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COMPARISON OF FOUR PRE-TRAINED MODELS OF SENTIMENTAL ANALYSIS ON COVID 19 NEWS HEADLINES

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ABSTRACT

This research paper presents a comprehensivecomparison of four pre-trained models for sentiment analysis applied to COVID-19 news headlines. The COVID-19 pandemic has triggered an unprecedented flow of information and public discourse, making it essential to understand the sentiments and opinions expressed in news headlines. The study evaluates the performance of RoBERTa, VADER, BERT, and TextBlob in this specific context. In this research, a diverse dataset of COVID-19 news headlines is collected and preprocessed. Each of the four models is employed to perform sentiment analysis on this dataset.The evaluation involves assessing the recall, accuracy, and F1 score of these models in capturing the nuances of sentiment and emotion within the headlines. The findings of this comparative analysis reveal important information. RoBERTa, a powerful transformer model,exhibits a robust performance in understanding the subtleties of sentiment in COVID-19 news headlines. VADER, a rule-based system, demonstrates its adaptability to this domain. BERT, a sibling ofRoBERTa, showcases its ability to discern sentiment nuances, albeit with some complexities. TextBlob, a simplistic rule-based library, provides a user- friendly approach to sentiment analysis.

Keywords: Sentiment analysis, Roberta, Bert, Vader,Textblob, Accuracy score, F1 score.

I.INTRODUCTION

In today's fast-paced digital age, news headlines serve as the first point of contact for readers seeking to understand the world around them. Newspaper headlines not only convey information but also have thepower to shape public perceptions and sentiments[4]. The ability to analyze these sentiments effectively is ofparamount importance, as it enables us to gauge public opinion, track evolving trends. Sentiment analysis holdssignificant importance in comprehending the public mood and emotional responses related to particular events or subjects [3]. In the context of COVID-19, it is vital to gauge public sentiment towards the pandemic toidentify trends, concerns, and public perceptions. In this analysis, we will assess how well four pre-trained models—RoBERTa, VADER, BERT, and TextBlob— perform in sentiment analysis when applied to COVID-19 news headlines.

1. VADER:

VADER, as an NLTK module, furnishes sentiment scores derived from the language employed. It is specifically tailored for social media text but can be applied to news headlines as well. We will explore VADER's effectiveness in detecting sentiment within COVID-19 news headlines and whether it can provide meaningful insights into public opinion regarding the pandemic.

2. BERT:

BERT stands out among models, showcasing its efficacy in various natural language processing (NLP) tasks. We will assess how BERT, a sibling ofRoBERTa, performs in sentiment analysis when exposed to COVID-19 news headlines. Its ability to understand context and semantics will be scrutinized.

3. TextBlob:

TextBlob is a simpler analysis library that is often provide quick sentiment analysis tasks. It might not match the complexity of RoBERTa or BERT, but it offers a user-friendly, straightforward approach to sentiment analysis. We will examine its performance inassessing the sentiment of COVID-19 news headlines and whether it can provide valuable insights with minimal complexity.

4. RoBERTa:

RoBERTa, a variant of the BERT model, is a natural language processing model known for its exceptional performance in various NLP tasks. Having undergone pre-training with an extensive corpus of text data, it possesses the capability to grasp the intricacies andnuances inherent in language.

In this comparison, we aim to understand the strengths and weaknesses of these four models in the context of COVID-19 news headlines sentiment analysis. By evaluating their accuracy, ability to handle domain-specific language, and their ease of use, we can provideinsights into the best model for this specific task. The results will help researchers, businesses, and policymakers better comprehend public sentiment and make informed decisions during the ongoing pandemic.

II. LITERATURE SURVEY

The COVID-19 pandemic, which emerged in 2019, hadan unprecedented effect on the world. Beyond its healthimplications, the pandemic has given rise to a flood of information and news coverage, with headlines often shaping public perceptions and reactions. Sentimentanalysis utilizes computational methods to discern the emotional tone or sentiment conveyed in text, spanningfrom positive to negative or neutral[1] .

The models under consideration are:

1. VADER is a pre-trained model tailored for sentiment analysis. It operates by analyzing text at the word and phrase level to determine sentiment polarity and intensity. The foundation of this model relies on a lexicon comprising thousands of words, each assigned sentiment scores spanning from -4

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(signifyingextremely negative) to +4 (representing extremely positive), where 0 signifies neutrality. Additionally, VADER incorporates rules to handle modifiers, intensifiers, negations, and punctuation, allowing it to accurately interpret sentiment in context.

During analysis, VADER considers factors such as the capitalization of words (emphasizing sentiment), degree modifiers (e.g., "very good"), and exclamation marks or emoticons to assess sentiment intensity. It also accountsfor the presence of special characters and slang commonly used in social media text. By combining these elements, VADER generates sentiment scores forinput text, providing a quick and effective way to gaugesentiment without requiring extensive training data. This makes it particularly useful for analyzing sentiment in short-form text data from sources like social media, customer reviews, or online forums.

2. <u>BERT (Bidirectional Encoder Representations fromTransformers)</u> is a pre-trained language model designedfor various natural language processing tasks, includingsentiment analysis. In sentiment analysis, BERT learns to understand the sentiment expressed in text by considering the context of each word and its surrounding words bidirectionally.

Here's how BERT works for sentiment analysis in a nutshell:

Pre-training: BERT is pre-trained on a large corpus of text data using unsupervised learning techniques, such as masked language modeling and next sentence prediction. During this phase, BERT learns to representwords in a dense vector space, capturing semantic relationships between words.

Fine-tuning: Following pre-training, BERT can undergofine-tuning on a smaller dataset labeled for thesentiment analysis task. Throughout this fine-tuningprocess, the parameters of BERT are refined to enhancethe accuracy of predicting the sentiment of input text,aligning with the labeled examples.

Sentiment analysis: When a new text input is provided,BERT tokenizes the text into sub words and converts them into embeddings. The embeddings derived from this process are subsequently inputted into a neural network classifier layered atop BERT. This classifier then forecasts the sentiment of the text, discerning whether it's positive, negative, or neutral, based on the acquired representations.

Overall, BERT's bidirectional context understandingand pre- training data enable it to effectively capture thenuanced sentiment expressed in natural language text for sentiment analysis tasks.

3. <u>TextBlob:</u>

TextBlob is a Python library that furnishes a straightforward API for typical natural language processing (NLP) assignments,encompassing sentiment analysis.Unlike BERT, TextBlob's sentiment analysis model is not as complex or deep-learning-based, but rather relies on a pre-trained pattern-based approach.

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Here's how TextBlob's sentiment analysis works:

Pre-trained model: TextBlob comes with a model. Thismodel is based on a combination of rule-based patternsand machine learning techniques.

Text processing: When a text input is provided, TextBlob tokenizes the text into words and sentences, then applies various natural language processing techniques such as part- of-speech tagging and noun phrase extraction.

Sentiment scoring: TextBlob's sentiment analysis modelassigns a polarity score to the input text, which ranges from -1 (indicating negative sentiment) to 1 (reflecting positive sentiment). Additionally, it offers a subjectivityscore, which denotes the degree of subjectivity or objectivity in the text, ranging from 0 to 1.

Rule-based patterns: TextBlob's sentiment analysis model utilizes predefined patterns to identify sentiment-bearing phrases and words in the text, such as positive and negative adjectives, adverbs, and idioms.

Overall, TextBlob's sentiment analysis model offers a simple and easy-to-use approach for sentiment analysis tasks, suitable for applications where deep learning models like BERT might be too computationally expensive or complex to implement.

4. <u>RoBERTa (Robustly optimized BERT approach)</u>RoBERTa is a deep learning model based on transformers that undergoes pre-training on extensive text corpora. In sentiment analysis, RoBERTa utilizes its comprehension of language semantics to categorize the sentiment conveyed within a provided text snippet.

Here's how it works:

Pre-training: RoBERTa is used to perform self- supervised learning tasks. This enables RoBERTa to learn rich representations of language.

Fine-tuning: During fine-tuning, RoBERTa adjusts its parameters to better capture sentiment-related features in the data.

Classification: Once fine-tuned, RoBERTa can classifythe sentiment of new text inputs. It processes the input text
through its layers, extracting contextual information, and then makes predictions based on the learned representations.

Output: The output of RoBERTa for sentiment analysisis a probability distribution over different sentimentclasses, indicating the likelihood of each class being expressed in the input text.

<u>Accuracy:</u> Accuracy represents the proportion ofcorrectly classified instances relative to the total instances within the dataset. As one of the most direct evaluation metrics for classification tasks, accuracy frequently serves as a primary measure for assessing model performance. However, it's essential to consider the context of your specific problem and dataset.

<u>F1 Score:</u> The F1 score serves as a metric for assessingthe effectiveness of a classification model. It is calculated as the harmonic mean of precision and recall.Precision represents the accuracy of the positive predictions made by the model, while recall represents the model's ability to correctly identify all positive instances.

The formula for F1 score is:

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F1=2× (precision × recall) (precision + recall)
Where:
Precision= True Positives

True Positives + False PositivesRecall= True Positives
True Positives + False Negatives

In this formula:
True Positives (TP) are the instances that are correctlypredicted as positive.
False Positives (FP) are the instances that are incorrectly
predicted as positive.
False Negatives (FN) are the instances that areincorrectly predicted as negative.

The F1 score ranges from 0 to 1, where a higher value indicates better model performance, with 1 being the best possible score.
*F1 Score range of different models are: 1. VADER:
F1 Score: Depends on the dataset and evaluation criteria, but typically ranges from 0.6 to 0.8 for sentiment analysis tasks.

Details. It's well-suited for social media text due to its focus on emoticons, slang, and informal language. However, its performance might be limited in more formal or nuanced language domains.

2. BERT (Bidirectional Encoder Representations from Transformers):
F1 Score: Typically achieves high F1 scores, ranging from
0.8 to 0.9 or even higher, depending on the dataset and fine- tuning process.
Details: It captures contextual information effectively through bidirectional processing, making it well-suited for various natural language understanding tasks. It canfurther improve its performance.

3. RoBERTa (Robustly optimized BERT approach):
F1 Score: Similar to BERT, RoBERTa achieves high F1scores, often surpassing 0.9 on sentiment analysis tasks.

Details: RoBERTa is an optimized variant of BERT that incorporates improvements in training methodology and hyperparameters. It addresses some of the limitations ofBERT, such as longer pretraining duration and larger batch sizes.

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4. TextBlob:

F1 Score: Typically lower than deep learning models like BERT or RoBERTa, ranging from 0.5 to 0.7 depending on the dataset and evaluation criteria.

Details: TextBlob is a lightweight and easy-to-use library for text processing and sentiment analysis. It relies on a pattern- based approach and a predefined sentiment lexicon to classify text inputs. While TextBlob is suitable for basic sentiment analysis tasks, its performance might be limited in domains with complex or nuanced language.

Overall, while lexicon-based approaches like VADER and TextBlob are straightforward and easy to use, they might not achieve the same level of performance as deeplearning models like BERT or RoBERTa, especially oncomplex or domain-specific datasets. The selection of atool relies on considerations such as the demands of thetask, the computational resources accessible, and the unique attributes of the dataset.

This literature review will assess the performance of these models based on criteria such as accuracy, F1- score, and computational efficiency. Additionally, itwill consider their ability to handle nuances in COVID-19-related sentiment, including the impact of rapidly changing information, evolving public attitudes, and theprevalence of medical jargon[3]. The research papers that have been taken into consideration during the course ofresearch and study are different from the paper in the following ways:

[1] The referenced paper analyzes tweets using BERT and other machine learning methods[6].There are various advantages of pre-trained model over other machine learning methods such as Transfer learning, Reduced Data Requirements, Lower Development Time, Better generalization. The referenced paper only analyzes onepre-trained model that lacks by other three in community support, ease of use, resource efficiency, simplicity and speed. [2]The referenced paper analyzes different models from Transformers and compares themon the basis of F1 score, MCC and accuracy score of themodels on news headlines[5] .The pre trained models that are used in this paper are best for real time application due to their speed and efficiency. they are preferred tobe used for real time application like social media monitoring and chatbots. In this paper, the news headlines that are specific to covid-19 are analyzed.

III. MODELS USED

In this analysis, we employed four separate pre- trainedmodels to assess the sentiment of COVID-19 newsheadlines. These models cover a spectrum of methodologies and complexity levels:

1. Roberta:

RoBERTa, short for "A Robustly Optimized BERT Pretraining Approach," stands as a machine learning framework designed for natural language processing. Renowned for its proficiency across a spectrum of natural language processing (NLP) tasks, RoBERTa hasundergone thorough pre-training on a vast corpus of data, empowering it to adeptly capture contextual nuances. In this study,

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RoBERTa was employed to assess its suitability for sentiment analysis on COVID- 19 news headlines.

2. Textblob:

TextBlob is an uncomplicated, rule-based sentiment analysis library that offers a user- friendly approach to conducting sentiment analysis. It relies on predefined rules and a sentiment lexicon to classify text as positive, negative, or neutral. While not as complex as transformer models like RoBERTa or BERT.

3. BERT:

Similar to RoBERTa, BERT is a transformer-based model employed for diverse natural language processing (NLP) tasks. It has demonstrated exceptional performance in understanding context and semantics intext. In this study, BERT was assessed for its capacity to identify and analyze sentiment.

4. VADER :

VADER, an NLTK module, furnishes sentiment scores grounded in the language of the text. Recognized for its straightforwardness and rapid processing capabilities, VADER is a widely-known tool. VADER is particularly useful for social media and short text analysis but can also be applied to longer texts, such as news headlines.

IV.RESULT ANALYSIS

We used a labeled dataset of newspaper articles, consisting of a diverse range of news topics, to train and evaluate the sentiment analysis models. The dataset was preprocessed to remove noise and irrelevant information, and then divided into training and testing sets.

Model Performance:

Table 1 presents the F1 scores and accuracy percentages obtained by each model.

Table 1: Model Performance for Sentiment Analysis

Model	F1 Score	Accuracy
RoBERTa	80.92%	87.85%
BERT	75.86%	83.00%
VADER	54.00%	54.00%
TextBlob	58.00%	60.00%

V. CONCLUSION

In conclusion, the experimental results suggest that transformer-based models, particularly RoBERTa, show promise for sentiment analysis in the context of newspaper articles. Further research and fine-tuning of these models could potentially enhance their accuracy and broaden their applicability in real-world sentiment analysis tasks.

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