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Offen im Denken

Master Thesis

on the Topic

Sentiment Analysis for Search Result Snippets

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by

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Abstract

This thesis explores the application of sentiment analysis to search result snippets that goes beyond textual analysis by incorporating visualization techniques to provide a comprehensive understanding of sentiment trends. Sentiment Analysis is a topic widely studied for the last few years due to its potential in extracting and analyzing subjective information and meaning from text. However,it has been more explored more for reviews, opinionated texts and tweets and not for search result snippets.For this reason, this thesis explores the application of sentiment analysis to search result snippets. Search result snippets are short summaries displayed on a search engine results page(SERP) to provide users with a preview of the contents as a response to a particular search query.The motive of this research is :

1. To perform sentiment analysis (SA) on search result snippets using hybrid approach

2. To create a visualization summary of these data taking also into account the SA output to capture the emotional tone of search results.

The core of the thesis lies in the development and evaluation of a sentiment analysis model tailored for search result snippets and explanation of analysis visaully to provide more insight.To perform sentiment analysis, fine-grained hybrid approach of sentiment analysis is used which employs both Lexicon-based analysis as rule based and support vecor machine (svm) as supervised machine learning algorithm. For lexicon based analysis, snippets are pre-processed,sentiment scores for each word in snippets are calculated using sentiwordnet lexicon from stanford library taking care of negations and finally total sentiment score of whole sentiment is computed.For SVM, the model is trained and tested using the labeled dataset from lexicon based method as well as a variety of datasets from different domains and then model is evaluated in terms of different evaluation metrics. Finally the hybrid model calculates the final sentiment score for the snippets which are then further intrepreted using different visualization techniques. For the visualization task

a JavaScript Framework library that provides functionality to display data in graphical charts (Recharts) is used.

In conclusion, this thesis explores the application of sentiment analysis to search result snippets and incorporates visualization techniques to provide a comprehensive understanding of sentiment trends.It also demonstrates the effectiveness of sentiment analysis in understanding the emotional tone of search results and provides valuable insights for further research in this field.

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Chapter 1

Introduction

1.1 Background

As the amount of Web content is rapidly growing and Web search has become the predominant method for people to fulfill their information needs, search engines have become an essential tool and the main entry point to those Web content. The various information requirements of users such as Social, Educational, Travel, Entertainment, etc. can be presented as search queries, and according to the algorithm of different search engines, results are generated and presented. For the same reason, the number of pages that are relevant to a query is growing, forcing users to trust the search engine in what it presents them.[28] A search engine (also: Web search engine; universal search engine) is a computer system that captures distributed content from the World Wide Web via crawling and makes it searchable through a user interface, listing the results in a presentation ordered according to relevance assumed by the system. However, one cannot rely on a single search engine. Studies have been performed to compare the overlap of the first page of results, which concluded that very few results were found by all search engines and more than half of the results were found by only one search engine. Therefore, it can be worthwhile to look at the results of multiple search engines.[10] Besides, search engine results have huge potential to influence the perception of individuals and could even lead to manipulation of feeling of the people towards some sensitive issues so the analysis of the result snippets for given query can give information regarding the emotional tone of the result which can be used to deal with such issue. Moreover, Visual representations of sentiment-related data provide users with a quick and intuitive way to comprehend the emotional context of search results. This work might have several implications for search engines and users.Users can select and filter results according to their personal interests and sentiments. It can also help organizations and companies to find and analyze brand value, reputation, and public opinions. Similarly, users can also get different information such as reviews, opinions etc about particular topic, person, news, products, services etc that might help in decision making.Furthermore, they can compare the sentiment of result snippets across different search engines and choose the most suitable search engine for specific query or study areas. In the same way, search engines can also use this technique to provide sentiment based recommendation and filtering and hence improve the ranking of results by analysing user preferences.

1.2 Search Result Snippets and Sentiment Analysis

As a result of a search query, search engines provide a textual excerpt of the corresponding Web page according to the keywords used in the query. The term "snippet" refers to the information displayed for an individual result on the search engine result page, each described by a title, a set of snippets, and its URL. Snippets help users to decide whether or not to look at a result document or to get an idea of the document before looking at it.[10] Currently, all major search engines display search results as a ranked list of relevant URLs accompanied by the returned pages' titles and small text fragments that summarize the context of search keywords. In general, snippets extracted from the retrieved pages, are an indicator of the pages' usefulness to the query and they help the users browse search results and decide on the pages to visit.[5]

Figure 1.1: Sample search result snippet for search query "Glühwein"

Sentiment analysis has gained more attention as one of the most active research areas with the increased and easy access of internet to the public around the globe and generation of enormous amount of digital data that may be related to any domain. Sentiment analysis or opinion mining, is a subset of NLP (Natural Language Processing) that performs text analysis to discover overall attitude, emotion and opinion expressed by the author or content creator. To be precise, mostly sentiment analysis is used to classify whether the text or content conveys negative, positive, or neutral sentiment toward the subject that is being described.

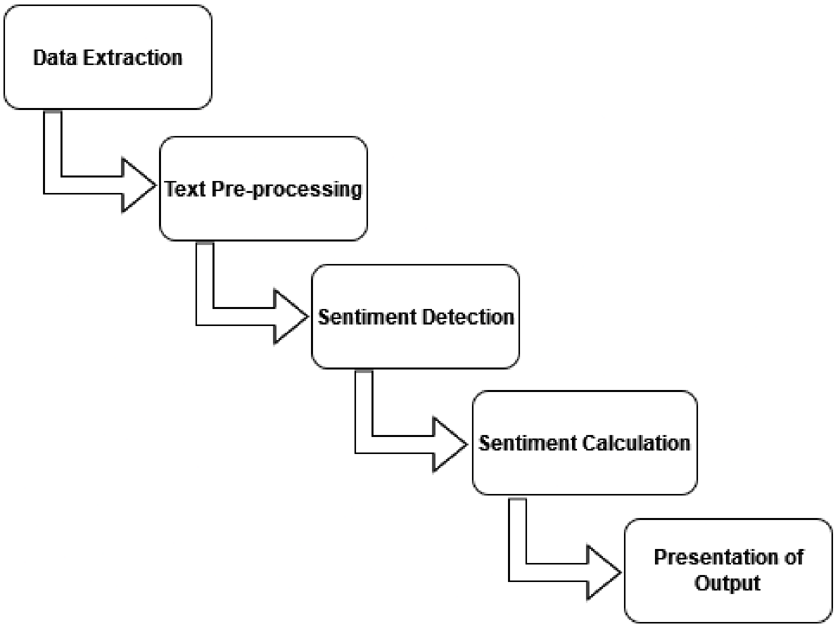


Figure 1.2: Process flow of sentiment analysis

1.3 Research Objectives

Statement of Research Question

“Can Sentiment Analysis comprehend the sentiment tone on Search Results?”

The research question can be further broken down into the following four questions, each of which will be addressed by this research:

i. Research Question I

To what extent does the sentiment tone of result snippets from different search engines (Google, Bing, and DuckDuckGo) for the same search query vary from each other?

ii. Research Question II

Do search results and their sentiment differ with the use of synonyms, positive and negative phrases?

iii. Research Question III

Do search engines (Management, engineers, or algorithms) unknowingly or privately support or discriminate on the basis of race, religion, ethnicity, geography, etc.?

iv. Research Question IV

What is the sentiment distribution for the query or set of (controversial) queries, and how does the distribution change when further result positions are considered?

The objective of this thesis is to find techniques to automatically determine the sentiment of search result snippets. It specifically aims at developing a hybrid model involving both lexicon-based and machine learning methods and visualizing the sentiments.

1.4 Outline

I will discuss all the research steps performed while analyzing sentiments of the search result snippets and visualization accordingly:

Chapter 2 discusses sentiment analysis in brief,the approaches used by other researchers to perform sentiment analysis using hybrid approaches and approaches used to implement sentiment analysis in search engine results.

Chapter 3 explains the the different technology used for this research, methodology and evaluation of this research.

Chapter 4 explains results and the analysis and visualization of sentiment analysis performed on search engine results.

Chapter 5 is on conclusion and future work for performing sentiment analysis.

Chapter 2

Literature Review

2.1 Sentiment Analysis

Since the early 2000s, sentiment analysis has grown to be one of the most active research areas in natural language processing. Sentiment analysis, also called opinion mining, it is a subset of Natural Language Processing (NLP) and the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes [34]. Sentiment analysis can also be defined as the automatic process of extracting the emotional tone from the piece of text by processing unstructured information and creating a model to extract the knowledge from it. Some popular examples include customer reviews and feedback about products and services [15], movies [17], hotels [4], news headlines and articles [4], election result forecasts [34], etc without being dependent on the surveys and other expensive and time-consuming procedures.

The time-consuming sentiment analysis procedure, which is used to compute sentiment, consists of five different steps. They are as follows:

1. **Data Collection :** The initial phase involves collecting user-generated content from various sources such as blogs, forums, websites, and social media platforms.Different methods such as using API and web scraping, purchasing data, custom data collection are used for gathering the data.

2. **Data Preparation :** Before analysis, the extracted data undergoes a cleaning process. This involves the identification and removal of both non-textual and irrelevant content This includes several process such as eliminating non-alphabetic and non-numeric characters, tokenization, removal of stopwords, stemming, lemmatization etc.

3. **Feature Extraction :** The next step in the process is to extract features from the cleaned data. Various methods like Bag-of-Words (BOW), TF-IDF, and Part-of-Speech (POS) tagging are employed based on the chosen model. These feature extraction techniques help to capture the relevant information and characteristics of the data, enabling the model to make accurate predictions or classifications

4. **Classification Model :** Classification models can vary depending on specific needs, available data, and resources. Different Classification model that are widely used are Lexicon Based Methods, Machine Learning Methods and Hybrid Methods that combines multiple approaches. Once model is selected, utilizing the selected model classification task is performed and given data are categorized into different labels like good and bad, positive and negative or any other relevant classifications.

5. **Model evaluation :** It the process of assessing a model's performance using various metrics like accuracy, precision, recall, and F1-score. By analyzing these metrics, we can determine how good or bad is the model perfoming and make necessary adjustments to improve its performance that involves changing and fine-tuning hyperparameters, considering a wider range of datasets, adjustment of sentiment calculation etc to optimize model's performance.

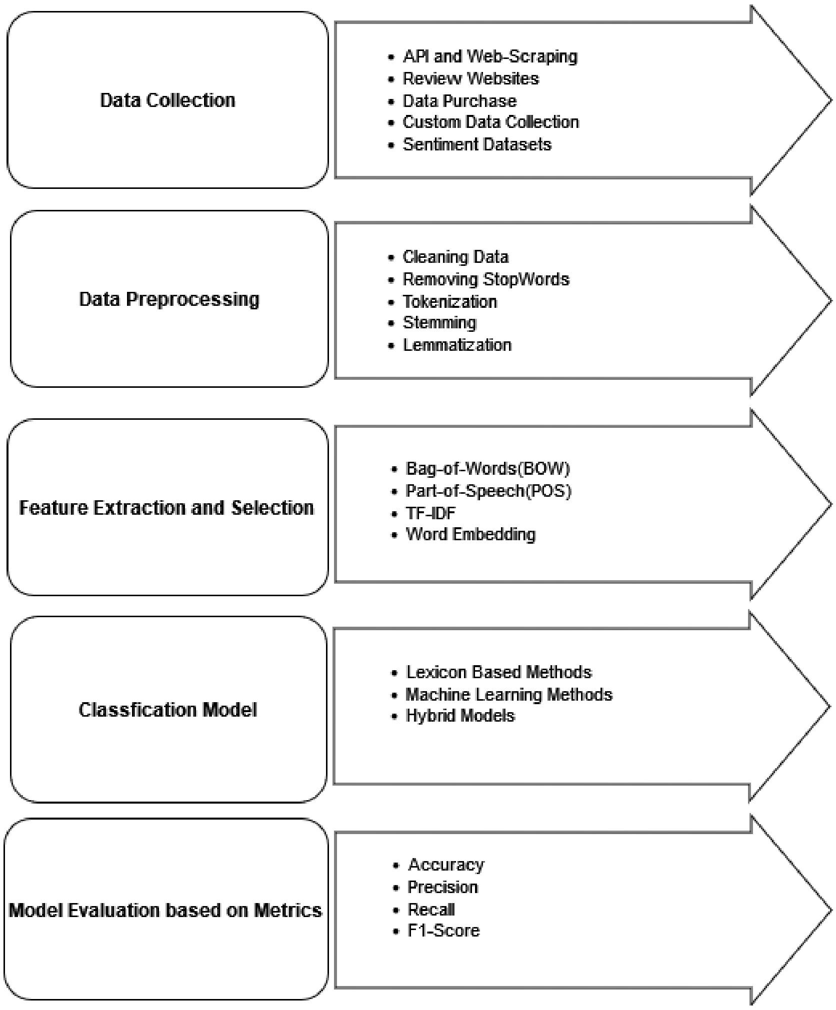


Figure 2.1: Processing steps of Sentiment Analysis

2.1.1 Types of Sentiment Analysis

There are various approaches to sentiment analysis, including lexicon-based methods, machine learning-based methods, and hybrid methods.

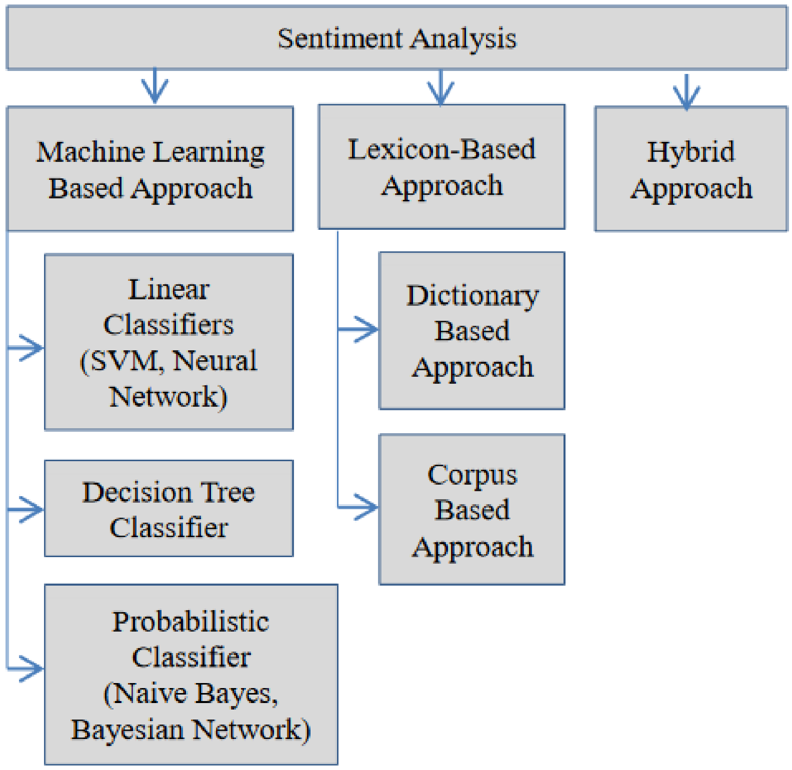


Figure 2.2: Sentiment Analysis Methods

1. **Lexicon Based Approach**

   Lexicon-based sentiment analysis, also known as lexicon-based opinion mining, is an approach to sentiment analysis that relies on predefined lists of words, known as lexicons or sentiment dictionaries, to determine the sentiment expressed in a piece of text. Each word in the lexicon is associated with a sentiment score (positive, negative, or sometimes neutral), and the sentiment of the overall text is calculated on the basis of presence and frequency of these words.This approach is more understandable and can be easily implemented in contrast to machine learning based algorithms.But the drawback is that it requires the involvement of human beings in the process of text analysis. The more prominent the information volume, the more noteworthy the test will be for sifting through the noise, identifying the sentiment and distinguishing helpful data from various content sources.

Lexicon based approach can further be divided into two categories: Dictionary based approach (based on dictionary words i.e. SentiWordNet, AFINN, VADER(Valence Aware Dictionary and Sentiment Reasoner),MPQA Subjectivity Lexicon etc.) and Corpus based approach (using corpus data, can further be divided into Statistical and Semantic approaches).[25]

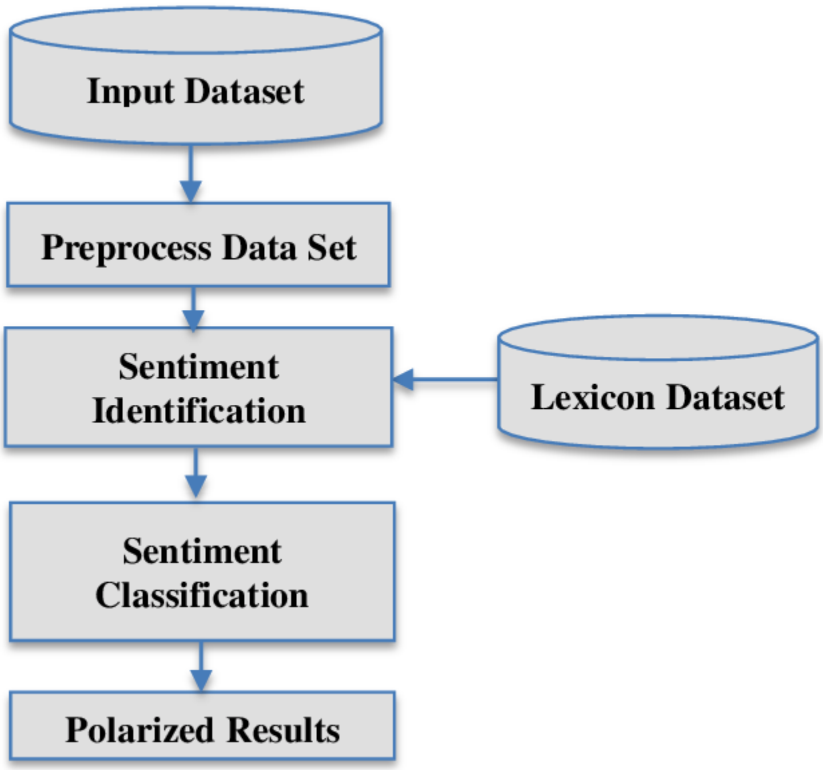


Figure 2.3: General Process of Lexicon-Based Sentiment Analysis

SentiWordNet 3.0:

SentiWordNet is a lexical resource for opinion mining.SentiWordNet assigns to each synset of WordNet three sentiment scores: positivity, negativity, objectivity.[1] It groups English words into sets of synonyms called "synsets", provides short, general definitions, and records the

[1]https://github.com/aesuli/SentiWordNet

various semantic relations between these synonym sets. Synset instances are the groupings of synonymous words that express the same concept. Some of the words have only one Synset and some have several. The goal is to create a merged dictionary and thesaurus that is easier to use and can be integrated into machine learning and artificial intelligence systems.The database and software tools have been released under a BSD style license and can be downloaded and used freely. The database can also be browsed online. SentiWordNet is the result of research carried out by Andrea Esuli and Fabrizio Sebastiani. Given that the sum of the opinion-related scores assigned to a synset is always 1.0, it is possible to display these values in a triangle whose vertices are the maximum possible values for the three dimensions observed. Figure 2.4 shows the graphical model to display the scores of a synset.[2]

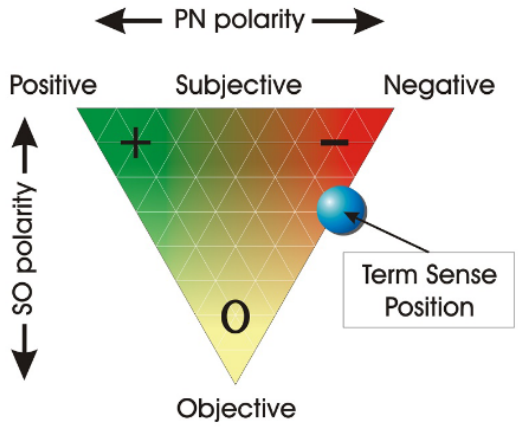


Figure 2.4: Polarity triangle of synset in SentiWordNet

2. Machine Learning Based Approach

In computer science, machine learning is one of the hot topics used in many fields such as natural language processing, sentimental analysis, industry automation, healthcare, agriculture,etc. The machine learning approach to sentiment analysis involves training a model using machine learning algorithms based on set of training data. The training data

[2]https://github.com/aesuli/SentiWordNet/blob/master/papers/LREC06.pdf

consists of texts that are either labeled with their sentiment, such as positive, negative, or neutral or unlaballed datasets. Examples of training data might be star-rated datasets, datasets of reviews by the public, twitter datasets etc .Based on type of algorithm,the machine learning algorithm then learns to identify patterns in the text. Once the model is trained, it can be used to predict the sentiment of new pieces of text.[1] In NLP task Supervised Learning Algorithms are used more oftenly because of its high accuracy. Lexicon based approaches makes use of knowledge of languages to predict the sentiment of the text but they have a lot of disadvantages as the model will be domain specific and cannot be used for texts of other domains while the sentiment of the word can vary from domain to domain. For example, ‘CHEAP’ may be positive in a review in electronics price domain whereas same token ‘CHEAP’ may be negative in electronics quality domain. Machine Learning approach can overcome these disadvantages and give better results when trained with lots of data and tweaked hyperparameters.[14]

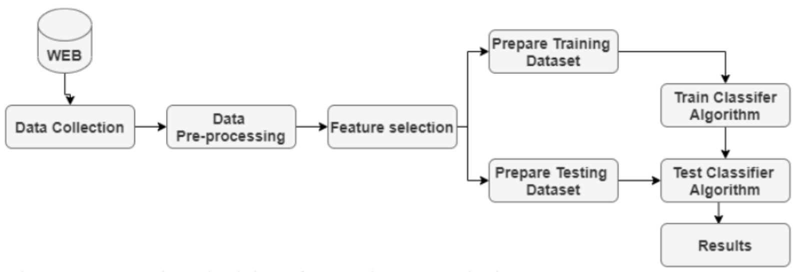


Figure 2.5: General Process of Machine Learning

Support Vector Machines (SVMs) [18, 33] and the Naive Bayes algorithm [19] are the most commonly employed supervised machine learning classification techniques and have shown great accuracies in many NLP tasks including Sentiment Analysis. The reported classification accuracy ranges between 63 percent and 84 percent, but these results are dependent upon the features selected.

Support Vector Machines (SVM):

It is a type of supervised machine learning algorithm used for classification tasks.The primary task of SVM is to create the best hyperplane or boundary that best divides the data into classes by maximizing the distance between the closest data points on each side of the dividing line so that we can place the unknown values in future and categorize it with at most precision.If the data cannot be linearly separated, SVM can transform it into higher dimensions to classify it.[3]

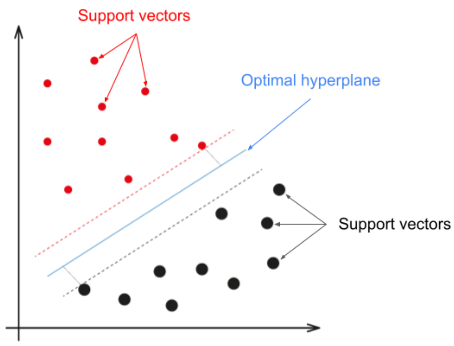


Figure 2.6: General Process of Machine Learning

3. **Hybrid Approach**

A hybrid approach in sentiment analysis refers to a method that combines multiple techniques or models to improve the overall accuracy of sentiment classification. By combining the strengths of different approaches, a hybrid model aims to overcome the limitations in individual methods. The combination may involve the integration of both lexicon-based and machine learning-based techniques or the fusion of sentiment analysis with other natural language processing (NLP) tasks. Lexicon-based methods may be good at capturing explicit sentiment, while machine learning models can learn more complex patterns in language and improve the accuracy.

2.1.2 Issues in Sentiment Analysis

Sentiment analysis, the task of classifying text as positive, negative, or neutral, can be considered a type of content categorization. However, sentiment analysis is a complex and challenging task due to several factors.Some of them are listed below :

1. **Sarcasm**

   When a user/author/content creator is using a positive sentence to describe anything but his/her intentions are negative or they mean just opposite then such sentences can be described as sarcasm. It is very difficult for a system to identify the sarcastic sentence and is a challenging task. Different users use sarcasm in a different manner. For example, 'This food is good enough to waste money' is a sarcastic sentence.

2. **Negation Detection**

   Negation Detection and handling is important aspect of sentiment analysis as it changes the polarity of the associated adjective and hence the polarity of the whole text is altered. For example, "The University is good" can be classified as positive or "The University is not good" can be classified as negative. But for sentences like "Not only the University is good, the learning environment is also very pleasing " , the negation handling can be more complicated.

3. **Polysemy**

   Short texts are usually rather ambiguous because of polysemy. Polysemy is the coexistence of multiple word meanings and commonly appears in every language. Various uses of a word may assign the word both positive and negative meanings.When words have more than one meaning (e.g."The suitcase is light, making it easy to carry." vs. "The room is too light, I prefer it darker."), then it becomes more challenging for the algorithm to differentiate what the intended meaning is. Thus, as the word is not evaluated in its context, the results of the analysis can be inaccurate.[29]

4. **Domain Adaptation**

   The context in which a word is used has a major impact on how it is viewed. Hence it is a domain change depending on the context of their referral. For instance, the word "soft" denotes warmth in a positive way, yet applying it to athletes may be offensive. It is a particularly important factor to think about when researching about sentiments.[24]

5. **Handling Multilingual Text**

   Sentiment analysis is a hard problem, while multilingual sentiment analysis is even harder due to the different expression styles in different languages. Although many methods for multilingual sentiment analysis have been developed in the open literature, most of them suffer from two major problems. The first is their excessive dependence on external tools or resources (e.g., Machine translation systems or bilingual dictionaries), which may not be readily obtained, especially for minority languages, The second is conflicting sentiments, i.e., The sentiment polarity of some parts of a text is inconsistent with its overall sentiment polarity.[13]

2.2 Related work on Sentiment Analysis for Search Result Snippets

Sentiment analysis is a growing area of research, and several studies have focused on analyzing sentiment in various forms of text data. While sentiment analysis has been applied to product reviews, customer feedback, and social media monitoring, relatively little research has been conducted on sentiment analysis for search result snippets. Here are some literature that provide a quick overview about some of sentiment analysis researches performed on search result snippets.

According to a study titled "OK, Google, Tell me about Birth Control: Sentiment Analysis of Anti- and Pro- Birth Control Headlines and Snippets" by Young et al., aimed to explore the difference between the information available online by comparing word usage, sentiments, and online popularity of headlines and snippets returned by Google Search engine.The sentiment analysis was focused on identifying the emotional tone (positive, negative, or neutral) conveyed in the birth control headlines and snippets.[36]

A research paper titled "Effectiveness of web search results for genre and sentiment classification" published in the Journal of Information Science examines the effectiveness of using search result snippets for genre and sentiment classification tasks.[16]

Similarly, another research paper titled "Sentiment Polarity Analysis for Generating Search Result Snippets based on Paragraph Vector," a method was proposed for extracting reputation sentences from search result snippets based on a given search query and generating search result snippets that consider sentiment polarity. Research method was based on this PV and logistic regression for analyzing sentiment polarities. The aim of the study was to generate modified snippets that are generated by considering sentiment polarity by analyzing sentiment polarities in web documents of search results.The proposed algorithm was implemented by showing modified search result snippets based on search results obtained from the Google search engine[31]

A study by X et al.,(2011) proposed an unsupervised learning approach for sentiment classification of Chinese online reviews based on search engine snippets. The approach involves extracting sentiment phrases and calculating sentiment orientation using snippets from search engines and the review is predicted as recommended or not recommended.[12]

Na et al.(2004) developed a prototype system that performed sentiment categorization of Web search results by classifying a document as positive or otherwise by analyzing either the document snippets from the search engine or the full document content pointed to by the URL.The motivation of the study was to enhance general topical search with a sentiment-based one where the search results (snippets) returned by the web search engine are clustered by sentiment categories. Firstly they developed an automatic method to identify product review documents using the snippets (summary information that includes the URL, title, and summary text), which is genre classification. Then the identified snippets were automatically classified into positive (recommended) and negative (non-recommended) documents, which is sentiment classification.In this study only the snippets rather than their original full-text documents were used, and a common machine learning technique, SVM (support vector machine), and heuristic approaches were applied to investigate how effectively the snippets can be used for genre and sentiment classification. The results showed that the web search engine should improve the quality of the snippets especially for opinionated documents[16]

A study conducted by Demartini and Siersdorfer utilized the search API from three commercial search engines (Google, Yahoo, and Bing) to gather the top 50 retrieved results for 14 controversial queries. In order to extract sentiment information and detect opinionated documents, the authors applied machine learning techniques (Support Vector Machines trained on Amazon review data) and lexicon-based approaches (based on SentiWordNet). The results revealed no significant difference between the three considered search engines, while variations in sentiments expressed in retrieved pages for different queries were observed. Furthermore, the study identified a relationship between rank and sentiment; for instance, results ranked first by search engines tended to contain, on average, a more positive opinion about the topic expressed by the query compared to other results.[28]

2.3 Related work on hybrid approaches for sentiment analysis

Moreover, some more literature can be taken into consideration that describes hybrid approaches that has been widely used in sentiment classification task.

In a research by Bhalerao [2], he proposed a hybrid technique of Lexicon and Machine Learning based Classification model to classify reviews by conducting Sentiment Analysis of Beauty products available on Amazon.com in order to help customers with the decision-making process by providing the product with the most positive ratings and negative ratings. In this research project, two feature extraction techniques, namely CountVector and TF-IDF, were used to perform classification using SVM, Naive Bayes, and Logistic Regression. The best results among all were obtained by Support Vector Machine (SVM) with an overall accuracy of 91%. The precision, recall, and f1-score for the same were 0.90, 0.64, and 0.75, respectively.

In a Conference proceedings paper entitled "Comparative Analysis of Customer Sentiments on Competing Brands using Hybrid Model Approach" [30], the authors utilized the sentiment analysis approach to derive individual user perceptions about the different features of the new releases of two leading Smartphone brands in India—Vivo and Oppo. The tweets pertaining to the two smartphones, Vivo Nex and Oppo FindX, were used as individual customer feedback, and the sentiment for each tweet was classified using a hybrid model, which was a combination of Lexicon-Based Sentiment analysis and Naive Bayes algorithms, thus obtaining better accuracy. As indicated by the statistics, the hybrid model's resultant training and testing accuracy was approximately 84% and 77%.

Gupta et al. [5] presented a hybrid approach to address Twitter analysis. In the first phase, they used the most frequent and general-purpose SentiWordNet (SWN) lexicon resource to generate the feature vector. In the second phase, they trained the Support Vector Machine (SVM) model on the SWN-based generated feature vector. To evaluate the effectiveness of the proposed hybrid approach, they used the publicly available SemEval-2013 competition dataset, achieving a testing accuracy of approximately 60%. Similiarly, Shindhe et al. [27] performed sentiment analysis on tweets using Text Mining methods such as Lexicon and Machine Learning Approach. In the first step, they searched for polarity words from a predefined lexicon dictionary (MPQA Lexicon) to determine the polarity of the tweets. In the second step, they trained the Support Vector Machine (SVM) machine learning algorithm using the polarities obtained in the first step.

A study by Haripriya et al. [8] used a model for performing real-time sentiment analysis of top trending events for a given location on social media. They developed a hybrid approach that combined various combinations of Sentiment lexicon, unigram and bi-gram language models, along with Naïve Bayes and Support Vector Machine learning algorithms, for analysis. The results obtained from these combinations were evaluated to check the performance of the model based on various parameters, such as data size, feature selection method, training and testing data set, and time. The hybrid model developed by combining sentiment lexicon, unigram language model with Support Vector Machine algorithm gave the maximum accuracy compared to other combinations on location-based real-time social media data, with the accuracy ranging from 60% to 90%.

Another notable work by Razali et al.(2023) proposed a new theoretical framework for predicting political security threats using a hybrid technique: the combination of lexicon-based approach and machine learning in cyberspace. In the proposed framework, NRC emotion lexicon together with Decision Tree, Naive Bayes, and Support Vector Machine were deployed as threat classifiers where the hybrid Lexicon-based approach with the Decision Tree classifier recorded the highest performance score for predicting political security threats. [23]

Rajeswari et al. [21] employed a hybrid approach that combined a lexical approach (SentiWordNet) with machine learning algorithms such as Support Vector Machine, Decision Tree, Logistic Regression, and Naive Bayes for sentiment analysis. The aim was to resolve neutral opinions beyond the binary categorization of customer reviews. In comparison, the results proved that Support Vector Machine and Logistic Regression algorithms outperformed the other two algorithms, achieving an accuracy of about 80%, which was on average different by 6% to 10% when compared to the other algorithms.

Although, there are many literature on performing sentiment analysis on short texts, only limited research are done specifically for search result snippets. Furthermore, all of these researches are based on specific domains which somehow helps to simplify the classification process and make more accurate predictions.Analyzing sentiment in snippets that lack specific domain seems to be a particularly challenging task.Nonetheless, only after evaluation of the proposed model's performance, we can draw conclusions.

Chapter 3

Implementation

This section contains a brief review of the architecture and implementation process of Sentiment Analysis taks that will be performed. In figure 4.1, the architecture of web development with Django and React is divided into different components. The description of each part is given separately.

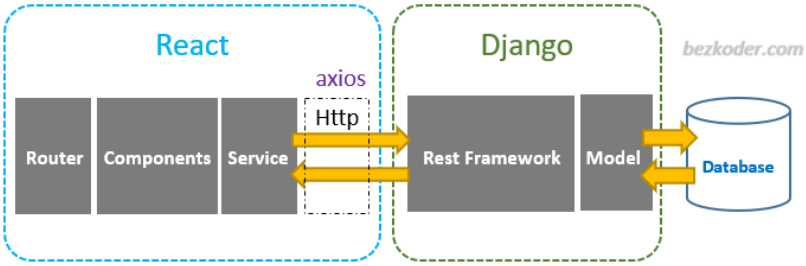


Figure 3.1: Processing steps of Sentiment Analysis

3.1 Backend

3.1.1 Django

Django is a high-level Python web framework that encourages rapid development and clean, pragmatic design. Built by experienced developers, it takes care of much of the hassle of web development, so one can focus on writing app without needing to reinvent the wheel.[1] It's free and open source.This framework was developed between 2003 - 2005 and has had many releases

[1]https://www.djangoproject.com/

since then and added much functionality and supports for new technology.[2] In figure 4.2, Django architecture is represented. and is desribed as follows.[3]

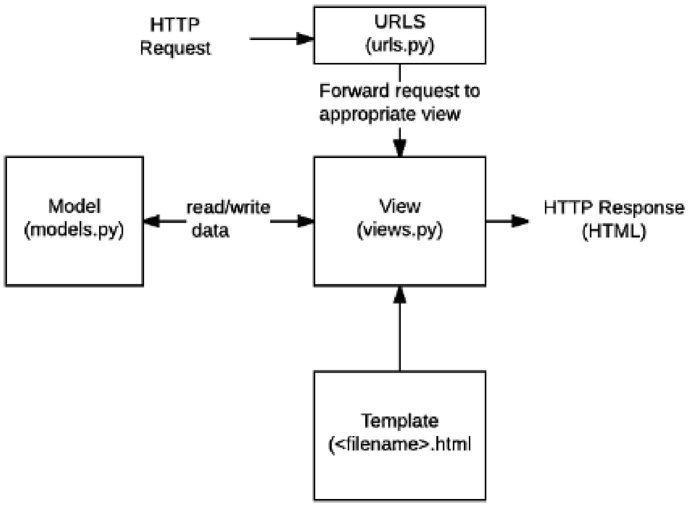


Figure 3.2: Processing steps of Sentiment Analysis

1. **URLs :** It is a convenient way to handle HTTP requests in Django. In order to redirect HTTP requests to a proper view, a URL mapper is present.

2. **View :** Django has the concept of "views" to encapsulate the logic responsible for processing a user's request and for returning the response. A view is functioning as a request handler. This function returns an HTTP response after processing HTTP requests.Models give views access to the data assign the response formatting to templates.

3. **Templates :** The template layer provides a designer-friendly syntax for rendering the information to be presented to the user. A template is a text file that defines the structure and layout of a file (such as an HTML page), with placeholders for actual content. A view can use an HTML template to dynamically construct an HTML page and populate it with data from a model.

[2]https://www.developer.mozilla.org
[3]https://docs.djangoproject.com/

4. **Models :** Django provides an abstraction layer (the "models") for structuring and manipulating the data of in web application. Models are Python objects that specify the structure of an application's data and provide techniques for managing (adding, modifying, and deleting) and querying database entries.

3.1.2 Django Rest API

Django REST framework[4] is a powerful and flexible toolkit for building Web APIs, which makes serializations easy. API is a way of access to a database. The API backend handles sending queries to the backend and usually gets a response in JSON format. These API requests are supported by the Django rest framework:

1. **GET :** Returns some data from the API based on the endpoint you visit and any parameters you provide.

2. **POST :** Creates a new record that gets appended to the database.

3. **PUT :** Looks for a record at the given URI you provide. If it exists, update the existing record. If not, create a new record DELETE Deletes the record at the given URI.

4. **PATCH :** Updates individual fields of a record

3.1.3 BeautifulSoup

Beautiful Soup is a powerful tool for web scraping, but it's also user-friendly for beginners. Beautiful Soup is a library that makes it easy to scrape information from web pages. It sits atop an HTML or XML parser, providing Pythonic idioms for iterating, searching, and modifying the parse tree.[5].Beautiful Soup provides a simple interface to navigate, search, and modify the parse tree, which makes it ideal for beginners. However, like any tool, it has its limitations. For instance, it can't interact with JavaScript on a webpage. For webpages that rely heavily on JavaScript, one might need to

[4] https://www.django-rest-framework.org/
[5] https://pypi.org/project/beautifulsoup4/

use other tools like Selenium. But for many web scraping tasks, Beautiful Soup is more than capable.[6]

3.1.4 NLTK

NLTK-(language processing modules and validation): The Natural Language Processing Toolkit (NLTK) is an open source language processing module of human language in python. Created in 2001 as a part of computational linguistics course in the Department of Computer and Information Science at the University of Pennslyvania. NLTK is a leading platform for building Python programs to work with human language data. It provides easy-to-use interfaces to over 50 corpora and lexical resources such as WordNet, along with a suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning, wrappers for industrial-strength NLP libraries.[7]

3.2 Frontend and Visualization

React (an open-source JavaScript library) is used for Frontend implementation, and on top of this framework, Recharts is deployed as visualization and design library.

3.2.1 React js

React.js, commonly referred to as simply React, is a JavaScript framework created by developers at Facebook, to solve the problem of building complex user interfaces in a consistent and maintainable way. React.js shrugs away common front-end conventions in an effort to make things more efficient.It was first released in May 2013, and is maintained by Meta (formerly Facebook) and a community of individual developers and companies.

React allows developers to create large web applications that use data and can change over time without reloading the page. It primarily aims to provide speed, simplicity, and scalability.The core principles behind React are component-based architecture, unidirectional data flow and virtual DOM. React also has a significant number of other advantages over other frameworks. It speeds up the development process due to its modular structure allowing developers to work in parallel on individual component.Each component will have its own structure, functions, and APIs that other components

[6] https://ioflood.com/blog/beautiful-soup/

[7] https://www.nltk.org/

can utilize. It is flexible and easy to maintain, it has been designed for high performance, and it allows for mobile development with React Native. Currently, React is one of the most popular JavaScript frontend frameworks with many popular organizations like Facebook, Instagram, Airbnb, Twitter, and Netflix using it extensively. [22, 6]

3.2.2 Recharts

Recharts is one of the best React charting libraries with the only downside of quite a massive bundle size. It supports server-side rendering, responsive charts, many different chart types, and features. Based on famous and time-tested D3.js, it shares similar extensibility principles and gives you control over the whole rendering. We will share some of the advanced tips for responsive server-side rendering, gradient shadows, and overlays.[8] Main principles of Recharts are:

1. **Simply** deploy with React components.

2. **Native** SVG support, lightweight depending only on some D3 submodules.

3. **Declarative** components, components of charts are purely presentational

[8] https://leanylabs.com/blog/awesome-react-charts-tips

3.3 Methodology

3.3.1 Overview of Methodology

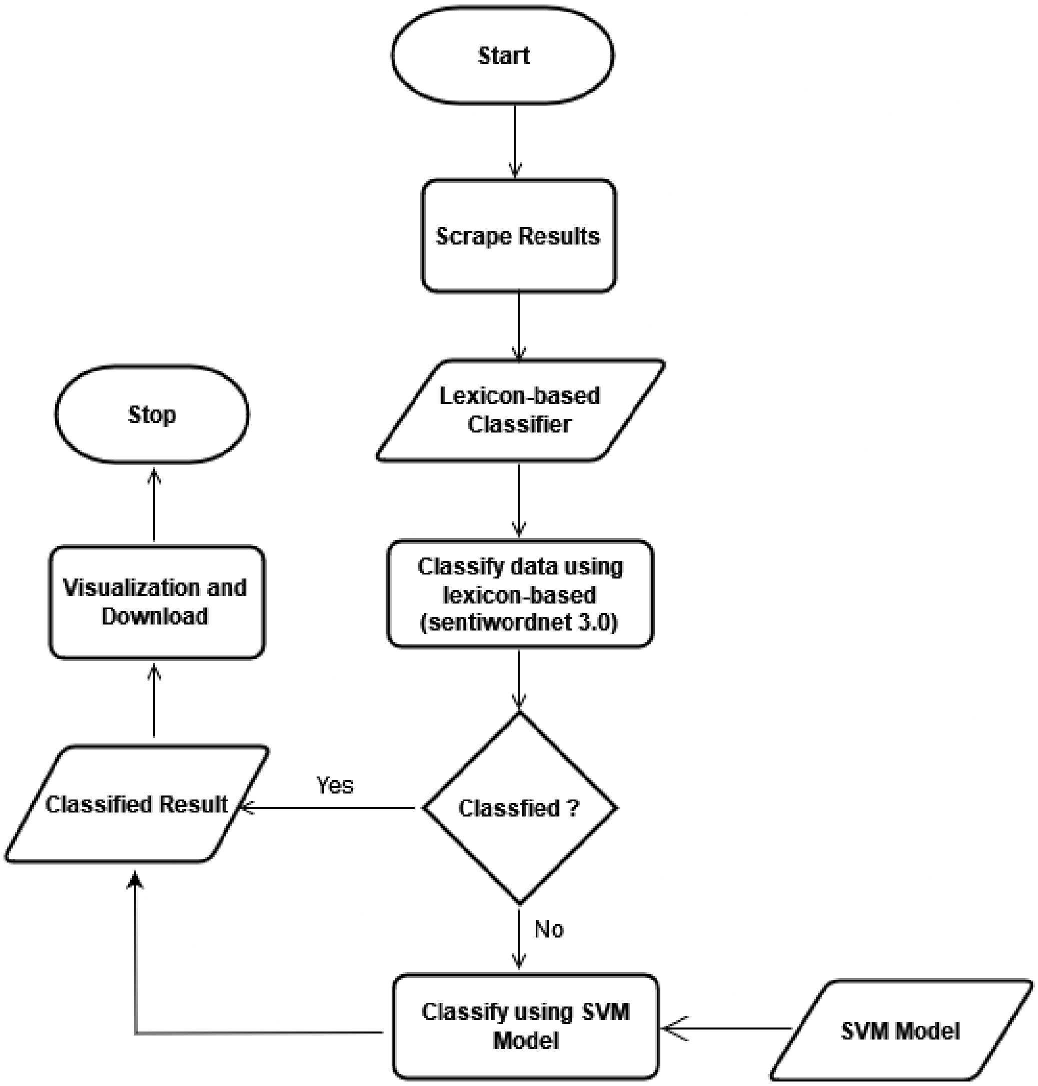


Figure 3.3: Methodology

Search result snippets may contain a variety of text such as informative, descriptive, summary, categorization, etc., that can be related to any domain. Sentiment analysis on such texts cannot be done accurately until the domain is classified because different words may have different sentiment labels in different specific domains. Furthermore, snippets contain very few words, so it can be difficult to decide which domain should be used for sentiment classification. To address this situation and to achieve a better perfomance and high accuracy, a hybrid sentiment analysis approach is proposed [20, 5, 7]. This hybrid approach combines a lexicon-based approach and a machine learning approach. The lexicon-based approach relies on a sentiment dictionary in the form of word data that contains a collection of words having different sentiment values. On the other hand, the learning approach implements a machine learning algorithm by using existing linguistic features [5]

3.3.2 Datasets used

In this process, We use two types of datasets. For the Lexicon based Sentiment Analysis (SA) approach, the datasets are collected using webscraping from different search engines (Google, bing, DuckDuckGo) for any query or the sets of multiple queries .Each data in scraped datasets contains three fields url, title and snippet.Only snippets of each data is used for sentiment analysis whereas url and title are used later for visualization task to give complete information about the results.The collected data may not be in suitable form to be used directly for sentiment analysis, so various pre-processing steps like removing symbols, converting into small letters etc. would be applied for cleaning of data.

In the context of employing a machine learning (SVM) model, the datasets obtained from the Lexicon-based Sentiment Analysis (SA) approach, consisting of snippets along with their associated sentiment labels is used as the primary source for training and testing the model.To improve the accuracy of predictions and make variations in the training data, additional datasets are used. Specifically, the Amazon Reviews for Sentiment Analysis datasets from Kaggle are utilized.[9] This additional dataset contributes diverse examples, enhancing the training process and improving the model's ability to apply sentiment patterns for diverse data.

Sample of datasets used for lexicon based approach as well as machine learning approach are given below :

[9]https://www.kaggle.com/datasets/bittlingmayer/amazonreviews

URL	**Title**	**Snippets**
https://www.nytimes.com/2022/01/29/opinion/holocaust-poland-europe.html	The New Wave of Holocaust Revisionism - The New York Times	The New Wave of Holocaust Revisionism. Mr. Grabowski is a professor of history at the University of Ottawa. WARSAW — The earth outside the tiny village of Treblinka, in eastern Poland, still ...
https://www.jstor.org/stable/j.ctv7xbrh4.38	The Holocaust Historiography on the Holocaust in Poland: An Outsider's ...	Historiography of the Holocaust in Poland. Therefore, in this essay I will present an outsider's view of the place of this historiography within the larger picture of. Confino, 1 Alon. Foundational Pasts: The Holocaust as Historical Understanding (Cambridge: Cambridge University Press, 2012), 1. The Holocaust
https://en.wikipedia.org/wiki/Poland%27s_Holocaust	Poland's Holocaust - Wikipedia	Poland's Holocaust: Ethnic Strife, Collaboration with Occupying Forces and Genocide in the Second Republic, 1918-1947 is a 1998 book by sociologist Tadeusz Piotrowski.
https://time.com/5534494/poland-jews-rebirth-anti-semitism/	How Poland's Jewish Community Is Emerging from the Shadow of its ... - TIME	In 1939, the city of Krakow was home to 70,000 Jews, a quarter of the city's population. Today around 100 Jews live there—or at least that's what the guidebooks say. According to Jonathan ...

Table 3.1: Example Dataset for Lexicon-based Method

Snippets	Sentiment
In September 1939, the Germans launched a campaign of terror intended to destroy the Polish nation and culture. Learn more about the German occupation of...	Negative
Jews lived in Poland for 800 years before the Nazi occupation. On the eve of the occupation 3.3 million Jews lived in Poland – more than any other country ...	Neutral
According to recent reliable reports received from leaders of the underground movement in Poland, the process of extermination of the Polish Jewish population ...	Positive
During World War II, the Nazis established ghettos, which were areas of a city where Jews were forced to live. Learn more about ghettos in occupied Poland...	Negative

Table 3.2: Example Dataset used for Training SVM

3.3.3 Data preprocessing

This is one of the key steps of any NLP task. The raw text data collected in the previous step has to be pre-processed to clean the data and optimize the classification. There are a number of pre-processes that need to be done on the raw text to feed into the next step. Figure 3.4 shows key steps of NLP pre-processing.

1. **Lowering and Punctuation :** This is the basic step of NLP pre-processing where the text is lowered and punctuations are removed to clean the text. Punctuation adds unnecessary information to the data, which should be removed to decrease computational cost and get better results. For example, consider the text "It is Good......." It will be converted to "it is good." The length of the text is reduced, but the meaning remains the same, and the orientation of the text is constant.

2. **Tokenization :** This is the fundamental step of pre-processing where we divide the text into smaller chunks or tokens to make further processes easier. Tokens are the minimum units, usually words. These tokens are further converted to vectors or numerical values to feed to

a classifier. For example, a review sentence "the food was good" after tokenization will be ['the', 'food', 'was', 'good'].[10]

3. **Stopword Removal :** At this stage, we remove the Stopwords from the tokenzied data.Stopwords are commonly used words that typically don't carry much sentiment or meaning on their own (e.g., articles, prepositions, conjunctions)[11].Removing stopwords will help reduce the vocabulary size without affecting the performance of the model. Here's a simple example to illustrate the impact: Original Tokens: "['the',' weather',' today',' is' ' not',' bad',' but',' i',' forgot',' my ','umbrella'] After Stopword Removal: ['weather',' today',' not',' bad','but',' forgot ','umbrella']

4. **Stemming :** Stemming is a process of converting a token into its stem form or root form. The prefixes and suffixes are removed in this step as they don't add any significant meaning to the token. For example, go, going, gone will be converted to go, as the base meaning and orientation of all the words are the same. This will help reduce the size of the vocabulary.[12]

5. **Lemmatization :** Lemmatization is the process of converting tokens to their lemmas. Morphological variations of the same word are avoided by converting tokens to their base form or lemmas.[13]

[10] https://www.nltk.org/api/nltk.tokenize.html
[11] https://pythonprogramming.net/stop-words-nltk-tutorial/
[12] https://nlp.stanford.edu/IR-book/html/htmledition/stemming-and-lemmatization-1.html
[13] https://nlp.stanford.edu/IR-book/html/htmledition/stemming-and-lemmatization-1.html

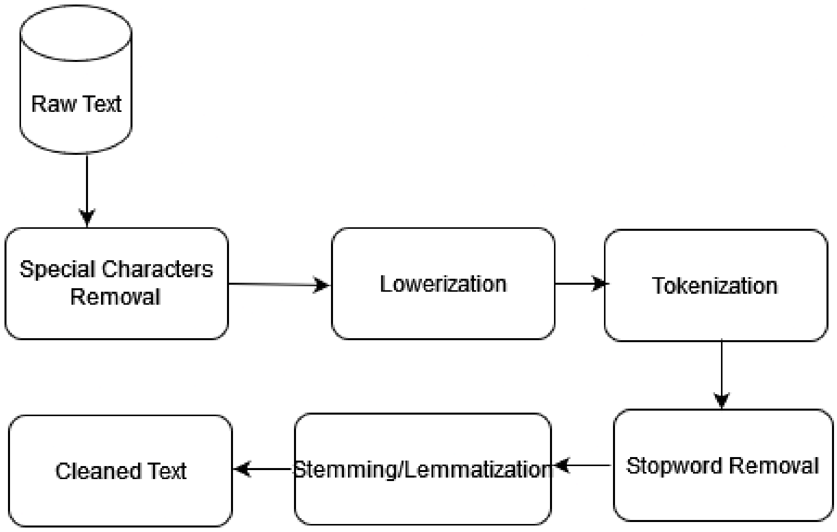


Figure 3.4: Processing steps of Sentiment Analysis

3.3.4 Feature extraction

Feature extraction is a process of extracting important information from text data.

1. **Pos Tagging:** Part-of-Speech (POS) tagging can be considered a form of feature extraction in lexicon-based sentiment analysis. POS tagging provides contextual information about words in a text, which can be crucial for accurately determining sentiment.[9] Part-of-Speech (POS) tagging in lexicon-based sentiment analysis is a process that involves assigning grammatical categories, such as noun, verb, adjective, etc., to each word in a text.In summary, POS tagging helps to understand the grammatical context of words in a sentence, which can be crucial for accurately determining sentiment in lexicon-based sentiment analysis.[32]

   NLTK POS tag is the practice of marking up the words in text format for a specific segment of a speech context is known as POS Tagging (Parts of Speech Tagging). It is in charge of interpreting a language's text and associating each word with a specific token. Grammar tagging is another term for it. A part-of-speech tagger, also known as a POS-tagger, analyses a string of words.[14]

   Finally, converting the POS tag to SentiWordNet POS tags is necessary with the following rules :

[14] https://www.nltk.org/book/ch05.html

Tag	Description	Example
CC	Coordinating conjunction	and, but, or
CD	Cardinal number	one, two, three
DT	Determiner	the, a, an
EX	Existential there	there
IN	Preposition or subordinating conjunction	in, on, at
JJ	Adjective	big, old, green
RP	Relative pronoun	who, which, that
RPS	Relative pronoun, possessive	whose
JJR	Adjective, comparative	better, faster, stronger
JJS	Adjective, superlative	best, fastest, strongest
NN	Noun, singular or mass	dog, water, love
LS	List item marker	1, One, I
MD	Modal	can, will, must
NNS	Noun, plural	dogs, waters, loves
NNP	Proper noun, singular	John, Paris, Fido
NNPS	Proper noun, plural	the Johnsons, the United States, the Beatles
PDT	Predeterminer	all, both, many
POS	Possessive ending	's, s'
PRP	Personal pronoun	I, you, he, she, it, we, they
PRP$	Possessive pronoun	my, your, his, her, its, our, their
RB	Adverb	quickly, slowly, well
RBR	Adverb, comparative	more quickly, more slowly, better
RBS	Adverb, superlative	most quickly, most slowly, best
UH	Interjection	oh, wow, ouch
TO	to	to
VB	Verb, base form	run, jump, eat
VBD	Verb, past tense	ran, jumped, ate
VBG	Verb, gerund or present participle	running, jumping, eating
VBN	Verb, past participle	run, jumped, eaten
VBP	Verb, non-3rd person singular present	run, jump, eat
VBZ	Verb, 3rd person singular present	runs, jumps, eats
WDT	Wh-determiner	which, what, how many
WP	Wh-pronoun	who, which, what
WP$	Possessive wh-pronoun	whose
WRB	Wh-adverb	where, when, why

Table 3.3: POS Tag Reference Table

(a) Noun (N) If POS tags are 'NN', 'NNS', 'NNP', 'NNPS', then the POS tags are changed into 'N'.

(b) Verb (V) If POS tags are 'VB', 'VBD', 'VBG', 'VBN', 'VBP' or 'VBZ', then the POS tags are changed into 'V'.

(c) Adjective (A) If POS tags are 'JJ', 'JJR', or 'JJS', then the POS tags are changed into 'A'.

(d) Adverb (R) If POS tags are 'RB', 'RBR', or 'RBS', then the POS tags are changed into 'R'.

2. **TF-IDF or Term Frequency –Inverse Document Frequency :** The pre-processed text cannot be directly fed as input to the machine learning classifier. The feature extraction is carried out using TF-IDF. It is a feature extraction method in NLP which also reflects how important a token is in the document in corpus of documents is a method for converting a document (sentence) in a corpus into a statistically measurable weight.This weight represents how important the word is in the document or phrase. [35] The TF-IDF model weights words according to their occurrence in each sentence. The basic formulas used for TF-IDF are given by:

$$\textbf{Term Frequency (TF)} = \frac{\text{Number of times token } t \text{ appears in a sentence}}{\text{Total number of tokens in a sentence}} \tag{3.1}$$

$$\textbf{Inverse Document Frequency (IDF)} = \log\left(\frac{\text{Total number of sentences}}{\text{Number of sentences with token } t \text{ in it}}\right) \tag{3.2}$$

$$\textbf{TF-IDF} = \text{TF} \times \text{IDF} \tag{3.3}$$

For instance, consider two sentences s1=" the view was bad" and s2=" the food was tasty". To covert these into vector using TF-IDF method, the vocabulary is created using both the sentences. V= 'the', view', 'was', 'bad', 'food', 'tasty'.

Tokens	the	view	was	bad	food	Tasty
S1	0	0.3465	0	0	0	0.3465
S2	0	0	0	0	0.3465	0.3465

Table 3.4: Term Frequencies

Tokens	the	view	was	bad	food	Tasty
S1	0	0.3465	0	0	0	0.3465
S2	0	0	0	0	0.3465	0.3465

Table 3.5: Inverse Document Frequencies

3.3.5 Sentiment Calculation

1. **Sentiment Calculation for Lexicon Based Model :** Snippets barely contains two to three sentences, so the score for each word is calculated first, and then the total score for the whole sentences are is calculated. SentiWordNet dictionary is used for assigning the polarity to each word. Then the polarity of the whole sentence is calculated by adding the polarity of each word. SentiWordNet is a lexical resource publicly available for research purposes.

   SentiWordNet is an opinion lexicon derived from the WordNet[15] database where each term is associated with numerical scores indicating positive, negative, and objective sentiment information. SentiWordNet is built via a semi-supervised method along with a Random Walk algorithm for refining the score. In this, the position of the word in the sentence is also referred.

   If the word is not found in the SentiWordNet dictionary, then the word is searched in the WordNet dictionary. WordNet[16] is a dictionary for the English language containing synonyms grouped into a set called a synset. The corresponding words associated with the word in WordNet are brought and searched in SentiWordNet, and their sentiment score

[15]https://github.com/aesuli/SentiWordNet
[16]https://wordnet.princeton.edu/

is taken for polarity calculation. This process helps to increase the accuracy of the proposed approach.

After obtaining the parts of speech (POS) for each word, a sentiment score is computed based on the 'Positivity' and 'Negativity' scores of each word. For example, consider the sentence "**Food was bad.**" Here, the word "**was**" is considered as a stopword and removed as part of preprocessing. For the remaining words, according to SentiWordNet:

$$\{'Word' :' food',' POS' :' NN',' Positivity' : 0.0,' Negativity' : 0.0416666666666\}$$
$$\{'Word' :' bad',' POS' :' JJ',' Positivity' : 0.0178571428571,' Negativity' : 0.66071428571\}$$

The word "**food**" has a Positivity score of 0.0 and a Negativity score of 0.0416. Similarly, the word "**bad**," has a Positivity score of 0.0178 and a Negativity score of 0.6607. The Sentiment Score for each word is computed as the difference between 'Positivity' and 'Negativity,'.

$$\text{Sentiment Score} = \text{Positivity} - \text{Negativity}$$

Sentiment Score("food") = 0.0 - 0.0416 = -0.0416
Sentiment Score("bad") = 0.0178 - 0.6607 = -0.6428

After Sentiment Scores per word are obtained, we have to do a total calculation to get sentiment score for whole sentence(Total Sentiment Score).Total Sentiment Score is determined by summing up all sentiment scores.

$$\text{Total Sentiment Score} = \sum \text{Sentiment Score}$$

Total Sentiment Score = Sentiment Score("**food**") + Sentiment Score("**bad**")
= 0.6844

Subsequently, the Total Sentiment Score is normalized to the range of(-1 to 1)using the hyperbolic tangent (tanh) function which provides a standardized sentiment score for the entire sentence within the specified range.

$$\text{Normalized Total Sentiment Score} = \tanh(\text{Total Sentiment Score})$$

For the sentence "**Food was bad.**" the Normalized Total Sentiment Score will be:

Normalized Total Sentiment Score = tanh(-0.6428) = -0.5734

Based on the value of Normalized Total Sentiment Score, Equation (3.1) is applied to get final sentiment label.

$$\text{Sentiment} = \begin{cases} \text{Positive} & \text{if Normalized Total Sentiment Score} \geq 0.25 \\ \text{Negative} & \text{if Normalized Total Sentiment Score} \leq -0.025 \\ \text{Neutral} & \text{otherwise} \end{cases} \tag{3.4}$$

The sentiment value is determined based on the Normalized Total Sentiment Score. If the Normalized Total Sentiment Score is equal to or greater than 0.25, the sentiment is considered Positive. Conversely, if the Normalized Total Sentiment Score is less than or equal to -0.025, the sentiment is categorized as Negative. For cases where the Normalized Total Sentiment Score lies between -0.025 and 0.25, the sentiment is labeled as Neutral. So for our sentence **"Food was bad"**, it will be classified as Negative Sentence.

In cases where Positivity or Negativity score is not found for any words in the entire sentence (i.e., a Total Sentiment Score of 0), the snippets are then forwarded to an SVM model for further classification. For example,
" The dinner wasn't what we expected. "

Here, there are only words with both Positivity and Negativity Scores zero so the SVM model will be used to determine the sentiment of such sentences.

Similarly, Negation words are the words that, when present in the sentence, reverse the polarity of the sentence. For example, in the text "this smartphone is not good," the negation word "not" reverses the polarity of the sentence. Similar to negation words, intensifiers such as "very" and "extremely" enhance or amplify the polarity of the statement and contribute to strengthen the positive or negative nature of the sentence. For example, "this smartphone is very good," the intensifier "very" magnifies the positive sentiment.

To handle this, fuzzy logic is used, which calculates the polarity based on some rules. The fuzzy logic rules are described as follows.

Case 1. There are few adverbs like very, really, extremely, always, absolutely, highly, etc., which may be used positively or negatively like very good, very bad etc.

$$\text{Sentiment Score} = \begin{cases} (\text{Sentiment Score (Adj)}) \times 2 & \text{if Sentiment Score(Adj)} > 0; \\ (\text{Sentiment Score (Adj)})^{0.5} & \text{if Sentiment Score(Adj)} < 0; \end{cases}$$

For example, the Sentiment Scores for adjectives "good" and "bad" are 0.54 and -0.56, respectively. If the adverb "very" comes together with both adjectives, the updated Sentiment Scores for "very good" and "very bad" will be as follows:

$$\text{Sentiment Score (good)} > 0, \text{ so}$$
$$\text{Sentiment Score} = \text{Sentiment Score(good)} \times 2 = 0.54 \times 2 = 1.08$$

$$\text{Sentiment Score (bad)} < 0, \text{ so}$$
$$\text{Sentiment Score} = \text{Sentiment Score(bad)}^{0.5} = (-0.56)^{0.5} = -0.7483$$

Case 2. Negation words such as "never" and "not" reverse the orientation of the opinion.
For example, the phrase "not good" may signify "bad." When such negation words are detected, the Positivity and Negativity scores of the corresponding word are swapped.
Original Positivity and Negativity scores for "good":

$$\text{Positivity} = 0.619, \quad \text{Negativity} = 0.005$$

$$\text{Sentiment Score} = \text{Positivity} - \text{Negativity} = 0.619 - 0.005 = 0.614$$

If a negation word is present, swap the scores:

$$\text{Positivity} = 0.005, \quad \text{Negativity} = 0.619$$

$$\text{Sentiment Score} = \text{Positivity} - \text{Negativity} = 0.005 - 0.619 = -0.614$$

Case 3. When Case 1 and Case 2 may appear together like "not very good"
$Sentiment\ Score = (A \times B)^{0.5}$
Where A = very/extremely/highly etc (Adj)
And B = (not/never) (Adj)

This fuzzy logic score is calculated and added to the score of the sentence, and the final score for a snippet is calculated.We can see the workflow of lexicon based sentiment classification in more detail in the figure 3.5.

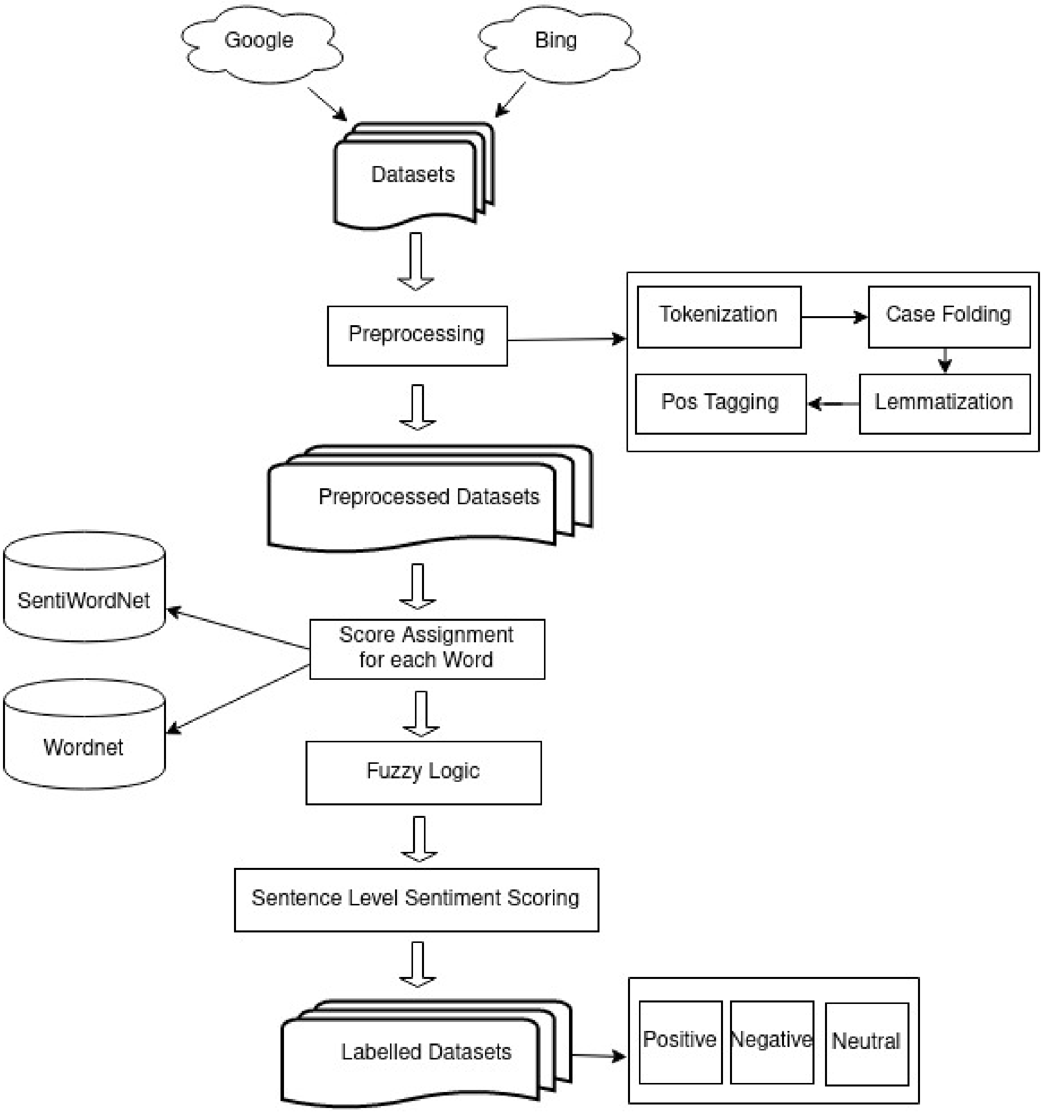


Figure 3.5: Workflow Diagram for Lexicon based Approach

2. **Sentiment Classfication for SVM :**

After the pre-processing stages, the features obtained from the training data were firstly extracted by using TF-IDF.After extracting the features using TF-IDF obtained from the training data, the term weight feature of the extracted TF-IDF is used as input to the SVM model. The data used to train SVM is the training data obtained from the classified words in the lexicon approach. In this research, scikit-learn library is used to assist the process of developing SVM models and TF-IDF.

The best parameter search is implemented to develop the best SVM model.The technique employed to find this parameter is the grid search cross-validation technique.In the grid search cross-validation technique, the searched parameter is evaluated using a certain fold cross-validation. Grid search is a commonly used hyperparameter tuning technique for SVM.It involves testing and evaluating every possible combination of hyperparameters within a specified range.The most important hyperparameters for SVM are the width of the kernel function γ and the error penalty parameter C.The optimal values of these hyperparameters are evaluated using cross-validation.For cross-validation, k-fold cross-validation technique will be used.

K-fold cross-validation is performed on the training dataset.The training dataset is divided into 5 folds.For each fold, a model is be trained on the remaining k-1 folds and evaluated on the current fold.The evaluation involves generating a confusion matrix to compare the predicted labels with the true labels of the validation data in each fold.Evaluation metrics such as accuracy, precision, recall, and F1-score is calculated from the confusion matrix for each fold.The average performance metrics from all k folds will provide an overall assessment of the model's performance.By performing k-fold cross-validation and evaluating the model on independent testing data, we can assess the approach's success in terms of its ability to accurately classify sentiment labels and generalize well to unseen data.The snippets that cannot be classified by lexicon based approach are used to predict the sentiment label using the trained model. We can see the workflow of lexicon based sentiment classification in more detail in the figure 3.5.

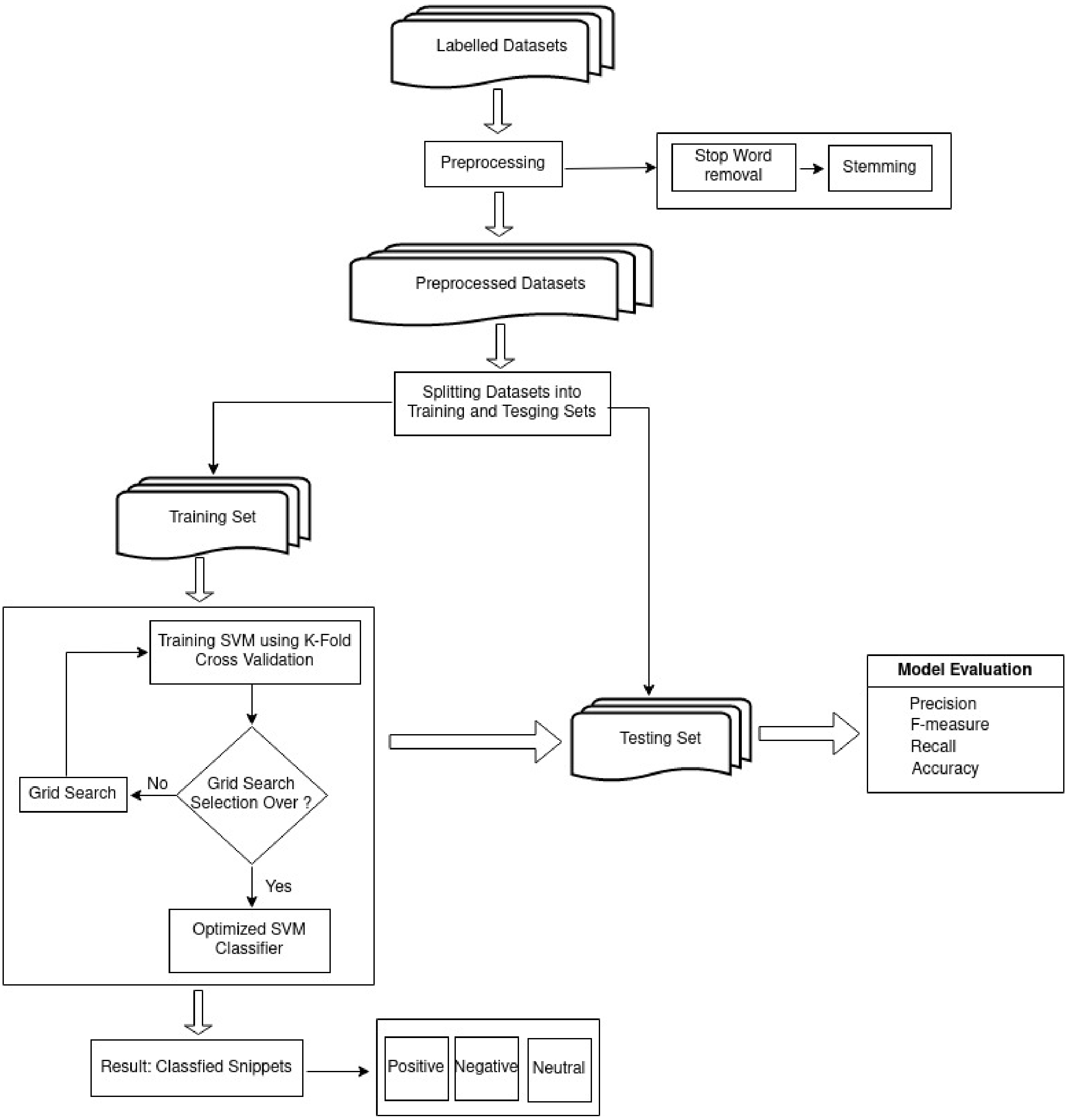


Figure 3.6: Workflow Diagram for SVM

3.3.6 Visualization Components

As the name implies, this research aims to perform a sentiment analysis on snippets that are output of search engines on any search query.To be more precise, only snippets and their corresponding sentiment labels i.e. Positive, Negative or Neutral do not provide any meaningful information. Therefore, to come up with meaningful information and derive knowledge from the information, visualization is considered as one of the main part of this research. Thus, the motive of this thesis is also to visualize the sentiment tone that has been classified by the above described proposed hybrid methodology and interact with the results visually to explore the possible hidden insights that can lead to new researches.Different colors are used to represent each snippets and their corresponding sentiment label to provide more distinct and clear understanding of classification.Example of snippets after performing sentiment analysis is shown in Figures as follows.

1. **Sentiment Meter :** The sentiment meter provides a categorical measure of the sentiments, helping to understand the emotional tone in the analyzed snippets.By aggregating the sentiment scores of all snippets related to a specific query, the sentiment meter provides an overall sentiment measurement for that query for selected Search Engines. It has ranging from "very negative" to "very positive".

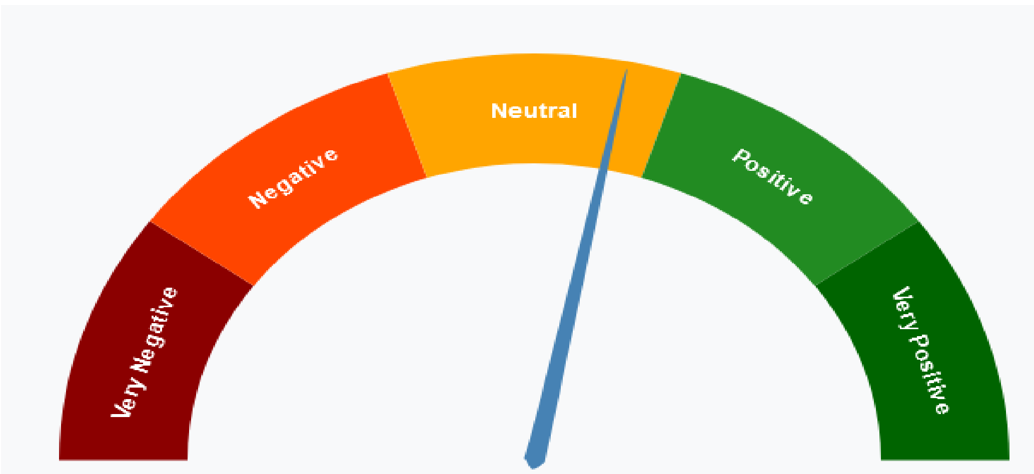


Figure 3.7: Sentiment Meter

2. **Sentiment Pie Chart :** The Sentiment Pie-chart visually represents the distribution of sentiments within a given sets of snippets, that are classified into three groups: positive, negative, and neutral.It computes

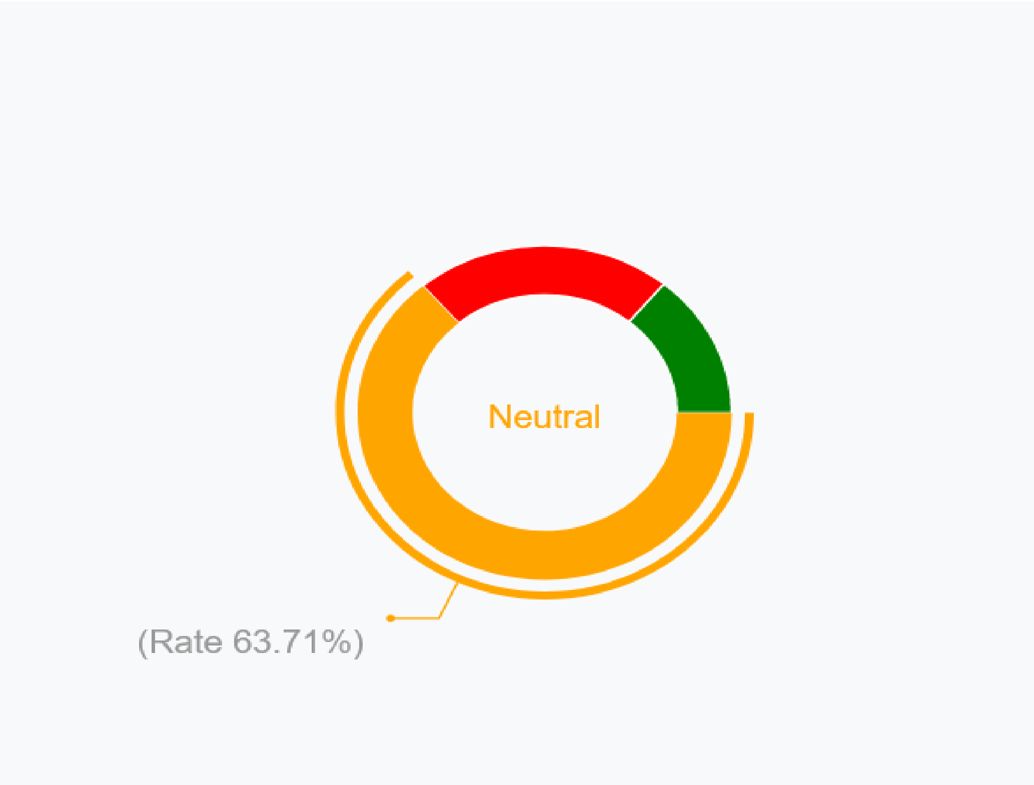


Figure 3.8: Sentiment Pie Chart

the total occurrence of each sentiment type across all snippets associated with a certain query and resulting sentiment pie chart delivers the evaluation of the overall sentiment tone for that query across selected search engines.

3. **Sentiment Area Diagram :** It's a line graph drawn on top of bars, with areas shaded in either green or red. The green area signifies positive sentiment, the red area represents negative sentiment, while if the bar aligns with the neutral axis or slightly leans towards positive (green) or negative (red), it is considered neutral.(See 3.4) The x-axis is labeled with "snippet" or "query," depending on the visualization task performed, and the y-axis features labels for "Positive," "Neutral," and "Negative" sentiments. This representation effectively depicts how the sentiment changes or moves for given set of snippet or queries and makes easier to analyze.

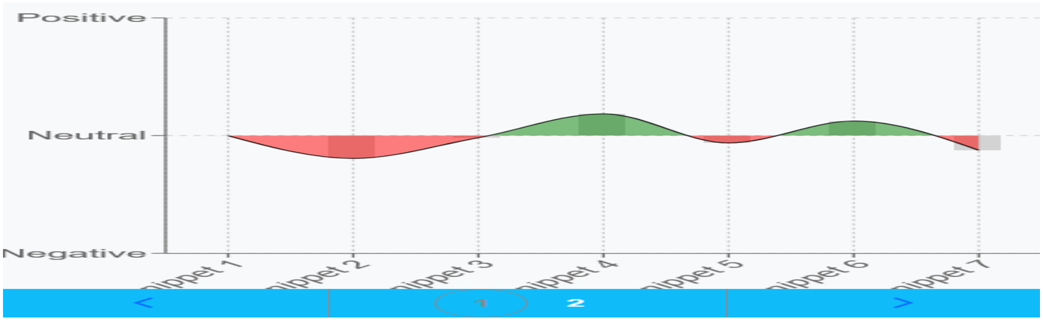


Figure 3.9: Sentiment Area Diagram for single query

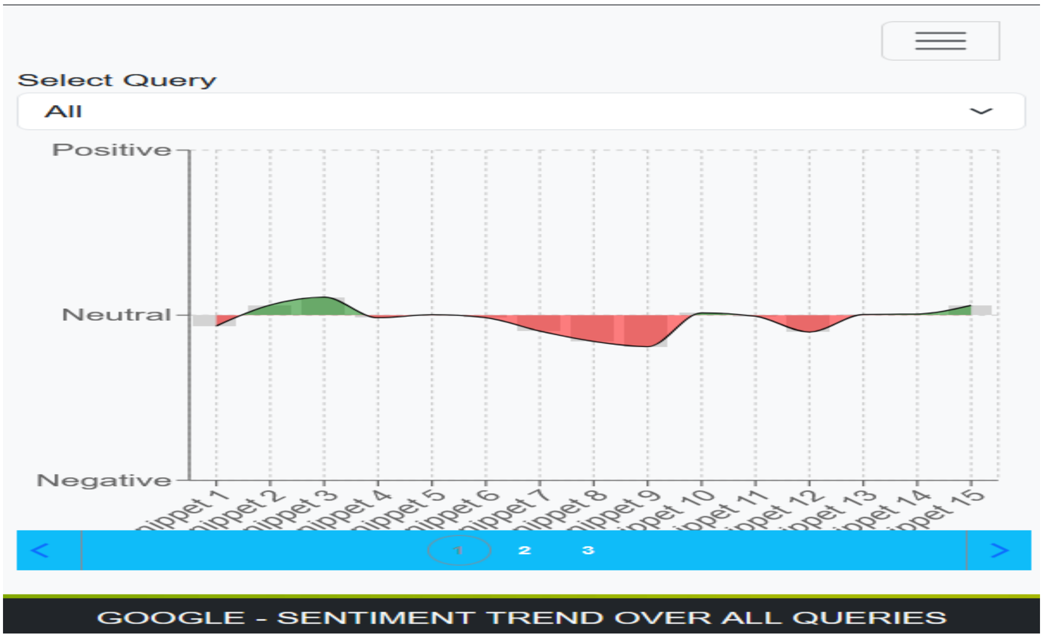


Figure 3.10: Sentiment Area Diagram for multiple queries

4. **Sentiment Classification Table :** The Sentiment Classification Table is a tabular presentation that includes snippets of text along with their corresponding URLs. Each snippet is labeled with a sentiment category, such as positive, negative, or neutral, and is assigned a sentiment score. These sentiment labels and scores indicate the emotional tone expressed in the associated text. The table essentially serves as a structured summary, providing an organized view of snippets, their URLs, and the assigned sentiment information providing a comprehensive understanding of sentiment distribution.

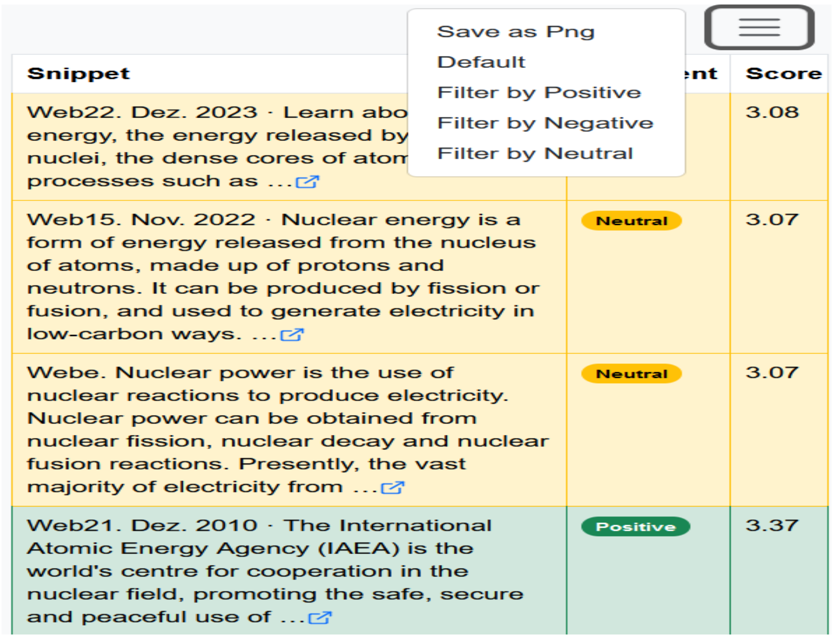


Figure 3.11: Sentiment Classification Table

5. **Sentiment bar-diagram for snippets :** It is a horizontal bar diagram that has both positive and negative axes.The horizontal axis has five categories labeled from left to right: “V.Neg”, “Neg”, “Neu”, “Pos”, and “V.Pos” that represents Very Negative, Negative, Neutral, Positive, and Very Positive respectively. The vertical axis represents the every snippets. Different colors and different emojis are used with each bar to represent the sentiment level of snippets on the basis of their sentiment score. The bars that move towards positive axis are considered as positive snippets, the bars that move towards negative axis are considered as negative snippets and the bars that are exactly in ”neu” axis or that move slightly towards either positive or negative axis are considered as neutral snippets. (See 3.4)

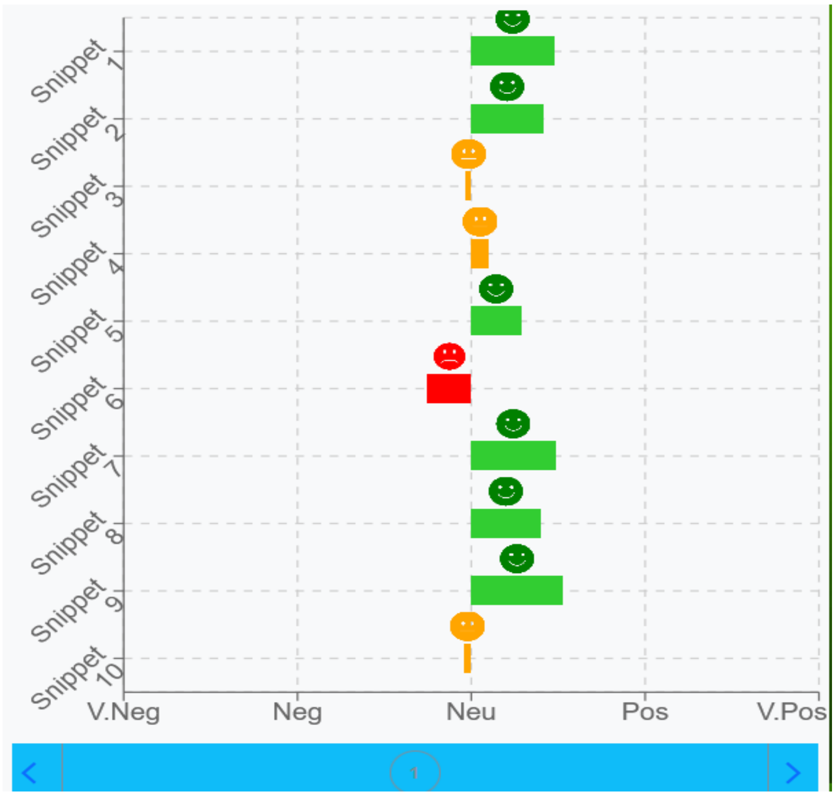


Figure 3.12: Sentiment Level of Individual Queries

6. **Sentiment bar-diagram for multiple Queries :** It is a combination of three bar diagrams.The graph is divided into three sections, each representing different sentiments: negative (red), positive (orange), and neutral (green). All snippets for each particular query that are given for a study are considered, total number of negatives, positives and neutral snippets are calculated and then plotted in each of these bar diagrams. X-axis represents the queries whereas Y-axis represents the number of snippets. The chart is designed to provide a visual representation of the sentiment tones of each query for easy comparison and understanding.

7. **Sentiment bar-diagram for single Query :** This bar diagram provides the overview of total positive, negative and neutral sentiments for a single query per page.The x-axis represents the pages for the query(Page A, Page B and so on..) and the y-axis represents the count of snippets in each category. Each bar shows the number of snippets for a specific page in either of three categories. The colors of the bars

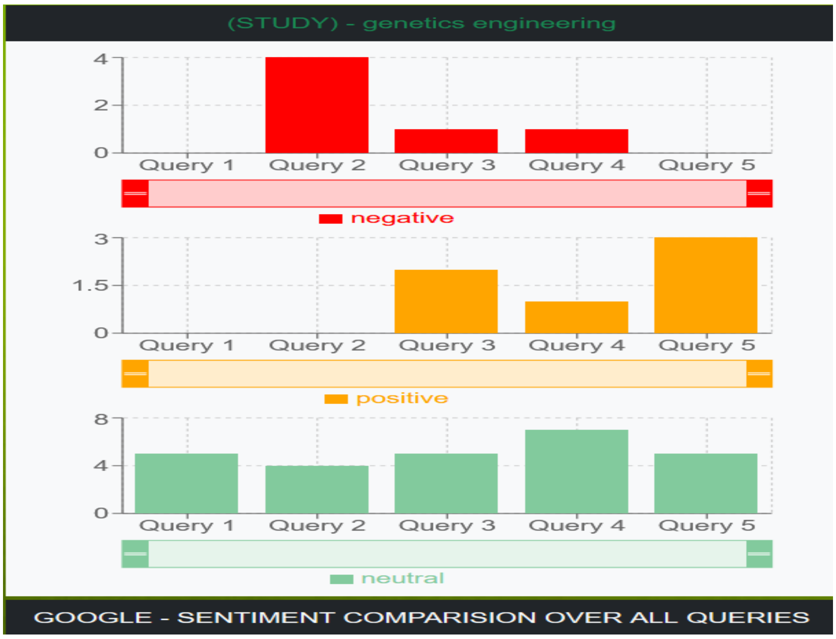


Figure 3.13: Sentiment Comparision for all Queries

used to differentiate the categories are green for positive sentiment, red for negative sentiment and yellow for neutral sentiment.The purpose of the bar diagram is to compare the sentiment distribution of snippets for two or multiple pages. .

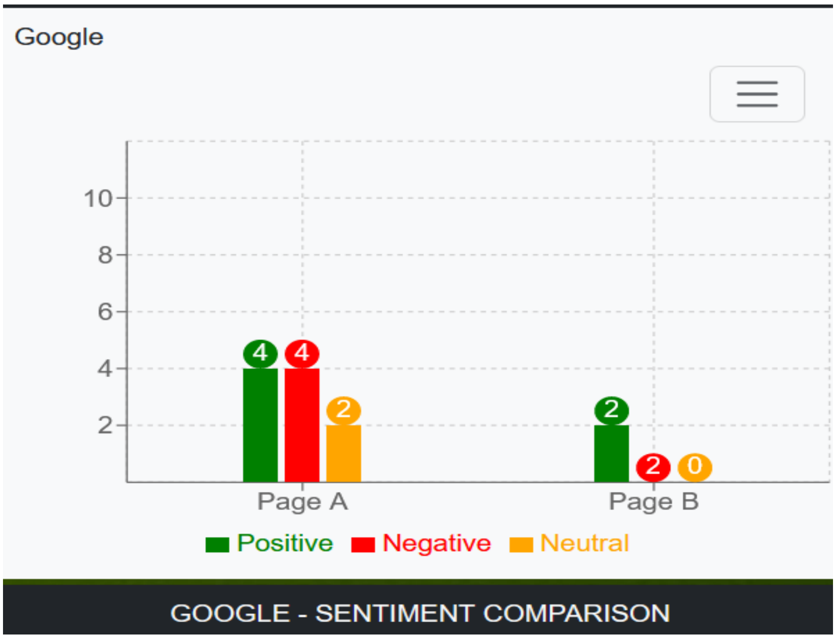


Figure 3.14: Sentiment Comparison for singe Query

3.4 Evaluation

3.4.1 Lexicon-based Approach

To assess the performance of the lexicon-based approach, a set of 160 snippets was gathered from four queries, "Nuclear Power," "Morality of Genetics Manipulation," "Positive and Negative Impacts of Social Media," and "The Ethics of Data Ownership." These snippets were obtained using Google and DuckDuckGo and were manually annotated as positive, negative, or neutral.

Following the lexicon-based classification, the predicted labels were compared with the manually annotated actual labels. The evaluation results include a confusion matrix, providing details of correct and incorrect predictions. Additionally, evaluation metrics (Accuracy, Precision, Recall, and F1-score) were computed. Below is the confusion matrix, with predicted labels on the columns and actual labels on the rows.

Similarly, the results for other evaluation metrics were:

- Accuracy: 0.68125
- Precision: 0.7002686308835411
- Recall: 0.68125

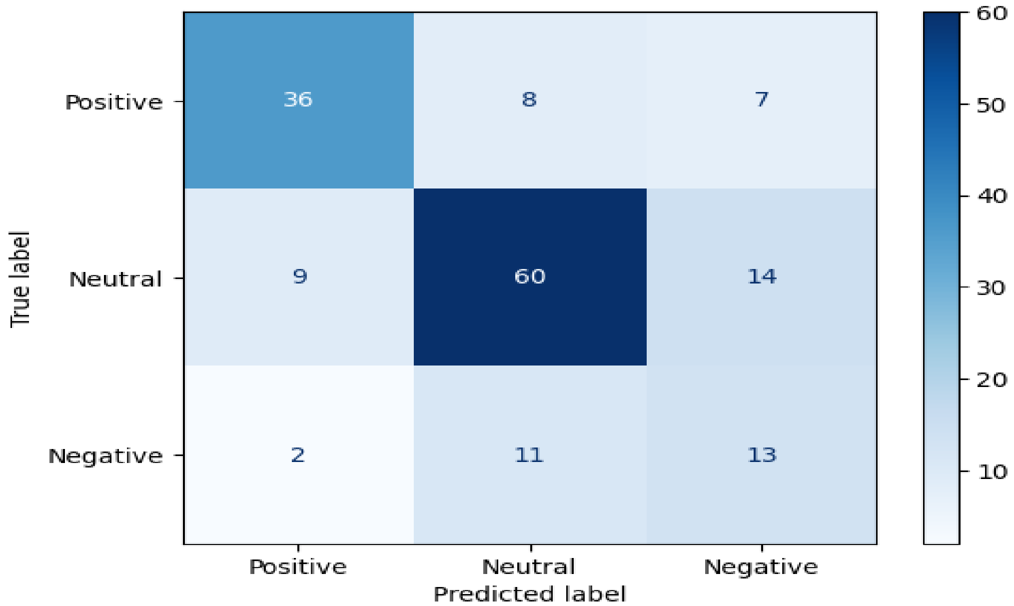


Figure 3.15: Confusion Matrix for Lexicon Approach

- F1 Score: 0.6888595993953137

Overall, the lexicon-based approach was able to classify text snippets with reasonable accuracy, precision, recall, and F1 scores.The accuracy of the approach is 0.68125, meaning that it has correctly classified 68.125% of the snippets.

3.4.2 Machine Learning Approach

In this approach, a dataset comprising 12,000 result snippets, initially classified using a lexicon-based approach was utilized.To ensure a robust training and evaluation process, dataset comprising of 90000 reviews for the product, service, food and film were used. So on these two data sets the model was trained and evaluated.

For the training phase, 80% of the total dataset was used. Within this training subset, a k-fold cross-validation technique was applied with 5 folds.The hyperparameters used for training the SVM model were determined through a grid search technique. Following the training with k-fold cross-validation and the optimal hyperparameters, the SVM model was tested using the remaining 20% of the dataset that was set aside for testing. The confusion matrix for the SVM model is presented below, where 1,2 are 3 refers to negative,neutral and positive sentiment labels respectively.

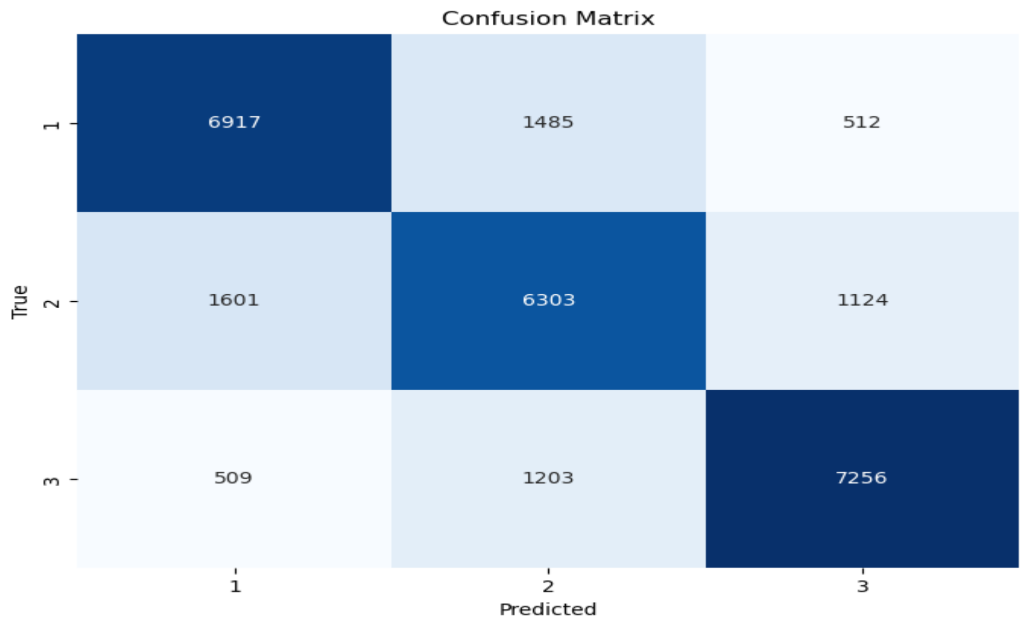


Figure 3.16: Confusion Matrix For SVM

Similarly, the results for other evaluation metrics are:

- Accuracy: 0.77
- Precision: 0.76
- Recall: 0.76
- F1 Score: 0.76

The precision, recall, and F1 score are all above 0.76, which indicates that the model is performing well. The precision score is slightly higher than the recall score, which means that the model is better at identifying true positives than it is at avoiding false negatives.

Here are the examples of a sentence that was previously unclassified using the Lexicon-based approach but has now been successfully categorized using our SVM Model.

Sentence	Lexicon-based Sentiment	SVM Sentiment
It is confirmed that the machine operates continuously untill the task is finished.	unclassified	positive
The computer processed data quickly than our expectation	unclassified	Neutral
The movie was a roller coaster of emotions.	unclassified	positive
The team didn't take it to the finals like previous year.	unclassified	negative
The dinner wasn't what we expected.	unclassified	negative
The store was out of bread.	unclassified	neutral
The project was finished before schedule.	unclassified	neutral
She is attending to the conference.	unclassified	positive
The fashion trends are influencing lifestyles	unclassified	positive
The Sales are increasing and the market is going up.	unclassified	positive

Table 3.6: Classification of sentiments by SVM

Chapter 4

Results and Analysis

Search engine users have a high level of trust in search engines and Google in particular. This has been shown in laboratory studies and (online) surveys. Laboratory studies also shows that users choose top results even if they are less relevant or less credible than results displayed lower in a ranked list. So the focus of this analysis will be solely on top results or top ranked list.[26]

Similarly we all should understand that search engines deliver results based on a variety of factors and filters, including user data, Device Types and Screen Resolutions, Personalization tools analytics tool etc. Therefore, it's not always accurate to say that the same query will yield the same results for different users. These personalization algorithms analyze user behavior, search history,device type etc to understand what kind of content a user is interested in which allows search engines to provide more relevant and personalized search results.[10] So we should take this in mind and perform the analysis.

To analyse the results, lets take the research questions as reference and analyze the results and main focus will be still on google, while Google and other well-known search engines are not very different.[10]

4.1 Sentiment Variation of Result Snippets Across Search Engines

The examination of sentiment variations among result snippets for the same query across three different search engines, along with the analysis of their positional impact, aligns with the first research question.
RQ1) To what extent does the sentiment tone of result snippets from different search engines for the same search query vary from each other?

For the Query **"Morality of Genetics Manipulation"**, result were scraped upto 20 position for all three search engines(Google, Bing and DuckDuckGo) and only the snippets with description were taken into consideration for sentiment analysis.The distribution of sentiments across the three search engines is summarized in Table 4.1 .

Search Engine	Total Results Analyzed	Positive	Negative	Neutral
Google	18	9	5	4
Bing	10	2	3	5
DuckDuckGo	20	13	3	4

Table 4.1: Distribution of sentiments

For this particular Query we can see variations in sentiment tone across different search engines. Google and DuckDuckGo have more numbers of postive results whereas Bing have least number of positive results and more neutral results .Additionally, there is a noticeable similarity in sentiment tones between Google and DuckDuckGo.

By looking at how different search engines handle the sentiment of search results for the same query we noticed some interesting things. If we imagine each search engine as a lecturer teaching the same subject, Google and DuckDuckGo seem to focus more on positive aspects in their descriptions, whereas Bing tends to be a bit more neutral.

4.2 Impact of Synonyms and Phrase Variations on Search Results Sentiment

RQ2) Do search results and their sentiment differ with the use of synonyms, positive and negative phrases?
To find the difference of sentiment with the use of synonyms, two queries **"Nuclear Energy"** and **"Nuclear Power"** were utilized and result were collected up to 20th position for Google and only the snippets with description were taken into consideration for sentiment analysis.

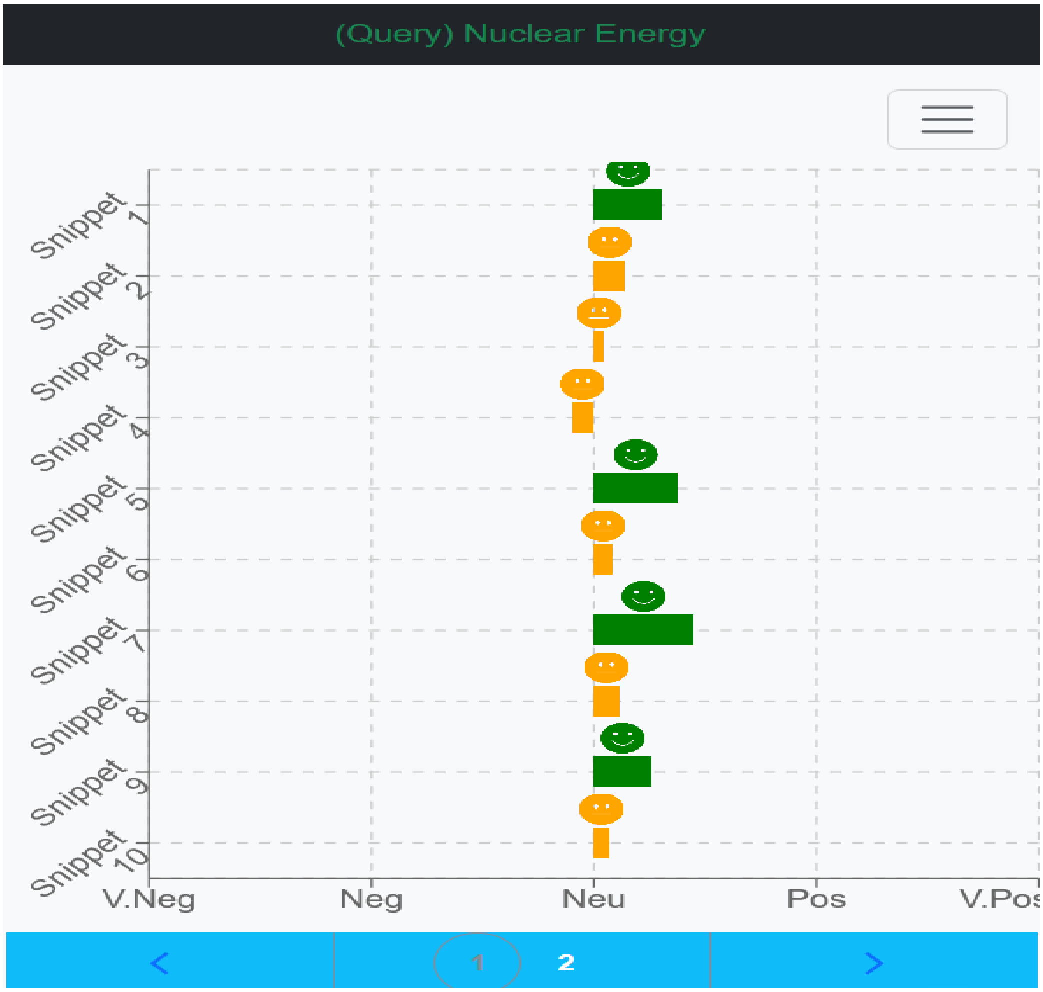


Figure 4.1: First 10 results for query "Nuclear Energy"

Looking at the horizontal bar chart above, it's clear that the first 10 results for the query "Nuclear Energy ", snippets are classified into either the

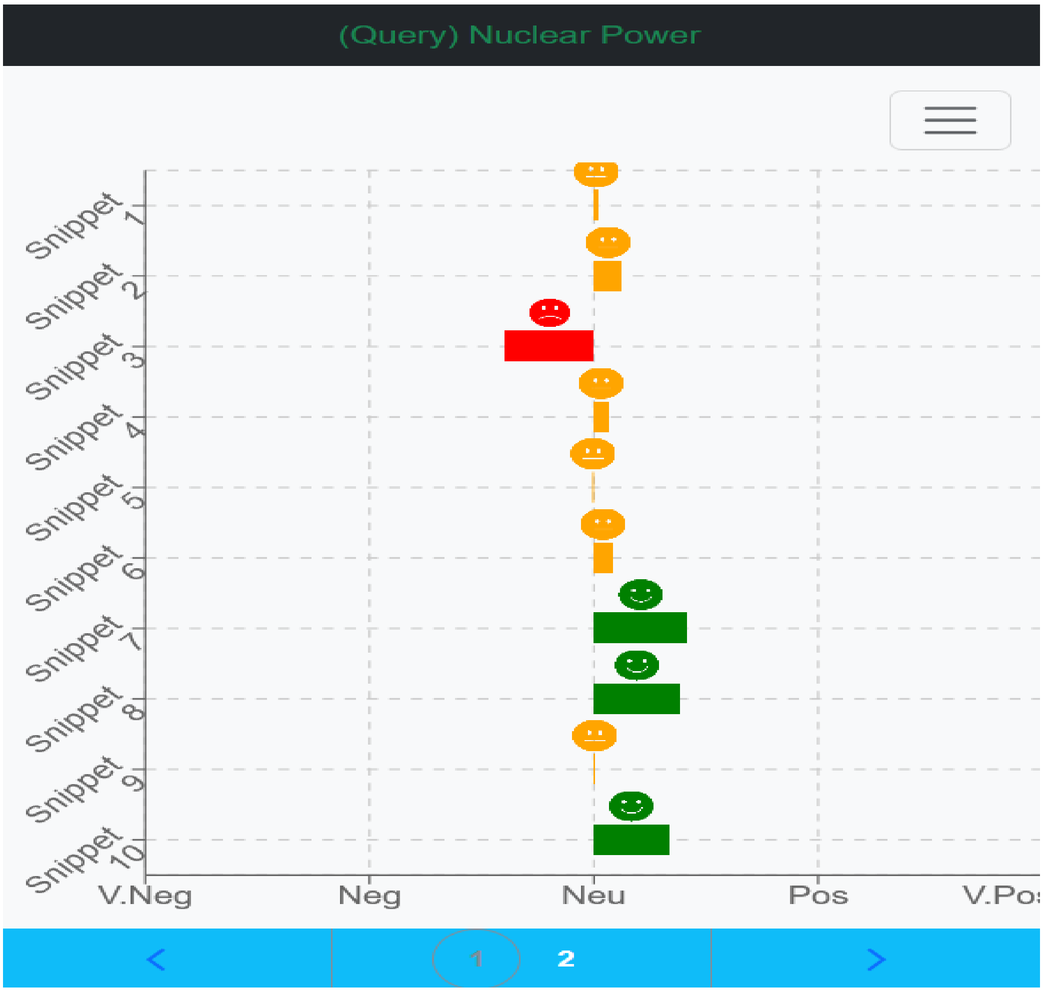


Figure 4.2: First 10 results for query "Nuclear Power"

positive or neutral category. Specifically, a significant portion leans towards the neutral side, with the remaining entries expressing positive sentiments. What is interesting is that none of the snippets in this group are marked as negative.They all seem to have a positive or neutral tone.
Similiarly, if we consider the second query "Nuclear Power" which is exactly the synonym for the the query "Nuclear Energy, and observe the result, then sentiment tones are different from that of previous query. For first 10 results, we can see that almost half of them are neutral, followed by positive and finally one negative sentiment.

This difference highlights how the selection of words, even those that are similar in meaning, can affect the overall tone or feeling of the search results.

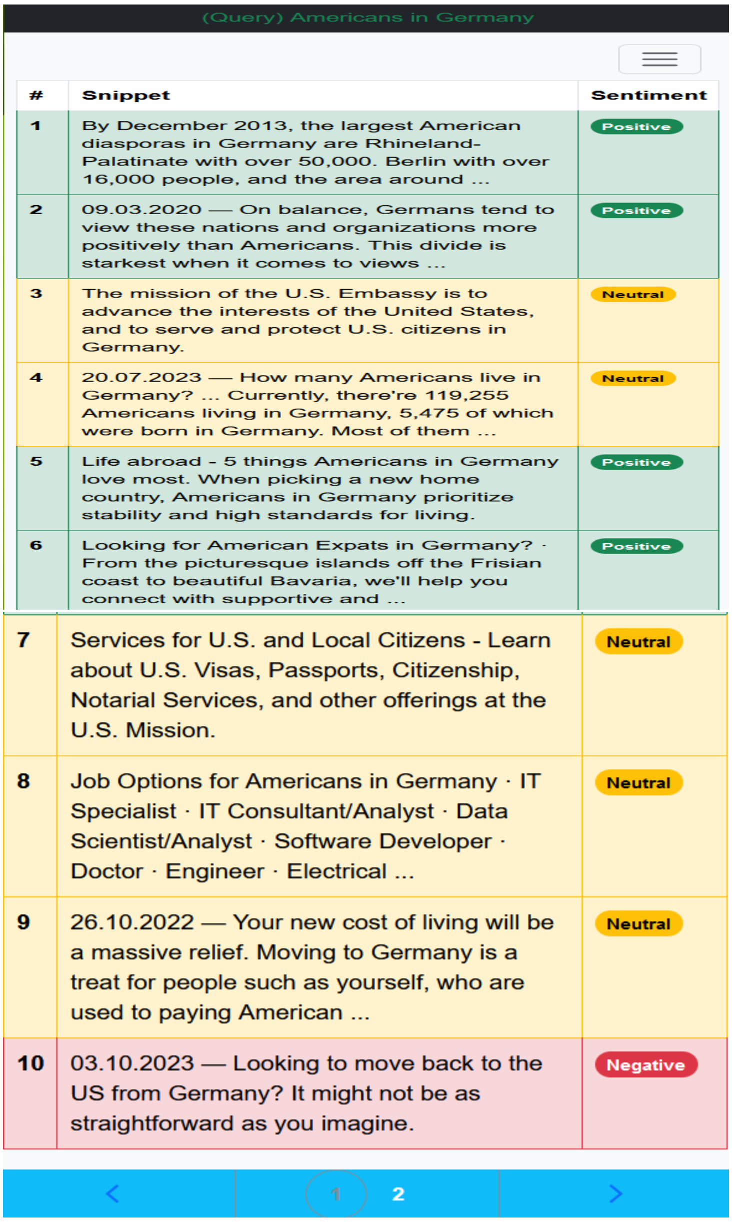
4.3 Potential Discrimination in Search Engine Results

To study the potential discrimination in search engine, let us try to find the answer to the research question 3.
RQ3) Do search engines (Management, engineers, or algorithms) unknowingly or privately support or discriminate on the basis of race, religion, ethnicity, geography, etc.?

To investigate this question, a comparison was conducted between the search results for two queries: "Americans in Germany" and "Germans in America." For both queries, the sentiment of the top 10 results from Google was analyzed.

The query "Americans in Germany" produced a more positive sentiment distribution, with four positive results, five neutral results, and only one negative result. The search results for this query focused on positive aspects of American life in Germany, such as cultural exchange ,expatriates and social integration.
On the other hand, for the query "Germans in America," the majority of results (8 out of 10) were neutral, with one negative and one positive result. The search results for this query emphasized the experiences of War related content, German immigrants and the historical context of the American-German relationship.

This comparison highlights the potential bias of search engines(intentionally or unintentionally) that can influence user perceptions.If the top 10 search results about Germans in America revolve around immigration and war, it might provoke negative emotions among Germans.If search results focus on the immigrants or refugees, it might accidentally support negative ideas or stereotypes whereas, if the results emphasize positive things about a specific group or place, it can also strengthen positive views. However, We should keep in mind that Search engines consider language factors when ranking results. Results in languages different from the language of the interface receive a lower ranking. For example, while the result sets for a certain query are the same in the German and the English versions of Google, the rankings are different.[11]


(Query) Americans in Germany

#	Snippet	Sentiment
1	By December 2013, the largest American diasporas in Germany are Rhineland-Palatinate with over 50,000. Berlin with over 16,000 people, and the area around ...	Positive
2	09.03.2020 — On balance, Germans tend to view these nations and organizations more positively than Americans. This divide is starkest when it comes to views ...	Positive
3	The mission of the U.S. Embassy is to advance the interests of the United States, and to serve and protect U.S. citizens in Germany.	Neutral
4	20.07.2023 — How many Americans live in Germany? ... Currently, there're 119,255 Americans living in Germany, 5,475 of which were born in Germany. Most of them ...	Neutral
5	Life abroad - 5 things Americans in Germany love most. When picking a new home country, Americans in Germany prioritize stability and high standards for living.	Positive
6	Looking for American Expats in Germany? · From the picturesque islands off the Frisian coast to beautiful Bavaria, we'll help you connect with supportive and ...	Positive
7	Services for U.S. and Local Citizens - Learn about U.S. Visas, Passports, Citizenship, Notarial Services, and other offerings at the U.S. Mission.	Neutral
8	Job Options for Americans in Germany · IT Specialist · IT Consultant/Analyst · Data Scientist/Analyst · Software Developer · Doctor · Engineer · Electrical ...	Neutral
9	26.10.2022 — Your new cost of living will be a massive relief. Moving to Germany is a treat for people such as yourself, who are used to paying American ...	Neutral
10	03.10.2023 — Looking to move back to the US from Germany? It might not be as straightforward as you imagine.	Negative

1 2

Figure 4.3: Top 10 Results for the Query "Americans in Germany"

(Query) Germans in America

#	Snippet	Sentiment
1	Als Deutschamerikaner (englisch German Americans) werden Bürger der Vereinigten Staaten bezeichnet, die selbst oder deren Vorfahren aus Deutschland oder als ...	Negative
2	The largest flow of German immigration to America occurred between 1820 and World War I, during which time nearly six million Germans immigrated to the United ...	Neutral
3	02.10.2018 — Germans constitute the biggest immigrant group in the USA. Here you can find out why they also have the least public visibility.	Neutral
4	1880s - In this decade, the decade of heaviest German immigration, nearly 1.5 million Germans left their country to settle in the United States; about 250,000, ...	Neutral
5	Famous for their practical skills, thrift, hard work, interest in the arts, and enjoyment of good living they have left their mark indelibly on American culture ...	Positive
6	From 1931-1940, approximately 115,000 Germans moved to the United States of America. Many were Jewish or anti-Nazi protesters who had to flee government ...	Negative
7	Today, approximately 58 million Americans claim German ancestry. They are most numerous in California, followed by Pennsylvania, Ohio, Illinois, and Texas. The ...	Neutral
8	According to the U.S. Census conducted in 2000, 42.8 million Americans identified themselves as being of German ancestry, representing 15.2% of the total ...	Neutral
9	22.11.2023 — In parts of the U.S. it was possible for German immigrants to live in a German-language bubble for much of the nineteenth century. The author ...	Neutral
10	26.10.2020 — For the first time since German reunification less than 10,000 Germans left their home in Germany and moved to the USA in 2019 · The United ...	Neutral

Figure 4.4: Top 10 Results for the Query "Germans in America"

4.4 Sentiment Distribution for list of Queries and Positional Impact

To determine the sentiment distribution for list of queries and their positional impact, lets take the research question 4 into account and analyze the outputs.
RQ4) What is the sentiment distribution for the query or set of (controversial) queries and how does the distribution change when further result positions are considered?

If we consider overall sentiments for the top 40 results for 5 controversial queries related to each other, "Ukraine crisis", "Russo-Ukrainian War", "Ukrainian military intervention in Russia","Invasion of Ukraine" and "Russian military intervention in Ukraine" only from google search engine then we can see the distribution of sentiments as follows in the given pie chart.

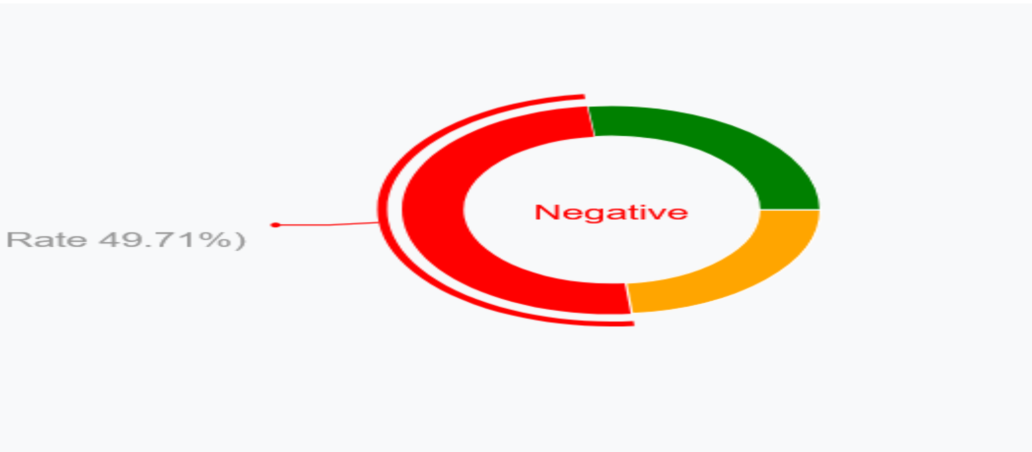


Figure 4.5: Distribution of overall sentiments when query "Ukraine crisis" in first position"

Neutral Sentiment: 23.43 %
Positive Sentiment: 26.86%
Negative Sentiment: 49.71%

If we keep on shifting the query "Ukraine crisis" to position 2, 3, 4 and last in the list of queries, the sentiment distribution for each of the corresponding position is provided by the following pie chart.

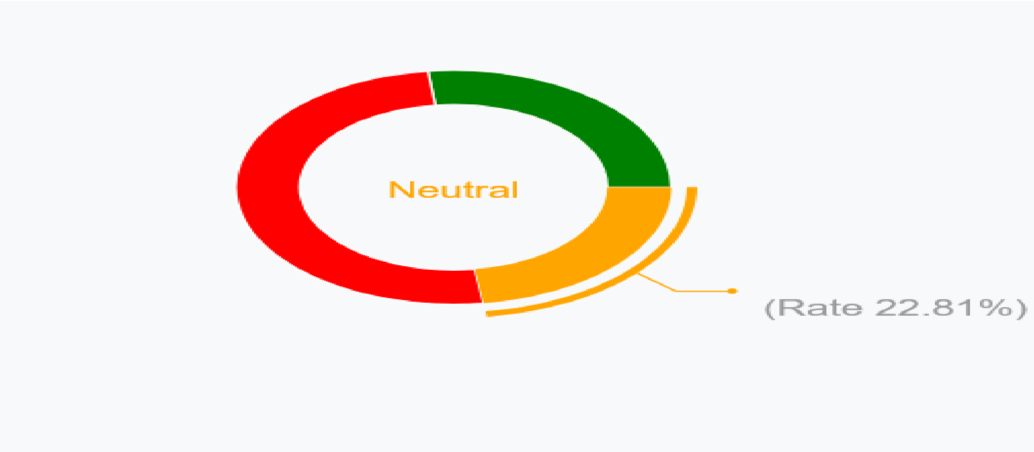


Figure 4.6: Distribution of overall sentiments when query "Ukraine crisis" in second position"

Neutral Sentiment: 22.81 %
Positive Sentiment: 26.90%
Negative Sentiment: 50.29%

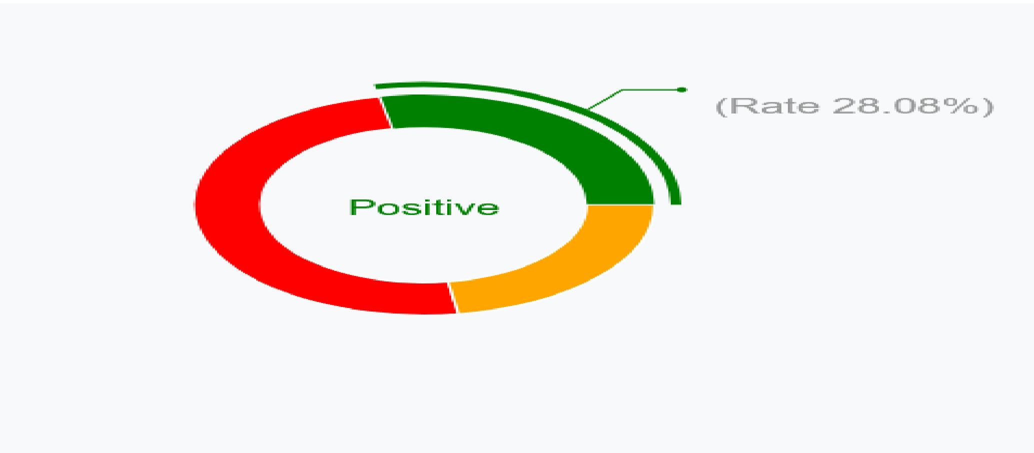


Figure 4.7: Distribution of overall sentiments when query "Ukraine crisis" in third position"

Neutral Sentiment: 22.60 %
Positive Sentiment: 28.08%
Negative Sentiment: 49.32%

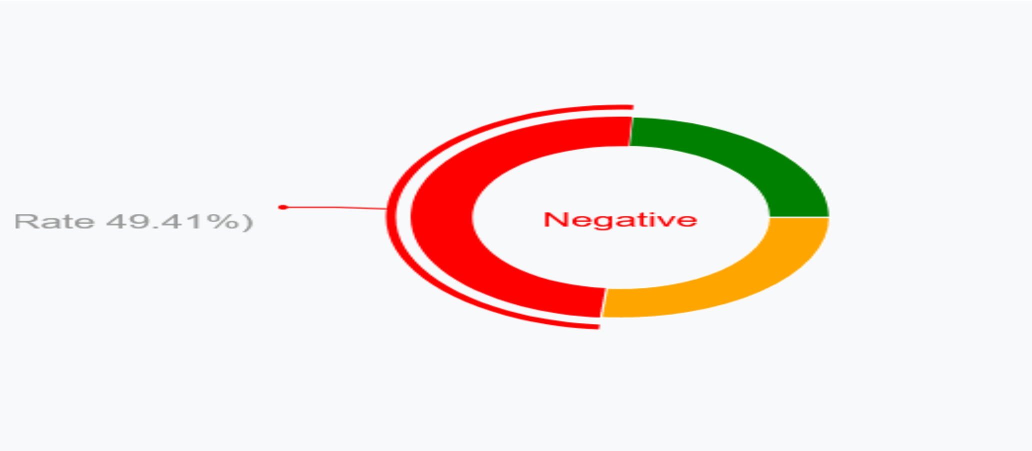


Figure 4.8: Distribution of overall sentiments when query "Ukraine crisis" in fourth position"

Neutral Sentiment: 26.47%
Positive Sentiment: 24.12%
Negative Sentiment: 49.41%

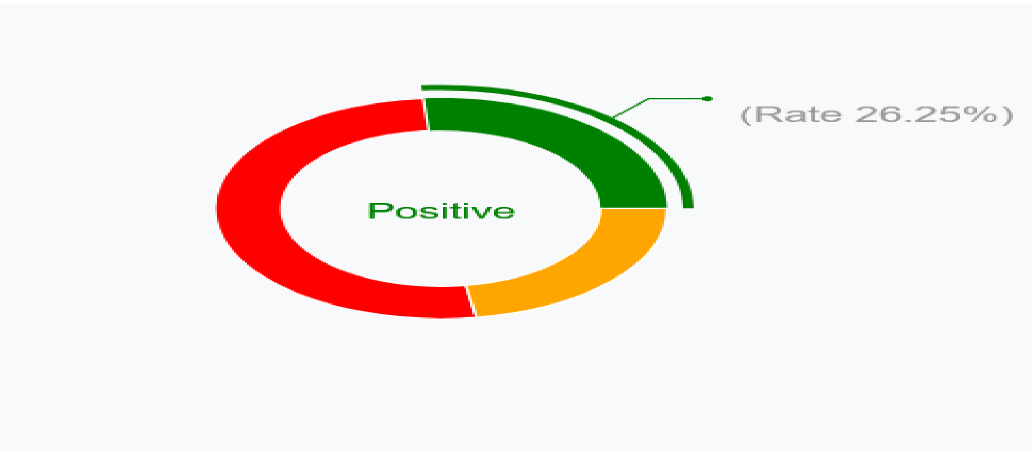


Figure 4.9: Distribution of overall sentiments when query "Ukraine crisis" in last position"

Neutral Sentiment: 22.50 %
Positive Sentiment: 26.25%
Negative Sentiment: 51.25%

The findings suggest that the sentiment distribution varied slightly across different result positions. For the first position, the distribution was 23.43% neutral, 26.86% positive, and 49.71% negative. The second position showed a similar distribution. The third position positive sentiments rises to 28.08%, whereas neutral and negative sentiments maintains similar position as before. In the fourth position neutral sentiments rises to 26.47% whearas positive sentiments falls to 24.12%. In the last position, neutral sentiments falls to 22.50% positive and negative sentiment has a slight increment.

Shifting the query to different positions (2nd, 3rd, 4th, and last) in the list of queries produces variations in sentiment distribution. The proportion of neutral and positive sentiments sentiment varies slightly across positions. Negative sentiment consistently occupies the majority of the distribution. Despite positional changes, the overall sentiment distribution remains relatively consistent. Negative sentiment consistently dominates, suggesting a general tendency for negative information in the search results related to the specified queries.

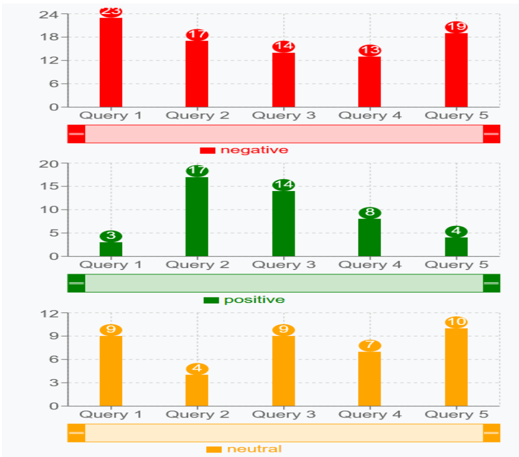
On other hand, if we consider the sentiment distribution only for the specific query "Ukraine crisis" at each result position, following bar-diagram and pie-chart depicts the findings.

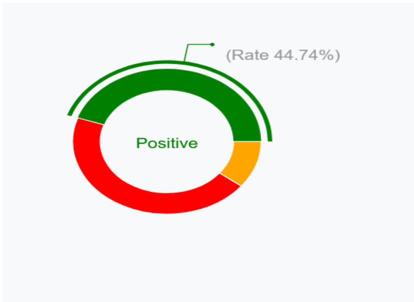
For the first position, out of 35 results scraped, there were 8 neutral sentiments, 13 positive sentiments, and 14 negative sentiments. In the first position, the negative sentiments dominates the total sentiments with (40%), followed by 37.14% of positives and 22.82% neutral sentiments.

Positive Sentiment: 37.14 %
Negative Sentiment: 40 %
Neutral Sentiment: 22.82 %

Figure 4.10: Distribution of sentiments of query "Ukraine crisis" for first position

In the second position, out of 38 results scraped, there were 4 neutral sentiments with (10.53%), 17 positive sentiments(44.74%), and 17 negative sentiments(44.74%). The numbers of neutral sentiments are decreased, while positive and negative sentiments are equally distributed.

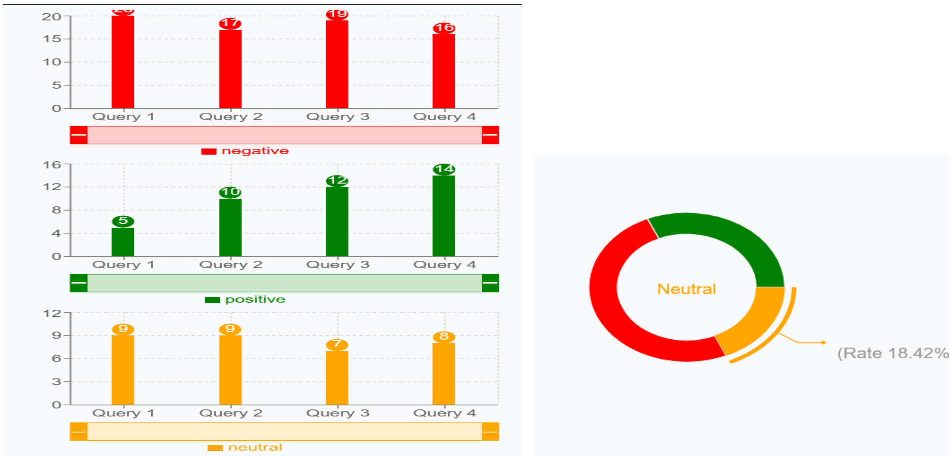




Positive Sentiment: 44.74 %
Negative Sentiment: 44.74 %
Neutral Sentiment: 10.53 %

Figure 4.11: Distribution of sentiments of query "Ukraine crisis" for second position

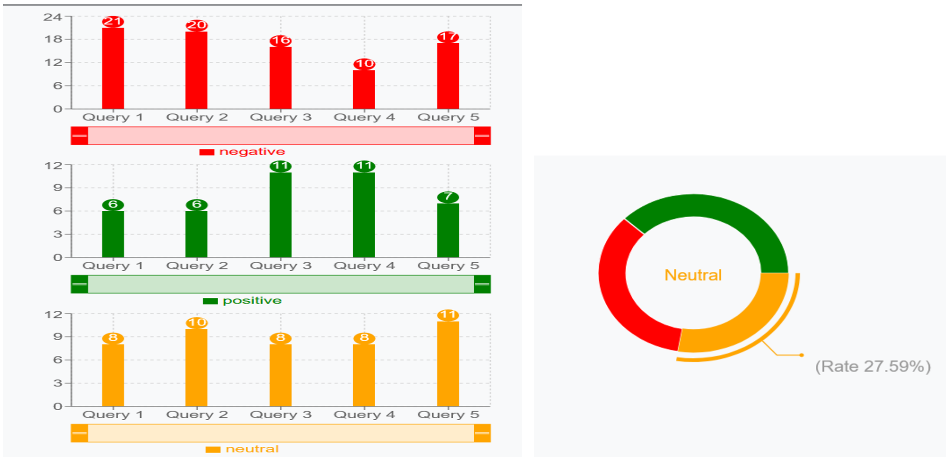
For the third position, out of 38 results scraped, there were 7 neutral sentiments, 12 positive sentiments, and 19 negative sentiments. The sentiment distribution for 38 results includes 18.42% neutral, 31.58% positive, and 50% negative sentiments.The negative sentiments are dominant in this position, indicating a shift towards a more negative sentiment pattern compared to the previous positions



Positive Sentiment: 31.58 %
Negative Sentiment: 50 %
Neutral Sentiment: 18.42 %

Figure 4.12: Distribution of sentiments of query "Ukraine crisis" for third position

In the fourth position, out of 29 results scraped, there were 8 neutral sentiments, 11 positive sentiments, and 10 negative sentiments.Out of 29 results, the sentiment distribution comprises 27.59% neutral, 37.93% positive, and 34.48% negative sentiments. There is a slight shift towards more positive and neutral sentiments compared to the third position.



Positive Sentiment: 37.93 %
Negative Sentiment: 34.48 %
Neutral Sentiment: 27.59 %

Figure 4.13: Distribution of sentiments of query "Ukraine crisis" for fourth position

Lastly, for the last position, out of 29 results scraped, there were 7 neutral sentiments, 10 positive sentiments, and 12 negative sentiments.The sentiments are mostly negative (41.38%), followed by positive (34.48%) and neutral (24.14%) which again shows rise in negative sentiments followed by decreased positive and neutral sentiments.

Positive Sentiment: 34.48 %
Negative Sentiment: 41.38 %
Neutral Sentiment: 24.14 %

Figure 4.14: Distribution of sentiments of query "Ukraine crisis" for last position

In conclusion, the sentiment distribution for snippets gathered from google varies across result positions, indicating a dynamic nature of sentiment expressions in the search results. This analysis highlights the importance of considering result position when evaluating sentiment distribution, as it can influence the overall perception of sentiment trends in the search results for a specific query. As we analyzed the snippets gathered solely from Google, we could also consider other search engines too and analyze the results to get more deeper understanding.

Chapter 5

Conclusion and Future Works

In conclusion, this thesis focused on the development of a sentiment analysis and visualization system for search result snippets based on three search engines namely, Google ,Bing and DuckDuckGo. It falls on one of the area of sentiment analysis which is not very commonly practised. The objective was to provide users with a comprehensive understanding of the sentiment associated with search results snippets. Through some research and experiments, a sentiment analysis model is developed that almost accurately categorizes search result snippets into positive, negative, or neutral sentiments. Additionally, visualization tool are implemented to present the sentiment analysis results in an understandable, intuitive and user-friendly manner.

The results have shown that sentiment analysis can be a valuable tool for improving search relevance and user search experience.Users can select and filter results according to their personal interests and sentiments. It can also help organizations and companies to find and analyze brand value, reputation, and public opinions. Similarly, users can also get different information such as reviews, opinions etc about particular topic, person, news, products, services etc that might help in decision making.Furthermore, they can compare the sentiment of result snippets across different search engines and choose the most suitable search engine for specific query or study areas. In the same way, search engines can also use this technique to provide sentiment based recommendation and filtering and hence improve the ranking of results by analysing user preferences.

Future Work

While this thesis has made significant progress in sentiment analysis and visualization on search result snippets, there are several areas for future work and improvement. Some potential directions for future research include:

1. **Exploring advanced natural language processing techniques:** The sentiment analysis model developed in this thesis utilized a basic hybrid approach. Future work could explore the integration of more advanced techniques, such as deep learning or neural networks. This would not only enhance the accuracy of the model but also address the challenges posed by domain orientation. Additionally, it is important to note that search result snippets primarily serve an informative role, offering factual information rather than subjective opinions.

2. **Expanding to multiple languages:** Currently, the sentiment analysis model and visualization tool are designed for English search result snippets. Future work could focus on expanding the system to handle other languages, allowing users to analyze sentiments across multiple languages.

3. **Expanding to multiple search engines:** Currently, our sentiment analysis is limited to the result snippets from three search engines: Google, Bing, and DuckDuckGo.However, to enhance the research experience, we can consider expanding this analysis to include additional search engines such as Yahoo, Baidu, Yandex etc.

4. **Implementing more visualization techniques and user customization:** The system could be enhanced by developing new visualization techniques that are more effective at conveying the emotional tone of text. Similarly, allowing users to customize the visualization of sentiment analysis results based on their individual preferences would provide a more personalized user experience.

To sum up, this thesis has successfully developed a sentiment analysis and visualization system for result snippets. The results explains that this approach is almost accurate in categorizing sentiments and presenting the results in a user-friendly manner. However, there are several areas for future work and improvement as listed above.These future developments will further enhance the system's capabilities as well as overall user experience.

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