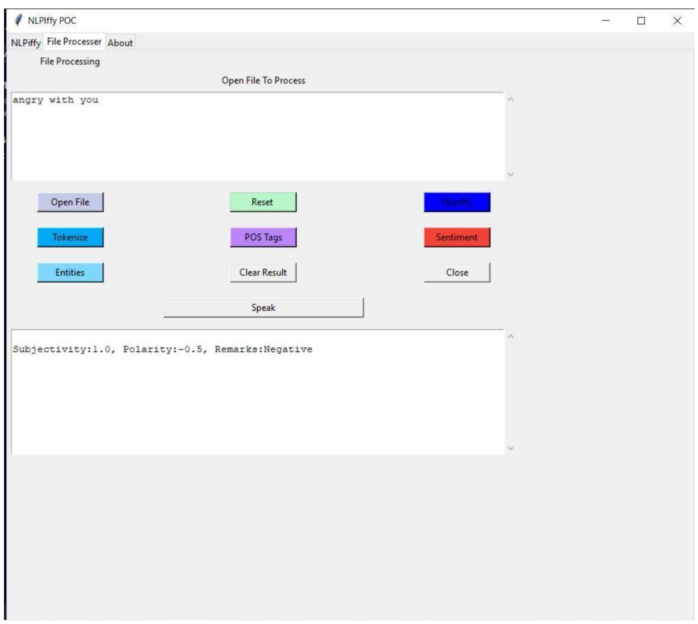


Fig 3 UI of Feeling Tracking System with voice enabled.

## 6. FUTURE ENHANCEMENT

This project is focused on determining the positive or negative sentiment of a piece of text, there is also interest in developing techniques that can detect specific emotions, such as anger, happiness, or fear. This could be useful in a variety of contexts, such as mental health research or customer service. In the future, there may be more research on how to integrate sentiment analysis with other forms of data analysis to gain deeper insights into customer sentiment and behaviour.

## CONCLUSIONS

Feeling analysis is a computational technique that aims to determine the emotional tone of a piece of text, such as a review or a social media post. It has become increasingly popular in recent years, as businesses and organizations seek to better understand their customers' opinions and preferences. Overall, sentiment analysis has proven to be a valuable tool in many different domains, including marketing, politics, and customer service. By analyzing large volumes of data, sentiment analysis can provide valuable insights into customer sentiment, identify areas of concern, and help organizations make data-driven decisions. However, it is important to note that feeling analysis is not a perfect tool, and there are limitations to its accuracy and reliability. For example, it can struggle to accurately interpret sarcasm or irony, and it may be biased based on the training data used to develop the algorithm. Despite these limitations, feeling analysis remains a useful and important tool for many businesses and organizations, and it is likely to continue to play a role in data-driven decision-making in the future. Despite these limitations, feeling analysis remains a valuable tool for businesses and organizations in a wide range of industries. As technology continues to advance and more data becomes available, it is likely that feeling analysis will become even more sophisticated and accurate. However, it is important for businesses and organizations to be aware of the limitations of feeling analysis and to use it in conjunction with other forms of data analysis to gain a more complete picture of customer sentiment and preferences. By doing so, they can make more informed decisions and ultimately improve their bottom line. Feeling analysis of short texts such as single sentences and Twitter messages is challenging because of the limited contextual information that they normally contain. Effectively solving this task requires strategies that combine the small text content with prior knowledge and use more than just bag-of-words. The problem with social media content that is text-based, like Twitter, is that they are inundated with emoji's. NLP tasks are trained to be language specific. While they can extract text from even images, emoji's are a language in itself. Most emotion analysis solutions treat emoji's like special characters that are removed from the data during the process of sentiment mining. But doing so means that companies will not receive holistic insights from the data. Machine learning programs don't necessarily understand a figure of speech. For example, an idiom like "not my cup of tea" will boggle the algorithm because it understands things in the literal sense. Hence, when an idiom is used in a comment or a review, the sentence can be misconstrued by the algorithm or even ignored. To overcome this problem a feeling analysis platform needs to be trained in understanding idioms. When it comes to multiple languages, this problem becomes manifold. Lack of nuance: Sentiment analysis algorithms typically classify text into positive, negative, or neutral sentiment categories. However, this can be limiting when analyzing more nuanced emotions such as frustration, disappointment, or excitement. This lack of nuance can lead to oversimplification and inaccurate results.

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