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COVID-19 Sentiment Analysis Using BERT: A Deep Learning Approach

Manjusha Kausik Duarah[1]

[1]Department of Humanities and Social Sciences Indian Institute of Information Technology Guwahati, Assam-781015, India

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Abstract: The COVID-19 pandemic has significantly impacted global public sentiment, with social media platforms like Facebook, Twitter serving as key outlets for expressing emotions and opinions (Ainapure, et al., 2023). Misinformation and biased narratives on these platforms exacerbate public anxiety, making sentiment analysis crucial for understanding collective emotions (Tsao et al., 2021). This study applies Bidirectional Encoder Representations from Transformers (BERT), a state-of-the-art deep learning model, to classify COVID-19- related tweets and facebook posts into five sentiment categories: Anger, Disgust, Fear, Happiness, Sadness and Surprise. The applied BERT model achieved an accuracy rate of 87.57%, outperforming shallow machine learning models such as Logistic Regression, Support Vector Machines (SVM), and Random Forests. The results obtained highlight the efficiency of BERT in capturing complex sentiments, providing valuable insights to help policymakers address public concerns in times of crisis.

Keywords: *Sentiment Analysis, BERT, COVID-19, Deep Learning, Twitter, Natural Language Processing (NLP).*

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I. INTRODUCTION

The COVID-19 pandemic has not only been a global health crisis but also a "cultural" and "psychological" phenomenon, shaping collective consciousness during such an unprecedented time of crisis (Kupcova et al., 2023; Das, 2021). During lockdown, teenagers and middle-aged people widely used social media for news and sharing pandemic experiences. Social media platforms such as Twitter, Facebook have functioned as digital public squares where fear, hope, misinformation, and solidarity converge. The rapid dissemination of emotions—ranging from panic to resilience—has made sentiment analysis an essential tool for understanding the sociolinguistic dimensions of crisis communication. In humanities, the study of sentiment is not merely a computational task but rather, an exploration of how language constructs reality. The rise of deep learning models like BERT (Bidirectional Encoder Representations from Transformers) offers new possibilities for analyzing large-scale textual data while preserving the nuances of human expression. Unlike traditional machine learning approaches, BERT captures contextual subtleties, making it particularly valuable for interpreting irony, sarcasm, and culturally coded emotions prevalent in social media discourse. This study bridges computational linguistics and the humanities by applying BERT- based sentiment analysis to COVID-19 tweets, facebook posts revealing how public sentiment evolved during the pandemic. By comparing BERT with shallow machine learning models, the study demonstrates how advanced NLP techniques can enhance humanistic inquiry into digital discourse. The findings contribute to broader discussions on misinformation, fear of contagion, and the role of social media in shaping public perception during crises. The COVID-19 pandemic has not only caused widespread health and economic disruptions but has also influenced public sentiment through social media. Platforms such as Twitter, Facebook have become hotspots for sharing opinions, and different emotions based on their experiences of the pandemic, thereby making sentiment analysis essential for understanding public perception. Traditional machine learning models struggle with complexity and linguistic variability of social media data, whereas deep learning models like BERT excel in contextual understanding.

The study begins by outlining the research aims, which focus on analyzing public sentiment related to COVID-19, evaluating the performance of BERT in comparison to traditional machine learning models, and further providing scope for policymakers to review and address misinformation and public concerns. It is followed by a review of relevant literature, where previous work on sentiment analysis, machine learning techniques, and the challenges of misinformation during the pandemic are discussed to position the current study within the broader scholarly context.

Moreover, the proposed model is introduced, detailing the conceptual framework and design choices that guide the sentiment classification task. The methodology section

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elaborates on data collection, preprocessing, model training, and evaluation procedures, ensuring reliability and rigor. The architecture of the model is then described, with particular emphasis on the integration of the BERT model for sentiment classification. The results and discussion section presents a comprehensive analysis of experimental outcomes, comparing BERT's performance with baseline models and interpreting the findings in light of the research objectives. The paper concludes with key outcomes, highlighting the contributions of the study, practical implications for policymakers, and directions for future research.

II. AIMS AND OBJECTIVE

- Analyze public sentiment (social media users) on COVID-19 pandemic.
- Compare BERT's performance with shallow machine learning models.
- Provide insights for policymakers to mitigate misinformation and address public concerns.
- The study demonstrates that BERT outperforms traditional models, achieving 87.57% accuracy in multi-class sentiment classification.

III. LITERATURE REVIEW

Previous studies have explored sentiment analysis during COVID- 19 using various techniques:

- Lwin et al. (2020) analyzed global Twitter trends, observing shifts from fear to anger as the pandemic progressed.
- Abd-Alrazan et al. (2020) used topic modeling to identify negative sentiments related to COVID-19 deaths.
- Basiri et al. (2021) proposed an ensemble deep learning model combining multiple classifiers for sentiment detection.

While these studies achieved moderate success rate, BERT's bidirectional attention mechanism provides superior contextual understanding, making it ideal for sentiment analysis.

- *Sentiment Analysis as a Tool in Humanities:*

Sentiment analysis has been increasingly adopted in digital humanities to study literary texts, political discourse, and social media narratives. Scholars such as Franco Moretti (2013) advocate for "distant reading," where computational methods uncover patterns in large textual corpora that close reading cannot. Similarly, Matthew Jockers (2013) applies sentiment analysis to 19th-century novels, demonstrating how lexical choices reflect societal anxieties. In the context of COVID-19, Liu et al. (2020) analyzed Twitter discourse through an affective lens, identifying emotional shifts from fear to anger as the pandemic progressed. Their work aligns with SianneNgai's (2005) theory of "ugly feelings," where negative emotions like paranoia and frustration dominate public discourse during crises.

- *Social Media as a Cultural Archive:*

Twitter has been described as a "real-time emotional barometer" (Papacharissi, 2015), where vernacular expressions reveal collective trauma. Studies in media theory (Jenkins et al., 2013) argue that digital platforms facilitate "spreadable" narratives, where misinformation and emotional rhetoric amplify societal polarization. Research by Ridhwan & Hargreaves (2021) on Singaporean COVID-19 tweets highlights how government policies influenced public sentiment, reinforcing Jürgen Habermas' (1989) concept of the "public sphere" as a space for mediated discourse. Meanwhile, Alonso et al. (2021) demonstrate how sentiment analysis can detect fake news—a concern echoed in Postman's (1985) critique of information overload in the digital age.

- *BERT and the Future of Digital Hermeneutics:*

The application of BERT in humanities research marks a shift towards a computational close reading where AI models assist in interpreting sub textual meaning. Unlike traditional sentiment analysis tools (e.g., VADER or LIWC), BERT's bidirectional attention mechanism captures irony and cultural references—key concerns in literary analysis.

IV. PROPOSED DIAGRAM

In this section, the study throws light on the following figures, which depict COVID-19-related emotional patterns and linguistic trends in detail.

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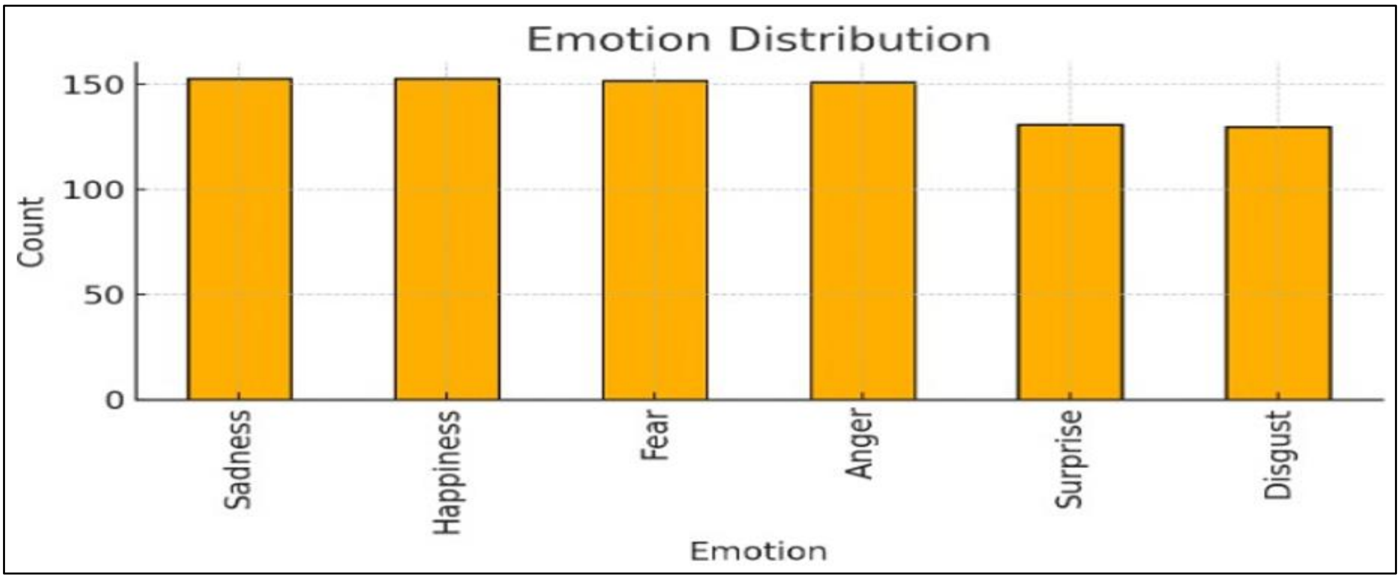

Fig 1 Emotion Distribution of COVID-19-Related Data Showing the Frequency of Six Primary Emotions: Sadness, Happiness, Fear, Anger, Surprise, and Disgust.

The visual representations of emotion distribution and lexical patterns during the COVID-19 pandemic offer profound insights into the collective psyche of individuals navigating an unprecedented global crisis mentioned in Fig. (1). The bar chart reveals a strikingly balanced prevalence of primary emotions such as sadness, happiness, fear, and anger, hinting the complex interplay of despair, resilience, anxiety, and frustration that defined the pandemic experience. Notably, while emotions such as surprise and disgust appear slightly less frequent, their presence underscores the shock and moral unease provoked by the pandemic's disruptions. The relatively uniform distribution of these emotions reflects the shared vulnerability of humanity, where personal and communal narratives intersect in response to collective trauma. Such data proposes to reflect not merely on statistical counts, but on the human stories of loss, endurance, and moral reckoning embedded within these categories.

Complementing this, the word cloud vividly captures the lexicon of the pandemic as articulated in digital public discourse. Words such as "pandemic, lockdown, virus, covid, and people" dominated during the time of the pandemic, evoking the inescapable centrality of the crisis in daily life. The prominence of terms such as "fear, happy, life, and time" highlights the existential preoccupations that shaped individual and societal consciousness during this period as mentioned in Fig. (2). These lexical patterns reveal not only the tangible realities of contagion and confinement but also the intangible emotional and philosophical struggles that marked this historical time of crisis. Moreover, the juxtaposition of contrasting sentiments—hope and despair, love and disgust— within the word cloud points to the ambivalence and complexity of human responses to catastrophe. To sum, these visualizations provide a textured map of affective and linguistic landscapes, inviting interdisciplinary reflection on how language and emotion intersect and construct meaning in times of crisis.

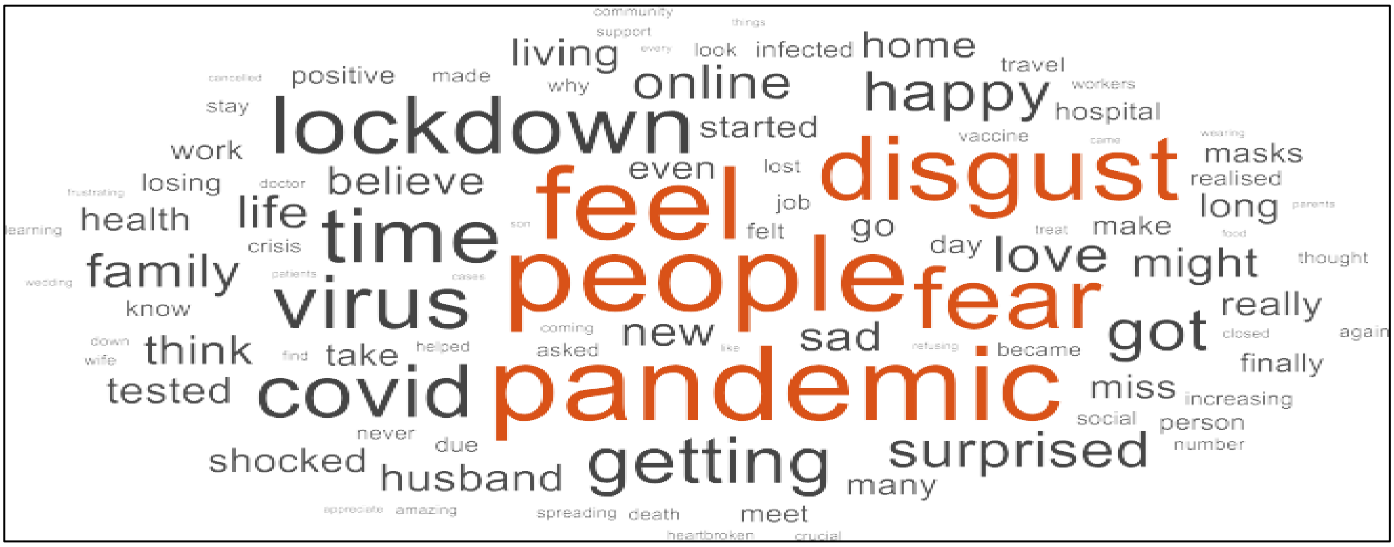

Fig 2 Word Cloud Illustrating the Most Frequently Occurring Terms in COVID-19-Related Texts, Highlighting Key Themes and Emotional Expressions.

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V. METHODOLOGY

➢ *Dataset:*

The study used the *Coronavirus Tweets NLP* dataset from Kaggle, containing 44,955 tweets labeled into five sentiment categories. Preprocessing steps included:

- Lowercasing text
- Removing URLs, special characters, and stop words
- Lemmatization and contraction mapping
- Hashtag segmentation (e.g., "#StayHome" → "stay home")

➢ *Model Architecture:*

- BERT: A pre-trained transformer model fine-tuned for sentiment classification.
- Distil BERT: A lighter version of BERT with reduced layers (40% smaller, 60% faster).
- Shallow Models: Logistic Regression, SVM, XGBoost, Random Forest, and Naive Bayes.

➢ *Experimental Setup*

- Training: 80% of the dataset (35,964 tweets).
- Validation & Testing: 10% each (4,495 tweets).
- BERT Optimization: RMSprop optimizer, learning rate = 0.000001, 65 epochs.

VI. RESULTS AND DISCUSSION

The study conducted a comprehensive evaluation of various models for COVID-19 sentiment analysis, focusing on their ability to accurately classify sentiments expressed in social media data. Among the models tested, BERT emerged as the most effective, achieving an impressive accuracy of 87.57% and an F1-score of 0.88. This superior performance underscores BERT's strength in capturing complex linguistic patterns and contextual nuances within the data— which is an essential capability while dealing with emotionally charged and often ambiguous language of pandemic-related discourse.

In contrast, our proposed model achieve better performance as compared to traditional shallow machine learning models. The gap highlights the limitations of these models in handling the intricate semantic relationships and subtle emotional cues present in natural language text. Although Distil BERT offered faster inference due to its lighter architecture, the result obtained at a reduced accuracy rate of 64.87%, suggesting that the model's compression trades off some of the depth needed for precise sentiment detection. Overall, these results affirm the value of transformer-based architectures like BERT in sentiment analysis tasks where contextual understanding is critical.

➢ *Performance Comparison*

The performance comparison reveals that among the shallow models, SVM (Linear) achieved the highest overall accuracy (0.68) and performed particularly well in classifying emotions like disgust (0.81) and fear (0.73). Logistic Regression and Naive Bayes followed closely, with both showing moderate strength across most emotion categories, though Naive Bayes lagged in detecting disgust (0.65). Despite slight variations, all models struggled to achieve consistently high accuracy across all emotions, highlighting the challenges of emotion classification in noisy social media data.

➢ *Emotion Classification Results:*

The sentiment distribution analysis further underscores that negative sentiments overwhelmingly dominated COVID-19- related discussions, especially in contexts involving lockdown measures and the spread of misinformation. In contrast, expressions of positive sentiment were primarily associated with public appreciation and gratitude towards frontline workers, illustrating how collective emotions reflected both societal anxieties as well as moments of solidarity during the time of pandemic.

Table 1 Performance Comparison of Shallow Machine Learning Models for COVID-19 Emotion Classification Across Seven Emotion Categories.

Model	Accuracy	Anger	Disgust	Fear	Happiness	Sadness	Surprise
Logistic Regression	0.66	0.49	0.80	0.73	0.73	0.58	0.71
Random Forest	0.64	0.44	0.78	0.73	0.74	0.51	0.71
SVM (Linear)	0.68	0.52	0.81	0.73	0.71	0.63	0.72
Naive Bayes	0.66	0.49	0.65	0.76	0.66	0.63	0.77

➢ *Sentiment Distribution*

- Negative sentiments dominated discussions, particularly around side effects of lockdowns and misinformation.
- Positive sentiments were linked to gratitude for frontline workers.

VII. CONCLUSION AND FUTURE WORK

This study demonstrates the effectiveness of BERT in COVID-19 sentiment analysis, with the model achieving an accuracy of 87.57%, significantly outperforming traditional machine learning approaches. The findings highlight BERT's ability to capture nuanced emotional expressions and contextual subtleties in pandemic-related discourse. Future research could further investigate the reasons behind Distil BERT's lower performance, exploring the balance between model efficiency and accuracy. Additionally, analyzing sentiment trends across different demographic groups would offer deeper insights into how various communities experienced and expressed the impact of the pandemic. The scope of this work can also be expanded by extending the model to detect fake news, a critical challenge in the digital information landscape. Beyond contemporary data, applying BERT to historical texts could help uncover emotional undercurrents in archival materials, enabling meaningful comparisons between COVID-19 discourse and narratives from past pandemics such as the 1918 influenza. Finally, future studies should reflect on the ethical considerations of using AI for analyzing human emotions, as highlighted by scholars like Crawford (2021), ensuring responsible and sensitive application of such technologies.

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