Vol. 06, No. 4 (2024) 1917-1928, doi: 10.24874/PES.SI.25.03A.016



Proceedings on Engineering Sciences



www.pesjournal.net

CHATGPT THROUGH INDIAN LENSES: A SENTIMENT ANALYSIS OF INDIAN TWEETS ON CHATGPT

| Aakanksha Jha ¹ |
|----------------------------|
| Seema |
| Harshita Gupta |
| Ankita |
| Nisha Rathee |

Received 06.01.2024. Received in revised form 20.02.2024. Accepted 18.03.2024. UDC – 004.8

Keywords:

ChatGPT, Generative AI, Sentiment Analysis, Twitter.

The importance of using sentiment analysis in various aspects of study and research has been increasing significantly across the globe. By utilising the benefits of the same, an extensive study has been proposed on the diversity of sentiments of Indian users about ChatGPT through the data gathered from Twitter. The purpose of this study is to understand the perspectives of early users and identify the major topics of discussion regarding ChatGPT in India specifically. To achieve the same, 27,275 tweets has been segregated from pre-existing Kaggle dataset which encompasses several tweets containing the hashtag 'ChatGPT' by the twitter users across the world, covering from the launch date i.e. 30th November, 2022 till 24th February, 2023. In order to understand them, topic classification has been performed using Latent Dirichlet allocation (LDA). Sentiment analysis has been conducted using three techniques VADER, ROBERTA and TEXTBLOB, through which the dataset is labelled. Further, five different classifiers have been applied on the dataset named as: Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), XGBoost Classifier and Decision Tree, to get the performance parameters. According to the results, Logistic Regression classifier with GridSearchCV has the highest accuracy of 86.52% using Count Vectorization.

© 2024 Published by Faculty of Engineerin

1. INTRODUCTION

ChatGPT was the most trending and popular AI tool of 2023, with 14.6 billion total visits throughout the year (Jackson, 2023). It has become one of the most frequently used AI chatbots by users for several narrative tasks. Due to its wholesome capabilities,

prospective applications in various domains, and competence, it has gained a lot of popularity in recent times and has been intensely used by people all around the world (Banafa, 2024). Earlier chatbots were primarily used in the IT industry; however, ChatGPT has brought about a revolution where common people have also started using chatbots to

¹ Corresponding author: Aakanksha Jha

ABSTRACT

Email: jha.aakanksha111@gmail.com

improve their efficiency and productivity; thus, it has become a vital tool now. It has conquered the market by its utility. From not only being used as a search engine but also being used for writing essays and codes as well as to generate (Scoccia, 2023) and understand literature, it has become an essential resource for users. The user's experience, emotions, and perspectives are the most essential parameters that actually define the success of any technology.

The studies have been conducted to comprehend the opinions of the early users of ChatGPT across the world (Sharma et al., 2023). But no such study has been conducted yet, which highlights how developing nations like India are perceiving this technology. Through this research, we'll be able to bridge this gap by diving deep into the perspective of Indian users on ChatGPT through a comprehensive analysis of Twitter conversations.

Utilising the highly spirited social media platform Twitter, which incorporates all kinds of sentiments, views, and opinions of public users. The aim is to unwrap the emotions corresponding to this interactive tool by collecting and analysing the tweets mentioning #ChatGPT posted by Indian users.

The main contributions of the study are as follows:

- To understand the viewpoints of Indian users regarding ChatGPT, which ultimately fills a critical gap in present research and explores the overall sentiment of the Indian tweets, divided into positive, neutral, and negative. The sentiment analysis would assist in determining the degree of adaptability.
- To understand the major topics of discussion about ChatGPT. It would help to understand the usability of ChatGPT and the fields and ways in which it is being utilised by the users.
- To explore the most widely used words in tweets discussing ChatGPT. It would help to acquire meaningful insights into general themes and concerns.
- To compare the sentiment of Indian users with global sentiment towards ChatGPT.
- To compare the results of different sentiment analysis tools used for labelling tweets and the results of different ML models for sentiment analysis used to highlight the reactions of Indian users towards ChatGPT.

The paper is structured as follows: Literature review is presented in Section 2. Section 3 contains the proposed methodology adapted for this study. The sentiment analysis, trending topics about ChatGPT and performance results of methods has been presented in Section 4. Section 5 presents future scope and concludes the paper.

2. RELATED WORK

Sentiment analysis has always been one of the most prominent ways to analyse and understand the sentiment of users regarding a certain topic or product. This includes collecting user reviews regarding any topic from social media sites like Twitter and Reddit or by directly interacting with the user and asking for their feedback. Once enough data has been gathered, the data analysis starts according to the understanding of what the sentiment of the user was while writing that review. Whenever there is an event that influences the public in a greater number, there has always been research for sentiment analysis on that. Some of these works are discussed below.

Gupta et al. used Twitter data from April 5, 2020, to April 17, 2020, a total of 12741 tweets that mentioned the keywords "India" and "lockdown" to prepare a database (Gupta et al., 2020). They used VADER and TextBlob to annotate the tweets and analyse how Indians are taking the idea of lockdown during COVID-19. The study concludes that the majority of Indians supported the lockdown enforced by the Indian Government. Also in this study, the author considered only a single phase of lockdown, which means that this research is only valid for the first phase of lockdown, and the sentiment of people may have changed after.

Ghasiya et al. investigated COVID-19 through sentiment analysis across four nations. Here, 100000 text reviews for 11 months were taken in the form of news headlines and analysed with the help of top2vec and RoBERTa tools (Ghasiya & Okamura, 2021). Top2vec was used to generate topics, top topics contain US, Economy, education showing significance of US in Covid. Usage of RoBERTa showed that the UK has the most negative news i.e.73.23% while South Korea was the most positive country with 54.47% positive news. In this research, a comparison was made between the news in four nations, i.e., the UK, India, Japan, and South Korea, and topic classification was done based on them.Their model achieved a 90% validation accuracy.

Kumar did a netnographic analysis for ChatGPT using the Brand24 platform to determine the volume of social mentions, contexts of discussion, most active web pages, most prominent web pages, and trending hashtags (Kumar, 2023). In addition, details like demographic distribution, age distribution, top countries using ChatGPT, and the interests of the audience have also been demonstrated with the help of SimilarWeb. This study concluded that most of the ChatGPT users belong to the age group of 24-34 years and majority of them were male users.

Sharma et al. manually classified a dataset of 217622 tweets mentioning ChatGPT, taken from Kaggle (Sharma et al., 2023). Sentiments from these tweets were analyzed using machine learning models, including logistic regression and support vector machines. They found that the words "AI" and "language model" are related with positive sentiment, while "bias" and "privacy" are related with negative sentiment.

Tubishat et al. collected 11830 tweets and applied NLP algorithms to identify common topics, perspectives and sentiments that are expressed for ChatGPT in the education field (Tubishat et al., 2023). This study also compared the performance of four classifiers, including Naive Bayes, Support Vector Machine, Random Forest, and K-nearest Neighbour, resulting in the best accuracy of 81.4% using SVM. Here most frequent positive and negative opinions were also extracted, where 'Good', 'Great', 'Free' were positive and 'Critical', 'Wrong', 'Hard' were top frequent negative words. The study concludes that ChatGPT has the ability to be a positive influence in the field of education and both educators and students are liking the platform.

Bharati et al. analysed the reviews on ChatGPT by people from diverse age groups and numerous educational backgrounds (Bharati et al, 2023). This study also compared the performance of four classifiers, including Naive Bayes, Support Vector Machine, Random Forest, Decision Tree and hybrid models. The best accuracy of 94% was achieved using SVM + Decision Tree. Textblob was used for analysing the polarity and subjectivity of a statement. The study concluded with 84% positive sentiments.

Kumari et al. used textblob, VADER and human annotations for sentiment analysis of ChatGPT (Kumari et al., 2023). They used a countVectorizer to extract features. This research used LeXma to identify sentiments and conclude the majority of positive and true emotions. The features were then passed to five different classifiers where 70% of the dataset was used for training and the rest 30% was used for testing. Here SVM gave the best results with the accuracy of 70.16%.

W. S. Ismail gathered a dataset of 15000 english tweets. The author wants to build a sentiment classifier to predict the sentiment of a tweet (Ismail et al., 2023). NTLK and VADER was used to classify the tweets into three categories- Positive, Negative and Neutral. The author utilised KNN and Naive Bayes with accuracy 91.87% and 78% respectively. Overall 81% of tweets expressed a positive sentiment.

Once ChatGPT was launched in 2022, vast research was done on its uses, functionality, and future. Wu et al. mentioned the strengths and impacts of ChatGPT (Wu et al., 2023). It was shown that ChatGPT has a huge impact on Intellectual Property Protection as it does not include copyright while searching or generating an answer, hence making the data protection less. The study also questioned the ethics and integrity of the text generated. It also mentioned the environmental threat it poses to handling large language models and data centres. Along with these concerns it highlighted the ability to understand and generate text. The study also appreciated strong reasoning and creativity of text generated.

In 2023, Gupta et al. and Koubaa et al. focused on the use of ChatGPT in cybersecurity for both defensive and offensive sides (Gupta et al., 2023, Koubaa et al., 2023). The studies discovered many threats and limitations, such as jailbreak attacks, malware creation with the help of ChatGPT, biases, and threats to the validity of solutions provided by ChatGPT. ChatGPT can be exploited to create scenarios where it can be used to create phishing attacks, hacking and other malwares. It was also mentioned that ChatGPT can be attacked to bypass its ethical and privacy safeguards using reverse psychology. They also mentioned that ChatGPT can be used to design new defence techniques, and to write and implement security codes and protection webs, including cyber defence automation, reporting and threat intelligence. They also mentioned Google Bard, Caktus AI, Replika, and Peppertype as competitors to ChatGPT in various countries. Future developments mentioned in these studies are domain-specific and low-resource multilingual, language processing to be introduced with ChatGPT as Large Language models put a lot of stress on the environment during their training process.

ChatGPT has also been used in different sectors. A. Shoufan explored students' perceptions of how it can help in education. Students mentioned that the tool is interesting and helpful in studies as long as they are aware of its limitations (Shoufan, 2023). The study was conducted with 56 senior engineering students. A survey was done before and after these students used the tool to complete their learning activities. They mentioned that the answers given by it are not accurate and require background knowledge to answer a query. Educators need to find creative methods to incorporate this technology to make learning more enhanced.

Ye et al. presented ChatGPT as a tool that will help increase trust between humans and robots by designing a system that can control a 7-degree-of-freedom robot arm to fetch and place tools (Ye et al., 2023). The use of ChatGPT increased human-robot interactions, performance, trust, and cognitive load. It is mentioned here that Large language models would help to develop an interactive, robust and communicative human-robot approach. This can be done due to ChatGPT's ability to catch language nuances and respond naturally.

M. N. Chu specified the application of ChatGPT in the business sector (Chu, 2023). Here, ChatGPT is used to increase customer satisfaction based on the quality of the system, information, and service provided. This

study was done based on a 361-questionnaire gathered from actual businesses. The author created a questionnaire of 361 questions from different actual businesses to analyse the impact of ChatGPT on industry.The research concluded that ChatGPT is still new and currently it does not have an impact on flexible organisational culture.

K. M. Caramancion intends to use ChatGPT v3.5 to identify fake news (Caramancion, 2023). A dataset containing headlines before September 2021 was taken. Here, the answers of ChatGPT were compared with those of other fact-checking agencies, and it was found that ChatGPT could find them with an accuracy of 100%. The tool was also able to predict if a news is half-true or not. The average response time to check if news is fake in text form is 0.74 seconds, while for image links, the response time is 1.22 seconds.

Banimelhem et al. tried using ChatGPT for emotion classification. In this study the author passed a text and the list of emotions as a prompt to ChatGPT and it replied with one of the emotions from the list (Banimelhem et al., 2023). The author tried various prompts but sometimes it returned emotions which were not present in the input list. The test used 285 samples from their dataset and compared ChatGPT's result with actual values of the emotions labelled using machine learning and achieved an accuracy of 58%.

H. Liu used ChatGPT to create a semantic search system. In this study the extracted features were fused with the semantic features of the sequences (Liu et al., 2023). It uses ChatGPT to generate description from the extracted semantic features. This resulted in generation delay of less than 500ms.

Wang et al. surveyed the working principles and security threats of Generative AI (Wang et al., 2023). They also explored the architecture and workings of AIgenerated content. They also concluded that text, images, and video could be easily generated with the help of AI. This research presented a framework to building knowledge factories containing domainspecific big models with the help of ChatGPT.

In this study, the primary objective is to examine the perception of ChatGPT among Indians using data from Twitter through sentiment analysis. Aim is to classify and analyse the topics on which the discussions about ChatGPT are happening in India. Further the target is to compare the sentiment of Indian users with that of worldwide users to study the mindset of Indians regarding ChatGPT.

3. PROPOSED APPROACH

In this section, a framework has been presented for the analysis of diverse perspectives and reactions of Indians to the launch of ChatGPT expressed via Twitter. The various stages of analysis of the tweets of Indian users are shown in Figure 1.

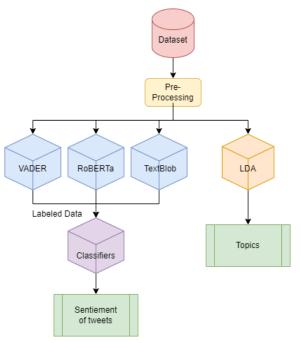


Figure 1. Flowchart of Methodology

3.1 Data Extraction

The emergence of ChatGPT, a large language model (LLM), sparked vast global interest. Initial reactions ranged from enthusiastic recognition of this NLP advancement to anxious scepticism. Analysis is performed on the tweets of Indian users posted on Twitter from the launch of ChatGPT, i.e., November 30, 2022, until February 24, 2023. The week-wise distribution of the tweets for the first 14 weeks from the launch date is shown in Figure 2. The requirement - specific data is not available, and hence a subset of the Kaggle dataset "Tweets on ChatGPT: #ChatGPT" (Bhattacharjee, 2023) has been obtained for the study in order to study how Indian Twitter users initially reacted to a new emerging Generative AI tool, ChatGPT.

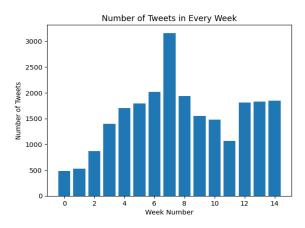


Figure 2. Number of Tweets in first 14 weeks of ChatGPT launch

This dataset contains 27,275 tweets with #ChatGPT, which were collected using web scraping techniques. It provides a perceptive look at the viewpoints of early Indian users. The tweets coming from Indian users have been segregated using location-based filtering so that focused study can be performed on the Indian context.

| Table 1. Attributes of D |
|--------------------------|
|--------------------------|

| Attribute Name | Attribute Type | Description |
|-------------------|-------------------|---|
| Date | Date | The date and time tweet was posted |
| Tweet | Text | The content of the tweet |
| User Verified | Boolean | Whether the user's account is verified or not |
| Likes | Numerical | The number of likes the tweet has received |
| Retweets | Numerical | Number of times tweet has been retweeted |
| Location | Text | The user's location, if available |

3.2 Data Processing

The dataset holds some noise like links, hashtags (starting with #), mentions (starting with @), stopwords, extra spacing, etc. These words do not hold any specific role in the analysis of the sentiment of the tweet but may create overheads in the process, so they must be removed before performing any sentiment analysis. The emojis and other non-alphabetic characters has been removed as well to enhance the readability of the text by the models.

As shown in Figure 3, the pre-processing involves the removal of mentions, URLs, etc. The complete tweets data is converted to lowercase to give equal weight to upper-case and lowercase phrases. Eliminating punctuation, stopwords, and short tokens helps to increase accuracy by removing the noise.



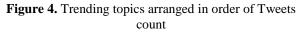
Figure 3. Flow chart of different steps of pre-processing

3.3 Topic Classification

LDA for topic categorization has been utilised, aiming to find out the trending topics and subjects amongst the Indian Twitter user's tweet collection. Extracting the highest and lowest frequencies from the gathered ChatGPT tweets helps find the most frequent and informative keywords. Next, LDA is used to find latent topics in text data and cluster the tweets into 10 different groups. Based on the group of terms that appeared most frequently in each cluster, a specific topic label was then provided to each cluster manually by considering the sets of keywords used in a particular cluster.

With the help of LDA, the viewpoints of the Indian audience about ChatGPT shared on Twitter has been extracted successfully, and the top 10 topics amongst the tweets are highlighted in Figure 4.

| 1 | Using language models for productivity |
|----|---|
| 2 | Impacts on Future Industry |
| 3 | Competition of AI Giants |
| 4 | New developments extending OpenAl |
| 5 | Availability of AI to the public |
| 6 | Chatbots and language models or education |
| 7 | ChatGPT's issues and reliabilities |
| 8 | Impacts on Future Businesses |
| 9 | Al as new Technology |
| 10 | The Future of AI in India |



3.4 Data Labelling

Topic classification has provided the trending topics about ChatGPT, but the sentiment of the tweets must be analysed in order to understand the positive to negative sentiment ratio. VADER, RoBERTa and TextBlob are used to label the tweets with positive, negative, and neutral tags. VADER and TextBlob are lexicon-based and rule-based methods, whereas RoBERTa is a deep learning-based method. VADER is good for social media text (Awajan et al., 2021) RoBERTa offers the highest accuracy but is computationally expensive (Tan et al., 2022); and TextBlob is a balance between accuracy and efficiency (Jayasurya et al., 2022).

3.5 Vectorization

As machines can't understand the words, the text needs to be converted into numbers, which can then be further passed as input to classifiers; thus, generation of features out of text data is required.'Countvectorizer' and 'TF/IDF vectorizer' have been used to achieve the same. Countvectorizer represents a document as a vector of dimension equal to the vocabulary size. The occurrence count of a word is filled in, corresponding to each element. For example, Tweet 1: "I love ChatGPT" and Tweet 2: "I use ChatGPT frequently for content writing." Countvectorizer creates a matrix as shown in Table 2.

| Tokens | Tweet 1 | Tweet 2 |
|------------|---------|---------|
| Content | 0 | 1 |
| ChatGPT | 1 | 1 |
| for | 0 | 1 |
| frequently | 0 | 1 |
| Ι | 1 | 1 |
| love | 1 | 0 |
| use | 0 | 1 |
| writing | 0 | 1 |

 Table 2. Countvectorizer Matrix

The term frequency-inverse document frequency (TF-IDF) vectorizer assigns weights to words to refine count vectors. The assignment of weights is dependent on the uniqueness and importance of the word across documents. The words like "of," "as," and "the" appear frequently in the document; using IDF, the weight of these words is minimised while making less frequent words have a higher impact.

3.6 Training and Testing the Classifiers

After performing feature extraction, the processed data has been passed to machine learning classifiers. The following five classifiers are used: Logistic Regression with GridsearchCV, Decision Tree Classifier, XG-Boost Classifier, K-Nearest Neighbor Classifier, and Support Vector Machine Classifier. 70% of the dataset has been utilised for training and 30% for testing the classifiers. Analysis on the data has been performed by applying the classifiers and processing it with two kinds of vectorizers, i.e., Countvectorizer and TF-IDF vectorizer.

Machine Learning Classifiers used in the study:

• Support Vector Machine

The goal is to minimise the errors in classification to obtain better accuracy so SVM has been applied which is a supervised learning approach to solve problems based on classification and regression. SVM transfigures the data into higher-dimensional spaces. So it can be summarised as, it focuses on finding the best hyperplane which further maximises the distance value, ultimately it fulfils the goal (Tubishat et al., 2023; Shannaq et al., 2022).

• Logistic Regression

Logistic Regression is a ML model, it has been extensively used for classification problems, specifically binary one's. It is used to uncover the relationship between two or more input variables and one output variable, where input variables are independent variables and output variables are dependent. It consists of an S-shaped curve due to the usage of sigmoid function which gives the output in the range of 1 and 0. So it can be considered that it basically predicts the probability of an event. Moreover, regressions problems cannot be solved by using this algorithm (Shannaq et al., 2022; Gururaj et al., 2022).

• K-Nearest Neighbour

KNN is a supervised classification algorithm and is widely used to solve the problems related to classification as well as regression. KNN has two hyperparameters: one is k, the number of neighbours, and the other is d, distance metrics. Training samples have been tracked by the KNN algorithm in fixed numbers from the last window of the observed samples. It uses Euclidean distance to calculate the distance between the new point and all other points present in the training data, in terms of selecting the nearest/closest neighbours among these samples, whenever new input data is received (Shannaq et al., 2022; Tubishat et al., 2023; Rojas et al., 2020).

• XGBoost Classifier

XG-Boost is a powerful tree boosting Machine Learning algorithm (Ghatasheh et al., 2022). As it incorporates a framework called gradient boosting framework which makes it scalable over other ML techniques. It is based on a decision tree algorithm (Shannaq et al., 2022). To get the final prediction from it, what actually happens is, successive trees are being trained on the residual errors of the previous tree which ultimately enhances the execution of the constructed tree. On calculating the sum of predictions of all individual trees the final prediction is obtained (Ghatasheh et al., 2022). Not only being scalable is the edge of XG-Boost, other than this it also possesses various other abilities such as proper handling of sparse data, appropriate dealing with missing values as well as utilising the potential of distributed and parallel processing (Shannaq et al., 2022).

• Decision Tree

Decision Tree algorithm is also used to construct classification as well as regression models. Its appearance resembles the tree-like structure. In accordance with that it works by breaking down a dataset into smaller subsets which consist of decision nodes and leaf nodes, where decision nodes can have two or more number of branches while a leaf node cannot have further branching, because it represents itself as an output or a decision.(Shannaq et al., 2022)

4. RESULT AND ANALYSIS

In this section, detailed discussion has been put together to get the insights into topic classification and the classifier's results based on accuracy, precision, recall, and f1-score. The analysis of the tweets using LDA resulted in identifying the reactions and adoption ways of ChatGPT by Indian users. Figure 5 shows the word cloud formed with the most prominent words from each cluster.

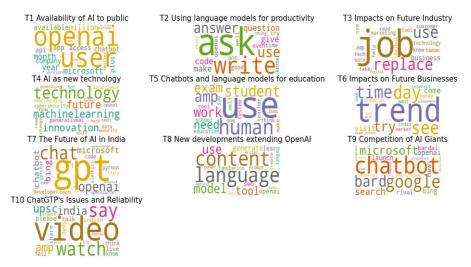


Figure 5. Word Cloud of each cluster of corpus

Performing the topic-wise classification study on the ChatGPT tweets of Indian Twitter users, it has been observed that there is a wide range of points of view that Indians have demonstrated, as shown in Figure 6. "Using language models for productivity" remains at the top of discussion forums, which highlights that people are wholeheartedly welcoming this upcoming technology to improve efficiency and productivity in their work in different sectors. "Impacts on Future Industry" is the second most discussed topic, which highlights the open-mindedness of the Indian people to analyse both sides of the coin and future impacts in different sectors. After analysing their perspectives, people not only discuss the positive side but also talk openly about the fears, issues, and reliability of ChatGPT, has been discovered.

Different modules have been utilised for labelling the dataset. VADER is a comprehensive tool that stands out from other conventional tools in terms of its ability to understand social media lingo such as acronyms, emojis, and slang (Awajan et al., 2021). It also has the unique capacity to understand sensitive emotions such as sarcasm, irony, etc., which helps improve the precision and comprehensiveness of the analysis. It doesn't need to be trained on training data before use; thus, its predefined set of rules helps to analyse the sentiment with low computational complexity.

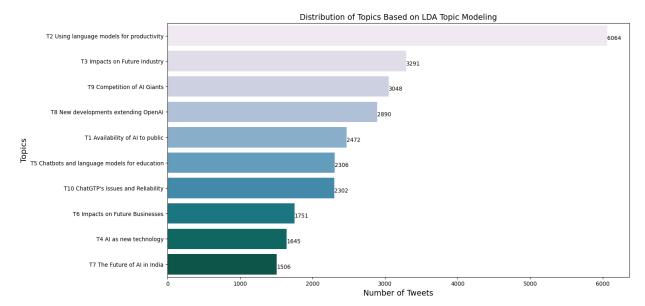


Figure 6. Distribution of Topic-wise tweets

By utilising the capabilities of RoBERTa (A Robustly Optimised BERT Pre- Training Approach), it became easier to delve deeper into the emotional web, woven by Indian Twitter users' reactions to ChatGPT . RoBERTa's complex algorithm is its fundamental component, which can work on different parts of a tweet, such as individual words, their relationships, and the context in which they appear simultaneously, by using a multihead attention mechanism (Ghasiya & Okamura, 2021; Tan et al., 2022).

Along with VADER and ROBERTA, one of the most prominent and easy-to-use tools, i.e TextBlob, for sentiment analysis is used. This is a widely used Python library used for various NLP-based tasks. The input data is in the format as required by TextBlob for sentiment analysis. To get the sentiment analysis using TextBlob, it returns two parameters in the form of a result: one is polarity and the other is subjectivity. Polarity defines the type of sentiment, positive, negative, or neutral, on the basis of the range, which is from -1 to 1, whereas the range for subjectivity is from 0 to 1. The sentiment analysis result for VADER, RoBERTa, and TextBlob is shown in Table 3. A visual comparison of the same is demonstrated in Figure 7. After comparing the labels assigned by the tools with respect to manual validation, it was observed that out of the three tools, RoBERTa labelled the tweet with the most relatable sentiment. RoBERTa is a deep-learning-based transformer model, which makes it accurate and can handle the complex sentiment and context of the tweets.

| Tool | Positive | Neutral | Negative |
|----------|----------|---------|----------|
| VADER | 43.1% | 45.0% | 11.9% |
| RoBERTa | 36.5% | 46.6% | 16.8% |
| TextBlob | 41.9% | 44.7% | 13.4% |

Table 3. Sentiment Analysis Result

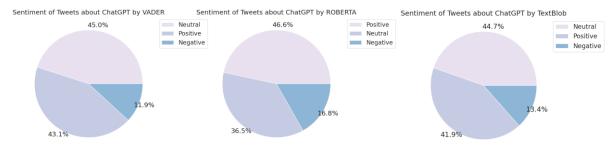


Figure 7. Comparative Study of sentiment analysis algorithm

RoBERTa was able to successfully interpret the sentiment of the tweet and has labelled 36.5% of the tweet with positive sentiment, 46.6% with neutral sentiment, and 16.8% with negative sentiment. The tweets with the same sentiment label assigned by VADER and RoBERTa have been used for further analysis, and the rest with different labels have been discarded. Out of 27,275 tweets processed, the number of unique tweets received are 15,927 for further analysis. The tweet count for each sentiment is shown in Figure 8.

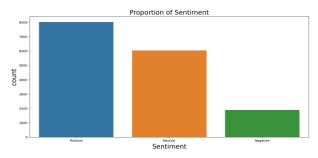


Figure 8. Bar Chart of Tweets Count of each sentiment

The Kaggle Dataset having tweets of worldwide users is analysed to understand the sentiment of people across the globe and compare it with the Indian perspectives as shown in the Figure 9.

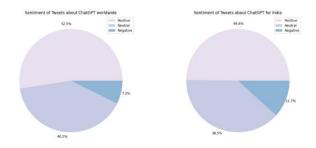


Figure 9. Comparative study of Global Sentiment vs Indian Sentiments towards ChatGPT

Looking at Table 4, the comparison of Indian sentiments with the worldwide sentiment of people across the globe gives an indication about the difference in the viewpoints and the acceptance level of a new technology. The positive sentiment of the world doesn't vary much with the Indians, which gives a good signal that people of India are keen to explore the new technology and make it a part of their day-to-day life. India is always at the top edge of taking up new opportunities to grow and flourish be it in terms of technology or business. As discussed above, the major topics people are discussing about ChatGPT highlights the overall mindset of India. The discussion involves the usage of the Large language models for productivity, new development extending OpenAI, availability of AI to the public, Chatbots for education, etc. The inclination of the users to understand the impact of this advancement on future industry and how the businesses would get benefitted from the AI highlights the futuristic mindset.

| | Global Count | Indian Count |
|----------|--------------|--------------|
| Positive | 157296 | 8032 |
| Neutral | 120569 | 6213 |
| Negative | 21910 | 1895 |

 Table 4. Tweets Count for different Sentiments

The slightly higher negative sentiment of the Indian users can be the effect of diversity in India and the barriers accompanied with it. The difference in languages and culture often becomes an obstacle towards development and technological enhancement,

To analyse the performance of the machine learning models, several parameters are used. Identification of TP, TN, FP and FN is the primary step where TP(True Positive) represents the correctly predicted positive entries, FP(False Positive) represents the negative entries predicted as positive, TN(True Negative) represents the correctly predicted negative entries and FN(False Negative) represents the positives predicted as negatives (Raghunathan & Kandasamy, 2023).

Utilising these 4 parameters the precision, recall and F1-score can be formulated. Precision describes the ratio of true positives over the total positives which includes True positives as well as False positives. Precision helps in understanding how well the model is able to correctly predict the positives. Recall, also known as sensitivity, is different from precision as it calculates the ratio of correctly predicted positives over total positive predictions which includes true positives and false negatives. F1-score is a measurement method which combines both precision and recall and is calculated by taking the harmonic mean of the two. It is a useful method as a lower score of either precision or recall would result in lower overall score and thus covers major aspects in one go (Raghunathan & Kandasamy, 2023).

The Count Vectorizer is used to generate features out of the tweets, and then classifiers are applied to the processed dataset. Table 5, shows the results and accuracy of the classifiers applied. Logistic regression with GridSearchCV gives the best results with 87% precision, 87% recall, and an 86 F1-score. The visual representation of the performance metrics for Countvectorizer is shown in Figure 10.

| Table | 5. | Classification | Report | of | Classifiers |
|---------|-------|----------------|--------|----|-------------|
| (Countv | ector | rizer) | | | |

| Classifiers | Precision | Recall | F1- Score |
|--|-----------|--------|--------------|
| Logistic Regression with GridSearchCV | 0.87 | 0.87 | 0.86 |
| Decision Tree Classifier | 0.86 | 0.86 | 0.86 |
| XGBoost Classifier | 0.87 | 0.86 | 0.85 |
| KNN with GridSearchCV | 0.66 | 0.52 | 0.50 |
| SVM with CV | 0.84 | 0.82 | 0.82 |

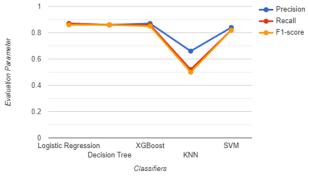


Figure 10. Visual Representation of Performance Metrics for Countvectorizer

Table 6 depicts the results of the classifiers applied to the dataset prepared after applying the TF-IDF vectorizer to create features out of tweets. The visual representation of the performance metrics for TF-IDF Vectorizer is shown in Figure 11.

Table 6. Classification Report of Classifiers (TF-IDFVectorizer)

| Classifiers | Precision | Recall | F1- Score |
|--|-----------|--------|--------------|
| Logistic Regression with GridSearchCV | 0.85 | 0.85 | 0.85 |
| Decision Tree Classifier | 0.82 | 0.82 | 0.82 |
| XGBoost Classifier | 0.82 | 0.82 | 0.82 |
| KNN with GridSearchCV | 0.71 | 0.38 | 0.21 |
| SVM with CV | 0.85 | 0.84 | 0.84 |

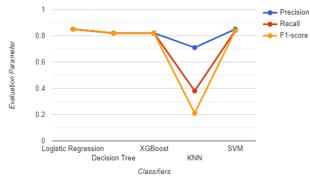


Figure 11. Visual Representation of Performance metrics for TF-IDF vectorizer

| classifiers | | |
|--|-----------------|------------------|
| Model | Count Vector | TF/IDF Vector |
| Logistic Regression with GridSearchCV | 0.865244 | 0.853526 |
| Decision Tree Classifier | 0.850198 | 0.786061 |
| XGBoost Classifier | 0.853606 | 0.783999 |
| KNN with GridSearchCV | 0.521657 | 0.380833 |
| SVM with CV | 0.823813 | 0.842854 |

 Table 7. Comparison of Accuracies of different classifiers

Logistic regression and SVM both have 85% precision, but logistic regression has better recall and F1-score than SVM, as shown in Table 7.

4. CONCLUSION

Talking about sentiment analysis, addressing the potential misinterpretations is also a task which was achieved constructively through this research. In conclusion, after segregating the tweets of the Indian user on launch of ChatGPT from the existing datasets, various tools of sentiment analysis are applied on the preprocessed dataset such as, VADER, ROBERTA and TEXTBLOB. It is transparent from the result that ROBERTA has given the most efficient classification of the sentiments into neutral, positive and negative categories as compared to the other techniques where it has 46.6% neutral category sentiment. 36.5% positive sentiments over 16.8% negative sentiments depicts that Indians are more inclined towards positive aspects of ChatGPT. Later on, when comparing the sentiments of Indian users vs users globally, it was found that 52.5% of the global users have positive sentiments whereas Indian users have 49.8%, which highlights that Indians are also on par with the world's technological development. On getting the labelled dataset, it was compatible to be applied on different classifiers on that particular dataset in order to obtain the accuracy. Therefore, prominent classifiers were applied such as, Logistic Regression classifier with GridSearchCV, Decision Tree Classifier, XGBOOST classifier, k-Nearest Neighbour (KNN) and Support Vector Machine (SVM). From this activity the highest accuracy comes out to be 86.52% for Logistic Regression with GridSearchCV. In future, on getting the views and opinions of those who are not Twitter users, more effective research can be done with the help of their contributions.

References:

- Awajan, I., Mohamad, M., & Al-Quran, A. (2021). Sentiment analysis technique and neutrosophic set theory for mining and ranking big data from online reviews. *IEEE Access*, 9, 47338–47353. doi:10.1109/access.2021.3067844
- Banafa, A. (2024). Transformative AI: Responsible, Transparent, and Trustworthy AI Systems. CRC Press. pp. 137-142.
- Bharati, A. U., Bhargavi, M., Harshith, K. S., & Reddy, S. (2023, July). A Comparative Sentiment Analysis on ChatGPT Reviews using Machine Learning Models, 14th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE, doi: 10.1109/ICCCNT56998.2023.10306609.
- Bhattarcharjee, M. (2023, February). Tweets on ChatGPT #ChatGPT, Version 3. Retrieved on September 10th, 2023 from https://www.kaggle.com/datasets/manishabhatt22/tweets-onchatgpt-chatgpt.
- Caramancion, K. M. (2023, June). Harnessing the power of ChatGPT to decimate mis/disinformation: Using ChatGPT for fake news detection. In 2023 IEEE World AI IoT Congress (AIIoT) (pp. 0042-0046). IEEE, doi: 10.1109/AIIoT58121.2023.10174450.
- Chu, M. N. (2023). Assessing the Benefits of ChatGPT for Business: An Empirical Study on Organisational Performance. *IEEE Access*, *11*, 76427-76436, doi: 10.1109/ACCESS.2023.3297447.
- Ghasiya, P., & Okamura, K. (2021). Investigating COVID-19 news across four nations: A topic modelling and sentiment analysis approach. *IEEE Access*, 9, 36645-36656, doi: 10.1109/ACCESS.2021.3062875.
- Ghatasheh, N., Altaharwa, I., & Aldebei, K. (2022). Modified genetic algorithm for feature selection and hyper parameter optimization: case of XGBoost in spam prediction. *IEEE Access*, *10*, 84365-84383, doi: 10.1109/ACCESS.2022.3196905.

- Gupta, M., Akiri, C., Aryal, K., Parker, E., & Praharaj, L. (2023). From chatgpt to threatgpt: Impact of generative ai in cybersecurity and privacy. *IEEE Access*, *11*, 80218-80245, doi: 10.1109/ACCESS.2023.3300381.
- Gupta, P., Kumar, S., Suman, R. R., & Kumar, V. (2020). Sentiment analysis of lockdown in india during covid-19: A case study on twitter. *IEEE Transactions on Computational Social Systems*, 8(4), 992-1002, doi: 10.1109/TCSS.2020.3042446.
- Gururaj, H. L., Lakshmi, H., Soundarya, B. C., Flammini, F., & Janhavi, V. (2022). Machine Learning-Based Approach for Fake News Detection. *Journal of ICT Standardization*, *10*(4), 509-530, doi: 10.13052/jicts2245-800X.1042.
- Jackson, A. (2023). These are the top 10 most popular AI tools of 2023, and how to use them to make more money. [Online]. Available: https://www.cnbc.com/2023/12/24/the- top-10-ai-tools-of-2023-and-how-to-use-them-to-make-more-money.html
- Jayasurya, G. G., Kumar, S., Singh, B. K., & Kumar, V. (2021). Analysis of public sentiment on COVID-19 vaccination using twitter. *IEEE Transactions on Computational Social Systems*, 9(4), 1101-1111, doi: 10.1109/TCSS.2021.3122439.
- Koubaa, A., Boulila, W., Ghouti, L., Alzahem, A., & Latif, S. (2023). Exploring ChatGPT Capabilities and Limitations: A Survey. *IEEE Access*, *11*, 118698-118721. doi: 10.1109/ACCESS.2023.3326474.
- Kumar, V. (2023, July). How Much Noise ChatGPT is Making: A Sentiment Analysis Approach. In 2023 World Conference on Communication & Computing (WCONF) (pp. 1-5). IEEE. doi: 10.1109/WCONF58270.2023.10235230.
- Raghunathan, N., & Kandasamy, S. (2023). Challenges and Issues in Sentiment Analysis: A Comprehensive Survey. *IEEE Access*, *11*, 69626-69642, doi: 10.1109/ACCESS.2023.3293041.
- Rojas, J. S., Pekar, A., Rendón, Á., & Corrales, J. C. (2020). Smart user consumption profiling: Incremental learningbased OTT service degradation. *IEEE Access*, 8, 207426-207442, doi: 10.1109/ACCESS.2020.3037971.
- Scoccia, G. L. (2023, September). Exploring early adopters' perceptions of chatgpt as a code generation tool, 38th IEEE/ACM International Conference on Automated Software Engineering Workshops (ASEW) (pp. 88-93). IEEE, doi: 10.1109/ASEW60602.2023.00016.
- Shannaq, F., Hammo, B., Faris, H., & Castillo-Valdivieso, P. A. (2022). Offensive language detection in Arabic social networks using evolutionary-based classifiers learned from fine-tuned embeddings. *IEEE Access*, 10, 75018-75039, doi: 10.1109/ACCESS.2022.3190960.
- Sharma, S., Aggarwal, R., & Kumar, M. (2023, April). Mining Twitter for Insights into ChatGPT Sentiment: A Machine Learning Approach, International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE) (pp. 1-6). IEEE, doi: 10.1109/ICDCECE57866.2023.10150620.
- Shoufan, A. (2023). Exploring students' perceptions of ChatGPT: Thematic analysis and follow-up survey. *IEEE Access*, *11*, 38805-38818. doi: 10.1109/ACCESS.2023.3268224.
- Tan, K. L., Lee, C. P., Anbananthen, K. S. M., & Lim, K. M. (2022). RoBERTa-LSTM: a hybrid model for sentiment analysis with transformer and recurrent neural network. *IEEE Access*, 10, 21517-21525, doi: 10.1109/ACCESS.2022.3152828.
- Tubishat, M., Al-Obeidat, F., & Shuhaiber, A. (2023, July). Sentiment analysis of using chatgpt in education. In 2023 International Conference on Smart Applications, Communications and Networking (SmartNets) (pp. 1-7). IEEE, doi: 10.1109/SmartNets58706.2023.10215977.
- Wang, Y., Wang, X., Wang, X., Yang, J., Kwan, O., Li, L., & Wang, F. Y. (2023). The chatgpt after: Building knowledge factories for knowledge workers with knowledge automation. *IEEE/CAA Journal of Automatica Sinica*, 10(11), 2041-2044, doi: 10.1109/JAS.2023.123966.
- Wu, T., He, S., Liu, J., Sun, S., Liu, K., Han, Q. L., & Tang, Y. (2023). A brief overview of ChatGPT: The history, status quo and potential future development. *IEEE/CAA Journal of Automatica Sinica*, *10*(5), 1122-1136, doi: 10.1109/JAS.2023.123618
- Ye, Y., You, H., & Du, J. (2023). Improved trust in human-robot collaboration with ChatGPT. *IEEE Access*, *11*, 55748-55754. doi: 10.1109/ACCESS.2023.3282111

Aakanksha Jha

Indira Gandhi Delhi Technical University For Women, New Delhi, Delhi, India <u>jha.aakanksha111@gmail.com</u> ORCID 0009-0007-4516-3101

Ankita

Indira Gandhi Delhi Technical University For Women, New Delhi, Delhi, India <u>ankita@igdtuw.ac.in</u> ORCID 0000-0002-9250-9511

Seema

Indira Gandhi Delhi Technical University For Women, New Delhi, Delhi, India <u>seema.032002@gmail.com</u> ORCID 0009-0004-6528-6748

Nisha Rathee

Indira Gandhi Delhi Technical University For Women, New Delhi, Delhi, India <u>nisharathee@igdtuw.ac.in</u> ORCID 0000-0003-3158-8874

Harshita Gupta

Indira Gandhi Delhi Technical University For Women, New Delhi, Delhi, India <u>harshitagupta1409@gmail.com</u> ORCID 0009-0004-6800-3037