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A Hybrid Deep Learning Approach for Sentiment and Emotion Analysis in Textual Data

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Abstract:

Sentiment analysis (SA) is an automated technique for detecting and understanding the emotions conveyed in text. In the recent ten years, SA has been increasingly popular in the field of natural language processing (NLP). When it comes to subjective judgments, SA can assist consumers transcend the haziness of human judgment and provide them with transparent, objective sentiment suggestions based on large datasets. Existing sentiment analysis systems could use some work to make them more accurate and robust. Marketing campaigns that rely on product reviews would benefit from a reliable way to forecast when opinions may vary. With the rise of several online platforms, social media analytics (SMA) has become an essential tool for organizations to understand customer sentiment and guide their advertising strategies. In addition, SA is used by researchers to address public sentiments on many matters. Using preexisting methods such as recurrent neural networks (RNNs) along with transformation models such as Bidirectional Encoder Representations (BERT), researchers may effectively assess the sentiment conveyed in literary works. These models are able to accurately determine the literary work's emotional tone because they learn intricate patterns and features particular to the setting. Sentiment analysis is an essential part of natural language processing since it helps us understand the feelings and thoughts conveyed in text. Word2Vec and Fast Text are two examples of word embeddings that are thoroughly examined in text for mapping that is closely related to real number vectors. However, deep learning and word embedding aren't perfect. Integrating word embedding with deep learning models is key to achieving high-performance sentiment recognition in natural language processing. Our BERT-BiGRU model, which employs NLP techniques, is part of a larger endeavor to enhance sentiment analysis. Several word embedding approaches are considered in the proposed model, which aggregates their attributes and uses them to classify texts based on their emotional tone. When compared to prior studies, the proposed model outperforms them in terms of sentiment classification.

Keywords- Deep Learning, BERT, GPT, Sentimental Analysis, word embedding, Emotion Classification, Ethical Considerations

1 .INTRODUCTION:

The rise of social media, advances in natural language processing (NLP), and the growing importance of big data analytics have all contributed to the remarkable progress made in opinion mining, also known as sentiment analysis, during the past few years [1]. The proliferation of user-generated content online has made sentiment analysis increasingly valuable for researchers, governments, and businesses in determining public opinion, following trends, and making data-driven decisions [2]. In recent years, sentiment analysis has evolved into more complex methods that go beyond the usual positive/negative/neutral polarity classification. These methods include aspect-based sentiment analysis, which recognizes emotions, and context-aware sentiment analysis [3]. By identifying specific characteristics or features within the text, aspect-based analysis of sentiment can be employed to discover the sentiment associated with each portion of the text. Emotion detection in text goes beyond simple polarity detection to include the identification of feelings such as joy, fury, sadness and or surprise [4].

People can learn a lot about a product's quality and reliability from consumer reviews posted on shopping platforms. In order to make a well-informed purchase, consumers prefer to know all the pros and cons of a product. It will take more time to develop faith in a product by researching all of its pros and cons, even if it is inexpensive. Buyers won't have enough time to peruse every review before committing to a buy. By analyzing a huge number of reviews on the same portal on various aspects of the product, they are looking for a scheme that highlights the pros and cons of a specific product. Customers' opinions on a product's features can be uncovered using sentiment analysis. Deep learning models, such as RNNs, CNNs, and transformer models, such BERT and GPT, have improved machine learning algorithms, allowing for more precise and robust analysis of sentiment [5].

These models can enhance the functionality of sentiment analysis systems in several domains and languages by learning intricate patterns and representation from massive volumes of text data [6]. New uses for sentiment analysis have emerged as a result of its incorporation into various AI systems, including chatbots, social listening tools, and recommendation systems. Monitoring brand sentiment, identifying consumer complaints, personalizing marketing strategies, and enhancing customer experiences are all ways businesses utilize sentiment analysis [7]. The public's views on policies, new problems, and citizen concerns can be better understood and addressed with the use of sentiment analysis. Social trends, public health concerns, and large-scale human behavior can all be better understood with the help of sentiment analysis. The use of NNs, or multiple-layer artificial neural networks, to address learning problems is called deep learning. Previously thought to be limited to a single layer or a small amount of data, it can take advantage of neural networks' learning capabilities. Artificial neural networks (ANNs) mimic the structure of the human brain by simulating its many layers of interconnected processing units (neurons). Like a real brain, it can learn new tasks (like classification) by adjusting the strength of connections between neurons.

According to previous research on sentiment analysis, deep learning is currently the method of choice over more traditional machine learning algorithms that are commonly used for classification, such as Naive Bayes, Support Vector Machines (SVM), Decision Trees, and Random Forests [8].When it comes to sentiment categorization, deep learning was first used by convolutional neural networks (CNNs) & recurrent neural networks (RNNs). Thanks to massive datasets and the cheap distribution of strong Graphics Processing Unit (GPU) cards, deep learning has recently surpassed machine learning in sentiment analysis tasks [9]. There are a lot of text categorization challenges where the algorithms and the methods used to represent texts need to be compatible. Excellent classification performance is within reach with the support of a well-designed representation of text and classification system. Figure 1 shows the fundamental feelings evoked by the content on social media.

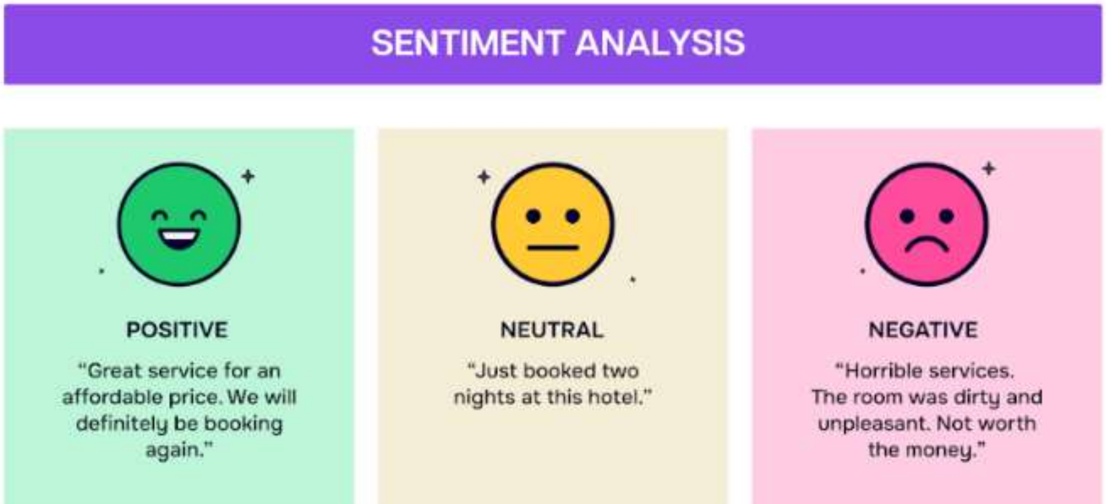

Figure 1.Basic Emotions in Sentimental Analysis

Every deep learning method has its own unique property that makes it useful for solving problems or analyzing datasets. There are advantages and disadvantages to both the text representation and the numerical format converter. In order to solve problems and achieve high accuracy, it is crucial to combine the best deep learning for sentiment analysis with the optimal text representation. Classification accuracy is improved by the use of several feature extraction techniques applied to text-based data. When it comes to numerically representing user emotion, any text representation method (e.g., embedding words, character-level integration) could fall short. Our goal is to address this challenge by integrating various deep learning models and methodologies for text representation. The fundamental procedures for analyzing social media sentiment are illustrated in Figure 2.

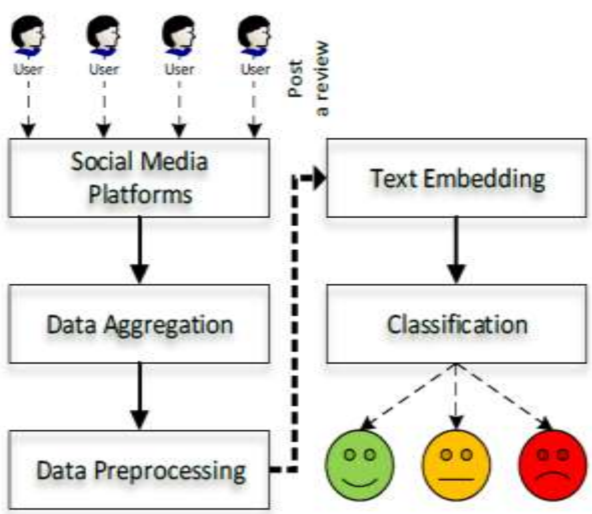

Figure2. Basic steps of sentiment analysis on social media[10][

The structure of the remaining paper is as follows: Section 2 deals with the current literature in Sentiment Analysis.Section 3 emphasizes the methodology known as Proposed BERT-Bi-GRU. Section 4 provides an analysis of the IMDb Dataset, while Section 5 evaluates the findings. Finally, Section 6 presents the concluding remarks of the work.

2. LITERATURE REVIEW:

Classical ML classifiers like SVM, Naive Bayes, and more have formed the basis of many sentiment analysis studies. The three main levels of techniques in sentiment analysis are the sentence level, the word level, and the document level. Sentiment analysis is applied at the word level to examine the location of the review's words and how they impact the evaluation. It finds the general orientation of the review after looking up the meaning of polarity in a dictionary. Sentiment analysis determines the general balance of a statement to determine its positivity or negativity at the sentence level.

Every phrase carries its own weight when it comes to the paper. One study that used social media data to examine the Taliban's impact in Afghanistan was Lee et al. [11]. By analyzing the conversation on social media, the researchers hoped to gain a deeper understanding of the issue. The results of the study on workplace discrimination by Lee et al. [12] were likewise generated from tweets that addressed the subject. They hoped to gain a better understanding of the frequency and nature of racism in the workplace by analyzing these tweets for trends. Using the TextBlob approach, they annotated data taken from Twitter. In terms of racism, the authors were 72% spot on. Mujahid et al. [13] looked at public opinion on online schooling in a different context during the COVID-19 outbreak. Researchers looked at social media data to try to understand people's feelings and opinions about distant learning during this tough time. Research like this highlights the significance of mining social media data for relevant insights across a variety of subjects. The vast quantities of user-generated content on social media platforms provide a goldmine of information for researchers interested in important topics. The researchers trained a support vector machine (SVM) model with 17,155 tweets as input, utilizing the SMOTE method and bag of word features, and achieved a precision of 95% [37].

Exploring people's perceptions about ChatGPT using Twitter data can yield useful insights, as it is a popular topic right now. These kinds of analysis have been done on a variety of subjects in a great deal of papers. The purpose of the research by Tran et al. [14] was to look at how customers feel about chatbots in different retail industries and how they expect to engage with human agents in the future. Using automated sentiment analysis, we found that, in online environments, people generally have a more positive attitude towards chatbots than they do towards human agents. To conduct the test, they gathered a small dataset of 8190 tweets and utilized ANCOVA. They don't make good use of performance indicators like accuracy; all they do is categorize tweets according to their precise thoughts. The use of chatbots led to a general decline in trust in human agents in the fashion and telecom industries, among others, but opinions differed across sectors. An efficient method for assessing and extracting feelings and mental health throughout the COVID-19 epidemic was the goal of the study [15]. We used hashtags and a mountain of data to train the BERT machine learning system to accurately categorize consumer opinions as favorable or negative. Our primary goal was to provide a secure environment where users could communicate with bots in an encrypted fashion, allowing them to better understand themselves and control their mental states. For chatbot-related automated sentiment classification, the researchers reached 95.6% accuracy and 95% recall. At various time periods for specific areas, several research, like [16], concentrate on sentiment evaluation of disaster-related tweets. The context and history of tweets are used to derive keywords using the LSTM network with phrase embedding. As a suggested algorithm, RASA sorts tweets into categories and finds location-specific sentiment scores. Compared to competing algorithms, RASA performs better, which helps the government with disaster management in the aftermath by revealing patterns and suggesting ways to avoid future occurrences. Predicting bitcoin prices using Twitter data is the focus of another study [17]. Using crypto currency-related tweets, they center their sentiment analysis & emotion detection efforts. To improve the accuracy of the analysis, an ensemble model called LSTM-GRU combines LSTM with GRU. We take a look at a bunch of different models and features, including ML and DL. Surprisingly, and surprisingly, the data suggest that the most common attitude is optimistic. The collection includes five different emotions, all derived from data collected from Twitter [18] [35] [36].

The proposed ensemble model attains an 83% accuracy rate for emotion prediction when applied to a balanced dataset. This study sheds light on public perceptions about crypto currency and their potential market impacts. Various methods for sentiment analysis can be employed, including hybrid deep learning and ensemble learning, in addition to the more conventional approaches to classification. One area of machine learning called ensemble learning combines the results of multiple learning algorithms to build a classification system that is more accurate in its predictions. An approach that combines support vector machine (SVM) with two algorithms for selecting features and the multi-verse optimizer was proposed by the authors of [19] [33] [34] as a hybrid technique to enhance machine learning performance. Deep learning is a branch of machine learning that aims to improve the predictive capacity of classification models via the use of supervised and unsupervised learning of nonlinear information and numerous hierarchical feature expression layers. Deep learning sentiment analysis models such as BERT, cognition-based attention, common sense, reinforcement learning, generative networks of adversarial networks, and cognition-based knowledge were all evaluated and contrasted in the study. Researchers in a recent study used five different RNN algorithms: RNN, LSTM-RNN, GLSTM-RNN, GRU-RNN, and UG-RNN [21]. The authors realized the importance of word embeddings while performing sentiment classification. According to their findings, the combination of the RNN algorithm with the glove feature extraction method produced the most subpar outcomes [30] [31][32].

The authors of [22] [26][27] shown that hybrid models can enhance sentiment analysis accuracy by comparing their findings to those of a single deep learning model. Multiple models, including CNN, LSTM, and SVM, were utilized by the writers. Features can be extracted by the CNN model, remembered by the LSTM model at the state nodes, and classified by the SVM model. For the goal of sentiment classification, a recent research study [23] introduced a CNN paired with an LSTM for machine learning. The LSTM was given a more generalized picture of the sequences by the CNN layer and the max-pooling layer working together [24]. A number of alternative deep learning algorithms and ML classifiers performed worse than CNN-LSTM [25]. Lastly, several researchers have found that blended deep learning models yield better performance [28] [29].

3. METHODOLOGY:

Preprocessing the input review statement correctly, extracting features from the given emotions review declaration appropriately, selecting an appropriate algorithm for sentiment classification, and finally, evaluating the performance of the sentiment classification results are the basic steps in the sentiment classification process. The initial step is to transform the sentiment review assertions into feature vectors. Extracting important features is crucial for sentiment tasks at the sentence level. The most critical step is to choose a suitable algorithm for sentiment analysis. Among the many applications of the BERT model are question answering, sentiment classification, and linguistic inference. The BERT model employs left and right contextual changes in all of its current layers to create a deep bidirectional representations from plain text. Here, we use BIGRU to classify sentiment at the phrase level. Due to its reduced parameter count, GRU is well-suited for deeper networks as it requires less training data for generalization and hence uses less training resources. Illustrated in Figure 3 is the proposed work's use of the BERT Tokenizer, BERT pre-training model, & Bi-Directional GRU (BIGRU) for sentiment classification in movie reviews.

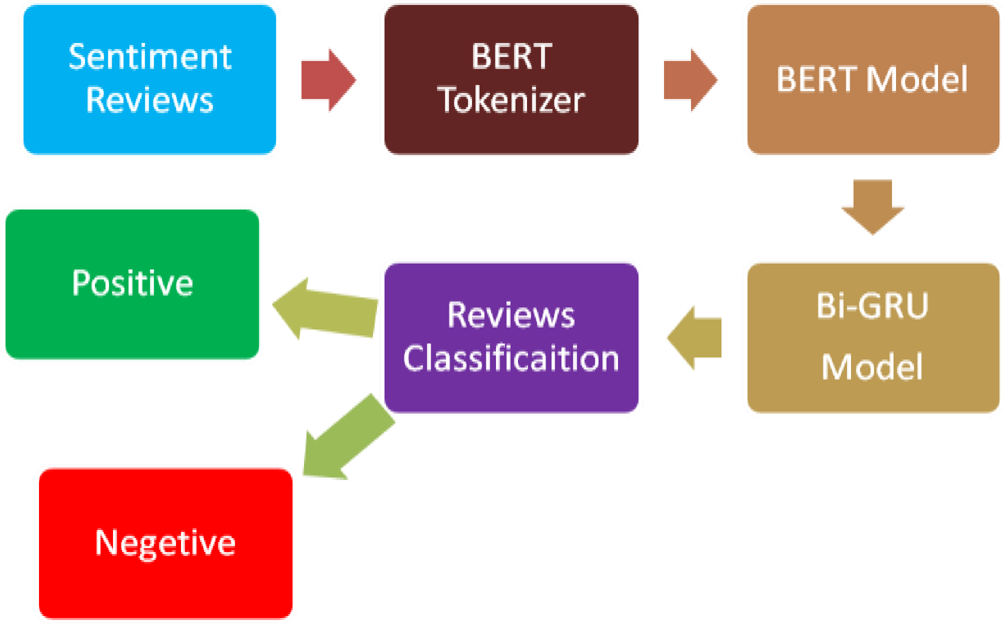

Figure 3.Proposed Model for Sentiment Classification

The first stage in cleaning up data is data preparation. Both the accuracy and efficiency of the classifier are enhanced by proper data preprocessing. The reviews of the data are written in English. The review information has been all lowercased throughout the preprocessing stage. Three distinct sets of data were created: training, test, and validation. The emotion labels that are positive are changed to 1 and the ones that are negative to 0. After that, either better contextual representation or feature-enhanced embedding dimensions can be generated using the BERT tokenizer. After that, a sigmoidal activation principle and fully connected layers improve contextual comprehension using the BIGRU model. The accuracy of sentiment categorization can be improved with well-executed feature extraction. When used to the feature extraction process, the BERT algorithm yields notable improvements. The BERT model uses bidirectional learning to train on a large dataset of 2.5 billion words, which allows it to understand the context of words in both left-to-right and right-to-left directions at the same time. The model that is being used has encoders that are more deep and more parallel. It presents two new tasks, Next Paragraph Prediction (NSP) and Masked Language Model (MLM). For the purpose of sentiment categorization, we suggest a deep learning model with a hybrid approach called BERT-BIGRU. This model combines the best features of both existing models. The following algorithm illustrates the specifics of the suggested the hybrid deep learning model for the purpose of performing sentiment categorization at the sentence level.

Algorithm 1:Sentimental Classification at Sentence Level Input: An ordered series of input review summaries S= {$REVS_1$, $REVS_2$, $REVS_3$......$REVS_N$} Output: Classification of review sentences into either positive or negative categories; Evaluation and comparison of model performance. Step-1: Examine the dataset S Step-2: Conduct preparation to obtain the cleansed data For every review comment that is input $REVS_i$ ε S do Step-3: Utilize the BERT tokenizer to preprocess review data for a BERT model.

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Step-4: Utilize the BERT Model to produce embeddings with improved feature dimensions.
end do
Step-5: Use the train-test split to divide the data into a training set & a testing set.
Step-6: Use the provided training data to train the BIGRU model.
Step-7: Model performance assessment using the test data
// Apply classification performance metrics like F1-Score, Accuracy, Precision, & Recall to generate sentiment classification results.

BERT makes use of attention mechanisms in a transformer architecture. Because of its contextualized depictions, bidirectional processing that captures complex context, previously trained language skills, transferable learning the ability for different tasks, efficient handling of out-of-vocabulary phrases, modern performance for different NLP tasks, and open-source availability, the BERT model is chosen for embedding subsequent generations in natural language processing applications in a powerful and versatile way.

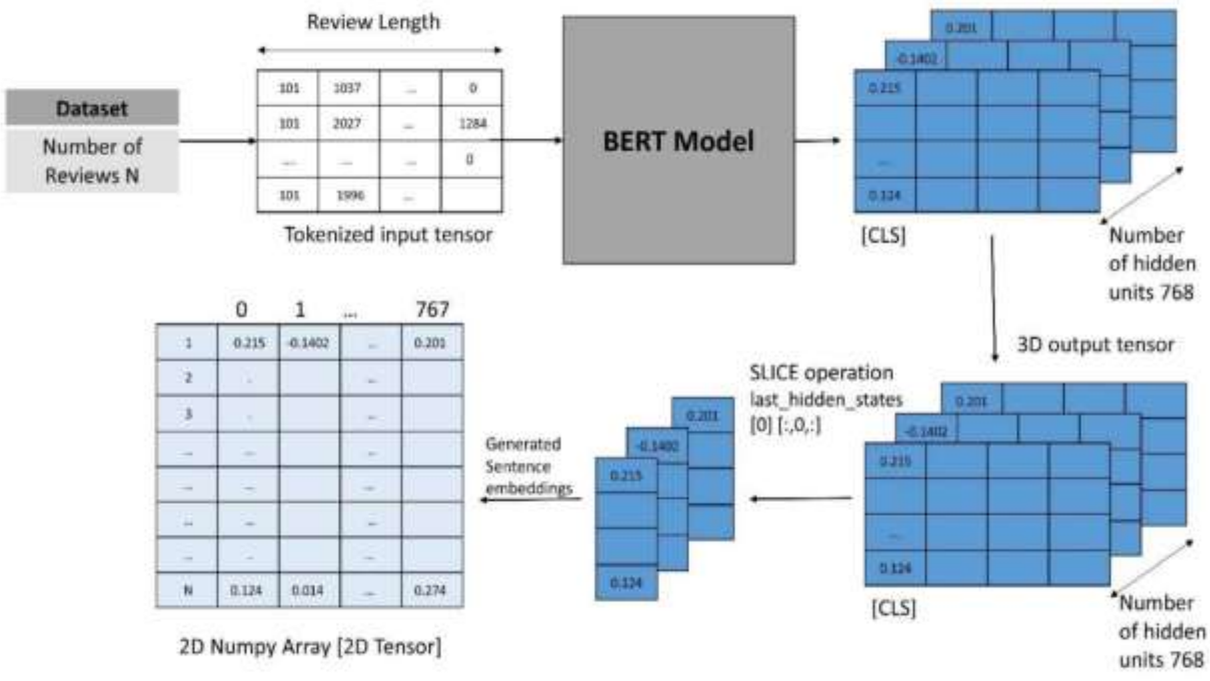

Figure 4 Sentence Embeddings using BERT Model

It all started with tokenizing the text using the BERT tokenizer. Additional special tokens [CLS] & [SEP] were included. Classification is abbreviated as CLS. To help with sentence classifications, the tokens [CLS] have been put at the beginning of the sentence and [SEP] at the end. You can handle unusual tokens & segment embeddings with the help of the BERT tokenizer, which also tokenizes the input text and converts tokens to input IDs. The BERT model receives this preprocessed data and uses it to perform additional processing. We can now run the review sentence via the BERT model with the correct structure. Twelve attention heads, seven hundred and sixty-eight large feed forward networks, and twelve encoder layers make up the BERT based model that we propose. The input to BERT is a stack of words, which are passed up the line.

After doing self-attention, each layer sends its output to the subsequent encoder via a feed-forward network. The size of the vector outputted at each point is 768. Figure 4 on the preceding page shows that the BERT model actually produces a three-dimensional tensor as an output. The [CLS] sentiment classification output at the sentence level takes tokens into account. Therefore, the [CLS] vector value is extracted using the slice operation; the resulting 2D numpy array contains the sentence embeddings for every sentence in the dataset. You may now feed this vector into a classifier. There is no sentiment class label generating included into the BERT model. Making contextualized representations of words or embeddings is its main purpose. The fine-tuning procedure involves building upon the pre-trained BERT model with a task-specific layer, commonly known as the classification layer. Using the contextualized representations given by BERT, this extra layer is tasked with producing labels or predictions. The suggested study employs a GRU model, which, in comparison to conventional LSTM, has less gating units. A partial solution to the gradient vanishing problem is the GRU's capacity to combine short-term and long-term memory through the use of precise gate control. To manage the flow of information within the unit, an additional memory cell is unnecessary. It is possible that training efficacy will improve with GRU compared to LSTM because it is easier to train. The design of even GRU is simpler than that of LSTM. There are just two gated units in GRU: the reset gate and the updated gate. It is by that the revised weight is chosen. The amount of data that has to be transported from past times to the future can be controlled by the update gate.. The following formulae calculate this.

$$X_n = \sigma(A_b W_t + M_b C_{t-1}) + D_b \quad \text{------} (3.1)$$

A linear interpolation among the candidate function $C_{t-1}$of activation and the prior activating function, as shown in the following equation, determines the GRU activation at time t.

$$C_t = (1 - X_n)C_{t-1} + X_n C_t \quad \text{-----------}(3.2)$$

As can be seen in equation 3 on the following page, GRU calculates the candidate function of activation in the same way as a normal RNN, since it is an RNN variation. This is where a set of reset gates and an element-wise multiplication $\otimes$ process come together.

$$C_{t-1} = f(W_z x_t + r_t \otimes \quad + U_h + D_n \quad \text{-----------}(3.3)$$

The amount of data that should be deleted or forgotten can be set using reset gates. For input analysis, the traditional GRU model could only look forward. Sentiment classification at the sentence level relies heavily on reverse sequencing. Consequently, the BERT model's output is also fed into the bidirectional GRU. First, the BIGRU model combines forward as well as reverse GRU, and then, with the help of two hidden layers, it processes data in both directions at the same time.

4. DATASET USED:

The dataset from the Internet Movie Database (IMDb) is utilized to conduct experiments using the proposed structure. Several scholars engaged in sentiment classification research have made extensive use of the 89,000 reviews that make up the IMDb Dataset to solve the challenge of binary sentiment categorization. There are a number of sentimental sentiments or words in every movie review. Many consider this to be a crucial aspect of this dataset. For training purposes, the IMDb dataset includes 440,000 positive instances and 450, 000 negative instances. For testing purposes, the dataset has 44,000 positive instances and 45,000 negative instances. As mentioned in the background and related work section, the primary rationale for selecting this dataset is that it is an equal set that serves as a common benchmark for academics to conduct their research. The primary steps in accomplishing sentiment classification at the sentence level are cleaning up the emotional data source and creating a dataset for the classification model.

5. PERFORMANCE EVALUATION:

Tensor Flow 2.13, Keras 3.0.1, and Python 3.12.4 were the versions used in this experiment. An Nvidia TITANX system, equipped with a 64-bit OS, 8GB of RAM, and an Intel(R) Core(TM) i7-8700K CPU running at 3.70GHz, was used to conduct the trials. The performance evaluation measures utilized for comparing existing deep learning models were accuracy, precision, recall, and F1-score.

A confusion matrix is used to measure how well Deep Learning algorithms work. As part of the statistical evaluation process, these confusion matrices have proven used for determining techniques' accuracy, precision, recall, and F1-Score, among others. The data is organized in a table format, with the actual values running down one side and the predictions running down the other. As seen in Figure 5, the confusion matrix is simplified. Following a comprehensive evaluation of both the current and proposed systems, Table1 presents the results of the various approaches.

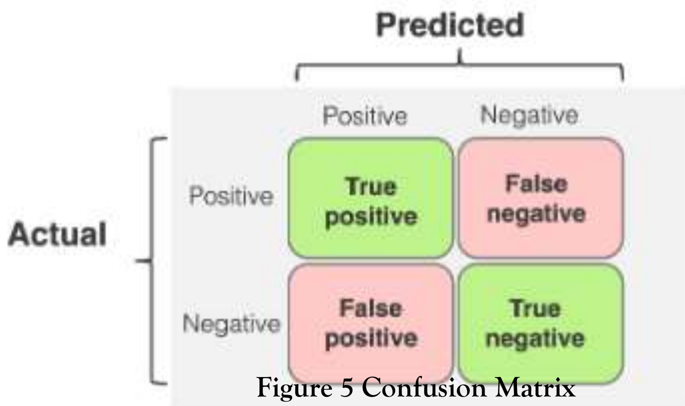

Figure 5 Confusion Matrix

Table1 Results Comparison of Applying Various Algorithms on the IMDb Data set

Model	Accuracy	Precision	Recall	F1-Score
CNN	73.45	75.42	76.45	77.42
LSTM	75.48	78.95	79.23	80.41
Bi-LSTM	79.89	80.42	81.56	82.49
GPT	84.54	84.89	85.42	86.32
BERT	89.74	88.45	90.45	91.78
BERT-Bi GRU	94.52	92.45	93.14	93.89

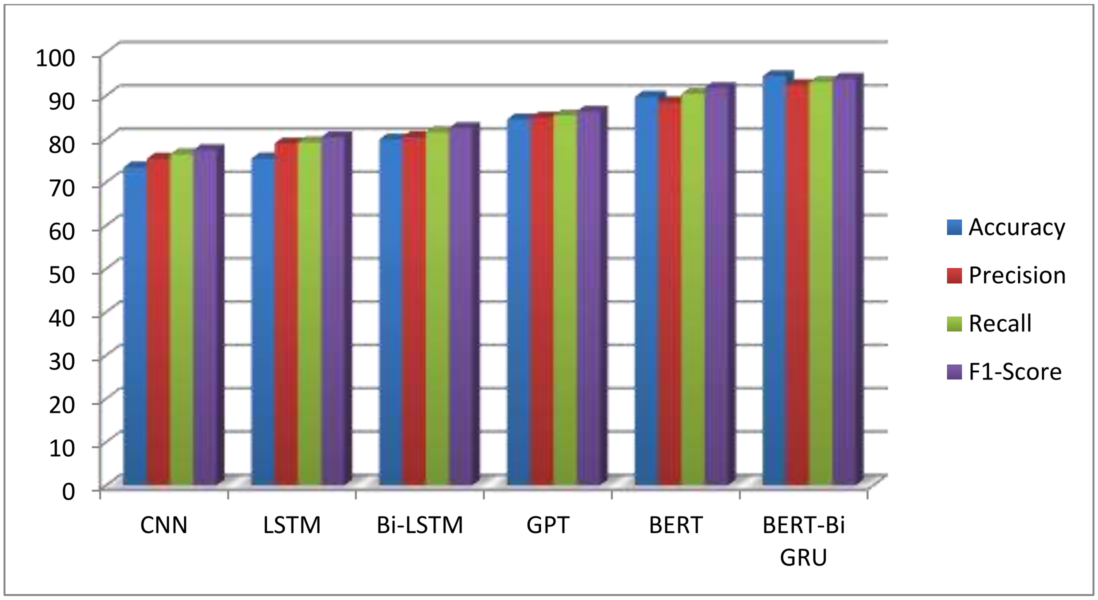

Figure 6 Comparative Results of Existing and Proposed algorithms for Sentimental Classification

The experiment included comparing the BIGRU model's efficiency to that of other deep learning models, including CNN, LSTM, BILSTM, GPT, and BERT. Both the CNN and LSTM models have the hidden dimension set to 100 and the output dimensions value set to 1. There is a batch size of 64 and an embedding dimension of 200. We utilized a fully connected layer, a pooling layer, and two convolutional layers for the CNN model embeddings layer. The Fully Coupled (FC) layer may detect positive or negative vectors and output them accordingly. Figure 6 shows the results of the comparative study using glove embeddings, which showed that the BERT-BIGRU model performed better than CNN, LSTM, BILSTM, and GPT. That is why we suggest the BIGRU model as a means to improve its performance. Among the deep learning models tested on the dataset, the proposed BERT-BIGRU performed better than CNN, LSTM, BILSTM, GPT, and BERT. The suggested hybrid model is effective, as shown by the performance results. The results of the experiment show that the suggested model outperforms the basic CNN, LSTM, BILSTM, GPT, and BERT.

6. CONCLUSION:

The entertainment industry has seen a shift in the role of social media apps, which have become more popular as an individual block & communication tool. The scope of user feedback regarding these apps is enormous. These massive datasets' user sentiments can now be better understood with the help of natural language processing and deep learning. The premise upon which the proposed model rests is that many deep learning models perform admirably when applied to various ways of representing text. By employing contextualized representations of words through a BERT model, sentiment categorization performed better. In order to create a feature vector representations of the word, the BERT model extracts more precise information. The next step is to feed this representation into a Bi-Directional-GRU model. This model improves sentiment classification accuracy for multiple reasons. To make a pre-trained BERT model more accurate and appropriate to the sentiment analysis task, it can be fine-tuned with a Bi-GRU. As for sequential processing, Bi-GRU is top-notch, but BERT is really good at collecting context. The model is able to provide more precise sentiment analysis by integrating contextual knowledge with sequential data. Processing contextualized embeddings with a Bi-GRU following BERT reduces computational cost and improves efficiency. Take use of BERT's knowledge of context and combine it with Bi-GRU's sequential processing capabilities by integrating a Bi-GRU after the BERT model in the sentiment categorization pipeline. Sentiment classification at the sentence level is improved in experiments utilizing the suggested hybrid deep learning system.

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