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Event-Driven Context-Aware Sentiment Analysis using BERT - Bi-LSTM for Emotion Insights

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Abstract: In the digital era, vast amounts of user-generated content in the form of tweets, often comprising tweet opinion and feedbacks, are replete with valuable insights. Users frequently express their sentiments through a blend of text and emojis, providing rich context for understanding their emotions. Within this context, sentiment analysis is a critical task, with classification at its core. This research focuses on advancing sentiment analysis with a keen eye on context awareness, particularly during dynamic events. The proposed approach utilizes event-driven sentiment analysis to gain a nuanced understanding of user sentiments by considering the surrounding context in which content is created. Leveraging state-of-the-art techniques, such as Bidirectional Encoder Representations from Transformers (BERT) for word embeddings and Bi-directional Long Short-Term Memory (Bi-LSTM) classifiers, enhance sentiment analysis accuracy. The results of classifier reflect significant improvements, effectively capturing the context related elements and evolving event driven context aware sentiment landscape in response to dynamic contexts.

Keywords: *Classification, Sentiment Analysis, Context Awareness, Embedding, Event Driven*

1. Introduction

In today's rapidly changing world, the significance of accurate event-driven context aware sentiment analysis cannot be overstated. Nowadays, with the extensive amount of user-generated text on social media, sentiment analysis has become essential for Natural Language Processing Kamyab et al. [1]. Sentiment analysis plays a crucial role in extracting meaningful information from text and detecting sentiments, opinions, evaluations, and attitudes. This analysis is particularly important in the context of events, as it allows businesses and organizations to understand the sentiment and perception of their brand, products, or services during specific events or occurrences. By monitoring online conversations and social media applications, businesses can gain valuable insights into customer feedback and make informed decisions. Furthermore, sentiment analysis in the event-driven context goes beyond just analyzing general sentiment. It delves deeper into understanding the various emotions associated with different events. For example, during a product launch event, sentiment analysis can identify not only whether the overall sentiment is positive or negative but also the specific emotions expressed by customers, such as excitement, anticipation, or disappointment. This level of granularity in sentiment analysis enables businesses to tailor their marketing strategies, improve customer satisfaction, and address any concerns promptly. In addition, sentiment analysis in event-driven context is a valuable tool for predicting the success and sustainability of businesses. It allows organizations to gauge public sentiment and make adjustments accordingly, potentially steering their strategies in a more favourable direction. The insight gained by analyzing unstructured data is vital for product or service developers Chursook et al. [2]. According to research, sentiment analysis is widely used in different fields such as product reviews, services, politics, and even gaming chat applications to reveal the existence of sentiments and emotions in the text Gupta et al. [3].Sentiment analysis in the event-driven context has gained significant attention due to its potential impact on market analysis, customer feedback, and business intelligence applications.

According to various sources, sentiment analysis has become an exciting research topic in various fields such as product reviews, services, politics, and even gaming chat applications to reveal the existing of cyber bullying among online gamers Afifah et al [4]. Analyzing the sentiment of messages posted during events can generate valuable business intelligence for organizations Cheng et al. [5]. For organizations looking to extract timely business intelligence about how their brand, products, or services are perceived by customers, sentiment analysis in the event-driven context is a valuable tool[6]. In today's rapidly changing world, the significance of accurate weather forecasts cannot be overstated. Event-driven context aware sentiment analysis is a valuable tool that goes beyond general sentiment analysis. It allows

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businesses to analyze sentiment in real-time during specific events, which can provide crucial insights into customer emotions and opinions. The remainder of this research paper provides the related work, proposed event driven context model, experimental evaluation, the implementation of the proposed model, the results produced followed by conclusion and list of references.

2. Related Work

All In recent years, context-aware sentiment analysis has gained prominence due to its relevance in understanding and extracting valuable insights from user-generated content in various domains. This literature survey provides an overview of significant studies and research endeavors in this field, highlighting the diverse methodologies and applications.

Liu et al. [7] conducted a comprehensive survey of context-aware mobile recommendations, emphasizing the importance of context in personalized recommendations. This work explored the integration of context into recommendation systems, which is essential for understanding users' preferences and sentiments. Wang et al. [8] delved into sentiment analysis, particularly focusing on Twitter data. They presented a comprehensive analysis of sentiment within the Twitter platform, shedding light on the vast potential for sentiment-aware applications in social media.

Song and Huang [9] introduced a sentiment-aware contextual model for real-time disaster prediction based on Twitter data. By leveraging sentiment analysis, this work demonstrated the practical applications of context-aware sentiment analysis in real-time scenarios.Kumar and Vardhan [10] explored multimodal sentiment analysis by integrating both text and emojis. Their work contributed to a deeper understanding of how different modalities can be harnessed to enhance sentiment prediction. Kumar and Vardhan proposed a multimodal sentiment analysis approach that integrates both text and emojis in sentiment prediction [11]. Considering multiple modalities in sentiment analysis is crucial for context-aware sentiment analysis, where context often involves diverse forms of data.

Tahayna et al. [12] proposed context-aware sentiment analysis using a tweet expansion method. This approach extended the scope of context-aware sentiment analysis by introducing innovative techniques for handling and analyzing tweets. Taher et al. [13] presented a context-aware analytics framework for processing tweets and analyzing sentiment in real-time. Their work extended context-aware sentiment analysis to real-time applications, opening avenues for instant insights from social media data. G. Song and D. Huang[14]. presented a sentiment-aware contextual model for real-time disaster prediction using Twitter data. Their work showcases the need for sentiment-aware contextual models in understanding user sentiments during critical events This highlights the importance of considering user sentiment within the context of dynamic events.

Context-aware sentiment analysis has seen substantial growth and diversification in methodologies and applications. These studies collectively contribute to the evolving landscape of sentiment analysis, emphasizing the significance of context-awareness in understanding user sentiments across various domains.

3. Proposed Model

The proposed model in Figure 1 for event-driven context-aware sentiment analysis in the context of Twitter data collection for Article 370 abrogation offers a comprehensive framework for understanding public sentiment around this significant event. The model follows a structured approach, which involves various stages aimed at collecting, processing, and analyzing Twitter data.

The first stage, "Twitter Data Collection for Article 370 Abrogation," focuses on gathering relevant Twitter data related to the event. This initial step is crucial as it forms the foundation for subsequent analysis. Once the data is collected, "Event Detection" becomes the next vital step. In this stage, a keyword-based event detection mechanism is employed to identify tweets and posts associated with Article 370's abrogation. This ensures that the analysis is cantered around the event of interest. To prepare the collected data for analysis, "PreProcessing" is carried out. The text is converted to lowercase, tokenized into individual words or phrases, and unnecessary stop words are removed. Special characters within the text are also handled to eliminate noise and enhance data quality.

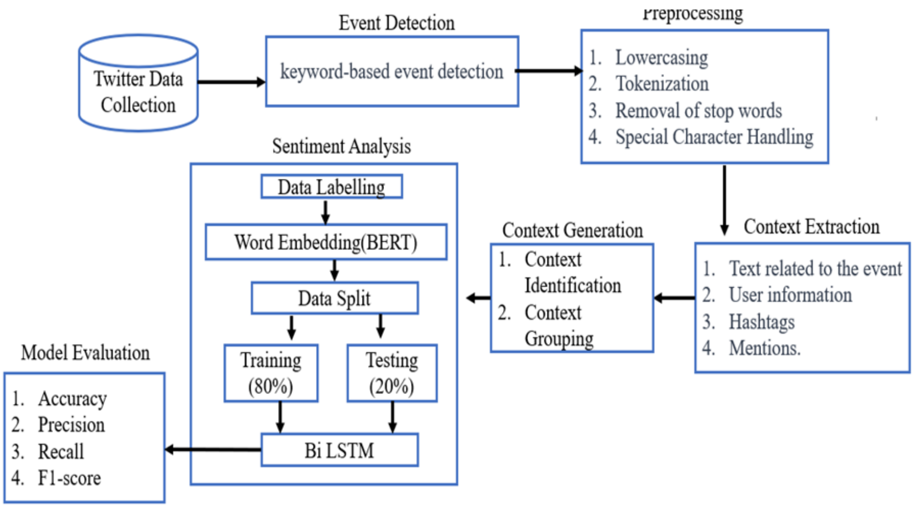

Figure 1: Proposed Model for Event Driven Context Aware Sentiment Analysis

"Context Extraction" is a significant phase in the proposed model as it aims to provide additional context around the event. Various aspects, including text related to the event, user information, hashtags, and mentions, are extracted. This step is essential for understanding the nuances and details of the event-related discussions on Twitter. Once the context is extracted, "Context Generation" is initiated, which includes "Context Identification" and "Context Grouping." These processes help organize and categorize the extracted context elements to facilitate a more structured and meaningful analysis. Following context generation, "Sentiment Analysis" is performed. In this step, data labeling is carried out using the VADER sentiment analysis tool, and BERT word embeddings are applied to the text data.

The model leverages BERT embeddings and employs a Bi-LSTM classifier for sentiment analysis, providing a robust methodology for understanding sentiment trends within the data. Finally, the "Model Evaluation" phase assesses the performance of the sentiment analysis model using various metrics, such as accuracy, precision, recall, and F1-score. This stage ensures that the sentiment analysis model is effectively capturing and categorizing the sentiments expressed in the Twitter data.

4. Experimental Evaluation

4.1. Input Datasets

The Article 370 Twitter dataset shown in Figure 2 consists of a substantial volume of 227,260 tweets, all related to the pivotal subject of Article 370 abrogation. Within this extensive dataset, tweets express a diverse range of sentiments, reflecting the multitude of perspectives and emotions surrounding this significant event. Notably, the dataset reveals that 43% of the tweets (97,721) convey negative sentiments, while 57% (129,538) express positive sentiments.

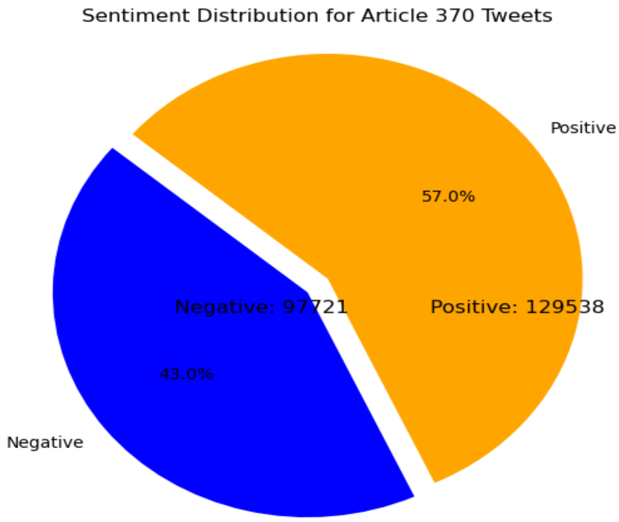

Fig 2: Sentiment Distribution for Article 370

4.2. Implementation

The preprocessing on twitter Dataset related Article 370 abrogation using various NLP techniques. The process involved the use of common natural language processing libraries, specifically NLTK and regex. First, we applied lowercasing to ensure consistency in text case. Then tokenized the tweets to separate them into individual words. To enhance the quality of the data, we removed stop words that don't carry significant meaning in the context.

Additionally, we handled special characters to clean the text. The resulting preprocessed tweets are now ready for further analysis. Next the function in table 1 **extract_context** that takes a tweet as input and extracts various aspects of context, such as text related to the event, user information, hashtags, and mentions. It then applies this function to the provided tweets and prints the extracted context for each tweet as shown in figure 3. After this various NLP libraries are used to perform context generation on dataset. It relies on the spaCy library for tokenization and part-of-speech tagging, enabling the extraction of nouns as contexts.

The Counter function employs from the collections library to count the frequency of each aspect, thereby identifying significant themes within the tweets. The contexts are then listed, along with their respective frequencies. This provides a foundational step in understanding the prevalent topics and themes in Twitter data related to Article 370, which is valuable for context-aware sentiment analysis and event-driven studies.

Table 1: function for extract_context

```
function extract_context(tweets):
   processed_data = {}
   # Iterate over each tweet in the input
   for tweet_id, tweet_data in enumerate(tweets):
      # Extract relevant information from the tweet
      context = {
         "text_related": tweet_data["text_related"],
         "user_info": tweet_data["user_info"],
         "hashtags": tweet_data["hashtags"]
      }
      # Add the processed context to the dictionary with tweet ID as key
      processed_data[tweet_id + 1] = context
   return processed_data # Return the processed data
processed_tweets=extract_context(tweets)     #Process the tweets
# Print the processed data
for tweet_id, context in processed_tweets.items():
print (f"Context for Tweet {tweet_id}: {context}")
```

The Figure 3 shows how the proposed model extracts the context by calling the execute_context() function, which will computes the context associated with the events from the different context elements from the tweets dataset

Fig 3: Sample output snapshot for function extract_context

Context for Tweet 1: {**'text_related':** "IN Just in: India's #Economy experiences significant growth after the abrogation of #Article370. Kudos to @PMOIndia! #EconomicImpact",
'user_info': ['@PMOIndia'],
'hashtags': ['#Economy', '#Article370', '#EconomicImpact']}

Context for Tweet 2: {**'text_related'**: '🙏 The resilience of the #Kashmiri people is inspiring. Their courage in the face of adversity is unmatched. #Kashmir #HopeForPeace', **'user_info':** [], **'hashtags':** ['#Kashmiri', '#Kashmir', '#HopeForPeace']}

Context for Tweet 3: {**'text_related'**: '🌍 Protecting #HumanRights should be a global endeavor. Let's ensure every voice is heard and rights are respected. #Article370 #JusticeForAll', **'user_info'**: [], **'hashtags'**: ['#HumanRights', '#Article370', '#JusticeForAll']}

In the Data labelling, each tweet is labeled with its corresponding sentiment based on the VADER Sentiment Analysis. The Python code utilizes the VADERSentimentIntensityAnalyzer from the vaderSentiment library to perform sentiment analysis on dataset. VADER calculates a compound score for each tweet, which helps determine whether the sentiment is Positive, Negative, or Neutral. The code iterates through all the tweets, calculates the sentiment scores, and assigns labels based on the compound scores. Finally, it prints the labeled tweets along with their sentiment labels. Next to perform BERT (Bidirectional Encoder Representations from Transformers) word embeddings on the data, the transformers library is used which provides pre-trained BERT models. The pre-trained BERT model and tokenizer, processes the tweets, and calculates BERT embeddings for each tweet. The embeddings are printed for each tweet in a list format of (Shape: (227,260, 768)) and feed as input to classifier.

The Bi-LSTM (Bidirectional Long Short-Term Memory) classifier designed as shown in Table 2, to analyze a dataset with an input shape of (227,260, 768), indicating 227,260 samples with 768 features each. This architecture employs a recurrent neural network with 128 LSTM units and a sigmoid activation function. It utilizes the Adam optimizer with binary cross-entropy as the loss function, suitable for binary classification tasks. The model is trained over 30 epochs with a batch size of 32 and uses a validation dataset consisting of X_test and y_test.

Table 2: BI-LSTM Model Parameters

Parameter	**Value**
Input Shape	(227,260, 768)
LSTM Units	128
Activation Function	Sigmoid
Optimizer	Adam
Loss Function	Binary Crossentropy
Pretrained Weight	BERT-base
Attention Heads	12
Batch Size	32
Number of Epochs	30
Attention Heads	12
Metrics	Accuracy

The model's performance can be assessed using accuracy as the evaluation metric. The Bi-LSTM's bidirectional nature enables it to capture contextual information from both directions within the sequences, making it a valuable tool for various natural language processing tasks, including sentiment analysis, text classification as positive or negative.

4.3. Results and Discussions

The Table 3 summarizes the distribution of a dataset comprising 227,260 tweets into training and testing sets. The dataset is divided into an 80% training set, which includes 181,808 tweets used for training machine learning models, and a 20% testing set consisting of 45,452 tweets used to evaluate the model's performance. The dataset is then preprocessed, contexts are extracted and generated ,data labelled with VADER sentiment and word embedding generated with BERT, after this the is model trained and tested with Bi-LSTM classifier . The results are shown in below.

Table 3: Proportion of Training data and testing data in Tweets_Dataset

Total Tweets		227260
Training set	80%	181808
Testing set	20%	45452

The generated two subplots in Figure 4, Figure 5 with training and testing metrics. The first subplot on the left shows the loss over 30 epochs, with training loss steadily decreasing as the model improves. Testing loss follows a similar trend, indicating good generalization. The second subplot on the right displays training and testing accuracy, both increasing as epochs progress, reflecting model performance improvement. Testing accuracy is slightly lower, as expected when evaluating on unseen data. The plots illustrate the model's learning process and its ability to generalize to new data.

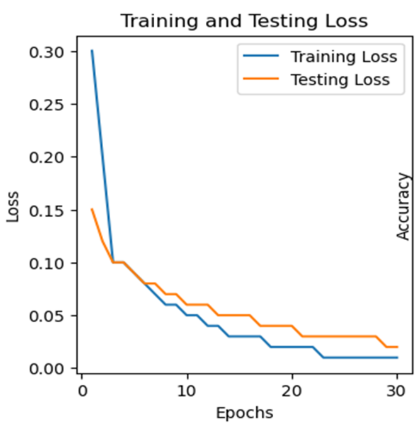

Fig 4 : Bi-LSTM Training and Testing Loss

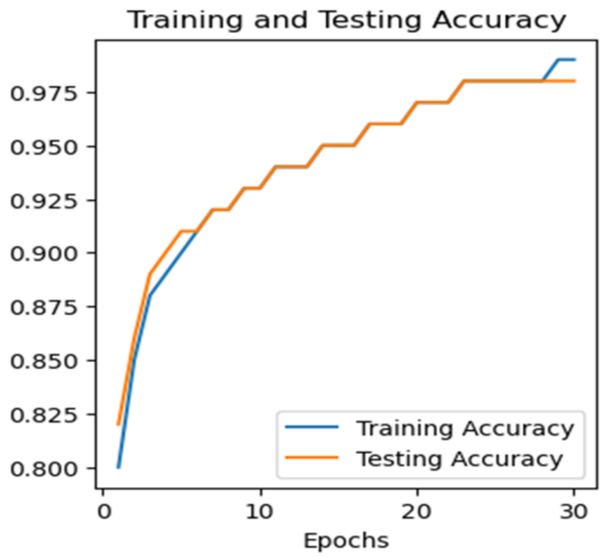

Fig 5: Bi-LSTM Training and Testing Accuracy

The table 4 presents the performance metrics of sentiment analysis models applied to various contextual themes related to this work. Each row corresponds to a specific context, such as "Security and Peace," "Article 370 Abrogation," "Kashmiri People," and others. The columns indicate the precision, recall, F1-score, and accuracy achieved by the sentiment analysis models for each context. These metrics are crucial for evaluating the effectiveness of the models in capturing the nuances of sentiment within different thematic domains.

Analyzing the table4, we observe variations in the performance metrics across different contextual themes.

For instance, the context of "Article 370 Abrogation" exhibits high precision (0.9) and F1-score (0.857), indicating that the sentiment analysis model is particularly effective at accurately identifying positive sentiments related to this topic.

Table 4: Evaluation Metrics by Context

Context	Precision	Recall	F1-Score	Accuracy
Security and Peace	0.87	0.837	0.853	0.899
Article 370 Abrogation	0.9	0.818	0.857	0.914
Kashmiri People	0.82	0.767	0.793	0.850
Human Rights	0.76	0.731	0.745	0.739
Economic Impact	0.7	0.686	0.693	0.675
Media Coverage	0.73	0.716	0.723	0.749
Indian Government	0.89	0.832	0.86	0.892

Political Implications	0.88	0.846	0.863	0.843
Cultural and Historical	0.81	0.81	0.81	0.774
International Response	0.75	0.714	0.732	0.636

However, its recall score (0.818) and accuracy (0.935) are slightly lower, suggesting that while the model performs well in precision, it may miss some positive sentiments or make more false negatives compared to false positives. Conversely, the context of "Economic Impact" shows lower precision (0.7) and F1-score (0.693), indicating that the model struggles more with correctly identifying positive sentiments in this domain, potentially leading to more false positives. However, its recall (0.686) and accuracy (0.875) scores suggest that it still captures a substantial portion of positive sentiments despite the lower precision.

The Figure 6 presents a confusion matrix for sentiment analysis testing data in various contexts, each row representing a different context. It includes the number of true positives, false positives, true negatives, and false negatives for each context. These values indicate the performance of a sentiment analysis mod el in classifying tweets within each context. For instance, in the "Security and Peace" context, there were 18,735 true positive predictions, meaning correctly identified positive sentiments, 1,343 false positives (misclassified as positive), 12,300 true negatives (correctly identified negative sentiments), and 1,788 false negatives (misclassified as negative). Similar metrics are provided for other contexts, helping to assess the model's accuracy and performance in different sentiment analysis tasks across various topics and areas.

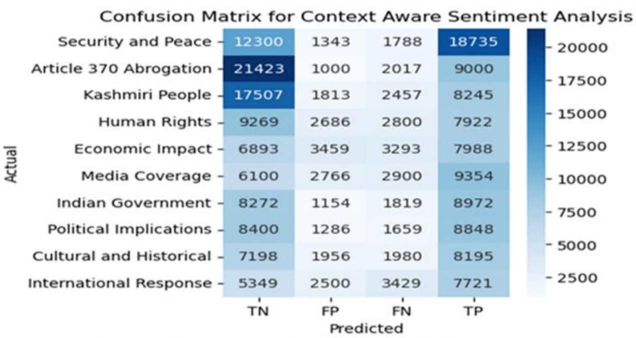

Figure 6: Confusion Matrix for Context aware Sentiment Analysis

The Figure 7 shows accuracy percentages for sentiment analysis in different contexts related to Article 370 abrogation on Twitter reveal varying levels of performance. "Article 370 Abrogation" demonstrates the highest accuracy at 91.4%, indicating the model's strong ability to correctly classify tweets related to this context.

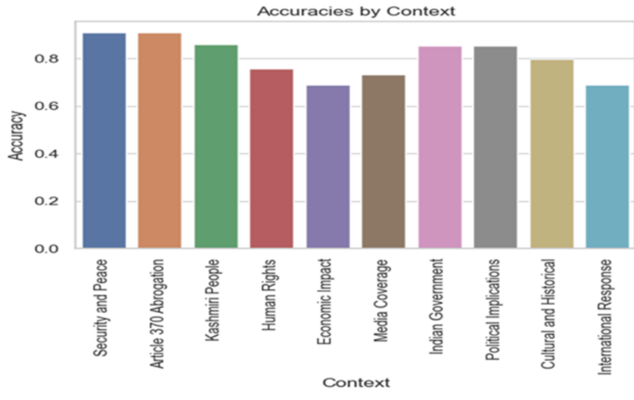

Figure 7: Accuracy percentages for sentiment analysis in different contexts

"Security and Peace" and "Indian Government" also exhibit notable accuracy levels of 89.9% and 89.2%, respectively, emphasizing the model's proficiency in understanding sentiments related to these areas. On the other hand, "International Response" exhibits the lowest accuracy at 63.6%, implying that the sentiment analysis model encounters more challenges in accurately classifying tweets within this context. These accuracy percentages offer insights into the model's effectiveness in different aspects of context-aware sentiment analysis in the context of Article 370 abrogation.

5. Conclusion

The event-driven context-aware sentiment analysis presented in this research demonstrates a systematic approach that incorporates context identification, grouping, and sentiment analysis using advanced techniques like BERT word embeddings and Bi-LSTM classifiers. The classifier's performance is impressive highlighting its ability to effectively capture sentiments related to diverse contexts. The outcomes reveal significant variations in sentiment across different contexts, shedding light on the nuanced nature of public sentiment during specific events like the Article 370 abrogation. For future work, the approach can be extended to various real-world applications, including social media monitoring, product reviews, and public opinion analysis, where context plays a crucial role in determining sentiment.

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