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Event Based Sentiment Trend Analysis using Deep Learning Techniques

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Abstract: -The ever-growing volume of social media data presents a unique opportunity to understand public opinion on various topics. This study focuses on sentiment trend analysis, which uses social media text to uncover evolving emotional patterns. By analyzing these trends, researchers can gain valuable insights applicable in diverse fields. The research proposes a framework for analyzing user tweets related to specific events, outlining steps like data retrieval, event prompts, data segregation, preprocessing, and sentiment analysis using deep learning (BiLSTMs and BERT), model evaluation, and sentiment trend analysis. The experiment uses Twitter data for events like the COVID-19 pandemic, Russia-Ukraine war, and IPL (Indian Premier League). Results show the effectiveness of the approach, with sentiment analysis models achieving over 90% accuracy in some cases. Sentiment Trends reveal predominantly negative sentiment surrounding the Russia-Ukraine war and positive sentiment associated with the IPL.

Keywords: *Sentiment analysis , Social media, Sentiment trend, Twitter data, Event,Data segregation, Preprocessing, BERT , Bi-LSTM , Deep learning.*

I. INTRODUCTION

The ever-growing volume of online data presents a unique opportunity to understand public opinion and societal trends. Social media platforms, news outlets, and online forums serve as a constant pulse of human sentiment, offering a wealth of information about how people feel about various topics. However, extracting meaningful insights from this vast ocean of text requires sophisticated tools and techniques. Sentiment analysis emerges as a powerful solution, enabling us to automatically detect and classify the emotional undertones within written text.

By analyzing sentiment trends over time, researchers can gain a deeper understanding of how public perception evolves. This information is invaluable across diverse fields. For instance, tracking sentiment during a political campaign can reveal shifts in voter preferences, while monitoring sentiment surrounding a product launch can provide crucial feedback for businesses. Moreover, sentiment analysis can be used to gauge public reactions to major events, such as natural disasters or policy changes, allowing for more effective responses and communication strategies.

This study looks closely at sentiment trend analysis to understand public opinion better in different situations. It also explores the latest advances in sentiment analysis, especially those using deep learning methods. The goal is to show how analyzing sentiment trends can give us valuable insights into public opinion and help us understand and respond to changes in public sentiment.

II. RELATED WORK

Sentiment trend analysis plays a critical role in understanding public opinion and behavior, particularly during significant events like the COVID-19 pandemic or celebrity incidents. This literature review aims to explore various studies and approaches used to analyze sentiment trends across different contexts. Chandrasekaran et al. (2020) [1] conducted a temporal infoveillance study on COVID-19-related tweets, analyzing topics, trends, and sentiments to monitor real-time information during global crises.

Valdez et al. (2020) [2] focused on US mental health during the pandemic, using Twitter data for longitudinal analysis. This study provided insights into mental health trends over time, demonstrating the potential of social media for mental health surveillance. In a financial context, Joshi et al. (2016) [3] proposed a stock trend prediction model using news sentiment analysis, predicting stock trends based on sentiment from news

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articles.Marouf et al. (2022) [4] studied sentiment trends and emotion patterns of Twitter users during the demise of a Bollywood celebrity, showcasing the use of sentiment analysis to understand public reactions to significant events. Jahanbin and Rahmanian (2020) [5] used Twitter and web news mining to predict COVID-19 outbreaks, highlighting the potential of social media data in predicting disease outbreaks and public health trends.

McKinney et al. (2011) [6] discussed time series analysis in Python using statsmodels, providing a foundation for analyzing time series data, which is essential for studying sentiment trends. Kaur and Sharma (2020) [7] focused on Twitter sentiment analysis of corona virus using Textblob, demonstrating the application of natural language processing techniques for sentiment analysis during a global health crisis.Medford et al. (2020) [8] leveraged high-volume Twitter data to understand early public sentiment for the COVID-19 outbreak, showcasing the role of social media in tracking public opinion during crises. Elbagir and Yang (2019) [9, 10] conducted Twitter sentiment analysis using NLTK and VADER sentiment, showcasing different approaches to sentiment analysis using readily available tools and libraries.

Li et al. (2021) [11] focused on aspect-based sentiment analysis of customer reviews for brand reputation management, highlighting the importance of analyzing specific aspects of customer sentiment for business insights. Torres et al. (2020) [12] conducted a survey on deep learning for time series forecasting, providing insights into the application of deep learning techniques for analyzing and predicting time series data, including sentiment trends.Daghriri et al. (2023) [13] modeled behavior and vaccine hesitancy using Twitter-derived US population sentiment during the COVID-19 pandemic, demonstrating the use of social media data for predicting vaccination trends. Geetha and Renuka (2021) [14] improved the performance of aspect-based sentiment analysis using a fine-tuned BERT Base Uncased model, showcasing the use of advanced deep learning models for sentiment analysis tasks.

Vimali and Murugan (2021) [15] developed a text-based sentiment analysis model using Bi-directional LSTM networks, highlighting the application of deep learning for sentiment analysis in textual data. Kumar and Vardhan (2022) [16, 17] proposed a multimodal sentiment analysis approach using prediction-based word embeddings, integrating text and emojis for more nuanced sentiment analysis, emphasizing the importance of considering multiple modalities for accurate sentiment analysis.The related work highlights a significant focus on sentiment trend analysis across various domains. However there is a gap in comprehensive studies integrating multimodal data sources for refined sentiment analysis in real-time contexts.

III. PROPOSED MODEL

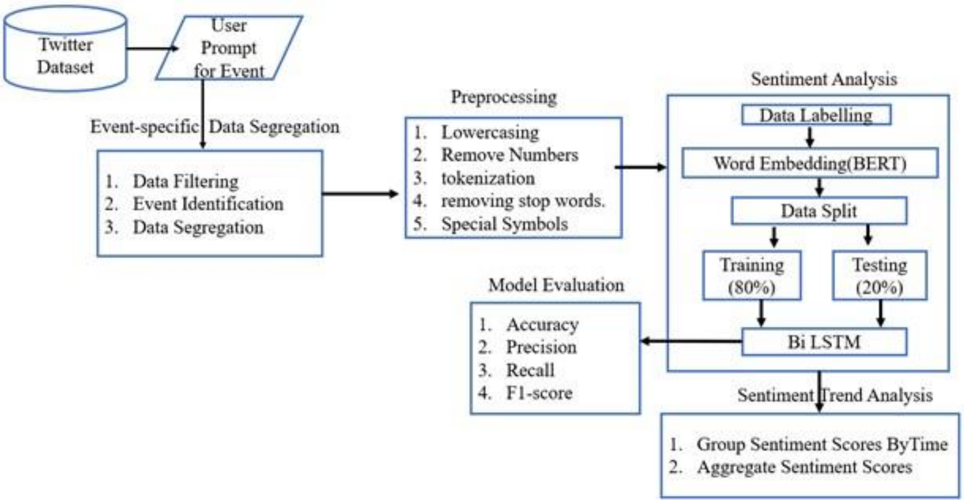

Figure 1: A Proposed Framework for Sentiment Trend Analysis of Specific Events

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Twitter Dataset: The initial step involves retrieving relevant data from a Twitter dataset containing tweets related to the specified event. This dataset serves as the foundation for subsequent analysis, providing a rich source of user-generated content reflecting public sentiment.

User Prompt for Event: Following the dataset acquisition, the user provides a query specifying the event they wish to analyze sentiment for. This step is crucial as it defines the scope of the analysis, ensuring that the subsequent sentiment analysis focuses on tweets related to the specified event.

Event-specific Data Segregation: This step comprises three sub-steps aimed at refining the dataset to include only relevant tweets. Data filtering is the first sub-step, where techniques such as keyword filtering or hashtag analysis are used to isolate tweets discussing the specified event. Event identification then delves deeper to identify tweets explicitly referencing the chosen event, ensuring the analysis remains focused. Finally, data segregation results in a refined dataset containing only tweets directly connected to the user-defined event, facilitating a more targeted sentiment analysis.

Data Preprocessing: Before sentiment analysis, the data undergoes several preprocessing steps to ensure consistency and enhance analysis accuracy. This includes lowercasing all text, removing numbers, tokenization to split text into individual words, removing stop words (common words like "the," "a," "an"), and removing special symbols. These steps help streamline the data and focus on sentiment-carrying words.

Sentiment Analysis: The sentiment analysis phase involves several key steps. Data labeling assigns sentiment labels (e.g., positive, negative) to the tweets. Word embedding, using techniques like BERT, converts the text data into numerical representations suitable for sentiment classification. The data is then split into training and testing sets, with 80% used for training and 20% for testing. The sentiment analysis model, often a BiLSTM network, is trained on the training data to classify sentiment based on patterns identified during training.

Model Evaluation: The trained sentiment analysis model is evaluated using the testing set to assess its performance. Evaluation metrics such as accuracy, precision, recall, and F1-score are employed to measure the model's effectiveness in classifying sentiment correctly, providing insights into its reliability and performance.

Sentiment Trend Analysis: Once a reliable sentiment analysis model is established, it is applied to analyze overall sentiment trends within the Twitter data related to the user's event prompt. This involves grouping sentiment scores by time intervals (e.g., daily, weekly) to identify trends and aggregating sentiment scores to provide a concise view of sentiment distribution over time.

This proposed framework provides a structured approach for analyzing sentiment trends of specific events using Twitter data. Each step is designed to ensure the analysis remains focused on the event of interest, enabling a deeper understanding of public sentiment dynamics.

IV. EXPIREMENTATION

4.1 SOFTWARE ENVIRONEMENT SETUP

Python was employed to create this model, utilizing the following Python libraries for developing the machine learning models in this experiment.Python 3.9, a high-level scripting language, was chosen for its readability and object-oriented nature. The NLTK 3.6.2 package was used for processing human language data, providing functionalities like tokenization, stemming, and tagging. Pandas 1.0.1 served as a data analysis tool, simplifying the data analysis workflow. Tweepy 3.10.0 facilitated the connection to the Twitter API for retrieving tweets, enabling real-time tweet streaming. NumPy 1.18.1 extended the functionality of arrays and matrices, offering mathematical functions. Scikit-learn 0.22.1, a tool for data mining and analysis, was employed for its simplicity and efficiency. Additionally, Matplotlib 3.1.3 and seaborn 0.13.2 were used for generating various plots and visualizations.

4.2 DATA COLLECTION

For this study, data collection from Twitter on the specified events was conducted using the Twitter API. The API was queried for each event, retrieving tweets based on relevant hashtags, keywords, and timelines. Data collection from Twitter for the mentioned events involves several steps to ensure the retrieval of relevant and informative tweets. Firstly, specific keywords, hashtags, and handles related to each event are identified and used to filter the Twitter stream. For the Russia-Ukraine War, keywords might include "Russia Ukraine conflict," "war in Ukraine," and relevant hashtags like "#RussiaUkraineWar." Similarly, for the COVID-19 Pandemic, keywords such as "COVID-19," "coronavirus," and relevant hashtags like "#COVID19" are used.

Monkeypox Outbreak, Grammy Awards 2022, Elon Musk's Acquisition of Twitter, IPL 2022, Farmer's Protest, and Assembly Elections 2022 would have their respective set of keywords and hashtags. Once the stream is filtered, tweets are collected using the Twitter API, ensuring a diverse and representative sample. Special care is taken to ensure the ethical handling of data, including user privacy and compliance with Twitter's terms of service.

4.3 EVENT DATA TIMELINE OVERVIEW

The Figure 2shows the timeline of events that have occurred in across the world between 2020 and 2022. The y-axis shows the event name, and the x-axis shows the start and end dates of the event.The longest event is the COVID-19 pandemic, which began on January 30, 2020 and ended on December 31, 2022. Other long events include the Farmer's Protest, which began on September 5, 2020 and ended on December 31, 2022; the Russia-Ukraine War, which began on February 24, 2022 and is still ongoing; and the Monkeypox Outbreak, which began on May 6, 2022 and is still ongoing.Some of the shorter events include the Assembly Elections 2022, which occurred from February 10, 2022 to March 7, 2022; Elon Musk's Acquisition of Twitter, which occurred from April 14, 2022 to April 25, 2022; and the Grammy Awards 2022, which occurred on April 3, 2022.

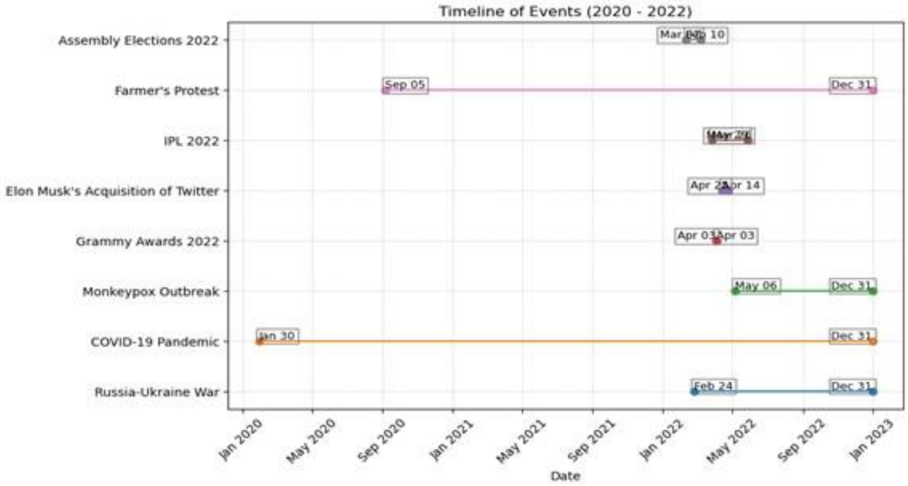

Figure2: Timeline of events

4.4 EVENT SPECIFIC DATA SEGREGATION

The algorithm EventSpecificDataSegregation takes a TwitterDataset as input and performs three main steps: data filtering, event identification, and data segregation. It initializes empty datasets for filtered and segregated tweets. It filters tweets relevant to the specified event, identifies tweets explicitly referencing the event, and segregates the data into separate datasets for each event. The algorithm outputs the segregated datasets.

```
Algorithm EventSpecificDataSegregation (TwitterDataset)
{
  FilteredDataset = []    // Initialize empty datasets for filtered and segregated tweets
  SegregatedDatasets = {}

// Step 1: Data Filtering
  for each tweet in TwitterDataset{
     if tweet is relevant to the specified event{
        Add tweet to FilteredDataset
        }
   }



  // Step 2: Event Identification
  for each tweet in FilteredDataset{
     if tweet explicitly references the specified event{
        Add tweet to SegregatedDatasets[event]
```

```
            }
        }
      // Step 3: Data Segregation
      For each event in SegregatedDatasets{
         Create a new dataset for the event
         For each tweet in SegregatedDatasets[event]{
            Add tweet to the event's dataset
            }
         }
      // Output the segregated datasets
      Return SegregatedDatasets
   }
```

4.5 DATA PREPROCESSING

The clean_tweet column in Figure 3 likely contains the original text content of a tweet after undergoing a cleaning process, such as Lowercasing, Remove Numbers, tokenization, removing stop words, removing Special Symbols. The compound, neg, neu, and pos columns are likely sentiment scores after performing data labelling, with compound representing an overall sentiment score ranging from -1 (negative) to +1 (positive), and neg and pos representing the negative and positive sentiment scores, respectively. The sentiment column likely contains a categorical sentiment label (e.g., positive, negative, neutral) assigned based on these sentiment scores.

	clean_tweet	compound	neg	neu	pos	sentiment
0	work close indian govern rapidli deploy addit...	0.0772	0.170	0.638	0.191	pos
1	flip flop fauci admit outdoor covid19 transmis...	-0.4019	0.398	0.442	0.159	neg
2	hi twitter tim man white hous covid19 suppli c...	0.0000	0.000	1.000	0.000	neu
3	pray countri battl worst surg world wit let ir...	-0.4215	0.306	0.522	0.172	neg
4	rapid invest nurs strengthen global covid19 re...	0.3182	0.000	0.723	0.277	pos
...	...	...	...	...	...	...
147470	northern hemispher summer season kick european...	0.0000	0.000	1.000	0.000	neu
147471	covid19 trend via	0.0000	0.000	1.000	0.000	neu
147472	goal reach per cent chines get covid19 jab end...	0.0258	0.000	0.901	0.099	pos
147473	covid19 uganda loom polit crisi	-0.2263	0.322	0.678	0.000	neg
147474	alhamdolillah got second dose covid19 vaccin m...	0.4404	0.000	0.805	0.195	pos

147475 rows × 6 columns

Figure 3: Sample output after data preprocessing and Data labelling

4.6 DATA PREPROCESSING

BERT (Bidirectional Encoder Representations from Transformers) is a powerful language representation model that is widely used for various natural language processing tasks. The BERT modelparameters in Table 1 are 'bert-base-uncased' is employed, along with the BertTokenizer for tokenizing input text. Padding and truncation are applied to ensure that all sequences have the same length, with a maximum length of 128 tokens.

The tokenized output is returned in TensorFlow tensor format. The output representation used for further processing is the last hidden state, specifically the [CLS] token. For the given tweet in Table 2, "work close indian govern rapidli deploy addit support suppli alarm," the shape of the word embeddings is tf.Size([1, 10, 768]), indicating that there are 10 tokens in the tweet, each represented by a 768-dimensional vector.

Table 1: BERT word embedding model parameters

PAREMETER	VALUE	DESCRIPTION
Model	'bert-base-uncased'	The pretrained BERT model to be loaded.
Tokenizer	BertTokenizer	The tokenizer to tokenize input text.
Padding	True	Whether to pad sequences to the same length.
Truncation	True	Whether to truncate sequences longer than the specified

		maximum length.
Max Length	128	The maximum length of input sequences after tokenization.
Return Tensor Format	'tf'	The format of the tokenized output (TensorFlow tensors in this case).
Output	Last_hidden_state	The output representation to be used for further processing

Table 2 : Sample tweet word embedding

Tweet Text: “work close indian govern rapidli deploy addit support suppli alarm “
Embeddings shape: tf.Size([1, 10, 768])
Word Embeddings tensor([[[0.1950, -0.4231, 0.3301, ..., -0.1554, 0.0567, 0.2228], [0.1950, -0.4231, 0.3301, ..., -0.1554, 0.0567, 0.2228], [0.1950, -0.4231, 0.3301, ..., -0.1554, 0.0567, 0.2228], ..., [0.1950, -0.4231, 0.3301, ..., -0.1554, 0.0567, 0.2228], [0.1950, -0.4231, 0.3301, ..., -0.1554, 0.0567, 0.2228], [0.1950, -0.4231, 0.3301, ..., -0.1554, 0.0567, 0.2228]]])

4.7 SENTIMENT ANALYSIS

After obtaining BERT embeddings for the text, the next step is to perform Sentiment Analysis. This involves dividing the labeled data into training (80%) and testing (20%) sets for model training and evaluation. The training set is used to teach the model to recognize patterns in the data, while the testing set is used to evaluate the model's performance on unseen data. For sentiment classification, models like BiLSTM (Bidirectional Long Short-Term Memory) is used. BiLSTM is a type of recurrent neural network that is capable of capturing long-range dependencies in the data by processing the text in both forward and backward directions. This allows the model to understand the context of words in a sentence and make more accurate predictions about the sentiment of the text.

4.8 MODEL EVALUATION

In model evaluation for sentiment classification, several performance metrics are essential for assessing the model's effectiveness. Accuracy is a fundamental metric that measures the proportion of correctly classified instances out of the total instances. Precision evaluates the model's ability to correctly identify positive instances among all instances predicted as positive, focusing on the relevance of the positive predictions. Recall, or sensitivity, measures the model's ability to correctly identify all positive instances, emphasizing the model's completeness. The F1-score combines precision and recall into a single metric, providing a balanced assessment of the model's performance. These metrics collectively offer a comprehensive evaluation of the sentiment classification model's accuracy and effectiveness.

4.9 SENTIMENT TREND ANALYSIS

Sentiment Trend Analysis for COVID-19, Monkeypox Outbreak, Russia-Ukraine War, IPL 2022 tweets involves temporal grouping and aggregation to understand sentiment trends over time. Firstly, the tweets are grouped into time intervals such as daily, weekly, or monthly. This grouping allows for a more granular analysis of sentiment changes over different time scales. Next, sentiment scores for each group are aggregated to provide a concise view of sentiment distribution over time.

This aggregation is done using averaging the sentiment scores for each interval. By performing these steps, one can identify patterns and trends in sentiment towards COVID-19, Monkeypox Outbreak, Russia-Ukraine War, IPL 2022 over time, which can provide valuable insights.

V. RESULTS

5.1 DATA OVERVIEW

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Figure 4 illustrates the distribution of positive and negative sentiments across different events on Twitter. Each event, ranging from the Monkeypox Outbreak to the COVID-19 Pandemic, is represented on the y-axis, while the x-axis indicates the count of tweets. The blue and red bars correspond to the positive and negative sentiments, respectively. Additionally, numerical annotations are strategically placed on top of each bar, providing a clear representation of the count for both positive and negative sentiments.

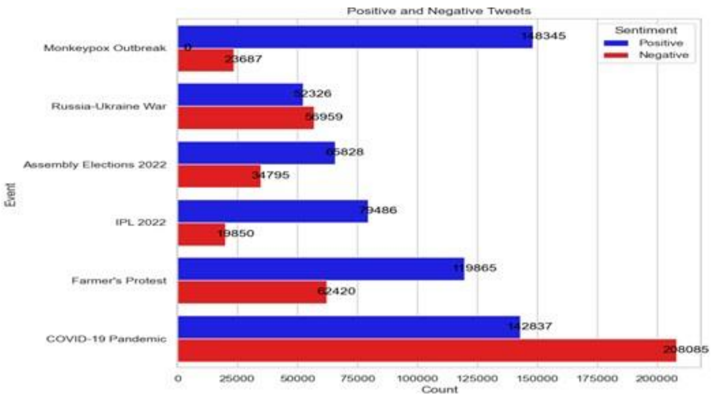

Figure 4: Dataset characteristics for different events

Table 3 : Training and Testing Tweets for different Events

Event	Positive			Negative		
	Training (80%)	Testing (20%)	Total Positive	Training (80%)	Testing (20%)	Total Negative
Monkeypox Outbreak	118676	29669	148345	18960	4727	23687
Russia-Ukraine War	41873	10453	52326	45567	11392	56959
Assembly Elections 2022	52690	13138	65828	27836	6959	34795
IPL 2022	63669	15817	79486	15851	3999	19850
Farmer's Protest	95914	23951	119865	50034	12386	62420
COVID-19 Pandemic	114269	28568	142837	166469	41616	208085

The training and testing datasets in table 3 for sentiment analysis on various events like the Monkeypox Outbreak, Russia-Ukraine War, Assembly Elections 2022, IPL 2022, Farmer's Protest, and COVID-19 Pandemic consist of positive and negative tweets. The datasets are split into training and testing sets, with each set containing a different number of positive and negative tweets. For example, in the Monkeypox Outbreak dataset, there are 118,676 positive training tweets and 29,669 positive testing tweets, totaling 148,345 positive tweets. Similarly, there are 18,960 negative training tweets and 4,727 negative testing tweets, totaling 23,687 negative tweets.

5.2 MODEL EVALUATION

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Figure 4 illustrates the distribution of positive and negative sentiments across different events on Twitter. Each event, ranging from the Monkeypox Outbreak to the COVID-19 Pandemic, is represented on the y-axis, while the x-axis indicates the count of tweets. The blue and red bars correspond to the positive and negative sentiments, respectively. Additionally, numerical annotations are strategically placed on top of each bar, providing a clear representation of the count for both positive and negative sentiments.

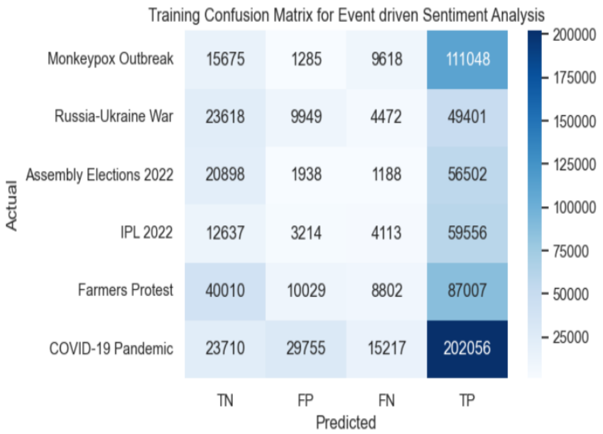

Figure 5 : Training confusion Matrix for different events

Figure 6 : Training accuracies for different events

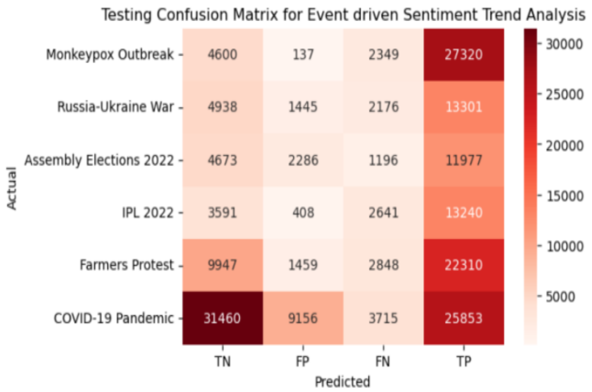

Figure 7 : Testing confusion Matrix for different events

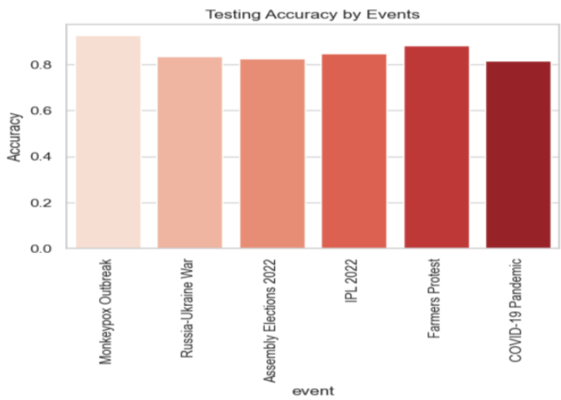

Figure 8 : Testing accuracies for different events

The accuracies in Figure 6,8 depicts sentiment analysis models trained and tested on different events vary across the Monkeypox Outbreak, Russia-Ukraine War, Assembly Elections 2022, IPL 2022, Farmer's Protest, and COVID-19 Pandemic. Training accuracies range from 90.5% for Farmer's Protest to 96% for Assembly Elections 2022, indicating how well the models learned from the training data. Testing accuracies, which evaluate the models' performance on unseen data, show similar trends but slightly lower values, ranging from 88.5% for Farmer's Protest to 92% for Monkeypox Outbreak.

5.3 SENTIMENT TREND ANALYSIS

Sentiment Trend Analysis for COVID-19, Monkeypox Outbreak, Russia-Ukraine War, IPL 2022 tweets involves temporal grouping and aggregation to understand sentiment trends over time. Firstly, the tweets are grouped into time intervals such as daily, weekly, or monthly. This grouping allows for a more granular analysis of sentiment changes over different time scales. Next, sentiment scores for each group are aggregated to provide a concise view of sentiment distribution over time. This aggregation is done using averaging the sentiment scores for each interval. By performing these steps, one can identify patterns and trends in sentiment towards COVID-19, Monkeypox Outbreak, Russia-Ukraine War, IPL 2022 over time, which can provide valuable insights.

The sentiment trend graph in Figure 9 for the Russia-Ukraine war shows mostly negative feelings throughout the conflict, with some brief moments of positivity. The lowest sentiment was at the start of the war when the invasion and its consequences were shocking. This negativity could be due to the high cost of human life and suffering caused by the war, leading to anger and sadness worldwide. Additionally, the war's impact on the global economy, like rising energy prices and disrupted supply chains, caused economic hardship, adding to the negative sentiment. Concerns about a wider conflict, even nuclear war, also fueled fear and negativity. Brief positive moments on the graph, like ceasefires and evacuations, were short-lived as the war continued. This graph shows how public opinion can change during conflicts, highlighting the war's devastating effects.

Figure 9: Sentiment Trend analysis for Russia-Ukraine war

The sentiment trend graph in Figure 10 for IPL 2022 shows that people mostly felt positive about the tournament, except for a few times when they felt negative. The happiest times were at the beginning, and the least happy times were during the playoffs. This could be because people are happier when their favorite teams are doing well and feel upset when they're not. Also, bad umpiring decisions can make people mad, and close, exciting matches make people happier.

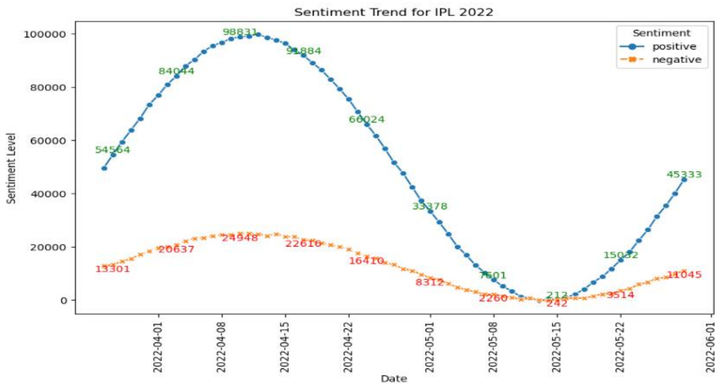

Figure 10: Sentiment Trend analysis for IPL 2022

The sentiment trend graph in Figure 11 depicts an overall negative sentiment towards the pandemic. The reasons for this negativity could be global impact of the virus, such as lockdowns and economic difficulties, concerns about health risks, dissatisfaction with government responses, and the emergence of new virus variants.

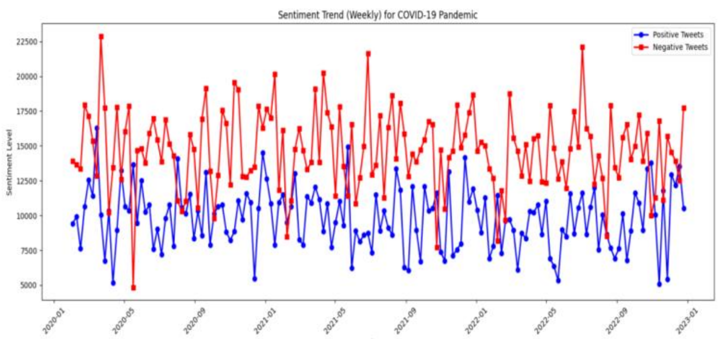

Figure 11: Sentiment Trend analysis for Covid-19 Pandemic

VI. CONCLUSION

In conclusion, sentiment trend analysis plays a crucial role in understanding public opinion and behaviour across various events and contexts. Particularly in the context of major events like the COVID-19 pandemic, political elections, and sports tournaments. By analyzing sentiment trends over time, can gain valuable insights into how public perception evolves, which can inform decision-making and communication strategies. The use of advanced techniques such as deep learning and BERT word embeddings enhances the accuracy and efficiency of sentiment analysis, enabling more nuanced insights. However, there is still scope for improvement, especially in integrating multimodal data sources for real-time sentiment analysis. Overall, sentiment trend analysis remains a valuable approach for gaining deeper insights into public sentiment and behaviour across diverse domains.

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