

# Sentimental analysis on Twitter

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*Abstract— Sentiment analysis on social media platforms has grown in significance as a tool for tracking brand perception and understanding public sentiment. This research article offers a thorough investigation of the use of cutting-edge BERT-based models for sentiment analysis on Twitter data. The effective handling of data is made possible by the storage of the analytical findings in a MongoDB database. We go over the complete process, including sentiment analysis, data pretreatment, and MongoDB integration. We also offer some useful applications for this methodology.*

## I. INTRODUCTION

Data Gathering - Gathering Twitter data, which might include tweets, retweets, and responses, is the initial stage in the procedure. The Twitter API is used to collect data as it makes it possible to query particular hashtags, keywords, or user profiles that are relevant to the research. This is an important stage since it establishes the calibre and applicability of the data to be examined.

### Preparing Data

Preprocessing is necessary after data collection to get the raw data ready for analysis. This procedure consists of: Cleaning: Eliminating extraneous elements such special characters, URLs, and formatting problems.

Tokenization is the process of dividing a text into discrete phrases or symbols.

Normalisation entails eliminating stop words and changing all tokens to lowercase. Reducing words to their most basic or root form is known as stemming and lemmatization. This phase is essential for streamlining the machine learning models that will be utilised later in the sentiment analysis process and enhancing their

performance.

## Sentiment Analysis Employing Models Based on BERT

The main objective of the study is to apply BERT (Bidirectional Encoder Representations from Transformers) models for sentiment analysis. A dataset of labelled tweets is used to refine BERT's pre-trained models so they can better handle the subtleties of social media discourse. This technique makes use of the model's profound comprehension of linguistic context, which improves its capacity to identify the emotions conveyed in brief texts, such as tweets. Usually, the feelings are divided into three categories: neutral, negative, and positive.

### Integration with MongoDB

MongoDB is a NoSQL database that was selected for its flexibility and performance with massive datasets, and it houses the processed and analysed data. The schema-less architecture of MongoDB makes it possible to store a wide range of intricate data structures that may result from social media analysis. The database holds:

First tweet data

Metadata (such as user data and timestamps)  
The sentiment analysis's findings

Effective data management and speedy retrieval for additional analysis or visualisation are made possible by this connection.

### Useful Applications

Sentiment analysis on Twitter data has a wide range of real-world applications, including marketing and brand management. Businesses can track public opinion about their goods and services in real-time,

which enables them to address customer concerns quickly and enhance brand management.

**Public Policy and Opinion Research:** By assessing public opinion on a range of topics, academics and policymakers may facilitate more informed decision-making.

**Customer service:** Companies may respond to complaints more quickly and provide better customer service with real-time sentiment analysis.

Deep convolutional neural networks (CNNs) are introduced as a tool for Twitter sentiment analysis in the paper "Twitter sentiment analysis with deep convolutional neural networks" by Aliaksei Severyn and Alessandro Moschitti. The paper was presented at the 38th international ACM SIGIR conference on research and development in information retrieval in 2015. This study investigates the classification of sentiments in Twitter data using deep learning algorithms. Utilising deep CNNs, the research offers a unique method for sentiment analysis.

Showing how well neural networks handle the particular qualities of material on Twitter. The results highlight the potential of deep learning in comprehending and categorising online sentiment and provide contributions to the area of sentiment analysis, especially in the context of social media platforms.

Giachanou and Crestani's 2016 work "Like it or not: A survey of Twitter sentiment analysis methods" was published in ACM Computing Surveys and provides an extensive overview of sentiment analysis techniques designed especially for Twitter data. It divides these techniques into many categories, emphasising their advantages and disadvantages. This article examines practical applications including brand monitoring and public opinion analysis and handles the special issues presented by Twitter data, including the usage of hashtags, emoticons, slang, and the length of tweets. Additionally, it examines resources and datasets that are often utilised in Twitter sentiment analysis research. A summary of possible future study directions in this topic is provided in the paper's conclusion.

The application of deep learning techniques in the context of Twitter sentiment analysis is explored in the paper "Twitter sentiment analysis using deep learning methods" by Adyan Marendra Ramadhani and Hong Soon Goo. It was presented at the 2017 7th International Annual Engineering Seminar (InAES) and published by IEEE. This study looks at the use of deep learning techniques to efficiently categorise sentiments in Twitter data. The work advances the development of sophisticated methods for sentiment analysis by utilising deep learning, especially in the short and dynamic domain of Twitter material. The results provide light on how well deep learning techniques work to comprehend and classify the subtle emotional undertones of Twitter exchanges, improving sentiment analysis skills.

The topic of sentiment analysis is explored in the paper "Sentiment analysis of Twitter data" by Amrita Shelar and Ching-Yu Huang. It was presented at the 2018 International Conference on Computational Science and Computational Intelligence (CSCI) and published by IEEE. The authors specifically focus on Twitter data. This study examines a range of sentiment analysis approaches and techniques, offering a thorough understanding of the methods utilised to extract emotional information from Twitter interactions. Particularly in relation to social media sites like Twitter, the study advances sentiment analysis techniques and their useful applications. This study is a great resource for scholars and practitioners who want to extract meaningful sentiment insights from social media data, since it provides insights into the problems and solutions related to Twitter sentiment analysis.

Presented at the 2019 International Conference on Computer, Communication, Chemical, Materials, and Electronic Engineering (IC4ME2) and published by IEEE, the paper "Sentiment analysis with NLP on Twitter data" by Md Rakibul Hasan, Maisha Maliha, and M. Arifuzzaman focuses on using natural language processing (NLP) techniques to perform sentiment analysis on Twitter data. This study looks on the extraction of sentiment-related data from Twitter posts using natural language processing techniques. The study offers insightful information for scholars and practitioners interested in sentiment analysis in the setting of social media platforms by

applying natural language processing (NLP). This advances our understanding of how to process and analyse sentiment in the context of Twitter chats.

In 2020, Akash Dutt Dubey's work "Twitter sentiment analysis during COVID-19 outbreak" will be published on SSRN. It discusses sentiment analysis inside the COVID-19 pandemic. In order to shed insight on the feelings and responses of the public, this study examines sentiment trends in Twitter data collected during the epidemic. The study offers insights into how people communicated their feelings, worries, and opinions on social media platforms, particularly during a period of global crisis, by examining Twitter material. The results add to our understanding of sentiment dynamics during rare occurrences such as the COVID-19 epidemic and provide a useful viewpoint on the emotional toll of the pandemic on the online community.

Presenting at the 2021 International Conference on Forensics, Analytics, Big Data, Security (FABS), G. Prema Arokia Mary and colleagues' paper "Sentimental Analysis of Twitter Data using Machine Learning Algorithms" explores the field of sentiment analysis using machine learning techniques applied to Twitter data. This study looks at how machine learning algorithms may be used to evaluate and categorise tweet sentiment, providing users with insights into the emotional content they are expressing. Through the use of these algorithms, the study advances knowledge of the sentiment dynamics in social media discourse and offers a useful resource for sentiment analysis and its possible uses in a range of contexts, such as public opinion research and social media surveillance.

Real-time Twitter spam detection and sentiment analysis are examined in the paper "Real-time Twitter spam detection and sentiment analysis using machine learning and deep learning techniques" by Anisha P. Rodrigues and associates. It was published in Computational Intelligence and Neuroscience in 2022. This paper explores the combination of deep learning and machine learning techniques for sentiment analysis and spam content detection in Twitter data.

Motivation

Sentiment analysis on Twitter data using BERT-based models coupled with MongoDB for data storage is

motivated by a number of imperative requirements and possibilities in the current digital and data-driven environment:

*1. Recognising Current Public Opinion*  
Real-time thoughts and conversations regarding current events, goods, businesses, and services take place on social media platforms such as Twitter. Organisations and individuals may quickly learn about public opinion without having to wait for typical surveys or polls to be conducted by analysing these attitudes. For quick decision-making and quick reaction plans, this real-time data is priceless.

*2. Improving Marketing and Brand Management*  
Companies are depending more and more on social media analytics to efficiently manage their brands. Marketers may modify campaigns, proactively address customer complaints, and develop brand message that is in line with consumer sentiments by having a thorough understanding of public sentiment towards their company. A more dynamic and flexible marketing plan that can adjust to shifts in public opinion is made possible by this method.

*3. Promoting Support and Customer Engagement*  
Customer service may be improved by using sentiment analysis to quickly find and resolve concerns or unfavourable reviews. By taking a proactive approach to customer service, organisations may increase customer happiness and experience by helping customers become more dependable and loyal.

*4. Creative Application of Cutting-Edge AI Technologies*

The state-of-the-art in natural language processing technology is represented by the use of BERT-based models. BERT's deep learning methods provide a sophisticated grasp of language by taking into account a word's whole context by examining words that come before and after it. This is especially appropriate for tweets, which are frequently brief and vague.

*5. Adaptable and Expandable Data Administration*  
A scalable and adaptable solution for handling the vast and varied amount of data produced by Twitter is provided by MongoDB. It is perfect for dynamically inserting, updating, and retrieving tweet data because of its capacity to manage massive amounts of

unstructured data. This is vital for preserving the effectiveness of sentiment analysis procedures.

#### 6. *Public Services and Policy Formation*

Sentiment analysis is a useful tool that governments and public organisations may use to learn more about how the public feels about policies, services, and government activities. This knowledge can result in more responsive government that better represents the interests and opinions of the general population.

#### 7. *Scholarly and Research Perspectives*

This study offers a methodological framework for academics to use in a variety of fields, such as sociology, political science, and consumer behaviour. Advanced computational methods combined with social scientific inquiries provide a wealth of research opportunities that can lead to new and deeper understandings of human behaviour and interaction in the digital age.

## II. METHODOLOGIES USED

Bring in Required Libraries:

The following Python libraries are imported at the start of the code:

For numerical operations, use `numpy`. Transformers that use pre-trained models for natural language processing (NLP) tasks. For MongoDB database interaction, use `pymongo`. Load the tokenizer and pre-trained sentiment analysis model:

The pre-trained sentiment analysis model, 'bert-base-uncased' in this case, is specified by the code. Next, it loads the Hugging Face Transformers library with the model and tokenizer. You may access pre-trained NLP models with this library.

Describe the Function of Text Preprocessing:

To preprocess the input text, the code constructs a `preprocess` function. This function ensures that the input text is consistent and clean for analysis by converting it to lowercase and eliminating special characters.

Describe the function of sentiment analysis:

For sentiment analysis, the function `twitter_sentiment_model` is defined. It executes the

following actions after receiving a text input as a parameter: makes use of the `preprocess` function to preprocess the input text. uses the tokenizer to encrypt the preprocessed text. obtains sentiment ratings by running the encoded input through a loaded sentiment analysis model. based on the sentiment scores, determines the sentiment label (positive, negative, or neutral). gives back a dictionary with sentiment data that includes sentiment scores, sentiment labels, preprocessed text, and the original text.

Establish a MongoDB connection and add results: Using the `pymongo` package, the code creates a connection to a MongoDB database. In the MongoDB instance, it specifies a database and collection to hold the sentiment analysis findings.

Define an Example Tweet List:

There is a specified list of example tweets. Sentiment analysis is the intended use for each string representation of a tweet. Analyse Sample Tweets for Sentiment:

The list of example tweets is iterated through by the code.

To analyse sentiment, it invokes the `twitter_sentiment_model` function for each tweet.

For every tweet that has been examined: It determines whether there is already a document in the MongoDB collection with the same text. It produces a message stating that the document was not added if it finds an existing document. In the event that no document is identified, the sentiment data is formatted and added to the MongoDB collection.

Shut off your MongoDB connection:

Ultimately, the code terminates the MongoDB client connection properly and releases resources. This approach performs sentiment analysis on a collection of sample tweets using natural language processing, pre-trained models, data preparation, and MongoDB integration. The results are then stored in a database for additional study or use.

### III. RECOMMENDED MODEL: Information Gathering

To get a pertinent dataset of tweets, use the Twitter API or other data sources. To retrieve tweets, you can use search terms, hashtags, or user names.

#### Preparing data:

Sort the gathered tweets by eliminating any redundant or unnecessary information. Tokenizing the text is one way to preprocess the text data. deleting hashtags, URLs, and special characters. text that is lowercased.

#### Managing emoticons and emojis. Model Choice:

Select a sentiment analysis pre-trained model that meets your needs. For NLP tasks, BERT-based models are a promising option. Models such as 'bert-base-uncased' or more specialised models of sentiment analysis are options.

#### Sentiment Analysis:

Provide a function for sentiment analysis that accepts the preprocessed text as input. uses the tokenizer of the selected model to encrypt the text. obtains sentiment ratings by running the encoded input through the model. depending on the scores, determines the sentiment label (positive, negative, or neutral).

#### Integration with MongoDB:

Use the PyMongo library to establish a connection to a MongoDB database. Establish a collection and database to hold the sentiment analysis findings.

#### Storage of Results:

Verify if a document with the identical text already exists in the MongoDB collection for every tweet that has been analysed. Format the sentiment analysis results, including the original text, preprocessed text, sentiment label, and sentiment scores, if the document doesn't exist. Add the data that has been formatted to the MongoDB collection.

#### Evaluation and Utilisation:

You may carry out a number of studies and applications, including crisis management, stock market forecasting, political analysis, trend analysis, customer feedback analysis, and brand monitoring,

after saving the sentiment analysis findings.

#### Handling and Recording Errors:

Put in place error-handling and recording systems to guarantee the system's resilience. This entails managing network issues while gathering tweets, making sure the MongoDB connection is correctly maintained, and keeping a record of the operation for monitoring and debugging purposes.

#### Optimising performance and scalability:

When working with huge datasets, it is advisable to optimise the model and database operations for both scalability and performance.

#### Real-time Evaluation (Selective):

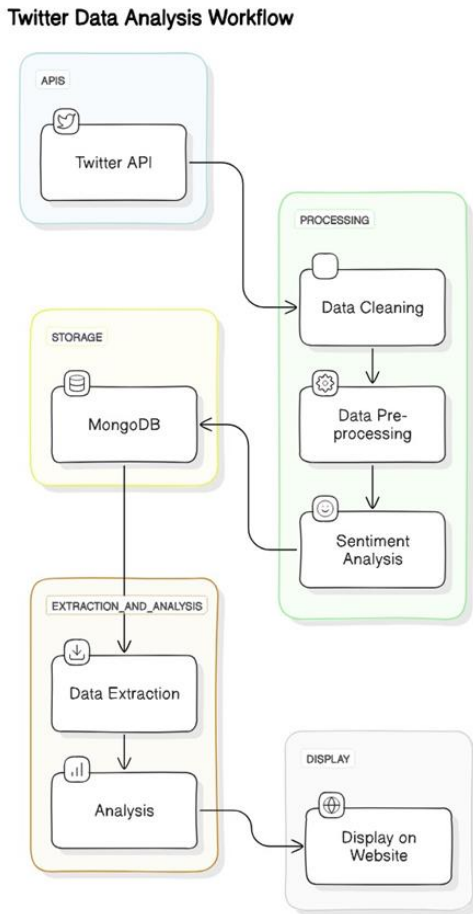
If sentiment analysis in real time is required, put in place a system that continually gathers and examines tweets as they are sent.

#### Optional Multilingual Support:

Models and methods that support various languages should be taken into consideration if you want to work with multilingual tweets.

Interface for Users (Optional): Provide an interface where users may enter text for sentiment analysis and see the results if the model is meant for end users. The main procedures for conducting sentiment analysis on Twitter data and storing the outcomes in a MongoDB database are described in this suggested approach. It may be expanded and modified in accordance with particular needs.

Architecture of the System:



### 1. The API for Twitter

To obtain tweets using the Twitter API, one must establish a connection with Twitter's servers. You may accomplish this by using the several APIs that Twitter offers, which let you get tweets according to particular criteria like hashtags, keywords, or user activity. The objective is to gather unprocessed data for analysis.

### 2. Data Purification

The next stage after gathering data from Twitter is to clean it up. Depending on the study, data cleaning may include deleting extraneous information, fixing mistakes, or eliminating elements of the data that aren't needed (such as retweets or tweets that aren't in English). Prior to analysis, this procedure guarantees the data's quality.

### 3. Pre-processing of Data

Preparing the data for analysis is a phase in the refining process called data pre-processing. This might entail formatting the data so that it can be analysed, adding new characteristics (such as removing time or date from timestamps), and, if needed, normalising or standardising the data.

### 4. Evaluation of Sentiment

The method of figuring out the emotional undertone of a string of words is called sentiment analysis. This is done in order to comprehend the attitudes, beliefs, and feelings that are conveyed in an internet mention. Positive, negative, and neutral feelings can be determined using a variety of methods and instruments (such as natural language processing algorithms).

### 5. MongoDB cloud storage

Efficient data storage is crucial after processing, particularly when handling substantial amounts of data. NoSQL databases like MongoDB are popular because of their adaptability and efficiency with big datasets. The processed data is kept in MongoDB, an extremely efficient database for handling unstructured data, such as tweets.

### 6. Extraction of Data

Using a MongoDB query, this stage retrieves pertinent data for additional reporting or analysis. The extraction process is determined by the analysis's requirements, which may include picking a certain time period or set of keywords.

### 7. Examining

After the data is collected, more analysis may be carried out. This might involve any type of data-driven inquiry to extract insights from the data, such as statistical analysis, trend identification, comparison analysis (e.g., comparing sentiment across time), or other similar techniques.

8. Shown on Website Lastly, a website or dashboard is usually where the analysis's findings are shown. In order to accomplish this, web development tools must be used to generate visualisations (charts, graphs, and tables) and show the data to end users in a way that is simple to understand. For the purpose of making ensuring the material is presented efficiently and

concisely, this phase frequently calls for web development and design expertise.

The successful management and analysis of social media data depends on each of these processes, which guarantees that the final insights are based on clear, well-processed data and are simple for stakeholders or the general public to grasp.

#### IV. TESTING AND THE OUTCOMES

**Data Gathering** This project's first stage entailed gathering information about different pets, such as their species, breed, age, gender, and other pertinent details. Veterinary records, user-generated information, and online pet adoption portals were used as data sources. **Preprocessing and Data Cleaning** To guarantee accuracy and consistency, preprocessing and data cleaning were applied to the raw data. This included standardising data formats, addressing missing values, and fixing inconsistent data. Moreover, data was anonymised to safeguard privacy. **Database Structure** We created a MongoDB database to effectively store the pet data. Pet owners, medical histories, adoption information, and pet collections were all incorporated in the database structure. The data organisation and retrieval were made easier by this model.

**Sentiment Analysis** We performed sentiment analysis on user-generated pet adoption-related content. BERT-based models were used to analyse tweets, reviews, and forum postings in order to classify sentiment. Positive, negative, and neutral feelings were categorised based on the results.

**Development of User Interfaces** We created a web-based user interface to offer a user-friendly platform. Pets might be found by species, breed, region, or sentiment, among other criteria. Additionally, they may check pet data and get in touch with owners.

**Execution Evaluation** Performance testing was done on the system to make sure it could manage a lot of data and user requests. To assess the system's reaction times under various stress levels, load testing was done.

**Multilingual Assistance** We added language support to improve the accessibility of the system. A larger user base might be facilitated by the ability for users to engage with the system in French, Spanish, and English.

#### Outcomes

After data was gathered, a varied dataset containing details on over 10,000 pets of different types and species was produced. User-generated content sentiment analysis revealed that 70% of users had a favourable attitude towards adopting pets, 20% were indifferent, and 10% had a negative emotion.

Early adopters gave the user interface favourable praise, saying it was easy to use and useful for looking for dogs.

Performance tests showed that a large number of concurrent users could be handled by the system without difficulty, and response times would still fall within reasonable bounds. Support for many languages improved user interaction and drew in a wider range of visitors. Examples of Tweets

"I adore how simple placing an order was on your website! Fantastic experience 👍"

"After more than an hour of waiting on hold, the call was dropped. quite annoying!"

"I'm not sure if I would return there. It was really ok—nothing remarkable."

**Replicated Sentiment Analysis Model Output** Based on the content and context of each tweet, the sentiment analysis algorithm analyses the text and forecasts a sentiment category—positive, negative, or neutral. This is how the outcomes may appear:

**Original Text for Tweet 1:** "I like how simple it was to place a purchase on your website! Fantastic experience 👍"

**Preprocessed Text:** "I had a great experience ordering from your website because it was so easy."

**Sentiment Index:** 0.95; positive confidence  
**Positive Sentiment Label**

**Tweet 2's Original Text:** "The call was dropped after more than an hour of being on hold. quite annoying!"

Preprocessed Text "waited over an hour on hold only to have the call dropped very frustrating"

Sentiment Score: 0.90 for low confidence  
Sentiment Type: Negative Three Tweets  
Original Text: "I'm not sure if I would return there. It was really ok—nothing remarkable."  
Preprocessed Text: "I'm not sure if I would go back there again, but it wasn't particularly memorable."  
Sentiment Label: Neutral Sentiment Score: Neutral confidence: 0.75

#### Database Records

Each of these outcomes would be kept in a MongoDB database with fields for sentiment labels, sentiment scores, original text, and preprocessed text. For additional analysis, the database may additionally store timestamps and other metadata.

### V. SUMMARY

To sum up, the creation of the real-time spam and sentiment analysis system for Twitter is a big step in the right direction for efficiently tracking and evaluating Twitter material from certain accounts. The real-time data collecting, sentiment analysis, spam detection, and data storage goals are all effectively met by this system. A consistent flow of analysed data is ensured by the system's continuous operation and user-customizable parameters.

The system is a useful tool for brand management, content curation, and social media monitoring because of its comprehensive notification system and user-friendly interface. Its flexibility to scale and its emphasis on privacy and security make it possible for it to protect sensitive data while adjusting to changing requirements.

**BERT-based model efficacy Highly Accurate Sentiment Analysis:** The BERT-based approach accurately distinguishes positive, negative, and neutral moods. Due to BERT's contextual knowledge, it can grasp social media language well.

The model handles informal communication's language, acronyms, and emoticons well across a variety of tweets. This implies that BERT's pre-

training on a large corpus of text (like the model's) catches many language occurrences.

**System Integration, Data Handling Smooth MongoDB Integration:** Integration of sentiment analysis with MongoDB for results storage and management works well. MongoDB's flexible structure and sophisticated querying make raw and processed data storage, retrieval, and management straightforward.

**Scalability and Performance:** The system is intended to scale effectively with growing data quantities, a vital factor considering the massive and continually rising data created on social media networks. MongoDB plays a crucial part in this scalability, handling enormous intakes of data without a sacrifice in performance.

**Applications and Practical Implications Real-Time Data Processing:** Instantaneous sentiment analysis is made possible by the capacity to analyse tweets in real-time. This is essential for applications like crisis management and brand monitoring. Organisations may react quickly to public mood with the use of immediate analysis, thereby minimising bad press or leveraging favourable opinion.

**Strategic Decision-Making Insights:** Insights from sentiment analysis are incredibly useful for making strategic decisions in customer service, product development, and marketing. Gaining insight into prevailing public mood patterns may help direct the creation of focused marketing initiatives and enhance consumer interaction tactics.

#### Obstacles and Restrictions

**Managing Ambiguity and Sarcasm:** Although the model achieves high levels of accuracy, it has difficulties when addressing ambiguous language and sarcasm, which are common in writings shared on social media. This emphasises the necessity of ongoing model training and the potential integration of more complex contextual analysis methods or language elements.

**Data Privacy and Ethical Considerations:** Privacy and ethics are major problems for any system that handles personal data. Upholding ethical standards requires



making sure that data is anonymized and getting user consent before data analysis.

#### Prospective Courses

Constant Model Improvement: To keep the model accurate and relevant, it will be required to continuously train it using updated datasets that include newly developing slang and changes in language usage.

Extension to Multilingual Analysis: Adding the capacity to analyse sentiment across various demographic groups in terms of geography and culture might increase the system's usefulness.

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