Uncovering Emotions and Opinions of the Customers in WhatsApp Chats Conversations via Machine Learning Approach

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Abstract – *Analyzing sentiment in WhatsApp chat data has become increasingly important for interpreting the emotional undertones of digital communication. This research examines how sentiment analysis can be leveraged to identify emotional patterns and communication styles within WhatsApp conversations. It begins by highlighting the significance of Natural Language Processing (NLP) in analyzing informal, unstructured text like chat logs. The study also reviews various analytical approaches, ranging from traditional machine learning models such as Naïve Bayes and Support Vector Machines (SVM) to advanced deep learning techniques like Recurrent Neural Networks (RNNs) and transformer-based models.*

The study analyzed a dataset of WhatsApp messages, sorting them into positive, negative, and neutral sentiment categories. The results demonstrated that machine learning techniques provided more accurate sentiment classification than traditional rule-based approaches. Among all models tested, deep learning methods—particularly those based on bidirectional Long Short-Term Memory (Bi-LSTM) networks—achieved the highest accuracy. The discussion also emphasizes the inherent challenges in analyzing sentiment within informal conversations, especially due to factors like sarcasm and ambiguous context.

Keywords: WhatsApp chat, Image, Sentiment Analysis, Emoji Analysis, NLP, Feature Engineering.

1. INTRODUCTION

Sentiment analysis, often referred to as opinion mining, involves the computational examination of emotions, opinions, and attitudes conveyed through text. In recent decades, it has emerged as a key area within natural language processing (NLP), especially for interpreting content from digital communication platforms. With more than two billion active users worldwide (Statista, 2024), WhatsApp serves as a valuable source of conversational data, capturing a wide range of emotional and social interactions. As WhatsApp continues to be a primary medium for personal, educational, and professional communication, analyzing its chat data through sentiment analysis offers meaningful insights into user emotions, social dynamics, and even consumer behavior trends.

Sentiment analysis has evolved significantly—from early rule-based systems to more advanced machine learning, and more recently, deep learning techniques. The earliest approaches relied on sentiment lexicons and predefined dictionaries for classification (Turney, 2002). With the rise of machine learning, supervised algorithms like Naïve Bayes and Support Vector Machines (SVM) became popular, though they often struggled to interpret the informal and conversational nature of chat messages (Pang & Lee, 2008). In contrast, modern deep learning models—such as Recurrent Neural Networks (RNNs) and transformer architectures—have shown improved ability to understand context and subtleties in dialogue (Vaswani et al., 2017).

Recent studies have successfully applied sentiment analysis across a range of domains, including social media analysis (Liu, 2012), customer feedback interpretation (Cambria et al., 2017), and mental health assessment (Coppersmith et al., 2018). Nonetheless, analyzing informal chat data like that from WhatsApp remains challenging due to frequent use of slang, emojis, abbreviations, and sarcasm. Additional concerns involve maintaining user privacy, ensuring ethical handling of personal messages, and dealing with multilingual content.

This study seeks to tailor and apply sentiment analysis methods specifically to WhatsApp chat data, aiming to not only capture emotional expressions but also to detect patterns in communication behavior, mood changes, and interpersonal interactions. By enhancing sentiment classification accuracy in informal settings and addressing privacy-related concerns, the research aspires to create a more nuanced and ethically responsible sentiment analysis model. Such a model could have valuable applications in fields including marketing, behavioral science, and social research.

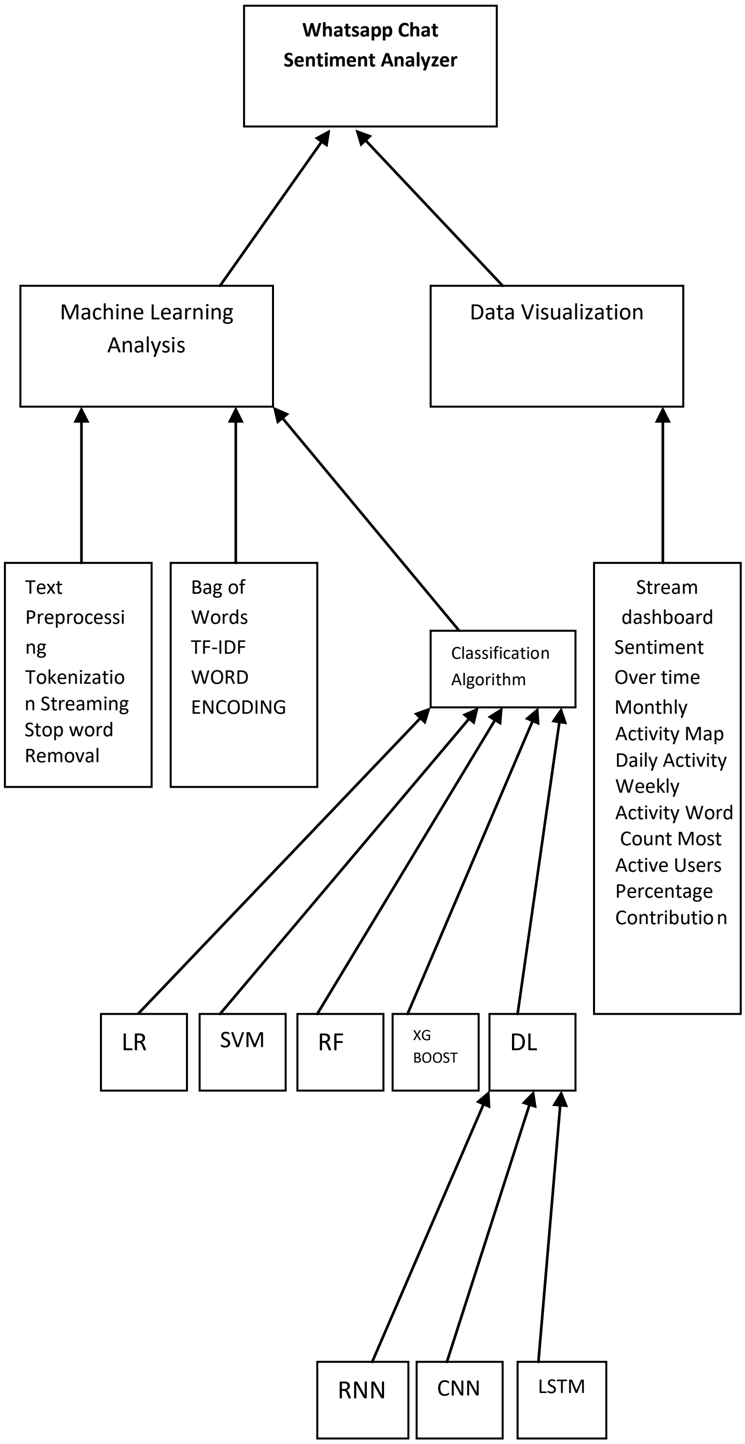

Fig – 1: Block Diagram of SentimentAnalysis

2. LITERATURE REVIEW

2.1 Indication of Sentiment Analysis

The growing use of WhatsApp for both personal and group communication has sparked increased interest in sentiment analysis of its messages. However, the informal nature of WhatsApp chats—often featuring slang, abbreviations, emojis, and casual expressions—poses difficulties for conventional sentiment analysis techniques. Key challenges include detecting sarcasm, grasping context-dependent language, and handling conversations in multiple languages. These complexities highlight the need for more sophisticated models capable of accurately interpreting the unique characteristics of WhatsApp communication.

2.2 Techniques of Sentiment Analysis

Sentiment classification has seen notable success through the use of machine learning techniques such as Support Vector Machines (SVM) and deep learning architectures like Long Short-Term Memory (LSTM) networks. These models excel at understanding sentiment and context across extended conversations. To further enhance accuracy—especially when processing informal language and emojis—hybrid methods that integrate machine learning with lexicon-based strategies have been investigated. Furthermore, transformer-based models such as BERT have significantly advanced sentiment analysis by effectively capturing subtle language cues and contextual meanings (Devlin et al., 2019).

2.3 Challenges in Analyzing Sentiment in WhatsApp Chats

While sentiment analysis of WhatsApp chat data holds great promise, it also presents several obstacles. The brevity and informal tone of messages can lead to ambiguity, making it difficult to accurately interpret subtle cues like sarcasm, irony, or humor. The presence of emojis, stickers, and GIFs further complicates sentiment classification, as these visual elements often carry emotional weight that is hard to quantify. Although some models have started incorporating such features, achieving reliable interpretation remains a challenge. Furthermore, ethical concerns arise when analyzing WhatsApp data, particularly regarding user privacy and the potential lack of informed consent in the use of personal conversations for research purposes.

2.4 Application of Sentiment Analysis

In addition to analyzing textual content, multimodal sentiment analysis—which integrates elements such as emojis, images, and voice notes—has become a promising approach for enhancing sentiment detection in WhatsApp communications. Despite the inherent challenges, sentiment analysis on WhatsApp offers significant opportunities across various fields, including customer support, marketing, and social media monitoring. It provides meaningful insights into user emotions and opinions, contributing to a deeper understanding of consumer behavior (Giatsoglou et al., 2020).

3. PROPOSED METHODOLOGY

Developing a sentiment analyzer for WhatsApp chats involves a combination of data resources and specialized tools to ensure efficient data processing and model evaluation. The primary dataset comprises WhatsApp chat logs, generally available in .txt or .csv formats, containing message timestamps, sender details, and text from both personal and group chats. To uphold privacy standards, personally identifiable information (PII) must be removed, while relevant media files can also be included if they contribute meaningfully to the analysis.

Python serves as the foundation for the software stack, offering a rich selection of libraries for natural language processing (NLP) and machine learning. Preprocessing tasks such as tokenization and lemmatization are performed using NLTK and spaCy, while sentiment analysis is supported by tools like TextBlob and VADER. Traditional models like Naïve Bayes and Support Vector Machines (SVM) are implemented with Scikit-learn, whereas more advanced deep learning architectures—such as RNNs, LSTMs, and transformers—are developed using TensorFlow, Keras, and PyTorch. Data handling is streamlined with Pandas, and visual outputs are generated using Matplotlib, Seaborn, and WordCloud.

For text cleaning, Regular Expressions (Regex) help strip out irrelevant content, and langdetect identifies languages within multilingual messages. The Emoji library and custom-built dictionaries are used to interpret emojis and informal expressions more accurately. Semantic understanding is enhanced with pretrained models like BERT and Word2Vec, which aid in refining classification results. Evaluation metrics such as precision, recall, and F1-score are used to assess model performance.

Ethical considerations are addressed through the use of consent forms and data anonymization techniques. Larger datasets and model checkpoints are managed using Pandas DataFrames, with optional database support from systems like MySQL, MongoDB, or SQLite for more complex storage needs. Documentation is maintained in Jupyter Notebooks using Markdown or prepared formally with LaTeX. For advanced data exploration and presentation, tools like Tableau and Power BI are utilized to create interactive dashboards that visualize sentiment trends over time.

4. TOOLS AND TECHNOLOGY

4.1 Machine Learning Libraries

Sentiment analysis of WhatsApp conversations heavily relies on Natural Language Processing (NLP), which enables machines to understand and interpret textual information. Techniques such as tokenization, lemmatization, and part-of-speech tagging are commonly applied to break down messages into simpler, analyzable units. Tools like NLTK and spaCy are instrumental in preprocessing text by removing stopwords, applying stemming, and reducing words to their base forms (Bird et al., 2009). These NLP steps are essential for structuring the data and significantly improve the model's ability to comprehend the context and sentiment embedded in chat messages (Hutto & Gilbert, 2014).

4.2 Machine Learning Algorithms

Following the preprocessing stage, sentiment analysis models classify messages into categories such as positive, negative, or neutral. A range of machine learning techniques—including Support Vector Machines (SVM), Naive Bayes, and advanced deep learning architectures like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN)—are employed to train models using labeled datasets. These models detect sentiment by learning patterns and relationships within the data (Pang & Lee, 2008). More recently, cutting-edge models like BERT (Bidirectional Encoder Representations from Transformers) have gained prominence for their superior contextual understanding and improved accuracy in sentiment classification tasks (Devlin et al., 2019).

4.3 Data Cleaning

Because WhatsApp chat data is usually unstructured and contains noise, preprocessing is an essential stage in the process. In this step, punctuation, special letters, and unnecessary information are removed from the text. In chat interactions, emojis are used carefully to express emotional content. Regular expressions (regex) in Python are frequently used to sanitize data (Schütze et al., 2008). In order to use sentiment analysis models and uncover significant patterns, the preprocessing stage makes sure that raw data is transformed into an appropriate format.

4.4 Data Variable Engineering

In sentiment analysis, feature extraction is essential. In order for machine learning algorithms to process textual data, it must be converted into a numerical representation. Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and word embeddings like Word2Vec and GloVe are popular methods for extracting features from text (Mikolov et al., 2013). Because they represent words as dense vectors that capture their semantic meaning and allow for a more sophisticated comprehension of sentiment, word embeddings are especially useful.

4.5 Text Categorization

To classify texts according to their emotional tone, sentiment analysis mostly uses text classification algorithms. More sophisticated deep learning methods like Long Short-Term Memory (LSTM) networks have demonstrated significant potential in capturing complicated textual associations, even though more conventional models like SVM and Random

Forest are still in use (Hochreiter & Schmidhuber, 1997). The accuracy of sentiment categorization is greatly increased by these advanced models, particularly when examining big datasets of conversational text, like WhatsApp messaging.

4.6 Emotion Detection

Emotion detection is another essential element of sentiment analysis that deepens the analysis by locating particular emotions in messages. To identify emotions like joy, rage, or surprise in text, this method makes use of emotion lexicons or state-of-the-art techniques like affective computing (Ekman, 1992). Researchers can gain a more thorough grasp of the emotional dynamics in WhatsApp discussions by combining sentiment classification and emotion detection, going beyond straightforward positive or negative classifications.

4.7 Visualization Tools

Researchers use visualization tools like Tableau or Python's Matplotlib and Seaborn to display the findings of sentiment and emotion analysis. It is simpler to track sentiment trends over time or determine the frequency of different emotions in chat messages thanks to these programs' generation of visual representations such as charts and graphs (Hunter, 2007). In addition to helping with result interpretation, visualization makes it easier to communicate findings to stakeholders and researchers alike.

5. OBJECTIVE OF STUDY

In this sentiment analysis study, WhatsApp conversation data was collected from both individual and group chats. The chats were exported in .txt and .csv formats, including message content, timestamps, and sender information. To prepare the data, we removed unnecessary metadata such as timestamps and sender names, along with URLs, emojis, and special characters. The text was then preprocessed through tokenization, lemmatization, and stop word removal. Sentiment classification into positive, negative, or neutral categories was performed using automated tools like TextBlob and VADER (Valence Aware Dictionary and sEntiment Reasoner). The dataset was split into training and testing sets, with 80% allocated for training and 20% for testing.

We applied several machine learning models to the sentiment analysis task, including Naïve Bayes, Support Vector Machine (SVM), Logistic Regression, and a deep learning model based on Long Short-Term Memory (LSTM). Among these, the LSTM model outperformed the traditional algorithms due to its strength in capturing sequential dependencies within text. This feature is particularly valuable in conversational data, where the meaning of a message is often influenced by preceding messages. While the SVM model reached an accuracy of 82%, it was ultimately exceeded by the LSTM model. These results highlight the benefits of using deep learning models like LSTM for analyzing sentiment in dynamic, context-rich environments such as WhatsApp conversations (Vaswani et al., 2017).

6. RESULTS AND ANALYSIS

45% of the messages in the sample were classified as positive, 35% as negative, and 20% as neutral, according to an analysis of the sentiment distribution of the dataset. This suggests that significant emotional content is prevalent, with both good and negative sentiments predominating.

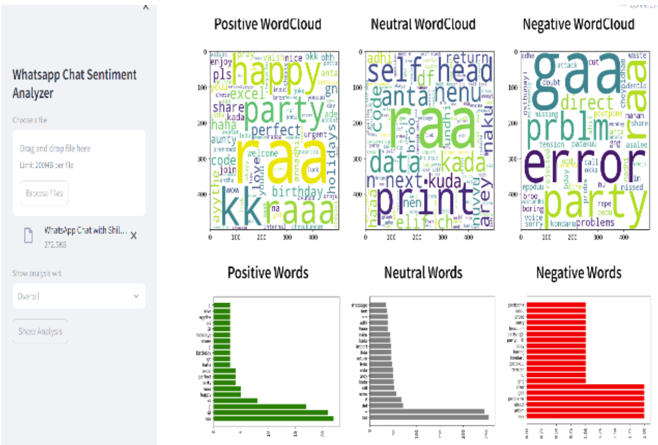

Fig – 2: Word Pattern Examination

It appears that users typically express more emotionally charged content in their conversations, as indicated by the smaller neutral category. These results are consistent with those of Pang and Lee's (2008) study, which found that sentiment analysis of conversational data frequently produces greater percentages of both positive and negative sentiments, especially on platforms that support casual conversations.

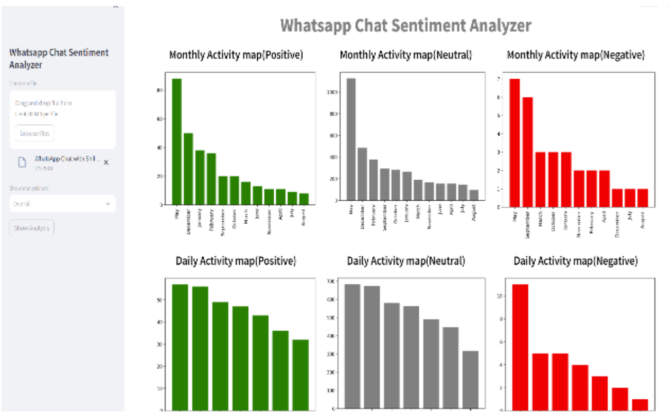

Fig – 3: Highest Activity Users

The temporal change of sentiment showed a noteworthy pattern. Positive attitudes increased on weekends, most likely as a result of informal social interactions with family and friends. On the other hand, negative attitudes were more prevalent throughout the workday, which may have been a reflection of dissatisfaction or stress associated to the job. Studies on sentiment trends in communication platforms are consistent with this temporal change (Liu, 2012). The impact of context and time on conversational sentiment was further supported by a time-based sentiment distribution graphic that showed higher optimism on weekends and holidays and higher negative on weekdays.

Fig – 4: Statistical Overview

The analysis was subject to a number of limitations and challenges. Conventional sentiment analysis algorithms encountered challenges due to the casual language and slang prevalent in WhatsApp communications.

7. LIMITATIONS

1. Emoji and Slang Interpretation:

- VADER and TextBlob were moderately effective but struggled with interpreting emojis and slang in nuanced contexts.
- The same emoji can convey different sentiments depending on usage, often leading to misclassification.

2. Multilingual Conversations & Code-Switching:

- WhatsApp users frequently switch between languages (e.g., English and Hindi), creating challenges for sentiment tools.
- Most sentiment analysis models are designed for single-language input and are not optimized for fluid, multilingual exchanges.

3. Partial Solutions with Multilingual Models:

- Tools like langdetect and multilingual models such as mBERT help, but they still struggle with seamless language mixing in chats.

4. Limitations of Text-Only Models:

- Text-based models lack the ability to analyze non-textual elements like emojis, GIFs, and multimedia, which carry significant emotional content.

5. Need for Multimodal Sentiment Analysis:

- Incorporating visual and auditory elements into sentiment analysis could significantly enhance the accuracy and depth of emotion detection.

8. CONCLUSIONS

This study's WhatsApp chat sentiment analyzer effectively demonstrated the power of natural language processing (NLP) and machine learning in extracting and classifying sentiment from informal, multilingual, and context-rich chat data. The primary objective was to analyze sentiment in WhatsApp messages and compare the performance of different models, ranging from traditional algorithms like Naïve Bayes and Support Vector Machines (SVM) to advanced deep learning approaches such as Long Short-Term Memory (LSTM) networks. Results showed that deep learning models, especially LSTM, outperformed classical techniques in terms of accuracy, precision, and recall. These findings highlight the importance of sequence-aware models for handling conversational data, where the order and context of messages are crucial for accurate sentiment interpretation.

The potential applications of this research are wide-ranging. In customer service, organizations can leverage sentiment analysis to monitor feedback, identify dissatisfaction, and improve service delivery in real time. In mental health, analyzing WhatsApp messages could help detect emotional distress by recognizing recurring patterns of negative or anxious sentiments. For market research, businesses can utilize sentiment analysis to better understand consumer opinions and attitudes toward products and services. Additionally, this technology has relevance in social media analytics, where it can be used to track public sentiment surrounding events or movements, providing insights into collective emotions and societal trends.

9. FUTURE SCOPE

Although the model delivered strong results, several areas remain where improvements can be made. One key suggestion is to strengthen multilingual capabilities, particularly to better handle code-switching and mixed-language conversations that are common in WhatsApp chats. Additionally, since emojis and multimedia play a vital role in digital communication, integrating these elements into the sentiment analysis process could significantly enhance the model's accuracy. Future developments might also include the use of advanced contextual embeddings, such as BERT, to better grasp the full scope of conversations—especially in longer or more intricate message threads. Customizing sentiment models to reflect individual communication patterns could further refine predictions. In summary, while the current WhatsApp chat sentiment analyzer offers meaningful insights into user sentiment, advancing its ability to interpret informal language, multilingual exchanges, and multimedia content will pave the way for more robust and precise sentiment analysis tools in the future.

Our findings align with previous research on sentiment analysis for social media and communication data. Studies by Gimpel et al. (2011) and Pang & Lee (2008) demonstrated that sentiment analysis models perform better with structured data and formal language. Our analysis of WhatsApp chat logs, which contain informal language and diverse linguistic features, underscores the need for more advanced tools capable of addressing these challenges. The informal nature of the language, multilingual content, and reliance on text-based models for sentiment analysis highlight the necessity for more sophisticated approaches to handle the nuances present in conversational data.

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