An Advanced BERT_LayerSum Model for Sentiment Classification of COVID-19 Tweets

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Abstract: The new coronavirus that triggered the global pandemic COVID-19 has had a profound effect on attitudes among people all around the world. People and communities have experienced a wide range of feelings and attitudes as a result of the pandemic. There was a great deal of apprehension following the original COVID-19 epidemic. People were worried about getting the infection or spreading it to their loved ones. These worries were heightened by the disease's unknown nature and quick dissemination. This paper proposes a novel model for sentiment analysis of tweets related to the COVID-19 pandemic. The proposed model leverages BERT as a base model and improves the last four layers of BERT for the sentiment analysis task. The embeddings of the last four layers of BERT are stacked and then summed, and the obtained embeddings are concatenated with the classification token [CLS]. The goal of the study is twofold: we categorize tweets into positive, negative, and neutral sentiments and we classify the user sentiment. The paper highlights the importance of sentiment analysis in tracking public opinion and sentiment towards the COVID-19 pandemic and demonstrates the effectiveness of the proposed model in accurately classifying the sentiment of tweets related to COVID-19. The proposed model is evaluated and compared with four widely used models: KNN, SVM, Naïve Bayes, and BERT, on a dataset of tweets labeled as positive, negative, or neutral. The results show that our proposed model achieved the highest accuracy, precision, and recall for negative sentiment classification compared to other models, indicating its effectiveness in sentiment analysis. The proposed model can be used for analyzing sentiment in order to provide valuable insights for decision-making processes.

1 INTRODUCTION

COVID-19, declared as pandemic by WHO (world health organization), is one of the most severe pandemic, we faced. It has not only caused health issues all over the globe but it created feelings of fear, anxiety among people. Many strategies such as social distancing, face mask, usage of sanitizers, COVID-19 infection testing kits, bans on gathering, travel restrictions, closures of schools, workplaces, distant learning etc. were adopted by many states and resulted in a positive outcome for the control of COVID-19 (Güner et al., 2020). Because of these constraints, world is facing a serious shutdown and now it demands a speedy recovery from all the negative impact caused by COVID-19. With the rapid spread of the virus and the resulting changes to our daily lives, there has been a significant shift in people's emotions and attitudes towards various aspects of life (Umair and Masciari, 2023).

The COVID-19 pandemic has had a profound effect on many facets of society and the global community. The following are some of the main COVID-19 effects:

- Health Impact: COVID-19 has been blamed for millions of fatalities, leading to a considerable loss of life worldwide. For some people who have recovered from the acute sickness, it has also led to long-term health issues.
- Economic Impact: As a result of the pandemic's impact on the world economy, numerous firms have been forced to shut down or reduce their operations. People and families all throughout the world have been impacted by job losses, declining earnings, and financial uncertainty. Although governments and central banks have taken a number of steps to lessen the impact on the economy, it will likely take some time for things to get back to normal.

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- Millions of students' educations have been disrupted by the pandemic's widespread school and university closures. Although there are now alternatives for remote learning, many students still face difficulties due to unequal access to resources and technology.
- Tourism and Travel Bans: To stop the virus from spreading, numerous nations imposed travel bans, closed their borders, and instituted quarantine procedures. Travel both domestically and internationally has significantly decreased, having a negative influence on the tourism business. Significant losses have been experienced by airlines, hotels, and businesses that depend on tourism.
- Effects on Mental Health: The epidemic has been hard on people's mental health because of things like loneliness, fear, anxiety, grief, and uncertainty. There has been a major negative influence on mental health, which has increased instances of depression, anxiety disorders, and other mental health diseases.
- Workplace Culture Shifts: The epidemic has accelerated tendencies in digital transformation and remote work. Due to the widespread adoption of remote work options, workplace culture and procedures have changed. This change has both positive and bad effects, including more flexibility but also difficulties juggling job and family obligations and social isolation.
- Healthcare Systems: With hospitals being overrun by COVID-19 patients, the impact on healthcare systems has been tremendous. The pandemic has exposed vulnerabilities and underlined the need for preparedness and investment in healthcare systems. Resources, manpower, and infrastructure have all been stretched.

As a matter of fact social media platforms have been increasingly used by population, thus creating user generated data on daily basis. Indeed, people share their thoughts, ideas or express their feelings about any item or service on internet in the form of social media posts or tweets (Yue et al., 2019). Users express their positive or negative sentiments about any particular item or product or service. Sentiment analysis can be used to identify these sentiments and categorize them to obtain the user's attitude and opinion (Manguri et al., 2020). Sentiment analysis involves the use of natural language processing and machine learning techniques to analyze and classify the emotions and opinions expressed in text data, such as social media posts, news articles, and customer reviews.

During COVID-19, sentiment analysis has been used to track public opinion and sentiment on the virus, government policies, healthcare systems (Ullah et al., 2023), and various other related topics (Nemes and Kiss, 2021), (Masciari, 2007). Some common themes that have emerged from sentiment analysis during COVID-19 include fear and anxiety, frustration with lockdown measures and restrictions, empathy for healthcare workers, and gratitude for essential workers (Umair et al., 2021). Additionally, sentiment analysis has been used to monitor the effectiveness of communication strategies, such as public health messaging, and to identify misinformation and conspiracy theories (Alamoodi et al., 2021), (Fazzinga et al., 2013).

In this paper, we propose a novel model for sentiment analysis. Our proposed model uses BERT as a base model. We exploited the last four layers of BERT for performing the sentiment analysis task. The embeddings of last four layers of BERT are stacked and then their sum is computed. Then, the resultant embeddings are concatenated with the classification token (CLS in what follows) in order to perform sentiment classification.

The rest of the paper is structured as follows: section 2 explains the related work in the domain of sentiment analysis during COVID-19. Section 3 describes the overall methodology used in analysing the sentiments of people during COVID-19 as well as the proposed algorithm. Section 4 provides explanation on experiments and describes the results of the experiments. Moreover, section 5 concludes the study.

2 RELATED WORK

COVID-19 has caused many adverse effects on the people's living and many researchers analysed the people's feeling about COVID-19 from different view points (Singh et al., 2021). Many people became frustrated with the disturbance the pandemic produced in their daily lives as it lingered. In certain circumstances, restrictions on travel, social events, and companies caused resentment and rage. There exists different tools, methods and techniques for performing the sentiment analysis. Researchers used different machine learning methods for extracting the sentiments of people about palliatives, which were distributed in COVID-19 days using tweets (Adamu et al., 2021). The mental of people specially students was very disturbed after COVID's destruction and the analysis of student's Mental condition by using different method of NLP and Twitter data (Agarwal et al., 2021) has been widely investigated. Similarly, in (Das and Dutta, 2020) the authors worked on sentiment analysis of people during lockdown using different techniques of plotting. Some the researchers also conducted surveys for gathering the data and tried to understand the peoples' thoughts and behaviours (Flint et al., 2021). In (Jelodar et al., 2020), the authors used Latent Dirichlet Allocation (LDA) to identify the dominant topics or issues faced by people during COVID. The restrictions imposed by governments or stats on restaurants motivated the authors to perform research on online restaurants reviews using different techniques of sentiments analysis in (Luo et al., 2020). Moreover, in (Lwin et al., 2020) the analysis of different condition of restlessness in society (Lwin et al., 2020) using Twitter data is presented, while in (Praveen et al., 2021) the authors discuss the attitude of Indian citizens. In (H. Manguri et al., 2020; Raheja and Asthana, 2021), authors used TextBlob to estimate polarity during COVID using Twitter data. As a matter of fact, after COVID-19 vaccine release, hesitancy to get vaccinated was a great obstacle in controlling COVID-19 spread as many people are not willing to get themselves vaccinated. Many work addressed this issue in order to understand what people think about vaccines by using Facebook and Twitter data to extract people's feeling about vaccines using several artificial intelligence methods(Hussain et al., 2021). In (Bao et al., 2022), the authors suggested creating opinion trees for aspect-based sentiment analysis. The goal of the Opinion Tree Generation is to locate every sentimental component in a review sentence and portray it as a semantic tree. A complete representation of the sentence structure, including aspect terms, opinion words, and semantic links, is given by the opinion tree. This method may show a more thorough aspect-level semantic structure, leading to more accurate sentiment element extraction. Modified BERT for target-oriented multimodal sentiment categorization has been suggested in (Yu and Jiang, 2019). The BERT architecture, on which the proposed model, TomBERT, is based, is frequently used to acquire contextualized word representations using its pre-trained model parameters from a huge corpus. They created a target attention mechanism, inspired by the self-attention mechanism, to further enhance their model. This mechanism automatically recognizes when opinion targets and visuals are aligned. In (Kwan and Lim, 2021), a system for examining opinions and conversations regarding COVID-19 among the general public using Twitter activity is suggested. The objective is to demonstrate TweetCOVID's capabilities, a system that uses tweets that are available to the public to study COVID-19's effects on the population. A wide range of features are available through the system, including data gathering and processing, sentiment and emotion analysis, subject modeling, controversy tracking, and visualization.

3 METHODOLOGY

We propose a novel sentiment analysis model for COVID-19 by leveraging BERT model. For this purpose we used publicly available Twitter data. Our framework for sentiment analysis on COVID-19 tweets is reported in Figure 1 and is composed of three stages.

- Stage One: We perform dataset collection and pre-processing.
- Stage Two: We extract sentiment labels for each tweet.
- Stage Three: We classify the tweets into positive, negative and neutral tweets.

3.1 Data Collection and Pre-Processing

Data collection involves identifying the relevant data sources, extracting data from them, and storing it in a format suitable for further steps, while data preprocessing involves cleaning and transforming the data to ensure that they accurate, complete, and in a suitable format for analysis. This may involve removing duplicates, filling in eventual missing values, transforming variables, and standardizing the data (Fan et al., 2021). Proper data collection and preprocessing are critical for ensuring the accuracy and reliability of the analysis.

3.2 Finding Polarity Using TextBlob()

TextBlob() is a Python library used for processing textual data. It has a built-in sentiment analysis tool that can be used to find the polarity of a given text. The polarity score ranges from -1 (most negative) to 1 (most positive) (Hiremath and Patil, 2022). In order to use TextBlob() for finding the polarity of a text, the following steps have been performed: 1) Install TextBlob using pip install textblob; 2) Import TextBlob from textblob module; 3) Create a TextBlob object by passing the text as an argument; 4) Use the sentiment property of the TextBlob object to get the polarity score.

3.3 BERT_LayerSum Model

Our proposed sentiment analysis model is shown in Figure 2. The BERT model is used as a base model

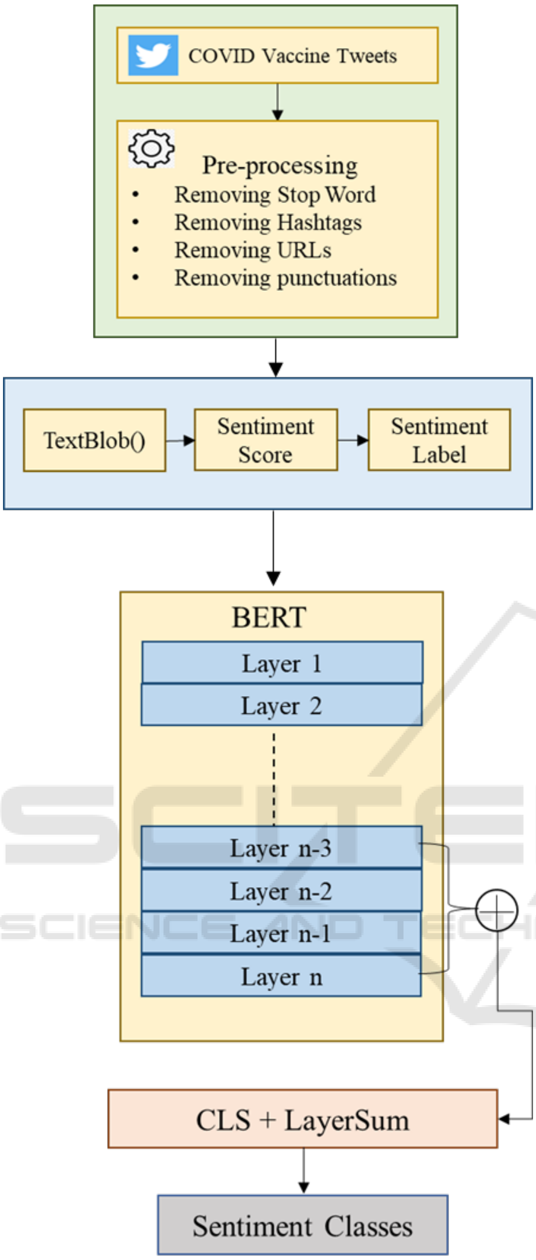

Figure 1: Proposed Framework of Sentiment Analysis Model.

and then its last four layers are stacked and summed using the Python functions. After this pre-processing step the resulting CLS is concatenated with the obtained embeddings and the classification is performed by assigning words to positive, negative and neutral classes.

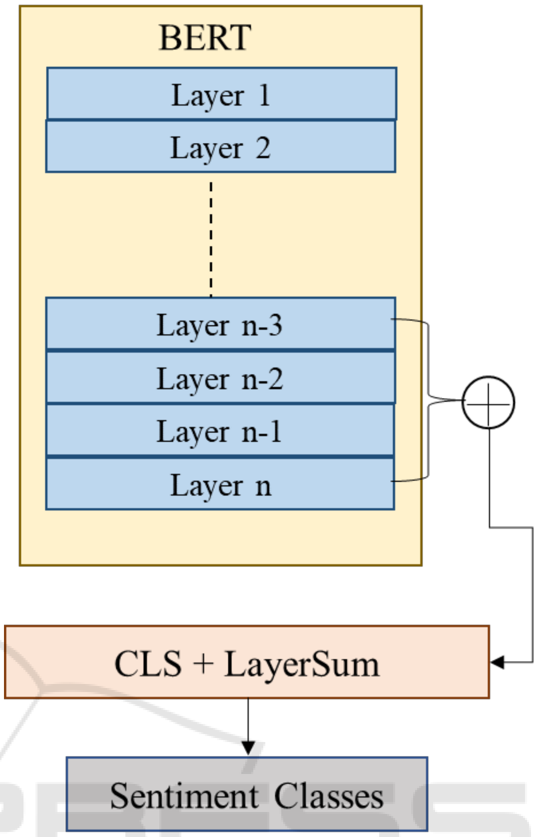

Figure 2: Proposed Sentiment Analysis Model.

3.3.1 BERT Model

BERT (Bidirectional Encoder Representations from Transformers) is a powerful pre-trained language model that has been shown to be highly effective in a variety of natural language processing (NLP) tasks, including sentiment analysis. In sentiment analysis, BERT can be fine-tuned on a labeled dataset of text and sentiment labels to learn to predict the sentiment of new, unseen text.

To use BERT for sentiment classification, the model is first fine-tuned on a labeled dataset of text and sentiment labels. During fine-tuning, BERT learns to identify the patterns and features in the text that are most predictive of the sentiment labels. Once the model has been fine-tuned, it can be used to predict the sentiment of new, unseen text by encoding the text using BERT's pre-trained language model, and passing the encoded representation through a classification layer that maps the encoded representation to a sentiment label.

One of the advantages of BERT is its ability to capture the contextual meaning of words and phrases in a sentence, as it uses a bidirectional transformer-based architecture that reads and processes the entire sentence at once. This allow us to better understand the sentiment of a sentence by taking into account the relationships between the words and the context in which they are used.

3.3.2 LayerSum Model

The hidden layers of BERT model can be exploited to extract the sentiment from the text. The research emphasizes the possibilities of using the BERT model's hidden layers for sentiment analysis. Being a potent pre-trained language model, BERT has powerful hidden layers that store rich contextual data that may be used to extract sentiment from textual input.

Researchers can learn more about the sentiment conveyed in the text by examining the BERT's hidden layers. These concealed layers hold abstractions of the input text at several levels, capturing both regional and global contextual data. According to the article, it is possible to find patterns and features related to sentiment by looking at the BERT's hidden layers. These patterns can be used to forecast a text's mood, such as whether it will be positive, negative, or neutral.

The proposed Algorithm 1 is shown in the following.

Algorithm 1: BERT-LayerSum.

```
1: Negative Tweets
2: Positive Tweets
3: Neutral Tweets
BERT_LayerSum(): Sum of Last Four Layers
D: Dataset
Input D
Steps:
n= BERT_Layers
for i=n-3 to n do
    Sum()
end for
for i = 1 to size of (D) do
    Final_Embeddings ← Concatenation(CLS(D_k), BERT_LayerSum(D_k)
    Tweet_Classification ← Classifier(Final_Embeddings)
end for
Output: Tweet_Classification (Class wise probabilities)
```

We have described an approach that stacks the embeddings of the last four BERT model layers. Bidirectional Encoder Representations from Transformers, also known as BERT, is a well-known pre-trained language model that has produced cutting-edge outcomes on a number of natural language processing tasks.

An enhanced representation of the input text is produced by stacking the embeddings from the last four layers. This may help the model better grasp the content and capture more contextual information.

We used the sum function on the stacked embeddings after acquiring them. By adding the embeddings' values, one may be able to highlight significant elements or patterns in the text.

We then combined the generated embeddings with the BERT model's CLS (classification) token. When utilizing BERT, a special token called the CLS token is appended at the start of the input sequence. It contains data related to the overall classification or prediction task.

The classifier then used the concatenated embeddings to estimate class-wise probabilities by using this representation. The concatenated embeddings are sent into the classifier, which then generates probabilities for each class, indicating how likely it is that the input belongs to that class.

By using this method, we can apply the pre-trained representations of BERT to a classification job and potentially enhance the model's performance.

4 EXPERIMENTS AND RESULTS

In order to evaluate our proposed model, we performed experiments with the state-of-the-art (SOTA). The SOTA models used for experiments are:

- BERT model: A cutting-edge pre-trained language model, the BERT (Bidirectional Encoder Representations from Transformers) model was released by Google AI in 2018. It has made major contributions to the field of natural language processing (NLP) and excelled in a number of NLP tasks. The Transformer architecture, a sort of neural network that makes use of self-attentional mechanisms to identify dependencies between various words in a sequence, serves as the foundation for BERT. BERT introduces the idea of bidirectionality by taking into account context from both the left and the right sides of a word, in contrast to typical models that process text in a left-to-right or right-to-left fashion.
- K Nearest Neighbour: K-nearest neighbors (KNN) is a straightforward but efficient technique used in machine learning for both classification and regression tasks. It is a non-parametric, instance-based learning technique that is predicated on the notion of data point similarity.
- Support Vector Machine: A supervised machine learning approach called a Support Vector Machine (SVM) is utilized for both classification and regression tasks. Although it may be expanded to handle multi-class classification problems as well, it is particularly good at handling binary classifi-

cation difficulties. The fundamental goal of SVM is to identify a hyperplane in a high-dimensional feature space that has the maximum separation between data points from different classes. Given that they are the crucial data points that establish the decision boundary, these hyperplanes are referred to as "support vectors."

- Naive Bayes: Naive Bayes is a simple but efficient classification algorithm built on the Bayes theorem and the assumption of feature independence. It is frequently employed in applications involving category or discrete features, such as text classification.

To compare the performance of our proposed model with the state-of-the-art, we used standard evaluation matrices. The evaluation matrices reports: a) Accuracy: the percentage of correctly classified instances out of the total number of instances; b) Precision: the percentage of correctly classified positive instances out of the total number of instances classified as positive; c) Recall: the percentage of correctly classified positive instances out of the total number of positive instances in the dataset.

4.1 Discussion on Results

The results of positive sentiment classification are reported in Figure 3. It can be seen from the plot that our model outperforms all state-of-the-art models by achieving maximum accuracy, maximum precision, and maximum recall. The proposed model achieved the highest accuracy of 0.82, which means that it was able to correctly classify 82% of the tweets. The precision and recall values for the proposed model are also high at 0.88 and 0.89, respectively. This indicates that the model not only classified the tweets correctly but also avoided mis-classifying tweets as positive or negative.

Comparing our model to other models, SVM achieved the second highest accuracy, but the precision and recall values were relatively lower compared to the proposed model. Classical BERT also exhibits a relatively high accuracy while KNN and Naïve Bayes show lower accuracy and precision values compared to the other models.

Figure 4 shows the comparison of our model with the state-of-the-art using accuracy, precision and recall for negative sentiment classification. The results shows that for the negative sentiment classification, our model still outperforms all other models by achieving highest accuracy, precision and recall.

Based on the information provided in Figure 5, it is easy to see that our model outperforms the state-of-the-art models in terms of accuracy, precision, and recall for neutral sentiment classification. The rationale for achieving better performance with our model can be understood by considering that we leverage BERT as a base model and the exploitation of the last four layers of BERT for performing the sentiment analysis task guarantee a fine-tuning that is not performed by competing approaches.

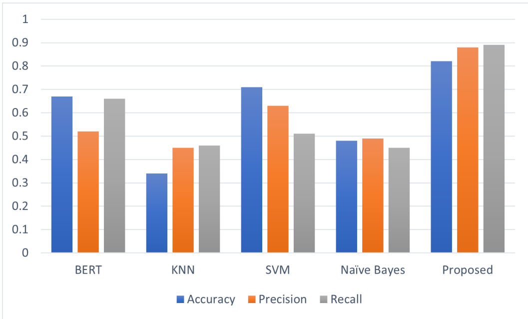

Figure 3: Results of Positive sentiment classification.

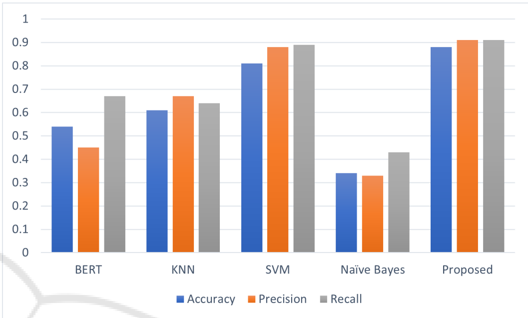

Figure 4: Results of Negative sentiment classification.

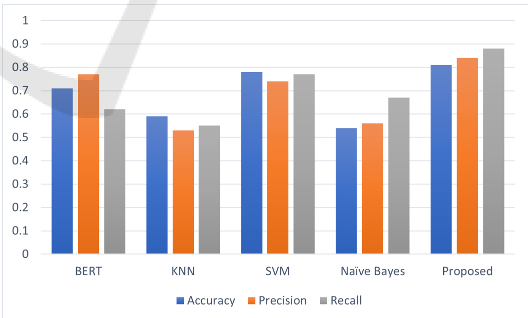

Figure 5: Results of Neutral sentiment classification.

More in details, KNN, Naive Bayes, and SVM, show lower performance compared to the proposed model (BERT-based) both in terms of accuracy, precision, and recall. Main motivations for these results are:

1. Limited feature representation: These models might not be able to capture the complex relationships and patterns in the data as effectively as

BERT, which is a pre-trained language model and can handle large amounts of data and complex relationships between words.

2. Model complexity: KNN, Naive Bayes, and SVM are relatively simpler models compared to BERT, and they might not be able to handle the complexity of the sentiment analysis task. In contrast, BERT has a deeper and more complex architecture, allowing it to capture more nuances in the data.
3. Hyper-parameter tuning: The performance of these models might improve with better hyper-parameter tuning, such as selecting optimal values for k in KNN, or choosing an appropriate kernel function in SVM. However, this can be a time-consuming and computationally expensive process.
4. Sensitivity to feature scaling: KNN relies on distance-based similarity measures, which can be affected by the scale of features. If the features used in the sentiment analysis task are not properly scaled or normalized, it can lead to suboptimal performance of the KNN algorithm.
5. Curse of dimensionality: KNN performance can degrade when dealing with high-dimensional data. As the number of dimensions (features) increases, the available data becomes sparse in the high-dimensional space, and the nearest neighbors may not accurately represent the underlying patterns.
6. Independence assumption in Naïve Bayes: Naïve Bayes assumes independence between features, meaning that the presence or absence of one feature is independent of the presence or absence of other features. This assumption might not hold true for sentiment analysis, as the sentiment expressed in a text often depends on the combination and context of multiple words and phrases. Violations of this independence assumption can lead to lower accuracy.
7. Lack of complex pattern capture: KNN and Naïve Bayes are relatively simple models compared to more advanced deep learning models like BERT or SVM. They may struggle to capture complex patterns and dependencies present in natural language data, which can result in lower accuracy in sentiment analysis tasks.

5 CONCLUSIONS AND FUTURE WORK

COVID-19 pandemic has significantly impacted people's emotions and attitudes towards various aspects of life. With the growing popularity of social media, sentiment analysis has become an essential tool for tracking public opinion and sentiment towards the virus, government policies, healthcare systems, and related topics. In this study, we proposed BERT_LayerSum, a novel model, for sentiment analysis using BERT as a base model. Our model aims to categorize tweets into positive, negative, and neutral sentiments and classify them using our proposed architecture. This paper provides insights into people's attitudes towards the COVID-19 pandemic, which can help policymakers in making informed decisions. Overall, BERT_LayerSum has been shown to be a highly effective approach for sentiment classification, achieving state-of-the-art results on Twitter dataset related to COVID-19. The paper's findings underline the importance of using the BERT model's hidden layers to extract sentiment from text. This strategy can improve sentiment analysis skills and support a number of applications, including opinion mining, social media monitoring, and customer feedback analysis.

Future sentiment analysis research employing BERT and its hidden layers may take the following directions: **Model Interpretability:** Investigating techniques for understanding the BERT's underlying layers and comprehending the particular characteristics or language signals that support sentiment analysis. This can involve employing strategies like saliency mapping, attention visualization, or probing methods to learn more about the inner workings of the model. **Examining methods** to fine-tune BERT for sentiment analysis tasks in particular domains or target languages. Transfer Learning and Domain Adaptation. The performance of BERT might be enhanced, and issues with domain-specific sentiment analysis could be resolved, by adapting it to various domains or languages. **Contextual Characteristics:** Sentiment analysis that takes into account the temporal and contextual characteristics of a situation by incorporating knowledge of the conversation, document structure, or sentiment evolution through time. **Bias and Fairness in Sentiment Analysis**: By locating and minimizing biases in the training data or the model itself, biases in sentiment analysis models can be addressed. Investigating debiasing techniques or creating fair sentiment analysis models that treat various groups fairly and prevent the perpetuation of biased trends are examples of this.

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