Robust Hybrid Model for Social Media Sentiment Analysis

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***Abstract*— Social media platforms are home to massive amounts of content created by users, which can offer insightful information on attitudes, beliefs, and feelings. In order to extract valuable information from the abundance of data, sentiment analysis is essential. This work presents a novel hybrid sentiment analysis model using the Bidirectional Encoder Representations from Transformers (BERT) and Robustly Optimized BERT Approach (RoBERTa) models. The strategy tries to improve sentiment classification performance by utilizing the advantages of both models. The complexities of social media text are often difficult for traditional sentiment analysis models, like rule-based systems and machine learning algorithms like logistic regression and support vector machines, to capture because of issues with contextual understanding, linguistic complexity, inherent data variability, and noise. This hybrid sentiment analysis, on the other hand, excels at understanding natural language semantics and gathering contextual information. Labelled data and an innovative training approach are combined to train the model. Reporting accuracy metrics is part of the performance evaluation process when using a test dataset. Additionally, a thorough classification report and confusion matrix are produced. A test dataset performance evaluation yields an accuracy of 82%.**

Keywords—* *Sentiment Analysis, Machine learning, Transformers, BERT, RoBERTa, Hybrid model, Accuracy metrics, Confusion Matrix.

I. INTRODUCTION

Social media is becoming a useful tool for expression and communication in the current digital era. Because of the huge volume of user-generated data, there is a rare opportunity to see how the public feels about a variety of issues. Extraction of insights from social media interactions depends heavily on sentiment analysis, the computer process of determining the emotional tone of text [2]. As a means of exchanging enormous volumes of user-generated material, social media platforms have evolved into essential components of contemporary communication. It is possible to gain a deep understanding of public perception and behaviour by examining the attitudes, views, and emotions contained in this content. In this area, traditional sentiment analysis tools have been widely used, such as rule-based systems and machine learning algorithms. But these techniques frequently struggle to capture the intricacies present in social media text. Traditional models' performance is limited by problems including noise and inherent data variability, linguistic complexity, and difficulties with contextual comprehension. Modern deep learning techniques, like Robustly Optimized BERT Approach (RoBERTa) and Bidirectional Encoder Representations from Transformers (BERT) [4], have been presented to overcome these constraints. The capacity of BERT and RoBERTa to extract contextual information from input text is one of their primary features.

Conventional language models tend to analyse words separately, which restricts their understanding of the connections between words in a phrase. But BERT and RoBERTa make use of a transformer architecture that permits bidirectional text processing, meaning that they can take into account a word's whole context within a sentence. The models are able to extract extensive semantic information and comprehend the complex meanings of words depending on the context in which they are used due to this bidirectional technique [5].

This work proposes a hybrid sentiment analysis model that combines the benefits of BERT and RoBERTa models in order to enhance sentiment categorization performance. Through the incorporation of these models, the methodology seeks to surmount the constraints of conventional sentiment analysis techniques and attain enhanced outcomes in the evaluation of social media sentiment. The utilisation of BERT and RoBERTa's contextual understanding skills facilitates the efficient extraction of subtleties from social media text.

The two main parts of the hybrid sentiment analysis model in this task are BERT and RoBERTa. Bidirectional attention mechanisms are used by the transformer-based model BERT to extract contextual information from both left and right contexts [7]. Its architecture, which consists of feed-forward neural networks and numerous layers of self-attention, allows it to learn deep contextual representations of text. Pre-training goals like next sentence prediction (NSP) and masked language modelling (MLM) are beneficial to BERT. On the other hand, RoBERTa is an improved version of BERT that improves training data augmentation, hyperparameter modification, and pre-training techniques. RoBERTa performs better when the NSP pre-training goal is removed and training is done on bigger datasets with longer sequences.

To improve text representations, RoBERTa also uses bigger batch sizes and dynamic masking during pre-training. When used in parallel, BERT and RoBERTa improve sentiment analysis performance by efficiently extracting syntactic and semantic information from social media text [9]. In a nutshell, this paper advances sentiment analysis methods by demonstrating how well hybrid models handle various types of textual data that are extracted from social media platforms. The suggested hybrid methodology offers a promising answer to the problems with conventional sentiment analysis techniques by fusing the advantages of the BERT and RoBERTa models. This opens the door to more precise and complex sentiment analysis in social media data.

II. LITERATURE REVIEW

Attention is All You Need (Vaswani et al., 2017), The Transformer architecture was first presented in this landmark study, and since then, it has become essential for tasks involving natural language processing because of its effective modeling of token dependencies [1]. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding (Devlin et al, 2018) By introducing a revolutionary pre-training technique, BERT considerably improved the state-of-the-art in sentiment analysis and other NLP tasks, it uses reciprocal context to extract text's underlying semantic implications [2]. Roberta: A Robustly Optimized BERT Pretraining Approach (Liu et al, 2019): RoBERTa, which built on BERT, suggested enhancing the pre-training procedure to enhance performance on subsequent tasks like sentiment analysis [3].

Document Modelling with Gated Recurrent Neural Network for Sentiment Classification (Tang et al, 2015): Although not directly related to Transformers, this paper explores alternative architectures for sentiment analysis, which can complement Transformer-based approaches [5]. GLUE: A Multi-task Benchmark and Analysis Platform for Natural Language Understanding (Wang et al, 2019): GLUE provided a benchmark suite for evaluating the performance of NLP models across various tasks, including sentiment analysis [5]. It serves as a reference for assessing the effectiveness of Transformer-based models like BERT and RoBERTa.

XLNet: Generalized Autoregressive Pretraining for Language Understanding (Yang et al, 2019): Showcasing improvements in pre-training methods that can help with sentiment analysis tasks, XLNet provided an autoregressive pre-training method that outperformed BERT on numerous NLP benchmarks [7]. Sentence-BERT: Sentence Embeddings using Siamese BERT-networks (Reimers & Gurevych, 2019): Sentence-BERT, a technique for employing BERT to generate fixed-size sentence embeddings, was introduced in this study. It has been successfully used for applications like sentiment analysis and sentence similarity. Sentiment Analysis based on BERT and RoBERTa (Wang et al., 2020): Wang et al. conducted sentiment analysis tasks using BERT and RoBERTa models, showcasing the efficiency of Transformer-based architectures in extracting sentiment data from social media text [8].

Recursive Deep Models for Semantic Compositionality over a Sentiment Treebank (Socher et al, 2013): Although not directly related to Transformers, this paper explores recursive neural network architectures for sentiment analysis, providing insights into alternative approaches in this domain. Learning Sentiment-Specific Word Embedding for Twitter Sentiment Classification (Tang et al, 2014): Tang et al. Look at sentiment-specific word embeddings to enhance Transformer models' ability to capture sentiment subtleties in sentiment classification on Twitter data [10].

III. METHODOLOGY

The method is distinguished by a well-structured architecture designed to address the specific challenges at hand.

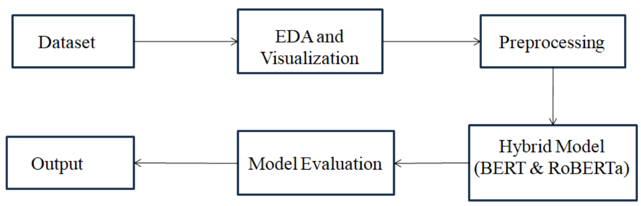

Fig.1: Model Architecture

As it is observed in Fig. 1, the model architecture is a structured technique consisting of six critical phases, all of which are essential in deciding the outcome of the project. These distinct phases include dataset exploration, preprocessing, model construction and evaluation, performance visualization, and prediction. Every stage makes a substantial contribution to the development and enhancement of the model's overall efficiency, culminating in a unique and comprehensive strategy for overcoming sentiment analysis through the incorporation of hybrid models.

Every stage in the architecture is explained in detail in the section that follows.

A. Dataset.

The model was trained on a properly produced and examined dataset named “sentimentdataset.csv”, which can be accessed by the general public on Kaggle. With the "Text" property acting as the main source of textual material for sentiment categorization, it has all the necessary attributes for sentiment analysis. Model training and evaluation are made easier by the "Sentiment" feature, which serves as the goal variable and assigns sentiment labels to every text entry. For a more in-depth examination, other attributes like "Timestamp," "User," "Platform," "Hashtags," "Retweets," and "Likes" provide context. Sentiment trend research is made possible by temporal information, while demographic and behavioral insights are revealed by user and platform specifics. Post significance is indicated by hashtags, retweets, and likes, which may have an impact on sentiment. Features such as "Country," "Year," "Month," "Day," and "Hour" provide temporal and geographical studies, enhancing comprehension of sentiment fluctuations.

B. EDA and Visualization.

Exploratory Data Analysis (EDA) and visualizations are necessary for understanding the patterns and properties of the information. A variety of methods were used to extract information from the social media sentiment dataset. Analysing the sentiment class distribution made sure that representation was balanced, which is important for model performance. The distribution of sentiment classes in the dataset was clearly shown by the pie charts and count plots shown in Fig. 2. These graphics offered a thorough summary of the percentage of cases that fell into each sentiment category, making it possible to spot any possible biases or imbalances.

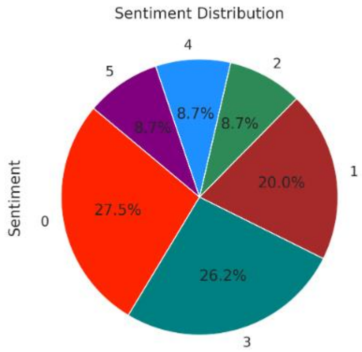

Fig. 2: Pie Chart of Sentiment Distribution

Analysis of word frequencies and text lengths, as shown in Fig. 3, provided insight on the complex nature and structure of the textual data.

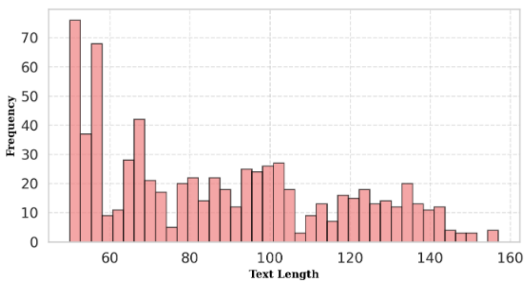

Fig. 3: Text Length Distribution for Social Media Sentiments Analysis Dataset

Furthermore, word clouds which are shown in Fig. 4 offered visual representations of the words that appeared most frequently in the text corpus. The word clouds provided qualitative information about the recurring themes and subjects found in the dataset.

Fig. 4: Word Cloud for Text in Social Media Sentiments Analysis Set

EDA and visualization played a crucial role in guiding preprocessing and modelling that came after, improving comprehension and decision-making.

C. Preprocessing.

Textual input must be cleaned and prepared using preprocessing procedures before a sentiment analysis model can be trained. Several preprocessing methods were used in this investigation to increase the quality of the data and make model training more efficient. Initially, all characters in the text were changed to lowercase using text normalization techniques such lowercasing. This contributes to the reduction of vocabulary size and guarantees uniformity in word representations. Tokenization was then used to separate the text into discrete words or tokens in order to make additional processing easier. By using tokenization, the model is better able to examine the text and comprehend the semantic meaning of each word. To guarantee consistent sequence lengths, additional special tokens were introduced to denote the start and finish of each text sequence.

Moreover, stopword removal was done to get rid of terms like "the," "is," and "and," which are frequently used but have no semantic significance. By concentrating on more pertinent terms, stopword removal reduces noise and increases the sentiment analysis model's effectiveness. Additionally, lemmatization or stemming approaches were used to decrease inflected words to their root or base form. By treating multiple inflections of the same word as similar, this helps to improve model generalization and reduce the complexity of the feature space. subsequently class labels were encoded in order to express categorical sentiment labels as numerical values. This improved the model's ability to perceive and anticipate sentiment during training.

D. Hybrid Model.

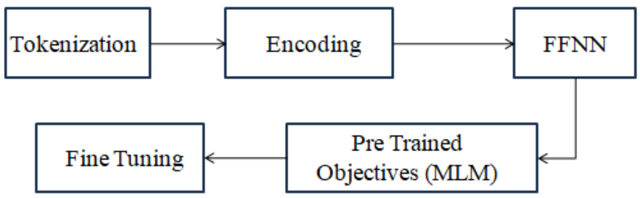

Fig. 5: Model Architecture for Hybrid model

The architecture of the hybrid sentiment analysis model put forward in this study is shown in Fig. 5. The BERT and RoBERTa transformer-based models are combined into one strong model. The hybrid technique combines these models in an effort to maximize their complimentary qualities and improve sentiment categorization efficacy. Reputable for their capacity to extract contextual information and process natural language semantics are BERT and RoBERTa. Bidirectional context information is best captured by BERT's bidirectional attention mechanism, while RoBERTa enhances BERT's architecture by improving pretraining tasks and training with larger batch sizes. The integration of both models results in a single hybrid design that capitalizes on their respective advantages.

Using a specified vocabulary, incoming text is segmented into sub words or tokens during the tokenization stage of the process. Next, a high-dimensional vector representation of each token is created. During encoding, these token embeddings move across several transformer layers. Different portions of the input sequence are prioritized by self-attention processes inside each layer, making it possible to record contextual information and comprehend the relationships and dependencies between tokens. After that, token representations are processed by feed-forward neural networks (FFNNs) to perform non-linear transformations, which improves the ability to extract patterns. Unsupervised learning objectives, including maximum likelihood matching (MLM), are used during pre-training on large text corpora in order to optimize model parameters.

By adjusting parameters on labelled data, this allows BERT and RoBERTa to adapt to certain downstream tasks, such as sentiment analysis. The BERT and RoBERTa parallel branches of the hybrid model architecture process the input text separately from one another. After being concatenated, the outputs from both branches are processed through additional layers. More accurate sentiment categorization is made possible by this design, which enables the model to incorporate a variety of contextual data and semantic representations from both BERT and RoBERTa.

E. Model Evaluation.

Several assessment criteria are frequently employed in the context of transformers for sentiment analysis to assess the efficacy and effectiveness of the models. Based on the given data, these measures aid in quantifying how effectively the model predicts software quality traits. These consist of:

Accuracy (Acc): It gauges how accurate the model's predictions are overall.

$$Acc = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{1}$$

Sensitivity (Recall): It measures the percentage of accurate positive predictions among all the model's positive predictions.

$$Recall\ (R) = \frac{TP}{(TP+FN)} \tag{2}$$

Precision: It determines the percentage of accurate positive predictions among all of the dataset's real positive occurrences.

$$Precision\ (P) = \frac{TP}{(TP+FP)} \tag{3}$$

F1-Score: It provides a fair assessment of a model's performance by representing the harmonic mean of precision and recall.

$$F1 = \frac{2 \times P \times R}{P + R} \tag{4}$$

Where, TP represents True Positive, TN represents True Negative and FP, FN represents False Positive and False Negative respectively.

F. Prediction.

The trained model processes the input data, examines the text content, and makes predictions about the sentiment indicated in the text during the crucial prediction phase of sentiment analysis. This method involves feeding a dataset of text entries into the sentiment analysis model in order to make predictions. After then, the model examines every sentence or text input on its own and extracts pertinent patterns and features in order to determine the sentiment being expressed. Sentiment labels, which classify text entries as positive, negative, or neutral based on the model's classification, are usually the outcome of the prediction process. Predictions aid in understanding public opinion, sentiment patterns, and emotional responses in a variety of scenarios by providing insights into the sentiment expressed in the text. This helps decision-making processes in a wide range of applications and domains.

IV. RESULT & ANALYSIS

A. Quantitative Analysis:

Sentiment analysis has come a long way in the last few years, especially with the introduction of hybrid models that combine the best features of several approaches. The purpose of this comparison study is to assess our hybrid sentiment analysis model's efficacy in comparison to more conventional methods. Based on measures like accuracy, precision, recall, and F1-score, Table 1 compares several sentiment analysis techniques, such as Random Forest, CNN, SVM, BERT, and hybrid models. Numerous measures, including accuracy, precision, recall, and F1-score, can be obtained from the confusion matrix to give a thorough knowledge of the model's classification performance.

Table -1: Comparative Analysis of Sentiment Analysis Methods

Method	Accuracy	Precision	Recall	F1 - Score
Random Forest [21]	75.99	71.66	60.00	66.00
CNN [22]	72.60	77.45	70.42	68.00
SVM [22]	75.92	64.35	67.72	71.30
BERT	79.82	69.27	61.33	62.29
Hybrid	82.00	75.61	80.34	80.50

Confusion matrices of BERT and Hybrid (BERT & RoBERTa) were depicted as Fig. 6, Fig. 7.

Fig. 6: Confusion matrix of BERT Model

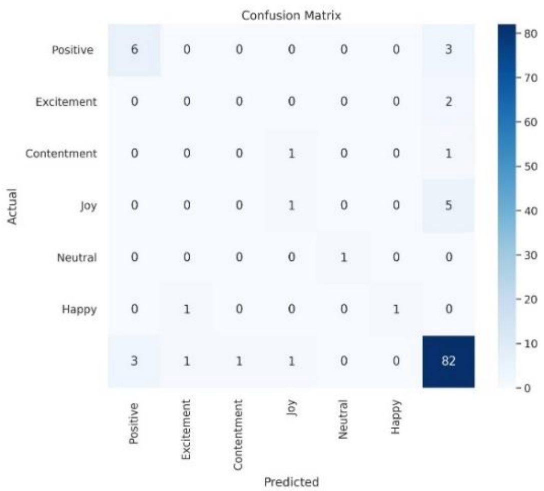

Fig. 7: Confusion matrix of Hybrid Model

B. Qualitative Analysis

The performance parameters of the sentiment analysis model were represented visually in the analysis through the use of a confusion matrix. Furthermore, Table 2 displays the categorization metrics for every sentiment category, including support, F1-score, precision, and recall. These metrics offer comprehensive insights into the efficacy and accuracy of the algorithm in identifying text entries according to their underlying sentiment. A comprehensive comprehension of the sentiment analysis model's effectiveness across several sentiment classes is attained by combining the visual depiction of the confusion matrix with the quantitative classification metrics shown in Table 2.

Table - 2: Sample Sentences with Sentiment Labels

Sentence	**Sentiment Label**
The weather is beautiful today.	Positive
I'm feeling happy about the news.	Positive
The service at the restaurant was terrible.	Negative
The product quality is good.	Neutral
The meeting went well.	Negative
It's neither good nor bad.	Neutral

V. CONCLUSION

Finally, the effectiveness of a hybrid sentiment analysis model that combines the BERT and RoBERTa architectures to improve sentiment classification performance has been shown in this work. The dataset was prepared for training and evaluation by means of comprehensive examination of its properties and substantial preparation procedures. The hybrid model increased the accuracy of sentiment classification by utilizing the contextual understanding powers of both the BERT and RoBERTa models. The assessment metrics precision, recall, F1-score, and support offered thorough insights into how well the model performed in various sentiment classes. Furthermore, a deeper comprehension of the model's advantages and disadvantages was made possible via visualization approaches including confusion matrices and classification reports. Overall, the hybrid model's analysis of social media sentiment showed encouraging results, highlighting the need of applying cutting-edge deep learning approaches to sentiment analysis jobs. Additional optimization techniques could be investigated in future studies, and the model's performance on various datasets and practical applications could be assessed.

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