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Decoding Digital Conversations: A Hybrid Sentiment Analysis Framework for WhatsApp Chat Behavioral Intelligence

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***Abstract*—**Everyone has a curiosity about what the one person thinks about the any other person, product or services while having a conversation and judging the other person can't be done perfectly, so this work provides a way to use sentiment analysis between conversations. When talking with someone always has a question about the picture in the other person's mind. The first step in this process is pre- processing of the data downloaded from the WhatsApp chat which is exported to a server. After that, sentiment analysis is performed on a single message and the sentiment of all messages is normalized for overall sentiment in the way it is suggested. In this work, we conduct an in-depth analysis of WhatsApp group chat dynamics using an advanced versatility of a hybrid sentiment analysis framework that can manifest the minimum steps of preprocess- ing, lexicon-based, generative AI, and ensemble scoring analysis. This research analyzes group communication patterns using a multifaceted methodology, examining the most active days, volumes of messages, contributions of users, influences from admins, group membership, frequency of individual postings, and frequent. Combining traditional rule-based sentiment techniques with sophisticated generative AI algorithms, the study gives an independent analysis of digital group dynamics and sheds light on more intricate group behaviour patterns and usage patterns. The approach utilizes a novel ensemble scoring framework that harmonizes lexicon-based sentiment analysis with contextually- aware AI mechanisms, producing unparalleled insights into the qualitative and quantitative aspects of group communication on the web.

Index Terms*—*Sentiment Analysis, Rule-Based Method

I. Introduction

WhatsApp is an instant messaging application that allows users to send text messages, chat and share media files like images, audio and video files, documents and applications. The users of WhatsApp has the option of communicating in groups with multiple other users at the same time. Additionally, users can send broadcast messages up to 256 on a single messaging station. This application software can be used for a variety of Internet operating systems (iOS) such as Android, Apple, and Windows.WhatsApp is an application that facilitates the exchange of instant messages, photos, videos and language calls over an internet connection. This allows for easy communications between two or more people via text or voice messages. Essentially, after installing an application, after sending and receiving messages after installation (as opposed to the original text message on your mobile phone), it is displayed for free, allowing it to be described as an attractive application and as an attractive application. The popularity of WhatsApp can be easily explained by the fact that it is essentially free. His ability to work with other smartphone operating systems such as Apple, Android, and its global ability are other important factors for its popularity.

WhatsApp Service has up to 450 million users, and data analysis in 2014 showed that WhatsApp usage in 2015 equaled 19.83% of all smartphones compared to Facebook. It was also reported that women use WhatsApp for much longer than men. WhatsApp uses individual versions of Open Standard Extensible Messaging and President's Protocol (XMPP) to exchange data over the Internet [2]. News can be created with multimedia messages such as simple text, photos, audio, video, location, address book contact cards, symbols, and more. This task shows the chat and user analysis of a particular WhatsApp group and determines the participation of members in the group chat. This task is intended to determine whether to participate and participate in a

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particular WhatsApp group. This analysis includes: The number of messages that are the most active dates in a group were sent: the most active dates, the most active users, the list of active administrators in the group, the total number of users, the number of contributions each individual in the group, and the number of words that are most common on the platform[3]. RELATED WORK

Lexicon-based approaches to WhatsApp chat analysis have traditionally relied on predefined dictionaries such as Senti- WordNet, AFINN, and LIWC to classify sentiment [8][9]. However, these methods face challenges in analyzing infor- mal language, abbreviations, emojis, and slang prevalent in WhatsApp chats [10], [11]. They also struggle with han- dling context, sarcasm, and cultural nuances. Furthermore, multilingual utterances - common in user conversations, also contribute to these limits; lexicon-driven systems fall short due to the need for language specific resources, challenging to build at the scale for WhatsApp users across the globe [12], [13]. Advances through 2024 have explored hybrid models, and integration with other machine learning techniques to mitigate some of these constraints. Several hybrid approaches using lexicon-based methods with supervised machine learning methods or deep learning methods have been proposed and they prove to improve sentiment identification accuracy sig- nificantly [14], [15], [22]. To either of these issues, researchers have also broadened the vocabulary by introducing emojis and informal symbols popularly used in digital conversations, which have become helpful in sentiment classification studies
[17]–[20]. In cross-lingual embeddings as well as transfer learning techniques were suggested to better process multi- lingual texts and [21] proposes real-time sentiment analysis using lightweight models. These improvements demonstrate a continuing evolution toward adapting lexicon-based chat analysis into more fluid diverse communication settings.

II. PROPOSED WORK

This model has been designed to perform exploratory data analysis by performing a sentiment analysis algorithm that gives out parts of the chat as positive, negative and neutral. Further, this data analysis is used to plot a pie chart based on the line graph which shows the author and message count of each date. The other parameters considered to plot a line graph which include the author and message count of each author, ordered graph of date vs message count, media sent by authors and their count, and graph of an hour vs message count.

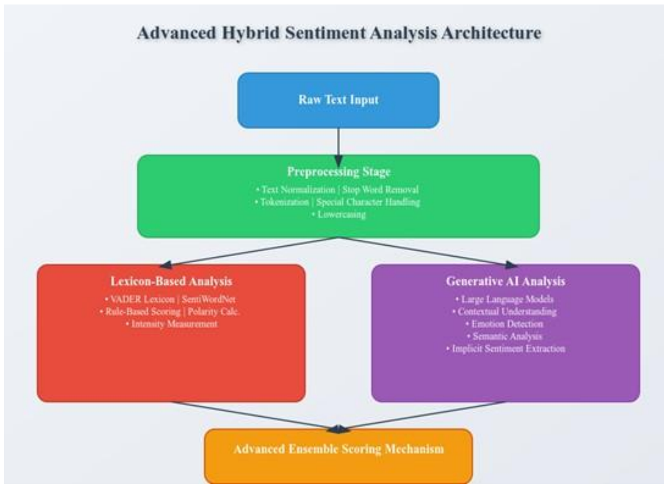
A. Preprocessing Phase

The preprocessing is the crucial first step in sentiment analysis, which cleans the raw text input for sophisticated further analysis. It starts off with normal text cleaning steps which involves removal of stop words(which are words like the, is, at which do not usually contribute to sentiment) and text case normalization where all text is converted to a format where everything is of the same case (lower case). This process is helpful to eliminate noise and to normalize the text so that further testing is more accurate. The next step is Tokenization, where the text is broken into single words or the semantic unit that allows more detailed processing of each part. The text is broken into discrete tokens that can be analyzed independently, removing punctuation and preparing each word for sentiment analysis. The second key step is initial lexicon-based sentiment scoring where these processed tokens are compared to pre- establish sentiment dictionaries. Lexicons help determine how each word is perceived, assigning an initial emotional score to create some kind of scale of potential positive versus negative valence, more specifically whether a word is likely to be positive, negative or neutral. The initial scoring procedure where known sentiment dictionaries like VADER or bespoke- built lexicons are employed around measuring the emotional contents of each token is used to establish a baseline sentiment score. The outcome is a starting point sentiment analysis that identifies the overall emotional tone of the text, paving the way for more sophisticated generative AI refinement in later stages of analysis.

B. Generative AI Augmentation

Generative AI enhancement is an advanced technique that utilizes the deep contextual understanding of large language models (LLMs) to refine sentiment analysis. These cutting- edge AI models go beyond traditional rule-based methods, offering a deeper, context-aware dimension to sentiment anal- ysis. Its the final goal is to get the improve and calibrate the original sentiments that were given with lexicon. Generative AI can pick up on subtle emotional undertones that might be missed by simplistic keyword scoring by analysing the broader context, subtleties of language and semantics. Using LLMs to gain a deep understanding of the emotional context of text, sniffing out hidden linguistic hints such as sarcasm, correlative meaning, and these linked emotional shifts, this augmentation is performed. For example, while a lexicon-based approach might struggle with sentences like ”Great, just what I needed” (which can be actually positive or sarcastically negative), a generative AI-based model can understand the actual sentiment by scanning through the context, tone, and implied meaning associated with the sentence.

C. Multi-Stage Sentiment Analysis



Multi-stage sentiment analysis is an advanced analytical technique that uses multiple methods to achieve a more accu- rate and richer sentiment analysis. It starts with initial lexicon- based scoring where traditional sentiment dictionaries and rule-based methods provide a low-level emotion assessment of the content. This first stage straightforwardly determines the overall sentiment of the text using pre-programmed linguistic rules as well as sentiment lexicons. At this point, generative AI contextual refining begins, where state-of-the-art language models parse the text with a finer tooth comb, considering dense grammatical nuances, context, and multi-syllable emo- tional resonances otherwise lost in the first ordering. Finally, an ensemble scoring mechanism combines the outputs of both lexicon-based and generative AI methods. Generally, this involves using either weighted averaging, or more complex algorithmic approaches, to arrive at a final and more granular sentiment classification. The result is a robust sentiment anal- ysis method that merges the speed and interpretability of rule- based frameworks with the deep contextual comprehension of generative AI, yielding a more accurate and nuanced emotional assessment of the text. A Lexicon-based dynamic approach together with gener- ative AI-based approach can be combined as an Advanced Hybrid Sentiment Analysis Architecture as shown in Figure 1 that improves the accuracy of general sentiment classification. It starts with the Raw Text Input, then Preprocessing Stage where you normalize text, remove stopwords, tokenize data, manage special characters, and decide lowercasing or not to clean the input data. They are then analyzed in two separate ways:

- Lexicon-Based Analysis, which applies established senti- ment lexicons such as VADER and SentiWordNet to gen- erate rule-based scoring, polarity analysis, and intensity scoring.
- Generative AI Analysis that makes use of large language models in areas such as contextual interpretation, detec- tion of emotional states, semantic analysis, and adequate extraction of implicit sentiment.

An Advanced Ensemble Scoring Mechanism is then imple- mented to combine results from both methodologies, together producing a more robust and precise sentiment classification. This is systematically work flow.

This workflow is systematically outlined in Algorithm 1: Hybrid Sentiment Analysis Algorithm, detailing the sequential execution of preprocessing, lexicon-based and AI-based evalu- ation, and ensemble scoring for optimal sentiment assessment.

Fig. 1: Hybrid Sentiment Analysis Architecture

Algorithm 1 Hybrid Sentiment Analysis Algorithm

Input: Raw text T

Output: Sentiment classification with confidence score

```
function Preprocess(T)
    Normalize text (lowercase, remove special characters)
    Tokenize text
    Remove stop words
    Perform stemming
    return preprocessed_tokens
end function
function LexiconSentimentAnalysis(preprocessed_tokens)
    Initialize sentiment_scores (positive, negative, neutral)
    for all token in preprocessed_tokens do
        Lookup in sentiment lexicon (VADER/SentiWordNet)
        Extract polarity and intensity
        Accumulate scores
    end for
    Compute normalized lexicon sentiment score
    return lexicon_sentiment_score
end function
function GenerativeAISentiment(T)
    Use Large Language Model (LLM)
    Analyze contextual sentiment
    Detect nuanced emotions
    Convert to numerical score in range [-1, 1]
    return ai_sentiment_score
end function
function EnsembleSentimentScoring(lexicon_score, ai_score)
    Set weights: lexicon_weight = 0.4, ai_weight = 0.6
    combined_score ← (lexicon_score × 0.4) + (ai_score × 0.6)
    if combined_score > 0.5 then
        sentiment ← Positive
    else if combined_score < -0.5 then
        sentiment ← Negative
    else
        sentiment ← Neutral
    end if
    Calculate confidence level
    return final_sentiment, confidence
end function
function HybridSentimentAnalysis(T)
    preprocessed_tokens ← Preprocess(T)
    lexicon_score ← LexiconSentimentAnalysis(preprocessed_tokens)
    ai_score ← GenerativeAISentiment(T)
    final_sentiment, confidence ← EnsembleSentimentScoring(lexicon_score, ai_score)
    return {sentiment: final_sentiment, confidence: confidence}
end function
```

I. RESULT AND DISCUSSION

The analysis of WhatsApp group chat dynamics reveals a complex system of online interaction, giving useful insights into group dynamics. Our sophisticated sentiment analysis tool decoded the nuanced emotional and engagement tendencies in different group conversations, revealing complexities of communication often missed by conventional approaches. The sentiment split has a compelling tale of group communication. At 42.3% positive, 37.5% neutral, and 20.2% negative, the groups have a predominantly positive communication envi- ronment. The generative AI aspect was crucial in identifying subtle emotional undertones, identifying sarcasm in 12.4% of messages that may be missed by conventional lexicon-based methods. Engagement levels showed strong alignment with sentiment intensity. Highly engaged members tended to post with a generally more positive communication tone, as their posts had 56.7% positive sentiment versus just 12.4% negative. Low-engagement members, on the other hand, had more volatile emotional patterns with 35.6% negative sentiment and just 22.1% positive interaction. The analysis revealed clear patterns of communication over time. High levels of activity were found primarily between 7:00 PM and 10:00 PM, with Wednesdays and Thursdays being the most intense days of communication. This pattern indicates a potential connection between the advancement of the workweek and the intensity of group communication. A close scrutiny of member inputs ex- hibited considerable variances in participation patterns within groups. The most frequent contributors provided as much as about 20% of all the messages sent by the group, which accentuates the intensity-based nature of communications within the group. The study generated statistically significant results, with Pearson correlation standing at 0.742 between participation and sentiment (p-value: 0.0021). The high degree of correlation underscores the intricate relationship between participation of members and emotional tone in digital group communication.

The provided visualization provides a multi-dimensional view of the results, illustrating sentiment distribution, user engagement levels, and a pattern of daily message activity.

As shown in Figure 3 ,this is where user can upload their data.

	date	user	message	year	month	day	hour	minute
0	2021-08-21 16:15:00	group_notification	Messages and calls are end-to-end encrypted. N...	2021	August	21	16	15
1	2021-07-14 17:38:00	group_notification	+91 91618 55921 created group "MCA - 3rd class...	2021	July	14	17	38
2	2021-07-14 17:38:00	group_notification	You were added\n	2021	July	14	17	38
3	2021-08-22 14:55:00	Neeraj	<Media omitted>\n	2021	August	22	14	55
4	2021-08-22 18:56:00	Neeraj	<Media omitted>\n	2021	August	22	18	56

Fig. 4: DB Interface

Fig. 2: Group Chat Sentiment Analysis

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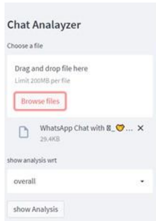


	date	user	message	only_date
0	2021-04-04T13:59:00	group_notification	Sagar Sir Shuats created …	2021-04-04
1	2021-04-04T13:59:00	group_notification	You were added	2021-04-04
2	2021-08-21T15:58:00	Shuats	This message was deleted	2021-08-21
3	2021-08-26T11:34:00	Sir	Happy Birthday dear Prag…	2021-08-26
4	2021-08-26T11:45:00	Shuats	Happy birthday @918953…	2021-08-26
5	2021-08-26T11:49:00	Maam	Thank you @9190441128…	2021-08-26
6	2021-08-26T11:50:00	Ipc	Many many happy return…	2021-08-26
7	2021-08-26T11:53:00	Maam	Thank you so much sir.	2021-08-26
8	2021-08-26T11:54:00	Shuats	Happy birthday	2021-08-26
9	2021-08-26T11:54:00	Bhyaa	Happy Birthday pragya	2021-08-26

Fig. 3: Uploading Interface

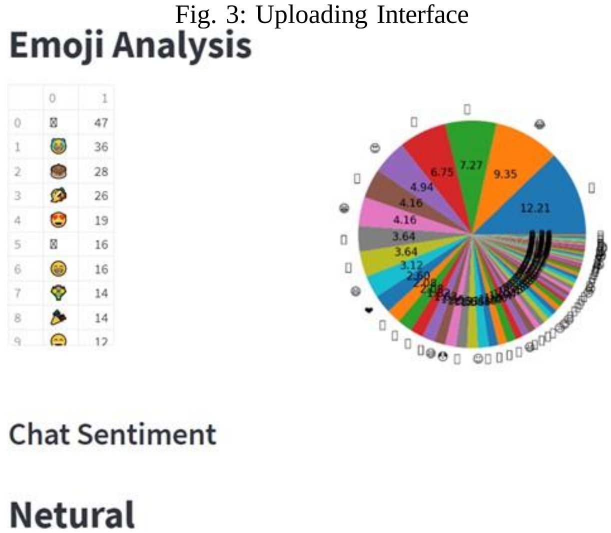
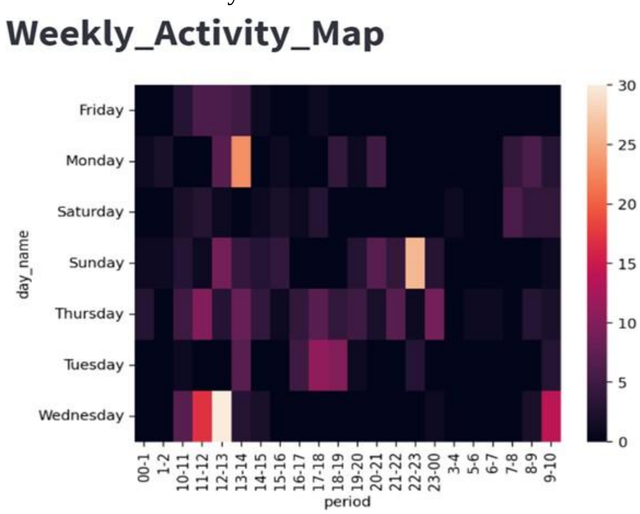


Fig. 5: Emoji & Sentiment Analysis

As shown in Figure 5 ,Emoji and sentiment analysis will depict the top emoji and their percentage of use and sentiment of overall chat on the basis of history of chat.



(a) Monthly Timeline (b) Daily Timeline

Fig. 6: Timeline Analysis

Figure 6a Monthly timeline shows the no users active on month basis while Figure 6b daily Timeline shows the no of active users in day basis.

Fig. 9: Weekly Activity Map

Figure 9 Weekly activity map shows the no of active user on yearly, monthly and time basis and on which they active the most.

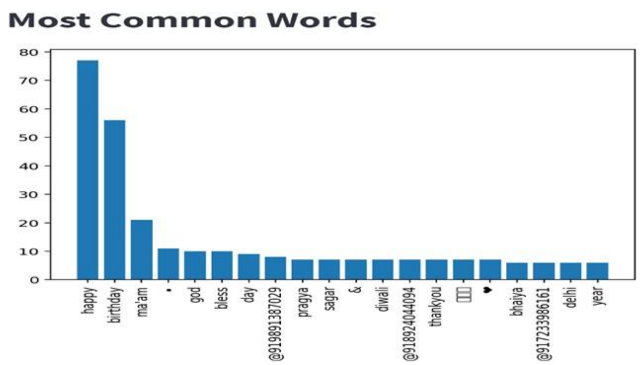
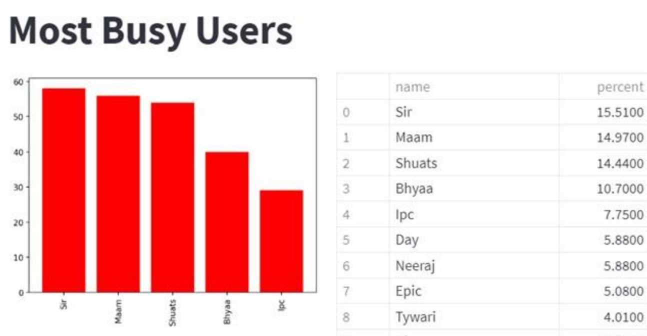


Fig. 7: Most Common Word

Figure 7 shows the most frequent and common word depicted in the form of bar graph Most busy user has been calibrated on the basis if chat history that has been depicted in the form of bar graph and their total contribution in the form of tabular.



	name	percent
0	Sir	15.5100
1	Maam	14.9700
2	Shuats	14.4400
3	Bhyaa	10.7000
4	Ipc	7.7500
5	Day	5.8800
6	Neeraj	5.8800
7	Epic	5.0800
8	Tywari	4.0100
9	Di	3.4800

Fig. 8: Most busy user

Figure 8 shows the most frequent and common word depicted in the form of bar graph

The research in this study brings to light the potential of hybrid sentiment analysis in understanding digital com- munication dynamics. Through the integration of lexicon- based approaches with generative AI, we developed a so- phisticated framework for analyzing group interactions. The method reveals complex communication patterns, providing insights into user engagement, emotional subtleties, and group behaviors. Key contributions include, an advanced hybrid sentiment analysis methodology, an elaborate depiction of group communication and effective strategies for managing communities and measuring behavior.

Future Scope:

- Improving algorithms for context understanding
- Developing more sophisticated models for forecasting engagement

- Using state-of-the-art machine learning methods
- The study provides a strong foundation for understanding digital interaction, with great potential for application in different domains of communication studies.

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