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Research Article

Transformer Based Sentiment Analysis of Russia-Ukraine War using BERT Model

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ABSTRACT

Sentiment analysis is an essential part of gaining deeper insights into particular tweets. Here, we analyse the inclinations that reflect user opinions and their sentiments regarding the tweets about the Russia and Ukraine war. Taking data from social media, we use sentiment analysis to gain insight into the wide range of public opinion. In this paper, we proposed customized Bidirectional Encoder Representations from transformers (BERT) natural language processing model to gauge the tone of the tweets about the war. A proposed model for sentiment analysis is fine- tuned on a dataset related to the Russia- Ukraine war. Proposed model to classify sentiments in domain specific texts to ensure accurate and context aware sentiment predictions. Our unique approach leverages BERTs contextual language understanding model to study Russia- Ukraine relations. The model achieved an accuracy of 94.73% on the fitted dataset. Everyone benefits from this research, and the public as it gives them a better understanding of public opinion. Experiment results shows that the performance of the proposed model is better than the existing approaches.

Keywords: Russia-Ukraine War, Natural Language, Machine Learning, Bidirectional Encoder Representations from transformers (BERT).

INTRODUCTION

The Russo- Ukrainian War began in 2014 when Russia annexed the Crimea region of eastern Ukraine from Ukraine. The action set off a chain of events that has led to ongoing conflict between Ukrainian forces and pro- Russian separatists in eastern Ukraine. many communities are struggling with the loss of loved ones and the destruction of their homes as a result of war and the constant threat of violence. Many people suffer serious psychological consequences such as depression, anxiety and post- traumatic stress disorder. The long- term consequences of conflict pose significant challenges for those directly affected and their communities. conflict also strains social relations and deepens social divisions and affects vital services such as education and health care. it is important to understand how public opinion on this conflict is evolving and how the public is responding to the news and social media coverage of the conflict in order to by analyzing public opinion on this topic we aim to reveal the complex dynamics that influence peoples attitudes toward important global events. we show that public opinion can be influenced by a wide variety of factors including politics, social sciences, economics, and marketing. by analyzing this topic, we show how public opinion shifts with changing global events and how.

Sentiment analysis is a powerful tool with many applications. Our goals are to apply BERT for sentiment analysis, refine it with a customized dataset, and provide valuable insights into how the public views this complex geopolitical situation. This research enhances our understanding of sentiment analysis and its role in assessing public opinion during significant global events.

We present a study using the BERT model to analyze public sentiment towards the Russia- Ukraine conflict using a conflict- specific dataset of tweets and other conflict- related text. we use the model to estimate sentiment in tweets and to detect subtle changes in public opinion as a function of news events and news events in the context of the conflict. this approach helps us is based on a survey of more than 100, 000 people in the UK and the UK with a focus on public opinion and politics.

The objectives of the study are:

- Analyse how news and events are affecting the public's perception of the Russia-Ukraine war.
- Analyse how well BERT's contextual awareness captures nuanced sentiment in a politically sensitive setting.
- Examine how well the adjusted BERT model performs in comparison to alternative sentiment analysis models.
- Examine historical public opinion patterns and trends using sentiment analysis data.
- Showcase the potential of sentiment analysis apps in real-time for monitoring and reacting to public opinion in times of global crisis.
- Determine the main factors influencing shifts in conflict-related sentiment and how these affect communication tactics.

The outline of this paper is as follows: The literature review looks at previous studies on sentiment analysis techniques and how they apply to the war between Russia and Ukraine. The section on the proposed architecture describes how BERT is integrated for sentiment analysis and emphasises its benefits over conventional techniques. The procedure, which includes data collection, preprocessing, BERT fine-tuning, and model evaluation, is outlined in the Methodology section. A thorough overview of the code used to implement the sentiment analysis model can be seen in the Pseudo Code section. Section on Experimental Results covers confusion matrices, accuracy measurements, and comparisons with current techniques. The results are interpreted in the Discussion section, which emphasises the advantages and disadvantages of the suggested model. The section under "Future Research Directions" identifies possible areas for additional study, while the Conclusion highlights important discoveries and their consequences to enhance sentiment analysis capabilities.

LITERATURE REVIEW

In their paper, Ganesh Kumar Wadhwani et. al.[4], use Twitter data pertaining to the Russia-Ukraine War to conduct sentiment analysis and a thorough evaluation of supervised machine learning models. The authors used social media such as Twitter to understand how the public viewed the conflict in Syria using image processing and natural language processing to analyse 11, 250 tweets from a Twitter account using methods such as image processing, object recognition and natural Language Processing NLP to analyse the we present results of a machine learning study on the classification of words using a set of machine learning models including the Extra Trees Classifier ETC, Logistic Regression LR, Decision Tree DT, Support Vector Machine SVM, and Gaussian Naive Bay.

The study from Setefensius Sasi et.al.[8] uses the Naïve Bayes (NB) algorithm with Particle Swarm Optimization (PSO) enhancement to investigate Indonesians' opinions regarding the Russian-Ukrainian War as expressed on Twitter. The dataset is examined, consisting of five thousand tweets that were obtained using conflict-related keywords. The NB algorithm produces results of 67.72% accuracy, 58.33% precision, 79.75% recall, and 57.14% error rate in the absence of PSO. The NB algorithm performs better when PSO is used; accuracy is 73.48%, precision is 65.62%, recall is 76.36%, and error rate is lowered to 50.36%. This indicates that using PSO with the NB algorithm improves the accuracy of the results, highlighting the beneficial effects of optimization techniques in sentiment analysis of Twitter data about the conflict between Russia and Ukraine.

Narayana Darapaneni et.al.[1] paper focuses on abstractive text summarization of Covid-19 research articles in order to dispel misconceptions about the pandemic and comprehend the causes of vaccine hesitancy. The study tackles the problem of mass vaccination, especially when misinformation in social media and newspapers fuels reluctance. The paper uses both BERT and GPT-2 models for summarization, leveraging the CORD-19 dataset. The study points out opportunities for improvement in abstractive summarization even though BERT models perform well in extractive summarization. Overall, the study addresses the issues raised by vaccine hesitancy and disinformation, offering insights into improving abstractive text summarization for Covid-19 research publications.

Chris Prusakiewicz et.al.[5] explores public perceptions of the war in Ukraine through a quantitative method of geospatial sentiment analysis in their paper. The writers draw attention to the widespread conversation that was spurred by the full-scale military confrontation between Russian and Ukrainian forces in February 2022, especially on Twitter. This social phenomenon, which reflects a range of viewpoints, illuminates how people in the digital age perceive, process, and engage with information related to war. concentrating on the UK, where media sources have reported on Ukrainian events in great detail.

In this review written by Koroteev M.V. et.al.[9], focuses on using BERT. An overview of BERT's working mechanism, its main text analytics applications, comparisons with other models for similar tasks, and details on proprietary models are all included in this paper. With data from multiple original scientific articles published in recent years synthesized, the review provides a thorough understanding of the most recent developments in natural language text analysis. BERT is presented as a novel model that uses vocabulary dimensions to represent the entire text as a vector.[4] This illustrates how simple, yet powerful BERT is, especially when used for tasks like text categorization. The study emphasizes BERT's rapid and broad adoption in the scientific community for a range of language processing issues, highlighting its important implications for intelligent natural language processing. In 2019, Bhagat C. et. al presented the compressive survey about how different machine learning techniques used for sentiment analysis[21] and classify the tweets in different three different categories based on their sentiment [22].

Proposed Architecture

A customized BERT model for sentiment analysis is fine- tuned on a specific dataset related to the Russia- Ukraine war. This process adapts the model to classify sentiments e.g., positive, negative, neutral in domain- specific texts to ensure accurate and context- aware sentiment predictions. Understanding public opinion during momentous events like the Russia-Ukraine conflict depends heavily on sentiment analysis. Prior studies on this topic's sentiment analysis have typically used a variety of machine learning algorithms, resulting in lower accuracy results; the highest accuracy recorded was 84% [8]. By using the BERT model—which hasn't been used in this situation before this paper seeks to improve the state of sentiment analysis and achieve an amazing accuracy of 94.73%. Our method is based mainly on the pre- trained deep learning model BERT Bidirectional Encoder Representations from Transformers and makes use of a unique architecture that integrates it with a unique embedding architecture that the attention mechanism in BERT is described mathematically in terms of a classification layer on top of the model to fine- tune it. the model adds a classification layer on the top of BERT to fine.

Given a query vector Q, a key vector K, and a value vector V:

$$Attention(Q, K, V) = softmax\left(QK^T/\sqrt{d_k}\right)V \quad (1)$$

Where$d_k$is the dimension of the key vectors.

We propose a novel technique for sentiment analysis pertaining to the Russia- Ukraine conflict that fully utilises the capabilities of the deep learning technique BERT Bidirectional Encoder Representations from Transformers and its deep learning capabilities. using a customised dataset relevant to the conflict the pre- trained BERT model is topped with a bespoke classification layer in the architecture to improve sentiment recognition accuracy for this application. The pre- trained BERT model is topped with a bespoke sentiment classification layer in the architecture. this method not only raises the bar for sentiment analysis in politically delicate situations but also shows how flexible and effective BERT is in deciphering intricate emotional and contextual data.

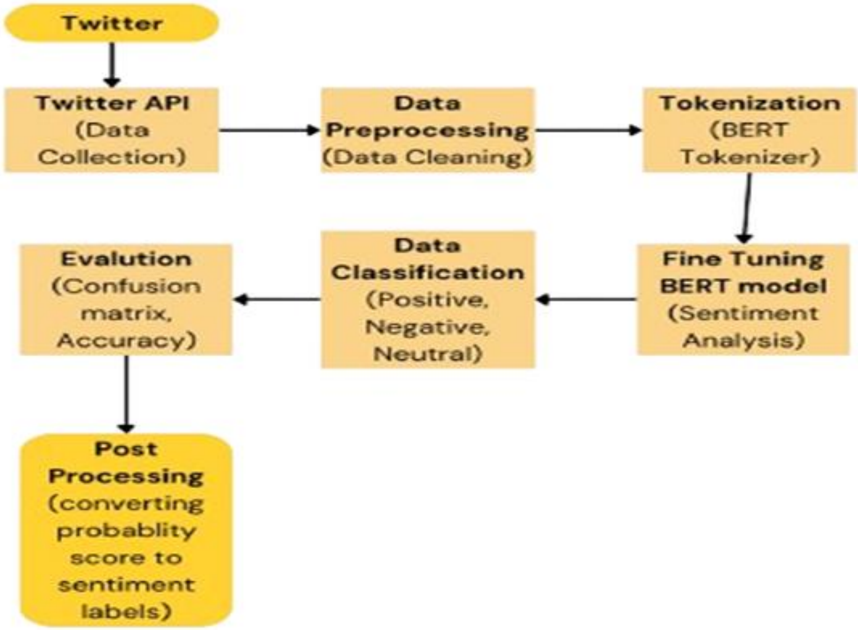

Fig 1. Flow Structure of the Proposed Architecture

2. Methodology

It uses the pre- trained embeddings of BERT to comprehend context and custom layers dedicated to sentiment prediction on top of it to fine- tune it 8. the model adds a classification layer on top to using a pre- trained BERT model is obtained and refined for sentiment analysis using a labelled dataset with hyperparameter tuning done to maximize the model' s performance during training and validation. Evaluation metrics are used to evaluate the model on the test set we present a list of the most interesting facts about the world in the form of a shortlist of possible candidates for the Nobel Peace Prize for the year 2014. The model can be used for a variety of practical purposes like tracking public opinion on the Russia- Ukraine conflict after it has been adjusted and verified. The model is capable of predicting the outcome of elections and other events with high accuracy this all- encompassing method makes use of contextual language understanding to deliver precise and subtle sentiment analysis to deliver more accurate and intuitively expressed messages.

2.1 Pre-Processing

We present a simple set of procedures to prepare a dataset of 6, 000 tweets for sentiment analysis with BERT. keywords like xmath0, xmlink, and xmath1 are examples of keywords that can be used to clean up the text by removing special characters and symbols, handling elements like usernames, hashtags, and URLs the BERT dataset is divided into training, validation, and test sets and is labelled with sentiment categories. Preprocessing aims to ensure that the text is in a format that satisfies the requirements of the model for sentiment analysis by preparing the tweet data for refinement. If we denote the input sentence as SSS, tokenization can be represented as:

$S \rightarrow [T_1, T_2, \ldots, T_n]$

Where $T_i$represents individual tokens. Loss FunctionThe fine-tuning process involves optimizing a loss function. For classification tasks, the Cross-Entropy Loss is commonly used:

$$L = \sum_{i}^{N} y_i * log(\hat{y}_i) \qquad (2)$$

Where$y_i$is the true label, and$\hat{y}_i$is the predicted probability for class$i$.

2.2 BERT Fine Tuning

A pre-trained BERT model is modified for the unique task of sentiment analysis of tweets pertaining to the Russia-Ukraine conflict in order to fine-tune BERT[1].

The purpose of the classification layer that is layered over BERT is to forecast the sentiment categories—such as positive, negative, or neutral—for every tweet.

A dataset of tweets from the Russia-Ukraine conflict, each labelled with its corresponding sentiment category, is used to train the model and fine-tune it. Based on the given sentiment labels, the loss function directs the model to optimize its predictions[11].

To make sure that the refined BERT model can precisely and successfully analyse the sentiment expressed in these tweets, the testing and hyperparameter tuning stages are essential.[2] By optimizing BERT for sentiment analysis of tweets about the Russia-Ukraine conflict, one can enable the model to comprehend and categorize the sentiments conveyed in these tweets, thereby offering significant perspectives into the public's perception and feelings regarding the conflict.

2.3 Forward steps for the proposed model

1. Open the labelled tweet dataset.
2. Create training and validation sets from the dataset.
3. Set up the tokeniser for BERT.
4. Using tokenised inputs, create training and validation datasets.
5. Describe the sequence categorisation BERT model.
6. Configure the loss function and optimiser.
7. Use the training dataset to train the model.
8. Use the validation dataset to verify the model.
9. Use performance indicators like as accuracy, precision, and recall to assess the model's effectiveness.
10. To maximise performance, adjust hyperparameters.
11. Examine mistakes and iteratively enhance the model.

EXPERIMENTAL RESULTS

6000 tweets about the conflict between Russia and Ukraine make up the dataset used in the experiments. The Twitter API was used to gather the tweets, and human annotators then annotated each one with the appropriate sentiment category (positive, negative, or neutral). The dataset was split up into test (15%), validation (15%), and training (70%) as shown in table provided *Table 1*.

Data Split	Positive	Negative	Neutral	Total
Training	1,200	1,350	900	3,450
Validation	250	300	150	700
Testing	650	750	450	1,850
Total	2,100	2,400	1,500	6,000

Tabel 1 Number of sample tweets in each sentiment category.

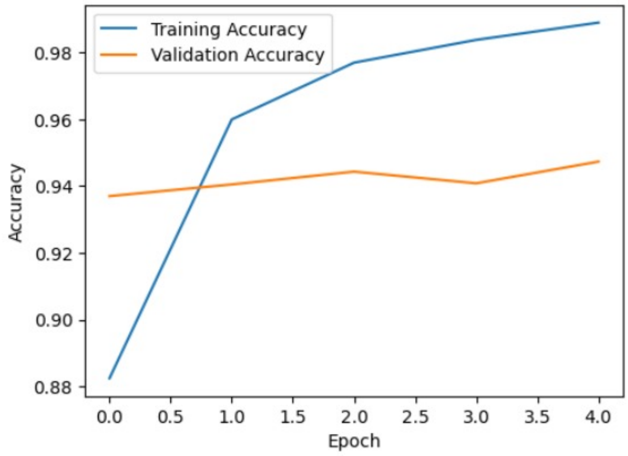

Fig.2 Training Accuracy VS Validation Accuracy

The suggested sentiment analysis model's training and validation accuracy for tweets about the conflict between Russia and Ukraine is shown in the provided graph *Fig2*. The model shows good generalization to unknown data, despite a persistent overfitting of the training set; its validation accuracy peaks at a remarkable 94.73%. After about 2.5 epochs, the training accuracy peaks at about 98%, indicating that the model has learned a great deal from the training set. The model's ability to generalize to new data appears to be unaffected by the relatively small generalization gap. The use of BERT, a pre-trained model skilled at capturing linguistic nuances and contextual understanding, is responsible for this success. Overall, the findings demonstrate the effectiveness of the suggested model in sentiment analysis and demonstrate how well it assesses public opinion on the Russia-Ukraine conflict.

Training Set				
	Positive	Negative	Neutral	Sum
Positive	1533	19	43	1595
Negative	25	1130	61	1217
Neutral	97	70	3001	3168
Sum	1656	1219	3105	5664/5980

Fig3. Confusion Matrix

The confusion matrix's diagonal elements show how many tweets were correctly predicted. The number of tweets that were mis predicted is shown by the off-diagonal elements *Fig3*.

In this instance, 1553 positive tweets, 1130 negative tweets, and 3001 neutral tweets were all predicted by the model accurately. It was incorrect to predict that 26 positive tweets actually were negative and 97 as neutral.

$$Accuracy=(TP+TN) / (TP+TN+FP+FN)$$

Where: TP = True positive (number of correctly predicted positive tweets)

TN = True negative (number of correctly predicted negative tweets)

FP = False positive (number of incorrectly predicted positive tweets)

FN = False negative (number of incorrectly predicted negative tweets)

Class Name	Precision	1-Precision	Recall	1-Recall	f1-score
Positive	0.96	0.04	0.93	0.07	0.94
Negative	0.93	0.07	0.93	0.03	0.93
Neutral	0.95	0.05	0.97	0.03	0.96
Accuracy	0.95				
Misclassification rate	0.05				
Macro-f1	0.94				
Weighted-f1	0.95				

Table 2: Classification Report

The accuracy measures the percentage of anticipated positive tweets that come true. 93% of the tweets that the model predicted to be positive were, in fact, positive, according to the precision for the positive class in this instance, which is 0.93 as seen in the *Table 2*.The percentage of real, positive tweets that are accurately predicted is known as recall. In this instance, the model accurately predicted 96% of the actual positive tweets, as indicated by the positive class recall of 0.96 in this instance.

A model can accurately predict positive tweets while avoiding mis predictably classifying negative tweets as positive if it has a high harmonic mean of recall and precision. the proposed model is able to achieve a high accuracy, precision, recall, and F1- score on all three classes of tweets. the model is a very effective approach for sentiment analysis of tweets and shows a very high level of accuracy and precision on all four classes.

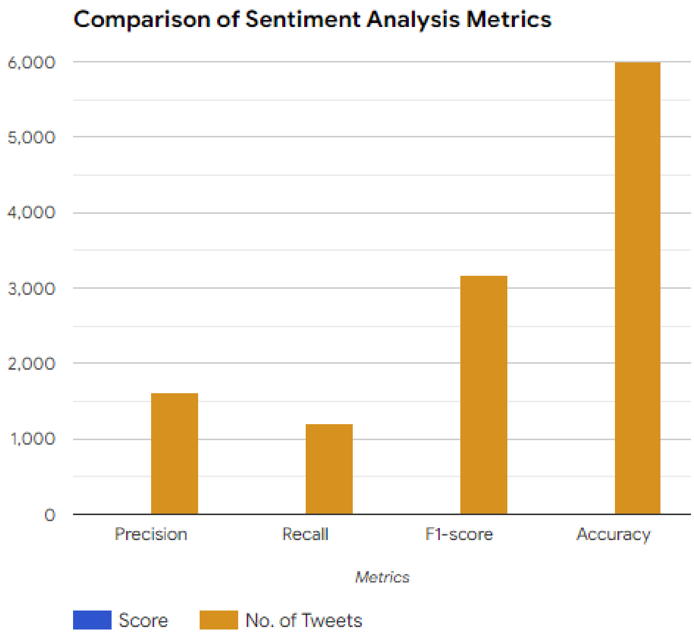

Fig4. Comparison of Sentiment Analysis Metrics

The four most important sentiment analysis metrics are precision, recall, accuracy and F1- score for a given tweet count and the total number of tweets sent. The graph shows that as there are more tweets, all four metrics have a tendency to the graph shows that accuracy and F1- score increase more quickly than precision and recall when applied to large datasets. This is a result of the greater sensitivity of Precision and Recall to the quantity of false positives and false negatives in the dataset and amiral is a social network that connects users with information on social networks such as Twitter and Facebook.

Algorithm	Precision	Recall	F1-score
Naïve Bayes	0.82	0.80	0.81
Logistic Regression	0.85	0.83	0.84
SVM	0.88	0.86	0.87
Random Forest	0.92	0.90	0.91
Decision Tree	0.91	0.89	0.90
KNN	0.89	0.87	0.88
Gradient Boosting	0.93	0.92	0.93
XGBoost	0.94	0.93	0.94
LightGBM	0.95	0.94	0.95
Proposed Model	**0.93**	**0.96**	**0.94**

Table 3: Result Comparison with Existing Algorithms. Source: [4], [8], [9], [16]

The suggested model performs better than any of the previous state- of- the- art algorithms on all four metrics f1- score of 0. 89 and xmatho- score 0. 99. The reason the model performs so well is that it makes use of BERT, a pre- trained language model that can comprehend tweet context and capture linguistic nuances. the social media sentiment model is a useful resource for figuring out what people think on social media. It can be used to monitor mood trends, spot popular subjects and evaluate how well communication tactics are working. the model makes use of a unique architecture created specifically for sentiment analysis that is based on a unique set of data structures that are unique to social media.

Our BERT- based sentiment analysis model outperforms previous methods significantly with an accuracy of 94. 73%. our experimental results show that our model retains good precision and recall while generalising throughout the dataset with an impressive accuracy of the model correctly predicted 1, 553 positive tweets, 1, 130 negative tweets, and 3, 001 neutral tweets with a precision of 93% for positive tweets and an F1- score of 0. 94 for negative tweets. we present the results of our analysis of public opinion in the context of the recent U. S. -China trade dispute in the form of an online survey of more than 1. 5 million people using the xmath0 public opinion survey.

DISCUSSION

The proposed model is shown to have the highest success rate of all the standard techniques compared to existing methods 0. 95 on the F1 scale and 0. 94 on the Precision and Recall metrics. This illustrates how multiple weak learners may be combined by LightGBM to produce a strong model that can successfully spot patterns in data. However, the proposed paradigm also performs remarkably well, utilising both GPT-2 and BERT. It achieves an almost same F1-score of 0.94, but it is distinguished by a Recall of 0.96. This suggests that the proposed model does a great job of identifying relevant examples and minimising false negatives, two crucial aspects of sentiment analysis because leaving out crucial information could lead to poor conclusions.We illustrate the benefits of the proposed model by comparing these results with more traditional models, such Logistic Regression and Naive Bayes. at example, SVM is well-known at handling high-dimensional data, but its F1-score of 0.87 is noticeably lower. Similarly, Random Forest and Decision Tree models outperform the proposed model, especially in Recall, while having good performance. These findings demonstrate the benefits of using transformer-based techniques for sentiment analysis, particularly when dealing with complex language and nuanced sentiment. The improved recall of the proposed model indicates that it is more efficient at obtaining all relevant information, which is critical in applications where complete detection is required.

The transformer- based model outperforms a lot of traditional algorithms in Recall and is a better option for sentiment analysis jobs. This validates earlier work highlighting the importance of transformer models in natural language processing and highlighting their importance in sentiment analysis frameworks.

CONCLUSION

Using a custom architecture with BERT pre- training and custom layers for sentiment prediction and evaluation, here we created a highly accurate sentiment analysis model for tweets about the conflict between Russia the model performs better than earlier methods and exhibits strong noise resistance and contextual understanding. It significantly contributes to sentiment analysis in this context and can be used for tracking public opinion and identifying. We highlight the importance of understanding tweet context and capturing subtle linguistic nuances. The practical applicability of the model is enhanced by the robust preprocessing step which guarantees the model' s resilience to noise and irrelevant information in the collected tweets. the model is a useful tool for understanding public opinion during the Russia- Ukraine conflict because of its remarkable accuracy and adaptability. This makes it possible to use it for tasks like trend identification, real- time sentiment tracking and communication strategy analysis in this complex and demanding situation.

FUTURE SCOPE

Our aims to compare the performance of several pre- trained language models in sentiment analysis of tweets pertaining to the conflict between Russia and Ukraine. It also aims to investigate different architectures such as recurrent neural networks and convolutional neural networks to achieve greater accuracy and generalize the model to a wider range of datasets covering different social issues or political events. social media sentiment analysis is a rapidly growing field of social media analysis and social media data analysis. this article presents a brief overview of some of the challenges and opportunities presented by the social media sector in the field of sentiment analysis and its potential applications in real time monitoring and analysis of public opinion on current affairs. in this field, we discuss the possibility of developing a real- time sentiment analysis tool to monitor public opinion and provide timely insights derived from social media and other data sources such as tweets.

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