Large Language Model and Their Impact on Sentiment Analysis

A Thesis Submitted
In Partial Fulfillment of the Requirements
for the Degree of

MASTER OF TECHNOLOGY

in

Artificial Intelligence

by

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May, 2024

ACKNOWLEDGEMENTS

I have taken efforts in this survey paper. However, it would not have been possible without the kind support and help of many individuals and organizations. I would like to extend my sincere thanks to all of them.

I am highly indebted to **Dr. Rohit Beniwal** for his guidance and constant supervision as well as for providing necessary information regarding the project & also for their support in completing this review paper. I would like to express my gratitude towards the **Head of the Department (Computer Science and Engineering, Delhi Technological University)** for their kind cooperation and encouragement which helped me in the completion of this research survey. I would like to express my special gratitude and thanks to all the Computer Science and Engineering staff for giving me such attention and time.

My thanks and appreciation also go to my colleague in writing the survey paper and the people who have willingly helped me out with their abilities.

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31 May 2024

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CANDIDATE'S DECLARATION

I, Gautam Kumar Jha, Roll No. 2K22/AFI/08 student of M.Tech (Artificial Intelligence), hereby certify that the work which is being presented in the thesis entitled "**Large Language Model and their Impact on Sentiment Analysis**" in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Artificial Intelligence in the Department of Computer Science and Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from August 2022 to Jun 2024 under the supervision of Dr Rohit Beniwal, Asst Prof, Dept of Computer Science and Engineering. The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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CERTIFICATE

Certified that **Gautam Kumar Jha** (Roll No. 2K22/AFI/08) has carried out the research work presented in the thesis titled "**Large Language Model and their Impact on Sentiment Analysis**", for the award of Degree of Master of Technology from Department of Computer Science and Engineering, Delhi Technological University, Delhi under my supervision. The thesis embodies result of original work and studies are carried out by the student himself and the contents of the thesis do not form the basis for the award of any other degree for the candidate or submit else from the any other University /Institution.

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ABSTRACT

The advent of large language models (LLMs) has significantly advanced the field of natural language processing (NLP), particularly in the area of sentiment analysis. This thesis explores the impact of LLMs on sentiment analysis, focusing on their ability to accurately classify and interpret human emotions in textual data. Utilizing LLM model such as BERT, this research examines how these advanced architectures improve sentiment classification in terms of precision, recall, and F1-score, compared to traditional machine learning techniques. Through comprehensive experimentation and analysis, we demonstrate the efficacy of LLMs in sentiment analysis tasks. For instance, using the BERT model on the Twitter US Airline Sentiment dataset, we achieved impressive classification metrics, including a precision of 1.00 for negative sentiment, and high overall scores in micro, macro, and weighted averages. The confusion matrix further illustrates BERT's capability to correctly classify sentiments, with minimal misclassifications across negative, neutral, and positive categories. This study also addresses the challenges associated with deploying LLMs, such as computational demands, model interpretability, and ethical considerations. Additionally, we explore the practical applications of LLMs in various domains, including social media monitoring, customer feedback analysis, and market research. The findings of this thesis underscore the transformative potential of large language models in enhancing sentiment analysis, providing valuable insights for researchers and practitioners aiming to leverage these models for more accurate and nuanced emotion detection.

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List of Abbreviations

SA	Sentiment Analysis
NLP	Natural Language Processing
LLM	Large Language Model
GPT	Generative Pre-trained Transformer
BERT	Bidirectional Encoder Representations from Transformers
GUI	Graphical User Interface
AI	Artificial Intelligence
ML	Machine Learning
DNN	Deep Neural Network
BILSTM	Bidirectional Long Short Term Memory
LSTM	Long Short Term Memory
CNN	Convolutional Neural Network
GRU	Gated Recurrent Unit
TF-IDF	Term Frequency-Inverse Document Frequency
MLM	Masked Language Model
GDA	Gaussian Discriminant Analysis
DL	Deep Learning
RMDL	Random Multi-model Deep Learning
GPU	Graphics Processing Unit
ROBERTA	Robustly Optimized BERT
KNN	K-Nearest Neighbor
SMOTE	Synthetic Minority Over-sampling Technique

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Sentiment analysis is important aspect of NLP that focuses on identifying, understanding and categorizing the sentiment of the text data. It is used to measure and evaluating the public opinion that has become increasingly important for companies, politicians and researchers. As the digital world is growing where millions of texts data are created daily via social media, reviews, forums and other channels.

Sentiment analysis mainly focuses on discovering the subjective opinions within the content. It aims to determine the emotions from the text if the piece of text contains positive, negative or neutral emotions. As the field grows it become possible to identify the specific emotions such as surprise, happiness, anger, and sadness. This ability will allows us to track customer feelings regarding the brands and products, understand political opinions, gauge the market trends and analyse the consumer reactions. The SA provides valuable insights from the text data that can influence the decision-making. [1]

Conventional methods frequently depended on manually created lexicons or rules containing lists of words and the emotions accompanying them. These approaches, however, could not capture the nuances and intricacies of language, including idioms, sarcasm, and meanings that vary depending on the situation. [2]

When using the traditional machine learning method SA suffer from the several important challenges that can limit its effectiveness and accuracy. Traditional methods such as rule-based systems and machine learning algorithms that uses bag-of-words and lexicon-based approaches. These methods often needed help with the nuances and complexity of the natural language failing to account for context and the semantic relationships between words. These traditional methods were more dependent on the feature engineering which required heavy use of domain related knowledge that was indigenously limited by the human ability to anticipate and encode linguistic nuances in a scalable way. This comprehensive process was time-consuming and lacked the flexibility to adapt to new unseen data or changes in the language used over time. [3]

In addition SA using LLMs had difficulty with the words that carry multiple meanings depending on context. Simple algorithms could not differentiate these words effectively that leads to errors in determining the sentiment of the text. Another problem was to handling of multiple sentiments within a the single text that covers various topics which the traditional models often oversimplified into single sentiment scores that will leads to losing the valuable subtleties.[4]

The deficiency of the deep contextual understanding and the lack of ability to process large volumes of data efficiently meant that earlier SA methods were often restricted to special contexts and lacked of generalizability across the multiple languages and text types. This made them less effective in the spite of the rapidly expanding and evolving nature of online content, where new slang, expressions and the communication styles continuously emerges.

The emergence of LLMs has revolutionized sentiment analysis, offering substantial improvements in understanding and interpreting complex language nuances. Traditionally SA methods relied on simpler machine learning models that struggled with irony, sarcasm, and context-dependent expressions. However the LLMs like GPT and BERT have shifted this paradigm significantly. These models trained on the extensive text data and it is good in capturing the intricacies of language due to their deep neural architectures that allow for an unprecedented understanding of context and semantics. [9]LLMs enhanced the SA by giving the accurate predictions and a deeper understanding of the words in the sentences. LLMs like BERT that enable it to understand the context of the word by analysing the words that comes before and after it. It provides the significant advantages while calculating the sentiment of the phrases where contexts play an important role for the SA.GPT can also produce the content that is basically both logical and important to context and that has been leveraged to understand better and predict sentiment even in the complex cases. [10]

Furthermore, because of the flexibility of LLMs these models may be optimized to carry out certain sentiment analysis tasks with relatively limited datasets which makes them extremely practical and flexible across a wide range of languages and many domains. This has created a new opportunities for the sentiment analysis applications such as the ability to identify subtle emotional overtones in social media posts and understand the customer sentiments in product evaluations from the range of geographic and demographic backgrounds.

LLMs have a significant impact on SA, resulting in more reliable, scalable, and accurate systems that can manage the vast amount of data produced. These models have the capability to revolutionize the businesses and organizations that engages with their stakeholders and customers by providing the better insights into human sentiment as they develop.

1.2 MOTIVATION

The motivation behind this work has the significant contribution that language models provide to the development of textual data understanding and interpretation on a variety of digital platforms. The businesses and organizations dependent more and more on the data-driven decision-making it is important to measure the sentiment in large volumes of text for a variety of applications from monitoring social media dynamics to improving customer experiences.

BERT and GPT are the LLMs that have revolutionized NLP because of their remarkable accuracy in tasks that is based on deep language understanding and the contextual knowledge. Due to their substantial training on text data these models can understand the idioms, colloquialisms and changeable syntax linguistic features that are often challenging for the traditional models. Because the sentiment often depends on context and subliminal hints, they are especially well-suited for SA due to their capacity to encode large volumes of contextual information. Some of the challenges occurs by the rapid growth of online material that is language, which is always changing due to the introduction of new slang and idioms. This means that our model should be able to quickly adapt for the new patterns. LLMs are ideal for handle the difficulties that are associated with SA because of their versatility and flexibility. There are more potent analytical tools are required because SA becomes more and more important in a variety of areas including marketing, finance, healthcare and public services. This crucial need can be met by LLMs who can provide sentiment assessments that are more complex and precise, improving decision-making. Businesses and academic institutions are actively investigating the shortcomings of these models in an effort to broaden the range of possible uses for machine learning in the comprehension of human language. Linguistics is advanced by research on LLMs and their impact on sentiment analysis. Beyond its impact on practical applications like customer service Chabot's and market trend analysis systems, this research also fuels technological innovation. This research is driven by the potential of LLMs to revolutionize SA. By leveraging LLMs, we aim to achieve significantly more accurate, efficient, and widely applicable SA methods, leading to a deeper grasp of online emotions and opinions. It aims to explore how these advanced models can be further optimized and applied to meet the growing demand for sophisticated, real-time language understanding tools in various industries.

CHAPTER 2

LITERATURE REVIEW

Kumawat et al. [16] investigated the various models including Electra, Roberta, and BERT. The model focused on the Sentiment dataset in order to demonstrate how much its performance has improved. The study highlighted LLMs' significant importance in NLP and showed how helpful they are in sentiment analysis. However, the publicly accessible portion of the work lacked specific F1 scores and other performance information other than test accuracy percentages for BERT (81.2%), Roberta (80.8%), and Electra (79.8%).

Chinnalagu and Durairaj [7] provided a comparison of sentiment prediction models, demonstrating the superior performance of BERT-base and deep learning models on sizable customer review datasets. It offered experimental research on the fastText Trigram and BERT Hybrid fastText-BILSTM models, as well as optimized BERT and Hybrid fastText-BILSTM models. The results showed that the refined BERT model outperformed other deep learning models in terms of accuracy and other performance metrics, demonstrating the effectiveness of pre-trained Transformers models for accurate sentiment prediction in NLP applications.

Sinha et al. [5] examined and contrasted deep learning techniques for SA using the IMDB movie review dataset. It aimed to identify the tested model that performed best for more research. Overall, the refined BERT models outperformed the other models, highlighting both the value of BERT in SA and its potential for development.

Georgios Fatouros et al. [18] investigated the ChatGPT's potential in calculating the SA in finance domains which is primarily concentrating on the currency market. This study compared the effectiveness of ChatGPT with the FinBERT model using a zero-shot prompting technique and it discovered that ChatGPT performed better than the FinBERT model. This underscored the effectiveness of LLMs in finance applications and the need for prompt engineering in zero-shot situations.

Istvan Uveges and Orsolya [12] presented the HunEmBERT which is model based on BERT. It is employed in Hungarian political writings to categorize the mood and feelings. This study used the individually annotated parliamentary speech data in order to build NLP applications in political domain. In the political area HunEmBERT performed better than traditional sentiment analysis algorithms and showed promising results in emotion categorization. This study includes topics related to irony identification and sarcasm which emphasizing the critical role that context plays in understanding moods and emotions. It also required assessing alternative models and researching aspect-based sentiment analysis to attain even higher performance advantages. HunEmBERT model showed the promise in classifying sentiment and emotions in Hungarian political literature suggesting that it could be a useful tool for political sentiment analysis. It gives the F1 scores for sentiment classification is 86.9%.

Munikar et al. [11] used the SST dataset for fine-grained SA after evaluating the BERT model. It demonstrated how effectively the BERT model and a simple architecture could classify attitudes into different groups. BERT Base performed better on the sentiment analysis task than the traditional machine learning models. This work used transfer learning and deep contextual understanding of the words in the sentence for finding the sentiment. It also compared the accuracy of BERT with the base models for sentiment classification on the dataset. For SST-2 and SST-5, the accuracy of the BERT-base model was 53.2% and 94.0%, respectively.

Patthamanan Isaranontakul and Worapoj Kreesuradej [3] constructed a SA dataset and evaluated the Bi-LSTM and Bi-GRU's use of GPT-3 for comparison. Both demonstrated a notable improvement in model accuracy, achieving accuracy of 0.84 and 0.85 on the simulated dataset created by GPT-3. According to these findings, sentiment analysis model performance may be improved by using synthetic data, particularly in resource-constrained languages or geographical areas.

Lubis et al. [8] compared transformer-based models, particularly BERT-LSTM and BERT CNN, with traditional machine learning models for SA on social media datasets. Because the transformer models employed self-attention strategies, they outperformed other models. BERT LSTM showed an amazing 93% accuracy with an F1 score of 81%, in contrast to 91% accuracy and a 78% F1 score for BERT-CNN. In contrast, traditional models like Random Forest, Naïve Bayes, and Logistic Regression had lower accuracy rates. At 87%, Naïve Bayes had the highest accuracy rate. This comparison showed the effectiveness of transformer models in complex SA applications.

Qiao et al. [17] examined the effectiveness of classifying datasets for aspect-based sentiment analysis utilizing LLMs, namely ChatGPT. Data set used here is a MOOC dataset and it was discovered that ChatGPT performs better than humans in terms of accuracy for aspect-based SA tasks. This study showed the GPT-3 performing better for data labeling tasks and also suggested that it can be used as an human annotation steps for the optimized result.
Bikku et al. [10] investigated the importance of the BERT model for calculating the sentiment for large amounts of data. The dataset used in this work contains 1.6 million sentences and classification is done in two categories those are positive and negative. The best result can be seen in the case of BERT Base layer and BERT Large layer with the Accuaracy is 0.886. This work focused on GPT that is LLM which classified datasets for aspect-based sentiment analysis.

Prasanthi et al. [2] implemented two models those are BERT and ROBERTA models for SA on Tweets. These models are extensively trained on tweets, and they were refined for sentiment analysis. The investigation showed that despite the colloquial language of social media, the algorithms were successful in classifying and analyzing sentiment in tweets. Over a ten-epoch period, the gains in BERT and ROBERTA's we got the accuracy of 0.9916 and 0.9970 which is highest in all the recent works .

Zhang et al. [9] suggested a unique method for financial SA that makes advantage of LLMs enhanced by retrieval. This method integrated LLMs that have been optimized to increase prediction accuracy and contextual understanding with retrieval enhancement modules. Compared to conventional models and general-purpose LLMs, this technique yielded performance gains in accuracy and F1 score ranging from 15% to 48%. The study demonstrated how improving instruction modification and adding external data could improve financial sentiment analysis.

Table .2.1 Summary of the studies undertaken for review

Author(s), & Year	**Model used**	**Dataset**	**Performance Parameters**	**Result**
Anandan Chinnalagu et al., 2023 [7]	BERT, FastText, FastText-BILSTM, LSTM	kaggle Amazon and Yelp's customer reviews	Precision, Recall, F1 score, Accuracy	BERT achieved the highest Accuracy of 91%
Georgios Fatouros et al., 2023 [18]	FinBERT, GPT-P1, GPT-P2, GPT-P3, GPT-P4	forex-related news headlines	Precision, Recall, F1 score, Accuracy, S-MAE	GPT-P2 shows good performance in terms of Accuracy, F1 score, Recall, and S-MAE.
ISTVÁN ÜVEGES et al.,2023 [12]	BERT, Hubert	ISEAR, HunEmPoli	Precision, Recall, F1 score	BERT achieved the highest F1 Score of 70.29%
Manish Munikar et al.,2023 [11]	BERT	Stanford Sentiment Treebank (SST)	Accuracy	$BERT_{BASE}$ and $BERT_{LARGE}$ both achieved Accuracy of 94%
Patthamanan Isaranontakul et al.,2023 [3]	Bi-LSTM, Bi-GRU	COVID-19	Accuracy	Bi-GRU achieved the highest Accuracy of 85%

Arif Ridho Lubis et al.,2023 [8]	BERT-LSTM, BERT-CNN	Twitter	Precision, F1 score, Recall, Accuracy	BERT-LSTM achieved the highest Accuracy of 93%
Kai Qiao et al.,2023 [17]	ChatGPT	course review	F1 Score, Accuracy, Recall	ChatGPT achieved an Accuracy of 78.3%.
Thulasi Bikku et al.,2023 [10]	BERT	Sentiment140 dataset	Precision, Recall, F1 score, Accuracy	BERT (large + Fine-tuning) achieved an Accuracy of 88.6%
Kundeti Naga Prasanthi et al.,2023 [2]	BERT, ROBERTA	COVID-19 NLP Text Classification dataset	Accuracy	ROBERTA achieved an Accuracy of 99.70%.
Boyu Zhang et al.,2023 [9]	FinBERT, BloombergGPT , ChatGLM2-6B, Llama-7B, ChatGPT4.0,	Twitter Financial News dataset and Financial PhraseBank (FPB) dataset.	F1 Score, Accuracy	The llama-7 B model performs better than others, achieving the highest Accuracy
Swapnil Sinha et al.,2022 [5]	BERT-LSTM, ,LSTM-CNN, GRU, BERT, BERT-CNN, CNN, LSTM	IMDB movie dataset	Precision, Recall, F1 score	Good Accuracy is observed in the BERT-CNN model
Spraha Kumawat et al.,2021 [16]	BERT, Roberta, Electra	Twitter US Airline Sentiment	Accuracy	BERT achieved the highest Accuracy of 81.2%

CHAPTER 3
METHODOLOGY

3. 1 DATASET

We have used the Twitter US Airline Sentiment dataset in our supervised model training efforts. This dataset contains data from travellers who tweeted about their experiences. Fourteen thousand tweets from six major US airlines—Virgin America, US Airways, Delta, United, and Southwest—were included in the data collection. The tweets were divided into three emotional classes: 0, -1, and +1. This shows how many sentences there are in each of the three classes. The data is divided into training and test sets. A common split was created, with 80% going to the training data and 10% going to each of the test and validation sets.

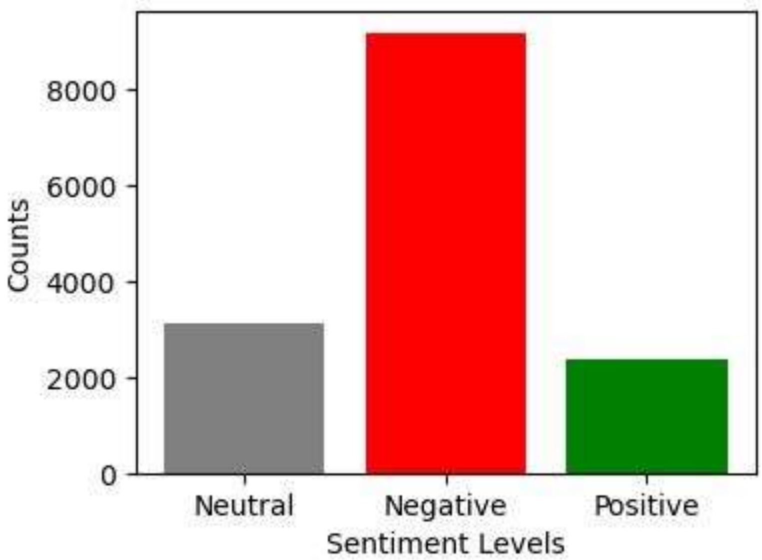


Fig. 3.1. Count of Sentiments

3.2 DATA PRE-PROCESSING

- **Handling Missing Values:** Missing values are a common problem with data; these can be filled in with statistical measures (mean, median, or mode), removed from rows or columns containing the missing data, or imputed using predictions.

- **Removing Noise and Outliers:** Machine learning algorithms can be skewed and affected by outliers that can lead to longer training time and ultimately worse outcomes.

- **Normalization and Scaling:** Included in this are transformations such as standardization, which involves turning variables into a mean of 0 and a standard deviation of 1, or scaling them to a range, such 0 to 1. This is important for methods like neural network gradient descent optimization or k-nearest neighbours (KNN), which presume that data is regularly distributed.

- **Feature Encoding:** converting values of categorical variables to numbers. Typical methods include binary encoding, label encoding, and one-hot encoding.

- **Discretization:** converting continuous characteristics into discrete values, a procedure that can be helpful for some algorithms that perform better with categorical data.

- **Feature Construction:** By applying domain knowledge to create new features from pre-existing ones, algorithms can gain more understanding.

- **Feature Selection:** selecting the most essential aspects for model construction. This increases model performance, expedites the learning process, and decreases the dimensionality of the input.

- **Feature Extraction:** In particular, dimensionality reduction techniques (e.g., PCA) or methodologies (e.g., bag-of-words, TF-IDF for text, and convolution operations for images) are applied in domains such as NLP and image processing.

- **Data Splitting:** Dividing data into testing, validation, and training set. In order to evaluate a model's capacity for generalization, it is helpful to train it on a subset of data and check its performance on another.

- **Handling Imbalanced Data:** Methods like resampling (either by under sampling the majority class or oversampling the minority class), creating synthetic samples (like SMOTE, or Synthetic Minority Over-sampling Technique), or applying specific cost functions or algorithms made to deal with imbalance well are a few examples of techniques.

3.3 LARGE LANGUAGE MODELS

A LLM is the advanced AI model which is designed to understand, generate, and also help interacting with the human’s language by analysing the large scaled collections of the textual data. These models are basically build with the help of using deep learning techniques and are basically characterized by the considerable number of the parameter which is often targeted to billions in numbers by making them allow to capture the complex language patterns. Predominantly it is based on the transformer architecture which can utilized the self-attention mechanisms. LLMs are capable in the processing and also in the understanding of language in a context specific manner. These capabilities enables them to perform NLP tasks which includes text generation, translation, summarization, question answering and sentiment analysis which is directly from the huge datasets in which they are trained upon that includes web pages, books, and articles.

Transformer-Based Models

These models are based on the Transformer architecture which uses self-attention mechanisms to efficiently process sequences of data. Transformer-based models have become the backbone for most modern LLMs due to their effectiveness in handling long-range dependencies and parallelizable training process.

- **BERT :**
  It is developed by Google.BERT is basically used to processes words in relation to all the other words in a sentence rather than one-by-one in order. This allows the model to learn the context of a word based on all of its surroundings.[2] [10][16]

- **GPT:**
  It is Created by OpenAI. The GPT models are trained using a left-to-right approach where each token can only attend to previously generated tokens in the self-attention process. It is designed to generate coherent and contextually relevant text based on a given prompt.[17]

3.4 CLASSIFICATION MODEL

In 2018, Google researchers unveiled BERT, an acronym for Bidirectional Encoder Representations from Transformers. Because it tackles one of the core problems in NLP, which is the requirement to understand the complete meaning of the word by studying the words that occur before and after it, the model provides a noteworthy advancement. BERT scans the full word sequence at once, in contrast to earlier models that processed text in a single direction. Compared to unidirectional models, the model's ability to comprehend the context more precisely is made possible by its bidirectional nature. [10]

BERT Architecture:

BERT is based on the Transformer model, specifically utilizing only the encoder part of the Transformer. BERT has significantly impacted the field of NLP due to its novel training approach and powerful model design. The architecture of BERT is mainly dependent on self-attention mechanisms to process input data.. BERT models are typically deep, consisting of multiple layers of the Transformer encoder. Fig 3.2 shows the detail architecture of BERT. [20]

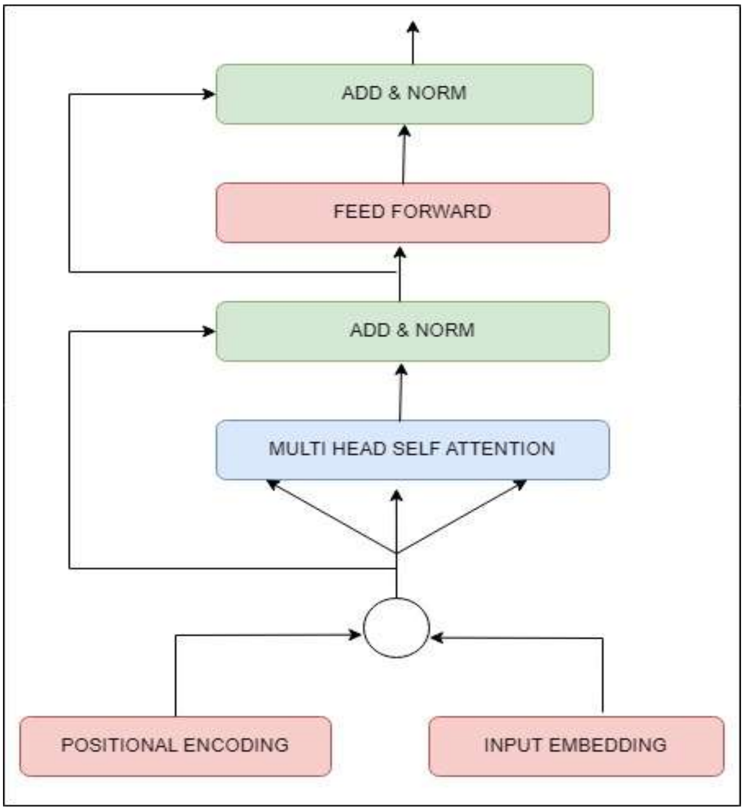
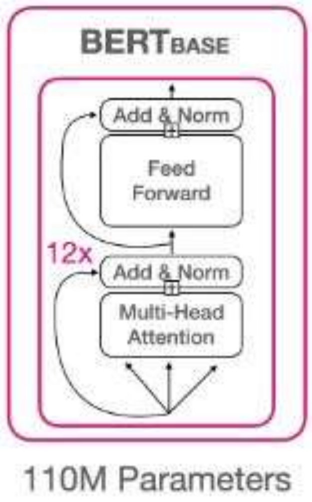


Fig. 3.2. BERT Architecture

There are two primary sizes of BERT. Table 3.1 shows the comparison of BERT Base vs BERT Large.

BERT Base	**BERT Large**
12 layers (transformer blocks)	24 layers
12 attention heads	16 attention heads
110 million parameters	340 million parameters

Table.3.1. BERT Base vs BERT Large



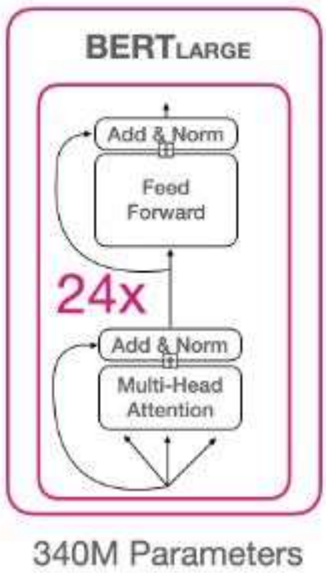


Fig.3.3 BERT Base . [21] Fig .3.4 BERT Large. [21]

Here's a detailed breakdown of BERT's architecture:

Positional Encoding:

Positional encodings is used to provide the information about the relative or absolute position of the tokens in the phrase, since the Transformer relies on self-attention rather than processing sequences in order like RNNs or LSTMs do. This guarantees that when deciding meaning, word order is taken into account.

Input Embedding's:

After the text is tokenized, it is divided into discrete units (words, sub words, or characters). An embedding layer is used to represent each token as a high-dimensional vector. The input tokens' syntactic and semantic content is captured by these embedding's.

Feed-Forward Neural Network:

Feed-Forward Neural Network is used to pass the representations through in order to add non-linearity and improve them even further. To improve gradient flow and training stability, residual connections and layer normalization are added to each sub-layer in the encoder.

Multi-Head Attention:

It is the brains behind the Transformer and BERT. This gives the model the ability to concentrate on various input sequence segments at the same time, giving it a deeper comprehension of the context. Different forms of interactions between words in the sentence, such as syntactic vs semantic relationships, may be the focus of each 'head' of the attention mechanism.

Add & Norm:

In the BERT model, as well as other Transformer-based architectures, "Add and Norm" layers, officially known as "residual connections" followed by "layer normalization," play a important role in the model's ability to train deeply. These components are integral to each block of the Transformer's architecture and help mitigate some of the issues encountered in training deep neural networks. The main purpose of residual connections, or "Add," in BERT is to help alleviate the vanishing gradient problem that can occur in very deep networks. As networks learn, updates to their weights either increase or decrease with each layer, and when a network has many layers, these updates can become so small that the lower layers learn very slowly, if at all ,this is the vanishing gradient problem.
Layer normalization is a technique used to improve the training of deep neural networks. Unlike batch normalization, which normalizes the input across the batch, layer normalization does the normalization for each input separately across its features. This is particularly useful in scenarios where the batch size is small or varies.

Pre-training and Fine-Tuning

First, BERT is pre-trained in an unsupervised fashion on a sizable corpus of text for two NLP tasks: Masked Language Modelling and Next Sentence Prediction.

- **Masked Language Model:**

  Many contemporary NLP models pre-train using the Masked Language Model (MLM), which is most famously employed in BERT. MLM is intended to support language models' better and more reciprocal understanding of context. Here a certain percentage of the input tokens are randomly masked, typically replaced by a special token like [MASK]. The model's objective is then to predict the original identity of these masked tokens, based solely on their surrounding context. For example, in the sentence "The cat sat on the [MASK]," the model needs to predict that the masked word is "mat," using only the other words in the sentence for clues. Fig.3.5 shows the working of masked language model.

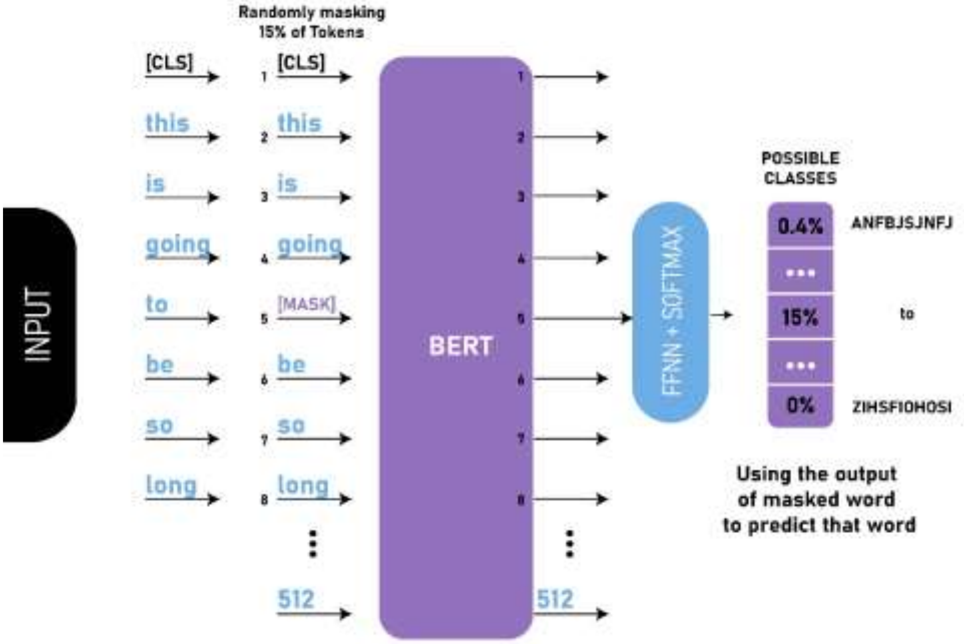


Fig. 3.5. Masked Language Model. [22]

- **Next Sentence Prediction:**

In NSP, the model is trained to predict if a given sentence B follows sentence A. This helps the model understand the relationship between sentences.
We are given two sentences and our objective is to determine if the second sentence in the original text is the one that comes after the first. In order to train the BERT, we use 50% of the data to represent the sentence that follows the original sentence and 50% of the time to represent a random sentence that doesn't follow the original text. Given that the task at hand involves classification, the [CLS] token is the first one. To further distinguish the two sentences that we fed into the model, this model furthermore employs a [SEP] token. Fig 3.6 shows how NSP working.

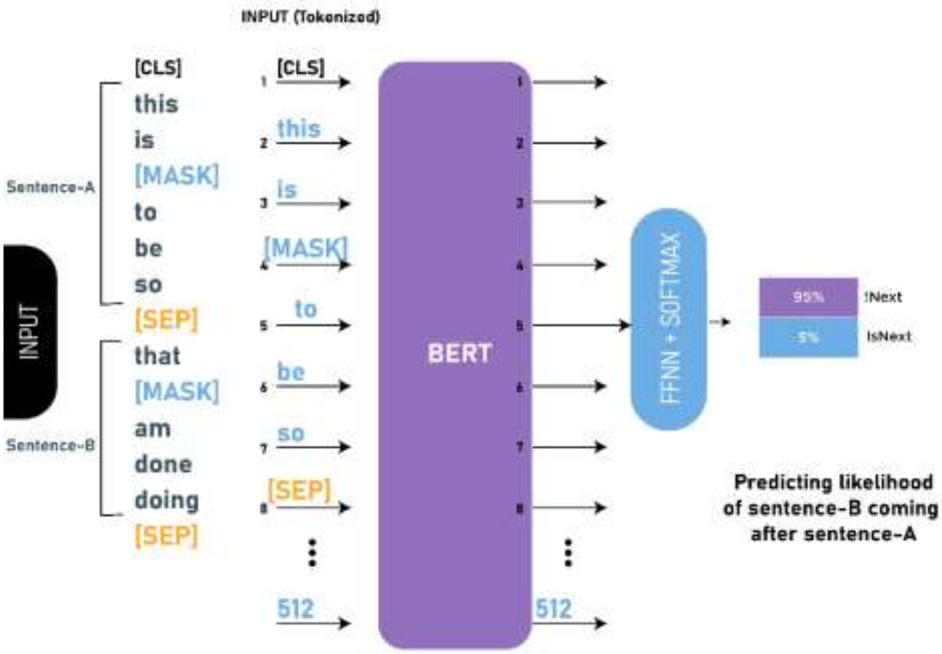


Fig.3.6. Next Sentence Prediction. [22]

3.5 OPTIMIZER

A well-liked gradient descent optimization technique for deep learning model training is the Adam optimizer. Adaptive Moment Estimation, or Adam for short, is an optimization approach that handles sparse gradients on noisy situations by combining the best features of the AdaGrad and RMSProp algorithms.

Adaptive Learning Rate:

In order to manage the sparse gradients on noisy issues, Adam modifies the learning rate for every parameter. It adjusts the learning rate for each model weight by using estimates of the first and second moments of the gradients, which aids in speedier convergence.

Efficiency:

Adam is a good choice for situations with plenty of data and/or parameters since he is computationally efficient, requires little memory, and is invariant to diagonal rescaling of the gradients.

Hyper parameters:

It has intuitive hyper parameters that typically require minimal tuning. The most common hyper parameters include:

- **α (alpha):** The learning rate or step size. The proportion that weights are updated (default is 0.001).
- **β1 (beta1):** The exponential decay rate for the first moment estimates
- **β2 (beta2):** The exponential decay rate for the second-moment estimates. This controls the moving average of the squared gradients.
- **ε (epsilon):** A very small number to prevent any division by zero in the implementation .

3.6 PERFORMANCE EVALUTION

For assessing the effectiveness of classification models, a basic machine learning tool is the confusion matrix. It offers a thorough examination of how well a model performs across several classes by breaking down the model's predictions against the true labels in detail. Confusing matrix applications are widespread for the following main reasons.

3.7 PERFORMANCE PARAMETERS

The performance parameters used to evaluate sentiment analysis systems can vary depending on the specific task and application. However, some common metrics is represented in Table.3.2:

KPI	Formula used
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1 score	$\frac{2*Precision*Recall}{Precision+Recall}$

Table 3.2 Performance Parameter

CHAPTER 4

EXPERIMENTAL SETUP & RESULT ANALYSIS

4.1 OBJECTIVE:

The aim was to evaluate the performance of the Large Language Model (BERT) for sentiment analysis on the Twitter US Airline Sentiment dataset. BERT was chosen due to its advanced capabilities in contextual understanding and its proven success in various NLP tasks.

4.2 DATASET DESCRIPTION:

The dataset was obtained from a publicly available source on kaggle.com, which contains tweets directed at various US airlines, capturing customer sentiment. This dataset contains data from travellers who tweeted about their experiences. Fourteen thousand tweets from six major US airlines—Virgin America, US Airways, Delta, United, and Southwest—were included in the data collection. The tweets were divided into three emotional classes: neutral, negative, and positive. The dataset contains seven columns.
The dataset was loaded using the Pandas library in Python. This step allowed for an initial examination of the data structure and understanding of the available features. Fig.4.1. describes the Twitter Us Airline Dataset

```
df
```

	airline_sentiment	negativereason	text	tweet_coord	tweet_created	tweet_location	user_timezone
0	neutral	NaN	@VirginAmerica What @dhepburn said.	NaN	24-02-2015 11:35	NaN	Eastern Time (US & Canada)
1	positive	NaN	@VirginAmerica plus you've added commercials t...	NaN	24-02-2015 11:15	NaN	Pacific Time (US & Canada)
2	neutral	NaN	@VirginAmerica I didn't today... Must mean I n...	NaN	24-02-2015 11:15	Lets Play	Central Time (US & Canada)
3	negative	Bad Flight	@VirginAmerica it's really aggressive to blast...	NaN	24-02-2015 11:15	NaN	Pacific Time (US & Canada)
4	negative	Can't Tell	@VirginAmerica and it's a really big bad thing...	NaN	24-02-2015 11:14	NaN	Pacific Time (US & Canada)
...	...	...	...	...	...	...	...
14635	positive	NaN	@AmericanAir thank you we got on a different f...	NaN	22-02-2015 12:01	NaN	NaN

Fig. 4.1. Dataset overview

The diagram given in Fig.4.2 is a pie chart illustrating the distribution of tweets related to different airlines within the US Airline Sentiment dataset. Each segment of the pie chart represents the proportion of tweets mentioning a specific airline, with the size of each segment corresponding to the relative frequency of tweets for that airline. The percentages indicate the share of the total dataset that each airline accounts for.

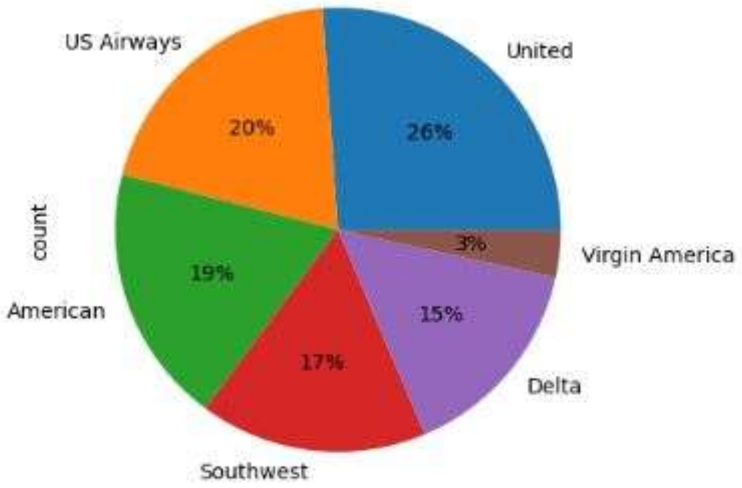


Fig.4.2. Distribution of tweets across different Airlines using Pie chart

4.3 DATA PRE-PROCESSING:

Missing values in the dataset were checked, particularly in critical columns such as the text of the tweets and sentiment labels. Decisions on whether to fill or drop these values were made based on their importance and quantity, ensuring the integrity of the data used for analysis. Additionally, a series of text cleaning steps were undertaken to prepare the tweets for analysis. URLs, which do not provide useful information for sentiment analysis, were removed. User mentions and special characters were also eliminated to focus solely on the textual content of the tweets. Furthermore, all text was converted to lowercase to ensure uniformity across the dataset and to prevent duplication caused by case sensitivity. This thorough pre-processing enhances the quality of the data, which is crucial for accurate sentiment analysis. Fig.5. shows the Data after pre-processing.

	airline_sentiment_encodded	cleaned_text
0	1	virginamerica user said
1	2	virginamerica plus added commercials experienc...
2	1	virginamerica today must mean need take anothe...
3	0	virginamerica really aggressive blast obnoxiou...
4	0	virginamerica really big bad thing
...	...	...
14635	2	user thank got different flight chicago
14636	0	user leaving minutes late flight warnings comm...
14637	1	user please bring american airlines blackberry
14638	0	user money, change flight, answer phones sugge...
14639	1	user ppl need know many seats next flight plz ...

14640 rows × 2 columns

Fig.4.3. Data after pre-processing

4.4 TOKENIZATION:

The cleaned text was broken down into individual words or tokens. This step was essential for the subsequent natural language processing tasks. Fig 6 shows the tokenized sentence.

```
Original:  virginamerica seriously would pay flight seats playing really bad thing flying va
Tokenized:  ['virgin', '##ame', '##rica', 'seriously', 'would', 'pay', 'flight', 'seats', 'playing', 'really', 'bad', 'thing', 'flying', 'va']
Token IDs:  [6261, 14074, 14735, 5667, 2052, 3477, 3462, 4272, 2652, 2428, 2919, 2518, 3909, 12436]
```

Fig.4.4. Tokenized sentence

4.5 ARCHITECTURE OF PROPOSED MODEL:

Designed the BERT Base model for sentiment analysis.
The diagram depicted Fig 4.5 shows the architecture of a BERT-based model for sentiment analysis task. The model comprised an input layer, a BERT layer, and a dense layer.

The model began with two input layers, each accepting inputs of shape (None, 128). These layers were designed to handle the input sequences of token IDs and attention masks, necessary for processing text data through BERT. Both input layers had no trainable parameters, as their role was to pass the input data to subsequent layers. The core of the model was the tf_bert_model layer, based on the TFBertModel from the Hugging Face Transformers library. This layer takes the input sequences and produced a sequence output of shape (None, 128, 768), where 128 denotes the sequence length, and 768 representes the hidden state size of the BERT model. The tf_bert_model layer contains 109,482,240 parameters indicating the depth of the BERT architecture. This layer includes trainable parameters, which were fine-tuned during the training process to adapt the pre-trained BERT model to the specific sentiment analysis task.

Following the BERT layer, it contains dense layer designed to output predictions for the sentiment classification task. This dense layer connected to the pooled output of the BERT model, which had a shape of (None, 768). The dense layer reduced this to an output shape of (None, 3), corresponding to the three sentiment classes. The dense layer had 2,307 trainable parameters, including weights and biases, which were adjusted during training to map the BERT representations to the sentiment labels accurately.

The overall model contained a total of 109,484,547 parameters, all of which were trainable. This included the large number of parameters from the BERT model and a smaller number from the dense layer. The model's architecture demonstrated a typical fine-tuning setup where a pre-trained BERT model was adapted for a specific task with an additional task-specific layer. The diagram highlighted the interconnectedness of the layers and the flow of data through the network, from input to output.

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                Output Shape                 Param #   Connected to
==================================================================================================
 input_1 (InputLayer)        [(None, 128)]                0         []

 input_2 (InputLayer)        [(None, 128)]                0         []

 tf_bert_model (TFBertModel  TFBaseModelOutputWithPooli   1094822   ['input_1[0][0]',
 )                           ngAndCrossAttentions(last_   40         'input_2[0][0]']
                             hidden_state=(None, 128, 7
                             68),
                              pooler_output=(None, 768)
                             , past_key_values=None, hi
                             dden_states=None, attentio
                             ns=None, cross_attentions=
                             None)

 dense (Dense)               (None, 3)                    2307      ['tf_bert_model[0][1]']

==================================================================================================
Total params: 109484547 (417.65 MB)
Trainable params: 109484547 (417.65 MB)
Non-trainable params: 0 (0.00 Byte)
```

Fig.4.5. Model Details with Number of Parameters

4.6 MODEL TRAINING:

During the training of the model, we employed a batch size of 32 and trained the model for 4 epochs. These parameters were chosen empirically based on preliminary experiments and computational resources available. For other crucial parameters, such as the maximum sequence length of 128 tokens, the learning rate of 2e-5, and the Adam optimizer epsilon value of 1e-8, we also used the default values. Our model demonstrated the usefulness of the selected configuration in capturing the subtleties of emotion indicated in Twitter data, with an accuracy of about 97% for BERT. The model was able to acquire strong representations of tweet sentiment through the combination of batch size, number of epochs, and default parameter settings, which helped to develop sentiment analysis methods for social media content. A variety of parameters such as computational overhead and the model's explainability will be taken into consideration when selecting the optimal categorization model in practice. We utilize the Accuracy as the primary model evalution criteria for highlighting the top performing model.

```
Epoch 1/4
758/758 [==============================] - 728s 867ms/step - loss: 0.5150 - categorical_accuracy: 0.7892 - val_loss: 0.3305 - val_categorical_accuracy: 0.8746
Epoch 2/4
758/758 [==============================] - 649s 856ms/step - loss: 0.2621 - categorical_accuracy: 0.9084 - val_loss: 0.2416 - val_categorical_accuracy: 0.9221
Epoch 3/4
758/758 [==============================] - 648s 856ms/step - loss: 0.1597 - categorical_accuracy: 0.9492 - val_loss: 0.2305 - val_categorical_accuracy: 0.9451
Epoch 4/4
758/758 [==============================] - 648s 855ms/step - loss: 0.1104 - categorical_accuracy: 0.9694 - val_loss: 0.2696 - val_categorical_accuracy: 0.9514
```

Fig.4.6. Training of BERT

4.7 CONFUSION MATRIX:

We used the US Airline Tweets dataset for drwaing the confusion matrix. The confusion matrix in Figure 4.7 demonstrated how well the BERT model is performing for sentiment analysis task. The matrix is a three-by-three grid that compares the counts of the expected and actual emotion labels.The confusion matrix indicates that BERT model identified positive and negative attitudes very well but slightly showing greater error rate when recognizing neutral and negative sentiments.

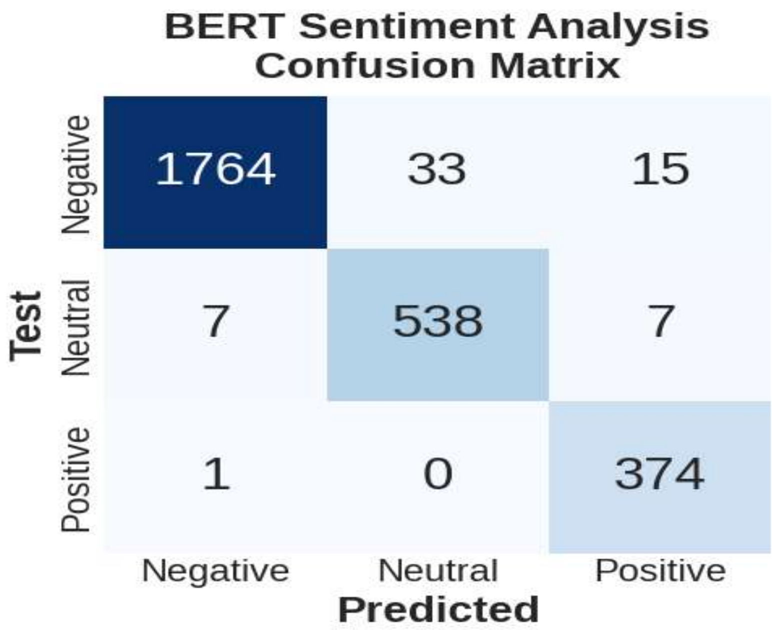


Fig.4.7. Confusion Matrix

4.8 CLASSIFICATION REPORT:

The classification report which we are generated which provides a comprehensive performance of the BERT model on the SA task for the US Airline Tweets dataset. It gives the detailed explanation regarding the precision, recall and F1-score for each sentiment class and also gives the detailed explanation about aggregated metrics.

For the negative sentiment class, the model achieved a perfect precision of 1.00 indicating all the instances that are predicted as negative were actually negative. The recall for this class was 0.97 indicating that model correctly identified 97% of all the true negative instances. Consequently the F1-score which balances the precision and recall which was 0.98. The support for this class was 1,812 indicating the total number of negative instances in the test set.

For the neutral sentiment class the precision was 0.94 it means that 94% of the instances which we are taken predicted as neutral were correct. The recall was calculated as 0.97 indicating that the model was successfully identified 97% of all true neutral instances. The F1-score for neutral class was 0.96. and support for this class was 552.

For the positive sentiment class the model achieved the precision of 0.94 which means 94% of the instances predicted as positive being accurate. The recall was perfect at 1.00, indicating that the model identified all true positive instances. The resulting F1-score was 0.97, reflecting high performance in predicting positive sentiments. The support for this class was 375.

This report also included aggregated metrics. The micro average precision, recall, and F1-score were all 0.98 are indicating the overall performance of the model. The macro average precision, recall, and F1-score were 0.96, 0.98, and 0.97 respectively, indicating a balanced performance across all sentiment classes. The weighted average calculated for each class which indicates the support for each class that showed the precision, recall and F1-score for all classes is 0.98.

Overall, the classification report highlighted that the performance of BERT model excelling in identifying negative and positive sentiments and slightly lower but still strong performance for neutral sentiments. The high scores across all metrics demonstrated the model's robustness and accuracy in sentiment classification tasks. Fig 4.8 shows the classification report.

Classification Report for BERT:

	precision	recall	f1-score	support
Negative	1.00	0.97	0.98	1812
Neutral	0.94	0.97	0.96	552
Positive	0.94	1.00	0.97	375
micro avg	0.98	0.98	0.98	2739
macro avg	0.96	0.98	0.97	2739
weighted avg	0.98	0.98	0.98	2739
samples avg	0.98	0.98	0.98	2739

Fig.4.8. Classification Report

CHAPTER 5

CHALLENGES

While BERT offers significant potential for improving sentiment analysis, implementing it comes with its own set of challenges:

Computational Cost: BERT models are known for their large number of parameters, making them computationally expensive to train and run. This can be called as a hurdle basically when if you have limited resources or you have a requirement real-time analysis of large datasets.

Data Requirements: BERT models perform the best when it is trained on the large amount of label sentiment data. These includes Gathering, cleaning, and annotating such type of data which can be very time-consuming and also too resource-intensive.

Domain Adaptation: BERT models are trained on common data that may not perform well on the specific type of domain with the unique language styles and terminology. We may also need to fine-tune the model on the domain-specific data for the accurate results.

Interpretability: This is an important understanding that how the BERT model can arrive at its sentiment classification which could be very difficult. This also lacks of interpretability that can be a huge challenge particularly when you need to explain the model's reasoning or we have to locate potential biases.

Bias and Fairness: Large language models can also inherit biases present in the data on which they are trained. It is very crucial to be aware of potential biases and implement techniques to mitigate them during the training and evaluation phases.

In addition to these type of general challenges here are also some specific type of considerations for using a BERT model that we have used in our study:

- **Choosing the right pre-trained model:** There are different pre-trained BERT models exist having its own strengths and weaknesses. It is important to select the most appropriate model for our specific sentiment analysis task which is very crucial for our work.
- **Fine-tuning the parameters:** We have identified that Fine-tuning a pre-trained BERT model on our sentiment analysis dataset is very necessary for the optimal performance of our finding. Also It is very important to find the right hyper parameters for the fine-tuning which can be a iterative process.

CHAPTER 6

CONCLUSION AND FUTURE WORK

The exploration carried out by our research helps to enhance the important developments and difficulties in the sentiment analysis which is made possible with the help of Large Language Models. Also in addition it also enlighten for giving a thorough review of our area by going deep inside the tough and complex designs of LLMs like BERT, GPT etc. Our study also explained that how new models that outperformed the previous models while obtaining the context and similarity that are radically changed which improves the process of how we are thinking about and also how we can handle natural language processing tasks. We also concluded while implementing the BERT model to analyse the sentiments in the US Airline Tweets dataset that helps to convert theoretical knowledge into a practical application. This study also showcased the real-world importance and applicability of BERT model by detailing the process of fine-tuning and adapting the model to the specific dataset which are characterized by the informal language and a huge text data. Our findings also highlights the BERT's efficiency in an accurately classifying the sentiments of air lines dataset issued by twitter that significantly covers in the deciphering customers emotions and opinions about the airline services hence by offering the valuable insights into the businesses while also enhancing the customer satisfaction.

In the future it is found that BERT will be integrated with multiple multimodal data sources for the further exploration. Currently the dataset of Customer feedback consists of voice notes, photos, and videos and text hence creating the multimodal models that can also interpret these several input data at the same time may also provide a more comprehensive understanding of the attitudes and preferences of the target audience. Future research should also explores the integration of LLMs with other the other AI models by the more refinement of the models for a better handle sentiment expressions such as sarcasm and irony, and the reduction of these computational demands to make these kind of models are more accessible and sustainable in the future.

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LIST OF PUBLICATIONS AND THEIR PROOFS

[1] G. Kumar Jha, and R. Beniwal, “Sentiment Analysis using Large Language Models: A Review”,in proceedings of the International Conference on Optimization Techniques in Engineering an Technology(ICOTET) 2024,Jun. 14,2024 .[**Accepted**]

[2] G. Kumar Jha, “Advancing Sentiment Analysis for US Airline Tweets:From Machine Learning To Transformer”,in proceedings of the International Conference on Intelligent Computing and Communication Techniques(ICICCT) 2024,Jun. 28,2024.[**Accepted**]