Combining BERT and CNN for Sentiment Analysis A Case Study on COVID-19

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***Abstract*—This research focuses on sentiment analysis to understand public opinion on various topics, with an emphasis on COVID-19 discussions on Twitter. By utilizing state-of-the-art Machine Learning (ML) and Natural Language Processing (NLP) techniques, the study analyzes sentiment data to provide valuable insights. The process begins with data preparation, involving text cleaning and length filtering to optimize the dataset for analysis. Two models are employed: a Bidirectional Encoder Representations from Transformers (BERT)-based Deep Learning (DL) model and a Convolutional Neural Network (CNN). The BERT model leverages transfer learning, demonstrating strong performance in sentiment classification, while the CNN model excels at extracting contextual features from the input text. To further enhance accuracy, an ensemble model integrates predictions from both approaches. The study emphasizes the ensemble technique's value for more precise sentiment analysis. Evaluation metrics, including accuracy, classification reports, and confusion matrices, validate the effectiveness of the proposed models and the ensemble approach. This research contributes to the growing field of social media sentiment analysis, particularly during global health crises like COVID-19, and underscores its potential to aid informed decision-making based on public sentiment.**

***Keywords*—Sentiment analysis; COVID-19; BERT; CNN; ensemble model; NLP; transfer learning**

I. Introduction

The global impact of the COVID-19 epidemic has shown a surge in communication and information sharing on social media platforms [1]. Notably, Twitter sentiment has emerged as a vital channel for individuals to express their ideas, concerns, and opinions regarding the pandemic. Understanding the sentiment conveyed in these tweets is crucial, as it provides valuable insights into the public's emotional responses [2, 3], concerns, and expectations related to the ongoing health crisis. This study embarks on a sentiment analysis journey, aiming to decipher the emotion and tone of tweets about COVID-19. Sentiment analysis has become indispensable for grasping how society perceives and responds to emerging events, such as the COVID-19 epidemic [4]. Analyzing tweet sentiments enables the identification of patterns in public opinion, tracking changes in public mood over time, and evaluating public satisfaction with governmental responses. In the era of rapid digital transformation, the global influence of social language cannot be overlooked. Platforms such as social media, Blogs, Online forums, and product review portals have become modern channels for expressing opinions, collectively forming a vast sea of User Generated Content that significantly impacts real-world businesses [5]. Analyzing public sentiment in these social media data entails Opinion Mining, deciphering the emotional intent behind comments or tweets – positive, negative, or neutral. This process, guided by patterns identified through text mining, enables the prediction of subsequent textual threads. Sentiment analysis also plays a crucial role in shaping a brand's presence on social media by providing inferences of an in-depth understanding of the target audience's perspective, Evaluation of competitors' emotional marketing, campaigns, responses, and identification of industry trends for strategic brand positioning and marketing [6].

Numerous studies have explored ML and DL models for sentiment analysis, particularly in the context of COVID-19-related tweets. The research in [7, 8] underscores the necessity and significance of sentiment analysis across various domains. Naïve Bayes classifier achieved an accuracy of 79% on a dataset comprising 11,974 COVID-19 tweets [9]. A comparative analysis of various ML models demonstrated their efficacy in COVID19 Tweets [10]. BERT outperformed traditional models such as Logistic Regression and Support Vector Machines (SVM), attaining an accuracy of 89% in the analysis of Indian tweets; however, the study was limited by its geographic focus and a lack of comprehensive dataset evaluation [11]. Furthermore, BERT exhibited high accuracy on Twitter datasets from Amazon and Hachette, though it did not thoroughly address biases inherent in social media data [12]. An RNN model surpassed SVM in global sentiment analysis, yet failed to consider data transparency and ethical implications [13]. In another study, fuzzy logic combined with deep learning yielded an accuracy of 81%, but lacked generalized recommendations [14]. Additionally, the Extra Trees Classifier demonstrated superior accuracy relative to other ML models [15]. Comparative studies in [16] and [17] emphasized ensemble techniques while acknowledging challenges in generalizing results to non-English datasets of COVID-19 tweets.

The research gap highlights the need for hybrid models that integrate ML and DL approaches, aiming to enhance accuracy and address biases in sentiment analysis across diverse datasets.

This study utilizes advanced ML and NLP techniques for this purpose, and to preprocess the Twitter dataset effectively, by eliminating extraneous data, links, and special characters, excluding tweets with insufficient text content to generate a focused and insightful dataset. Subsequently, we explore two distinct modeling strategies. The first leverages BERT, a DL model recognized for its exceptional ability to capture context and semantics due to pre-training on extensive text data. The second method involves a CNN, a prominent ML model, to extract local text characteristics. These models are analyzed based on accuracy, utilizing various categorization criteria to determine their effectiveness. Additionally, we employ an ensemble strategy that merges predictions from both models to enhance overall accuracy. Ensemble modeling leverages the strengths of each model, which is known to strengthen outcomes while mitigating individual model drawbacks. In the ongoing COVID-19 outbreak, this study aims to illuminate public sentiment on social media. Decision-makers, public health experts, and politicians can utilize these insights to stay informed about evolving public opinions and concerns related to the pandemic. The objectives of this study are, evaluate the effectiveness of BERT and CNN models in classifying COVID-19 Twitter sentiment using accuracy, classification reports, and confusion matrices, and enhance sentiment analysis accuracy through an ensemble technique combining BERT and CNN predictions, providing more reliable results.

The rest of the manuscript is organized. Section II details the ML models used for analysis. Section III describes the proposed work, dataset, and methodology. Section IV presents the results, and Section V concludes with future directions.

II. Sentiment Analysis

This study employs BERT, CNN, and ensemble models to conduct sentiment analysis on COVID-19-related tweets. By leveraging BERT's contextual understanding in combination with the feature extraction strengths of CNN, the ensemble approach enhances both accuracy and robustness. The insights generated aim to deepen understanding of public sentiment during the pandemic, offering valuable information for decision-makers.

A. Bidirectional Encoder Representations from Transformers

Natural language processing has seen a revolutionary development, primarily due to the advancements made possible by deep learning and advanced neural network architectures. Among these developments, the pre-trained transformer-based model BERT has been crucial in changing the field of NLP applications [18]. In contrast to conventional unidirectional models, BERT's bidirectional approach considers both words that come before and after to grasp the context of a sentence. This fundamental change allows BERT to gain a deep comprehension of context, which helps it become skilled at managing linguistic subtleties. With massive corpora of pre-trained text, BERT is proficient in understanding syntactic structures and semantic links, producing rich contextual representations that provide a solid basis for a range of NLP applications. BERT is pre-trained on large text data using two tasks: masked Language Modeling and next-sentence prediction [19]. One noteworthy application of BERT is sentiment analysis, demonstrating its ability to identify the dominant sentiment or mood in each text [20, 21]. Sentiment analysis models with BERT can refine accuracy and granularity by utilizing rich contextual embedding's to decode minor variations in sentiment within the textual content, and architecture for tweets input and output is depicted in Fig. 1.

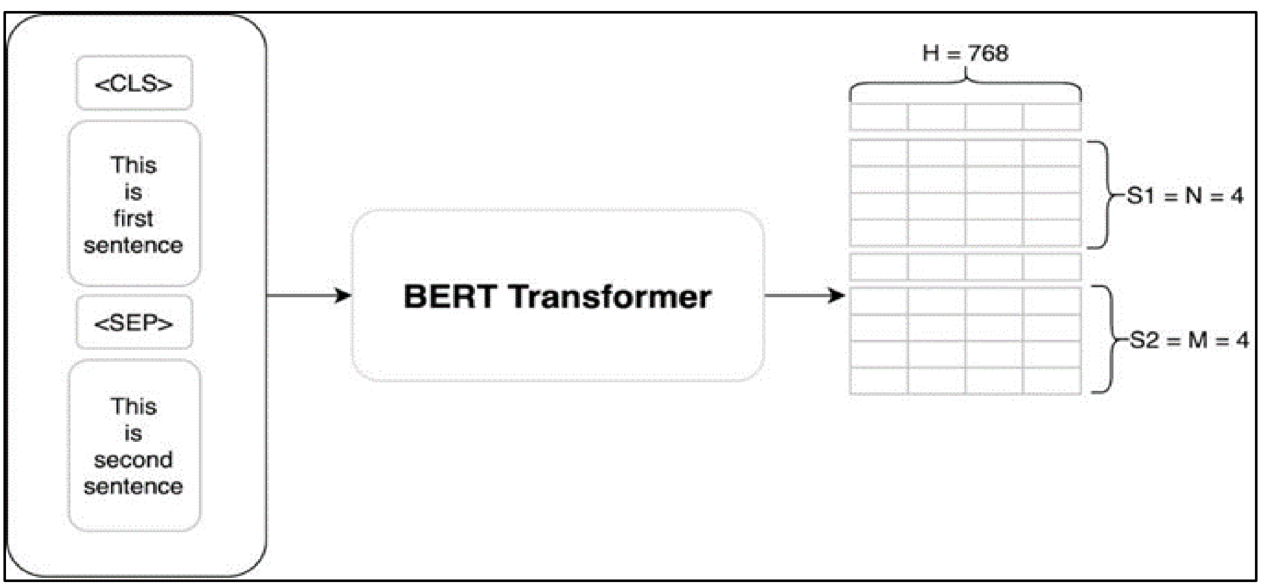

Fig. 1. BERT architecture for tweets input and output.

B. Convolutional Neural Network

The CNN-based COVID-19 sentiment analysis model architecture includes layers for token embedding, convolution, max-pooling, and fully connected neural networks [22]. Convolutional layers extract local text features, and max-pooling determines standout features, enabling CNN to effectively comprehend complex sentiment within tweets. CNNs excel at automatically learning and extracting features from structured data. It consists of four layers: the convolutional layer, pooling layer, fully connected layer, and output layer, as shown in Fig. 2. The convolutional layer includes convolutions where filters are applied to extract useful information and post-convolution, a Rectified Linear Unit (ReLU) function is used to introduce non-linearity. Pooling layers reduce the spatial dimensions while retaining significant information. Next, the information from previous layers is flattened into a one-dimensional vector in fully connected layers. This is further processed in dense layers, which combine the extracted features to make the final predictions. The final layer in CNN is the output layer, which typically uses a softmax function (for classification tasks) or another activation function depending on the needed task.

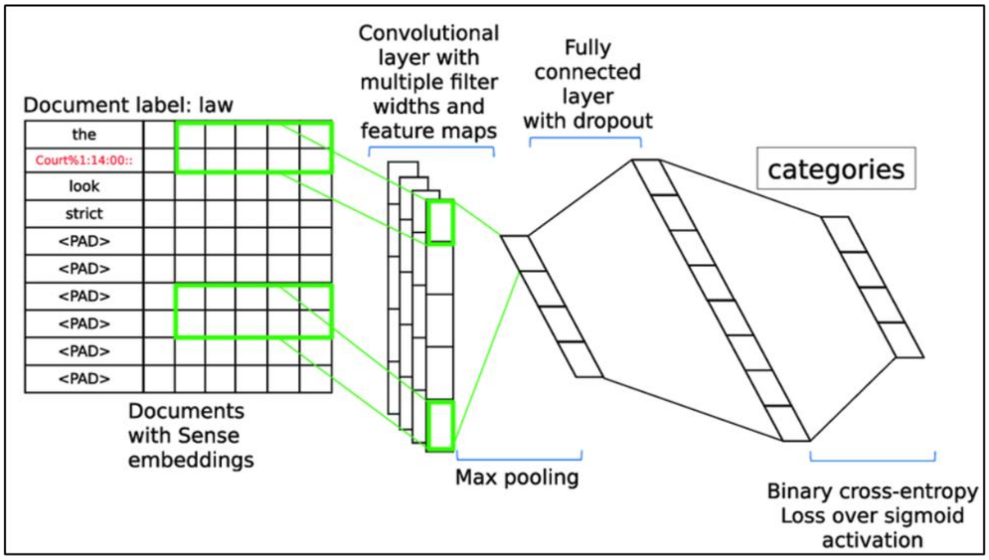

Fig. 2. CNN architecture [23].

C. Ensemble Model

Combining multiple models' advantages, ensemble models considerably improve prediction accuracy, resilience, and generalization. They are essential to many high-achieving machine learning systems, especially in challenging and vital applications. To improve COVID-19 sentiment analysis, the ensemble model shown in Fig. 3 combines predictions from the BERT model with the CNN. Through the process of average outcomes, the ensemble makes the most of the unique qualities of each model, so increasing the overall efficacy and reliability of sentiment classification. By removing individual model limitations, this ensemble technique fully understands public sentiment [24].

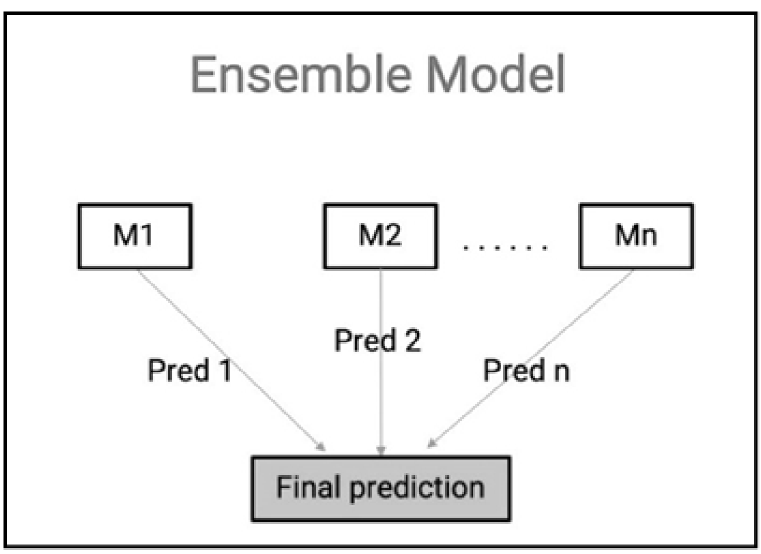

Fig. 3. Ensemble model.

III. Methodology

The suggested methodology outlines the steps involved in applying sentiment analysis to a corpus of tweets about COVID-19 and categorizing them as "Negative," "Neutral," or "Positive." It includes a series of crucial procedures intended to suitably set up, model, and assess the sentiment analysis. The steps include data preprocessing, text vectorization, machine learning, and deep learning model-based prediction. Furthermore, an ensemble model is constructed, which improves sentiment classification accuracy by combining the benefits of two different and efficient methods. The approach offers insights into public opinion on social media regarding the COVID-19 epidemic by showcasing the application of well-liked models and techniques for sentiment analysis on textual data for IMDB review dataset of 25000 samples [25]. This systematic process guarantees a thorough strategy for insightful analysis and outcomes.

A. Library Imports

The code begins by importing the necessary Python libraries for DL like Tensor Flow and Keras, ML libraries like Scikit-learn, and for data manipulation NumPy, and Pandas, for NLP NLTK, and for data visualization Matplotlib and Seaborn have been used. Furthermore, libraries such as Transformers for BERT- based models and Emoji for handling emojis are imported and installed.

B. Data Loading and Exploration

In this study, COVID-19 dataset consists of tweets collected over a 15-day period from March 16 to March 31, 2020. Twitter samples were used to analyze the trend and sentiment of COVID-related topics. Mounting Google Drive to access the dataset is how the code starts. Pandas Data Frames are loaded with two CSV files. df, which contains training data, and df_test, which contains testing data. To perform exploratory data analysis and display tweet counts by date and location, data pretreatment entails deleting duplicates, changing the 'TweetAt' field to date format, and more, as shown in Fig. 4 which shows that the tweet count by Date for half of a specific Month, and number of tweets by people across the Globe are considered for a complete month for a realistic analysis of their sentiments during Pandemic. Fig. 5 shows tweets across the Globe by different citizens; 15 states across the USA and Europe have been considered. Fig. 6 and Fig. 7 show a graphical analysis of COVID-19 tweets based on the length of tweets. Fig. 6 analyses of tweets with less than 10 words for the training dataset, whereas Fig. 7, represents a graphical representation of tweets with a length of less than 10 words with test data.

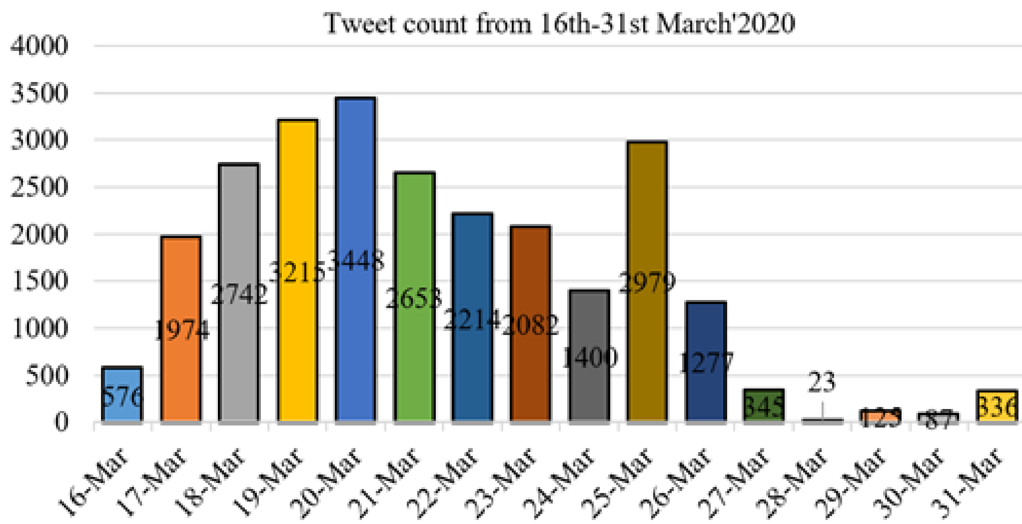

Fig. 4. Tweet count by date.

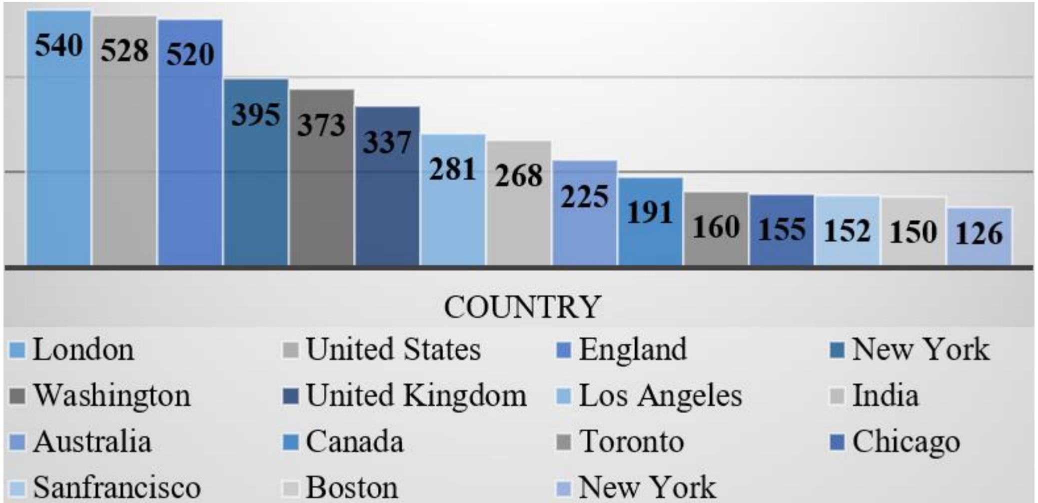

Fig. 5. Tweet count by country.

C. Data Preparation

In this study, Data Preparation is done using four stages: Text Preparation, Text Length analysis, Data balancing, and Text Vectorization. In the initial stage of Text preparation, Custom functions are employed for cleaning and preparing text data. These functions eliminate emojis, punctuation, links, mentions, and special characters, as well as handle hashtags. The pre-processed text is then saved in the Data Frames as new columns. In Text Length analysis the code computes the length in number of words of each pre-processed tweet and visualizes the tweet length distribution. The resulting histograms are illustrated in Fig. 6 and Fig. 7. Neural networks and machine learning rely heavily on data, but the quality of that data determines how well a model performs. Data science and data mining initiatives frequently deal with imbalanced datasets, which are those in which one class called a minority class has a comparatively smaller number of instances than the other classes. In preparing the training dataset, to address the class imbalance in sentiment labels using the RandomOverSampler from the imbalanced-learn library, resulting in a total of 15,148 samples. In the final stage of text preparation, authors vectorize the data using Count Vectorizer and Tfidf Transformer, converting textual information into numerical features suitable for training machine learning models. The Count Vectorizer transforms text data into a count matrix, which is then normalized into a TF or TF-IDF representation. Here, TF refers to term frequency, while TF-IDF combines term frequency with inverse document frequency. This widely used term weighting scheme is effective in information retrieval and document classification. For the proposed approaches, 3,787 data samples were utilized to evaluate model performance. The cleaned text is visualized in Fig. 8.

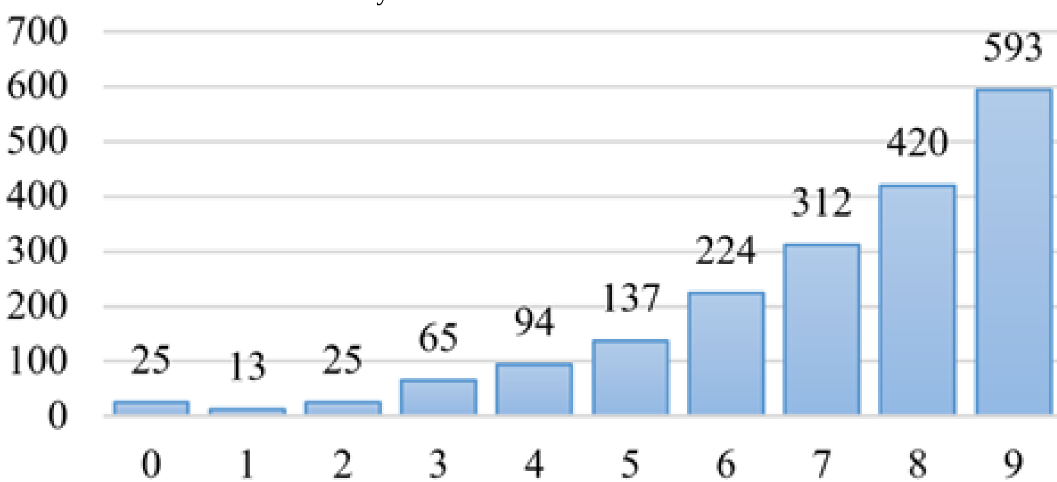

Fig. 6. The training dataset for COVID-19 tweets with a length of less than 10 words.

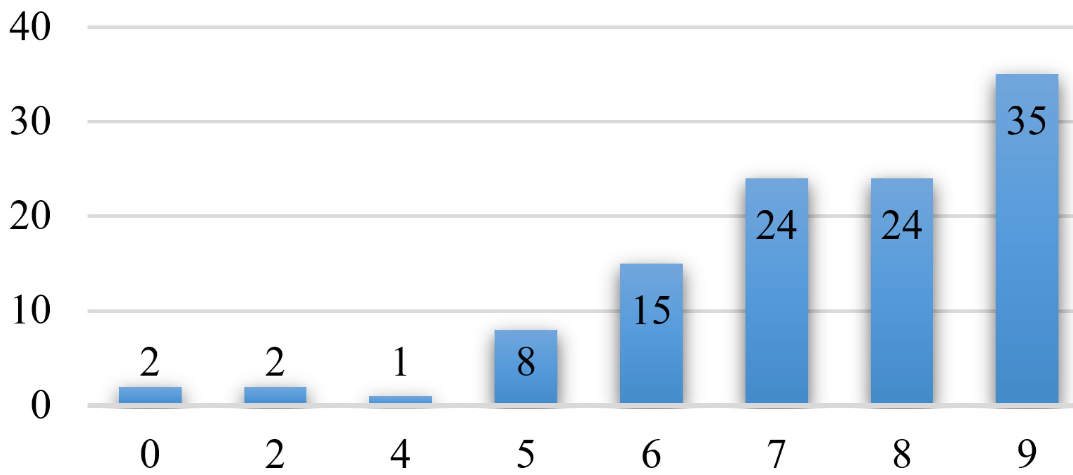

Fig. 7. Testing dataset for COVID-19 Tweets with length less than 10 words.

	OriginalTweet	Sentiment	text_clean	text_len	token_lens
3505	Stop misusing ur privilege amp grow up Some1 c...	Positive	stop misusing ur privilege amp grow up some1 c...	57	73
1789	For those that are cashlong, patient,calm&...	Extremely Positive	for those that are cashlong patientcalmamphave...	44	71
855	Lidl is total chaos, queues as long as the ais...	Extremely Negative	lidl is total chaos queues as long as the aisl...	62	70

Fig. 8. Text vectorization of the tweets.

D. Model Preparation

The algorithm optimizes a sentiment analysis pre-trained BERT model using the Hugging Face Transformers library. Text data is tokenized and transformed into BERT model input features. The model is trained on oversampled data and tested on new data, with a confusion matrix and classification metrics computed. Using a CNN model for sentiment analysis is defined and trained, incorporating an embedding layer, convolutional layers, and fully linked layers. The CNN model is tested based on the test data, and its accuracy is estimated.

Predictions from the BERT and CNN models are averaged to create an ensemble model [25]. The accuracy of the ensemble model, along with a confusion matrix, is computed, and a classification report is generated [26, 27].

IV. Results and Discussion

The results section presents the findings and performance metrics of the sentiment analysis conducted on the COVID-19-related Twitter dataset. This analysis utilized a comprehensive methodology that included data preprocessing, machine learning, deep learning, and an ensemble model to categorize tweets as "Negative," "Neutral," or "Positive" [28, 29]. The assessment metrics provide insight into the effectiveness of each method employed, facilitating a comparative analysis of model performance to determine the most suitable approach for this dataset. The fine-tuned BERT-based model demonstrated significant efficacy, achieving a test accuracy of 0.884. The confusion matrix for the BERT model is illustrated in Fig. 9, while a detailed classification report in Fig. 10 offers a thorough evaluation of its classification capabilities. In contrast, the CNN model designed for sentiment analysis achieved a commendable test accuracy of 0.817. The model's performance is further elucidated through visual representations, including a confusion matrix depicted in Fig. 11 and a detailed classification report in Fig. 12. Notably, the ensemble model, which aggregates predictions from both the CNN and BERT models, attained a test accuracy of 0.90. Fig. 13 showcases the ensemble model's effectiveness in accurately categorizing tweets into their respective sentiment categories, supplemented by a confusion matrix. The classification report for the ensemble model is presented in Fig. 14, providing additional insights into its performance. Overall, these results underscore the effectiveness of the applied methodologies in sentiment classification tasks.

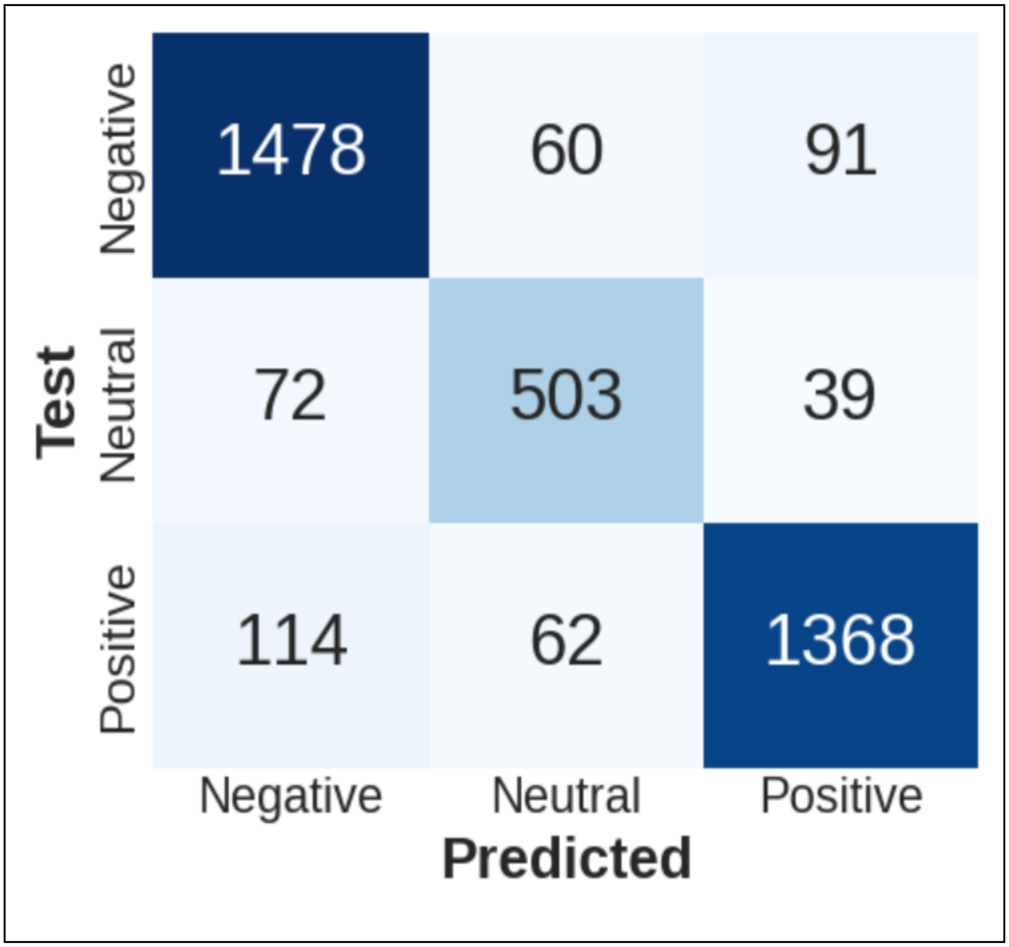

Fig. 9. Confusion matrix of BERT sentiment analysis.

Classification Report for BERT:

	precision	recall	f1-score	support
Negative	0.89	0.91	0.90	1629
Neutral	0.80	0.82	0.81	614
Positive	0.91	0.89	0.90	1544
micro avg	0.88	0.88	0.88	3787
macro avg	0.87	0.87	0.87	3787
weighted avg	0.88	0.88	0.88	3787
samples avg	0.88	0.88	0.88	3787

Fig. 10. Classification report for BERT.

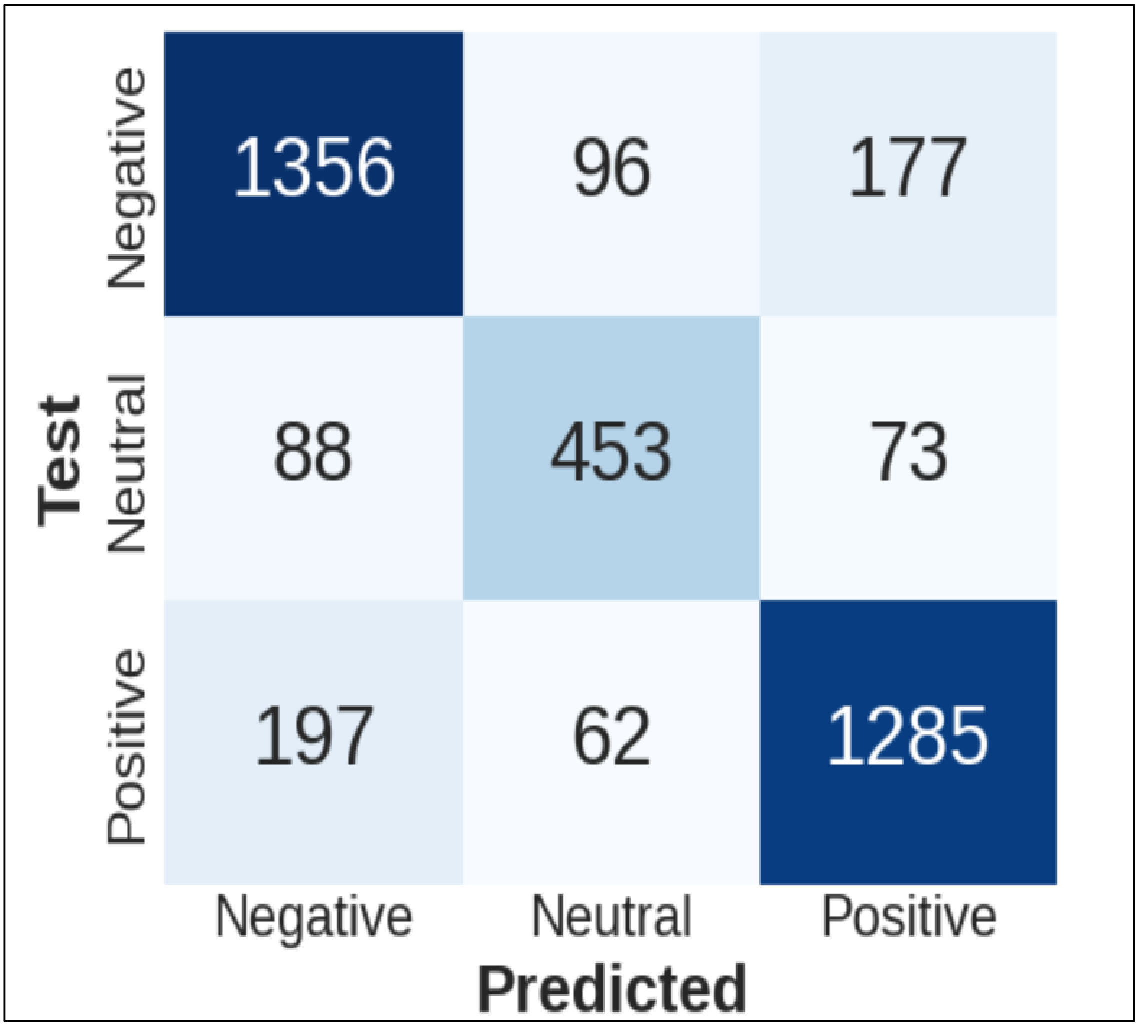

Fig. 11. CNN confusion matrix.

CNN Classification Report:

	precision	recall	f1-score	support
Negative	0.83	0.83	0.83	1629
Neutral	0.74	0.74	0.74	614
Positive	0.84	0.83	0.83	1544
accuracy			0.82	3787
macro avg	0.80	0.80	0.80	3787
weighted avg	0.82	0.82	0.82	3787

Fig. 12. CNN classification report.

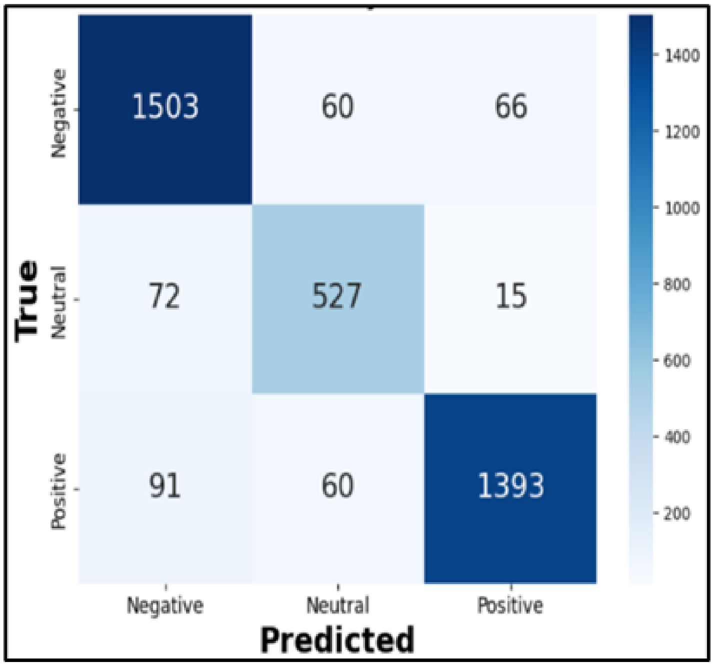

Fig. 13. Confusion matrix of ensemble model.

Classification Report:

	precision	recall	f1-score	support
Negative	0.90	0.92	0.91	1629
Neutral	0.81	0.86	0.84	614
Positive	0.95	0.90	0.92	1544
accuracy			0.90	3787
macro avg	0.89	0.89	0.89	3787
weighted avg	0.91	0.90	0.90	3787

Fig. 14. Ensemble model classification report.

In cases where the BERT model outperforms the ensemble, the results reflect the BERT model's dominant influence within the ensemble framework. This reliance underscores the necessity for a more sophisticated approach to balance the contributions of different models. Simply averaging predicted probabilities may not sufficiently mitigate the impact of one model over another, especially when there are significant imbalances in prediction probabilities. Despite this challenge, the ensemble model remains the preferred choice due to its robustness, stability, and versatility in handling diverse data patterns. This study focused on sentiment analysis of COVID-19-related tweets, providing practical insights for various sectors. Stakeholders in social sciences, digital marketing, public health, and policymaking can leverage these insights to understand public sentiment effectively. Sentiment analysis plays a critical role for public health officials, policymakers, social scientists, marketers, and emergency responders by tracking public opinion during crises. It informs decision-making, enables strategic adjustments, and enhances communication efforts, ensuring that responses align with public sentiment during emergencies. A comparative analysis with existing research, is presented in Table I.

TABLE I. COMPARATIVE STUDY WITH EXISTING LITERATURE

Ref.	Multiple ML models were tested before the final selection	Ensemble model selected	Data Preparation	Data Balancing	Data Vectorization	Results		
						F1 Score	Recall	Precision
[30]	NO	Yes	Yes	NO	Yes	High	High	High
[31]	Yes	NO	Yes	NO	NO	High	High	Satisfactory
[32]	NA	Yes	Yes	NO	Yes	High	High	High
[33]	Yes	No	Yes	No	No	NA	NA	High
Proposed work	Yes	Yes BERT and CNN	Yes 4 stage Data Preparation	Yes, using Random Oversampling	Yes, using the Count Vectorizer and TF-IDF transformer	High	High	High

V. CONCLUSION

In our study, a range of methods, from advanced deep learning techniques to conventional approaches, were discussed and assessed for the construction and assessment of sentiment analysis models. The work illustrated the revolutionary benefits of BERT, a cutting-edge transformer-based sentiment analysis methodology. About the test dataset, the BERT-based model demonstrated an impressive accuracy of 88.4%. The Naive Bayes model which had a respectable accuracy of 70% despite its streamlined architecture was also investigated. A CNN model was also a part of the investigation, and it demonstrated a commendable accuracy of 83%. Finally, an ensemble technique that merged predictions from BERT and CNN showed an accuracy of 89%, highlighting the potential of ensemble approaches to improve overall performance. Overall, the findings substantiate a combination of BERT and ensemble learning for enhancing sentiment analysis research across various domains with reliable and accurate classification. This study scouts the subtleties of the COVID-19 tweet sentiment analysis as well as the usefulness of sentiment analysis in a variety of contexts. Using state-of-the-art NLP and ensemble models of ML, the study offers an asset for anyone aiming to use public sentiment data for informed decision-making and for enhanced communication. For future research, expanding the sample size would enhance the evaluation of model performance. The results can also be utilized for policy-making in certain domains.

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