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SENTIMENT ANALYSIS OF FINANCIAL NEWS USING THE BERT MODEL

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ABSTRACT

Financial decisions are strongly reliant on correct sentiment analysis. Traditional methods frequently fall short of capturing hidden sentiments. A financial market dataset comprising 5,842 reviews was collected for analysis. Among these, 1,852 reviews were positive, 860 were negative, and 3,130 were neutral. After downsampling, the data was divided into two groups: the training set and the test set. The training set was employed to train the model, while the test set was reserved for evaluation. This study applies a deep learning approach using the Bidirectional Encoder Representations from Transformers (BERT) model to train the dataset. The performance of the model was measured using accuracy, precision, recall, and F1-score. The model gave a high performance with an accuracy of 95.29%, precision of 95.37%, recall of 95.24%, and a minimal loss of 9.07%. Notably, the F1-score, which provides a balanced evaluation of the model's efficiency, is 95.32%. These findings highlight the BERT model's effectiveness in conducting sentiment analysis in financial markets. The study not only enhances the field of financial sentiment analysis, but it also emphasises the practicality and dependability of using deep learning techniques to extract significant insights from financial data.

I. INTRODUCTION

The swift expansion of web-based applications such as social media platforms and blogs has resulted in an explosion of comments and reviews about daily life activities. Financial analysis is useful for identifying economic trends, developing financial strategies, and developing long-term corporate goals [1]. These provide critical information to shareholders about a company's revenue, expenses, profitability, and debt. Financial reporting and analysis refer to the systematic collection and monitoring of a company's financial data, which includes both revenues and expenses [2-3]. Sentiment analysis has become an important technique for extracting information from social networks. It is commonly used in real-world scenarios to gather feedback on products or services and develop marketing predictions [4–5]. It also helps with data identification and quantification in Natural Language Processing (NLP), computational linguistics, text analysis, and other domains by using machine learning algorithms to detect biassed text and extract useful information from presented textual data [6-7].

Natural Language Processing (NLP) is an essential artificial intelligence area that helps computers analyse human spoken and written language [8]. The process of sentiment analysis has been studied at different levels. However, sentiments and opinions can be observed primarily at the document, sentence, or aspect levels [9-12] as shown in Figure 1.

i. **Document Level:** The method is based solely on the document, which means that the complete document is considered as a whole for sentiment analysis in order to determine the polarity [13].
ii. **Sentence Level:** Sentiment is analysed for each sentence at this level to determine the polarity of each sentence [14].
iii. **Aspect/Feature Level:** This level performs fine-grained analysis because it aims to find sentiments with respect to the specific aspects of entities [15-16].

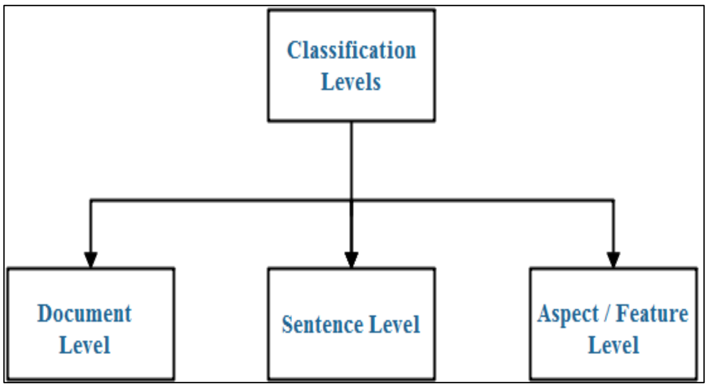

Figure 1: Sentiment Classification Levels.
Source: Authors, (2024).

Machine learning techniques are classified into two types: traditional approaches and deep learning approaches. Deep learning was introduced by G.E. Hinton in 2006 as a machine learning approach connected to deep neural networks [17-18]. It is also known as a subset of machine learning that revolutionised the field of sentiment analysis by enabling the extraction of complex sentiments and contextually rich information from textual data. It is popularly known as multi-layered neural networks inspired by the interconnected sensory neurons of the human brain [19]. The most prominent deep learning approaches include transformer networks, deep neural networks, recursive neural networks, recurrent neural networks, and hybrid neural networks [20]. However, the most commonly used transformer networks for sentiment analysis are Bidirectional Encoder Representations from Transformers (BERT), Generative Pre-trained Transformer (GPT), Robustly Optimised BERT Pre-training Approach (RoBERTa), and eXtreme MultiLingual Pre-training for Language Understanding (XLNet) [21].

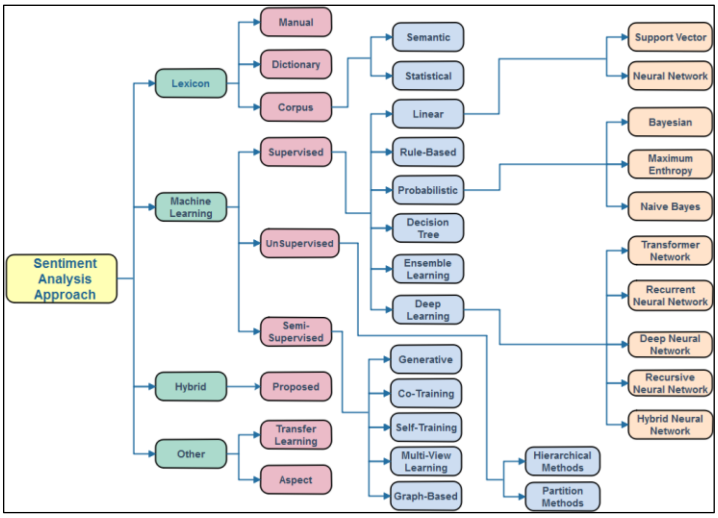

Figure 2: Sentiment Analysis Approach.
Source: [20].

Sentiment analysis classification employs four primary approaches: lexicon-based, machine learning-based, hybrid, and other methods [22] as shown in Figure 2. Lexicon-based systems rely on prepared word lists that have either positive or negative connotations. To anticipate sentiment in new data, machine learning systems use algorithms trained on labelled data. To improve classification performance, the hybrid technique integrates both methods [23-25]. Other approaches include rule-based and deep learning algorithms [26].

There have been numerous surveys and review articles on sentiment analysis. Medhat et al. [9] proposed a detailed survey studying and presenting sentiment analysis methodologies and applications. The authors also covered related disciplines to sentiment analysis, such as emotion recognition and resource development. Rauf et al. [27] investigated the polarity of the IMDB dataset using sentiment analysis to develop a transformer-based model, such as BERT. The BERT model outperformed most previous machine learning and deep learning-based models on the supplied dataset, according to the findings analysis. Gong et al. [28] proposed a transformer-based method that combines knowledge distillation and text augmentation. This method reduces processing costs and training time while improving overall performance. The accuracy for emotion recognition in text is 93.28%, with BERT at 93.38%, ALBERT at 92.06%, and mobileBERT at 92.74%.

Bharti et al. [29] proposed a hybrid model using support vector machines alongside CNN and Bi-GRU as deep learning components. This approach yielded an accuracy of 80.11% across diverse datasets (phrases, tweets, and conversations). Paredes-Valverde et al. [30] used the CNN and word2vec in sentiment analysis to improve product quality. The experimental outcomes on a vast Twitter corpus of 100,000 tweets verified its effectiveness, showing high precision, recall, and F-measure values of 88.7%. Souma et al. [31] investigate historical news sentiments in order to estimate financial market attitudes. They gather news feelings from stock returns following an article. The study evaluates Thompson Reuters News Archive and Dow Jones Industrial Average stocks (2003-2013) using TensorFlow and word vectors from Wikipedia and Gigaword. Choosing news based on sentiment scores improves forecasting accuracy significantly.

Mula et al. [32] used the machine learning models to predict sentiments in developer comments, demonstrating the power of embedding approaches, feature selection, class imbalance handling, and deep learning architecture in sentiment prediction. The efficiency of their models was proven by experimental data. Chen et al. [33] used CSI 300 share value data from the Chinese SM to compare standard N.N. price prediction with deep learning and discovered that deep learning prediction performance outperformed conventional N.Ns. Rangila et al. [34] investigated BERT and LSTM models for sentiment analysis on transcribed audio. BERT, a Google-developed algorithm, performed well in terms of speed and accuracy, obtaining 98% accuracy in just two epochs. LSTM, on the other hand, only achieved 51% accuracy after five epochs. BERT is the recommended option due to its higher accuracy and efficiency.

II. THE BIDIRECTIONAL ENCODER REPRESENTATIONS FROM TRANSFORMERS (BERT) MODEL

The BERT framework is divided into two stages: pre-training and fine-tuning. Initially, it is trained on a large amount of unlabeled data for various NLP tasks. Fine-tuning then uses labelled data to customise it for specific tasks [35]. BERT, which is based on the Transformer network, has encoder blocks with multi-head attention and feedforward layers. This enables it to attend to several segments of the input at the same time and grasp links between tokens. This architecture improves contextual comprehension for a wide range of natural language processing applications.

III. METHODOLOGY

The study conducted a sentiment analysis on financial market datasets by leveraging advanced natural language processing techniques using the Bidirectional Encoder Representations from Transformers (BERT) model. This method intends to detect sentiments within financial texts, allowing for more informed investment decisions. This procedure entails thorough data collection, preprocessing, model training, and evaluation as shown in Figure 3 with brief explanation what each functional block means in the section below.

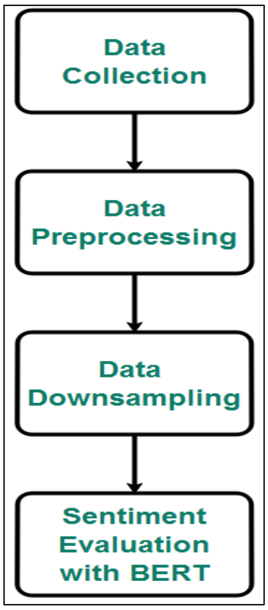

Figure 3: Block Diagram of Sentiment Analysis Process with BERT Model.
Source: Authors, (2024).

A. **Data Collection:** The data was collected using a financial dataset for sentiment analysis, which included 5842 test samples from the FiQA and the Financial PhraseBank [36]. The sentiment labels in this dataset are as follows: neutral (3130), positive (1852), and negative (860). Essential Python libraries such as Keras, TensorFlow, NumPy, scikit-learn, and PyTorch were used to efficiently handle this dataset.
B. **Data Preprocessing:** The BERT model requires multiple phases of data preprocessing before it can be used for sentiment analysis. Text cleaning begins by removing noise such as special characters and HTML elements. Tokenization then divides the text into manageable parts for study. Padding ensures that the model's input length is consistent. Label encoding assigns numerical values to sentiment categories. These processes work together to improve the initial data.
C. **Data Downsampling:** It is used to ensure a balanced distribution of classes. An equitable representation is ensured by reducing both neutral and positive sentiment labels to 860 labels, which correspond to the negative sentiment count from the test set. This eliminates any bias towards a specific sentiment category, allowing for more accurate sentiment analysis. As a result, the model is trained on a large dataset, which improves its capacity to make accurate predictions across a wide range of sentiment labels.

Table 1: Distribution of the dataset.

	Neutral	Positive	Negative	Total
Train	3130	1852	860	**5,842**
Test	860	860	860	**2,580**

Source: Authors, (2024).

D. **Sentiment Evaluation with BERT:** Key metrics for evaluating sentiment using BERT include accuracy, precision, recall, and F1-score. These metrics assess the model's ability to correctly identify sentiments, giving critical information for reliable sentiment analysis in financial texts.
   i. **Accuracy:** Accuracy measures the proportion of correctly classified sentiments to total forecasts. It provides a comprehensive view of the model's performance, but its dependability is affected by data imbalances, which may distort its interpretation.
   ii. **Precision:** Precision is the ratio of true positive forecasts to overall positive predictions. It emphasises the model's capacity to properly recognise positive feelings, decreasing the probability of false positives and ensuring reliable results.
   iii. **Recall:** The ratio of actual positive predictions to true positive cases is represented by recall. It assesses the model's sensitivity in detecting all positive attitudes, eliminating false negatives and improving overall efficacy.
   iv. **F1-Score:** The F1-score is a balanced measure that is calculated by taking the harmonic mean of precision and recall. It provides a full evaluation of the model's effectiveness, which is especially useful in cases where the impact of both false positives and false negatives is significant.

IV. RESULTS AND DISCUSSIONS

The performance evaluation involved using the BERT model to analyse a financial dataset encompassing 5,842 reviews. Figure 4 shows ten sentences along with their corresponding sentiment labels from the pretrained financial dataset. This data visualization provides a tangible representation of sentiment analysis, offering the raw data as presented.

	Sentence	Sentiment
0	The GeoSolutions technology will leverage Bene...	positive
1	ESI onlows, down1.50 to $2.50 BK a real po...	negative
2	For the last quarter of 2010 , Componenta 's n...	positive
3	According to the Finnish-Russian Chamber of Co...	neutral
4	The Swedish buyout firm has sold its remaining...	neutral
5	$SPY wouldn't be surprised to see a green close	positive
6	Shell's $70 Billion BG Deal Meets Shareholder ...	negative
7	SSH COMMUNICATIONS SECURITY CORP STOCK EXCHANG...	negative
8	Kone 's net sales rose by some 14 % year-on-ye...	positive
9	The Stockmann department store will have a tot...	neutral

Figure 4: Data Visualization.
Source: Authors, (2024).

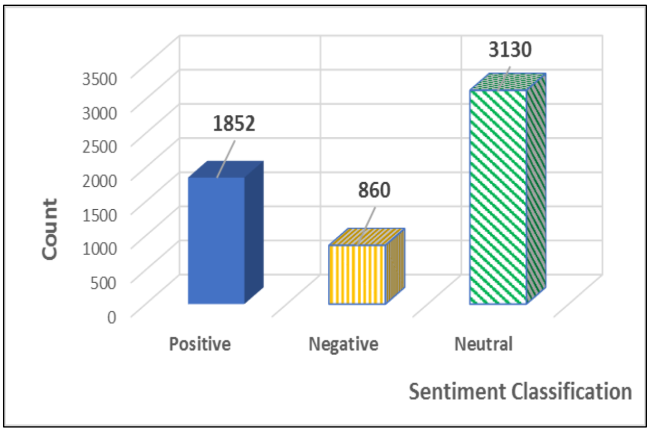

Figure 5: Bar chart depicting sentiment classification.
Source: Authors, (2024).

Figure 5 presents a chart showcasing the sentiment classification of the raw data from the pretrained financial dataset consisting of 5,842 reviews. This data breakdown reveals that 1,852 reviews were classified as positive, 860 as negative, and 3,130 as neutral sentiments.

	Sentence	Sentiment
0	the geosolutions technology will leverage bene...	positive
1	esi on lows down 150 to 250 bk a real possibility	negative
2	for the last quarter of 2010 componenta s net...	positive
3	according to the finnishrussian chamber of com...	neutral
4	the swedish buyout firm has sold its remaining...	neutral
5	spy wouldnt be surprised to see a green close	positive
6	shells 70 billion bg deal meets shareholder sk...	negative
7	ssh communications security corp stock exchang...	negative
8	kone s net sales rose by some 14 yearonyear i...	positive
9	the stockmann department store will have a tot...	neutral

Figure 6: Data visualization of a cleaned dataset.
Source: Authors, (2024).

In Figure 6, a visual representation illustrates the dataset post-application of the data preprocessing techniques, resulting in a cleaner and more organised dataset. These visualisations offer a concise and informative summary of the sentiment analysis findings and emphasise the importance of data preprocessing in enhancing data quality and subsequent analysis accuracy.

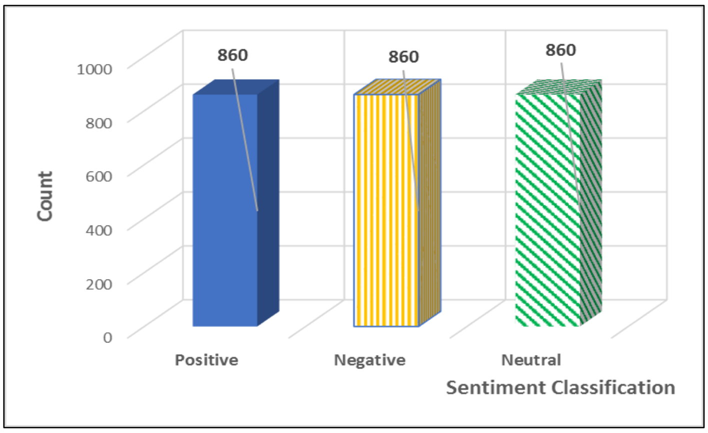

Figure 7: Bar chart depicting count plot after downsampling.
Source: Authors, (2024).

Figure 7 displays a bar chart presenting the count plot after implementing data downsampling. Downsampling is crucial to balance the class distribution in the dataset, especially when dealing with imbalanced sentiment data. It involves reducing the number of instances in the overrepresented class, which in turn prevents the model from being biassed towards the majority class. This ensures a more accurate and fair sentiment analysis by allowing the model to equally weigh the contribution of each sentiment category, leading to more reliable results in financial sentiment analysis.

```
Model: "model_4"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_5 (InputLayer)           [(None, 53)]         0           []

 embedding_18 (Embedding)       (None, 53, 36)       261792      ['input_5[0][0]']

 dense_45 (Dense)               (None, 53, 36)       1332        ['embedding_18[0][0]']

 tf.__operators__.add_4 (TFOpLa  (None, 53, 36)      0           ['dense_45[0][0]']
 mbda)

 layer_normalization_8 (LayerNo  (None, 53, 36)      72          ['tf.__operators__.add_4[0][0]']
 rmalization)

 multi_head_attention_4 (MultiH  (None, 53, 36)      37668       ['layer_normalization_8[0][0]',
 eadAttention)                                                    'layer_normalization_8[0][0]']

 dense_53 (Dense)               (None, 53, 64)       2368        ['multi_head_attention_4[0][0]']

 flatten_4 (Flatten)            (None, 3392)         0           ['dense_53[0][0]']

 dropout_9 (Dropout)            (None, 3392)         0           ['flatten_4[0][0]']

 dense_54 (Dense)               (None, 3)            10179       ['dropout_9[0][0]']

==================================================================================================
Total params: 313,411
Trainable params: 313,411
Non-trainable params: 0
__________________________________________________________________________________________________
```

Figure 8: Trainable parameters in BERT.
Source: Authors, (2024).

Figure 8 illustrates the trainable parameters within a BERT (Bidirectional Encoder Representations from Transformers) model. These parameters are elements of the model that can be adjusted and fine-tuned during the training process, enabling BERT to adapt and excel in various natural language understanding tasks, including sentiment analysis and text classification.

```
Epoch 1/30
114/114 [==============================] - 5s 33ms/step - loss: 1.0714 - accuracy: 0.4225 - precision_14: 0.4916 - recall_14: 0.0648 - val_loss: 1.1884 - val_accuracy:
0.0000e+00 - val_precision_14: 0.0000e+00 - val_recall_14: 0.0000e+00 - lr: 0.0010
Epoch 2/30
114/114 [==============================] - 3s 29ms/step - loss: 0.7347 - accuracy: 0.6736 - precision_14: 0.7410 - recall_14: 0.5722 - val_loss: 0.8258 - val_accuracy:
0.6742 - val_precision_14: 0.6899 - val_recall_14: 0.5742 - lr: 0.0010
Epoch 3/30
114/114 [==============================] - 3s 28ms/step - loss: 0.3107 - accuracy: 0.8819 - precision_14: 0.8895 - recall_14: 0.8722 - val_loss: 1.9616 - val_accuracy:
0.4226 - val_precision_14: 0.4225 - val_recall_14: 0.3871 - lr: 0.0010
Epoch 4/30
114/114 [==============================] - 3s 29ms/step - loss: 0.1772 - accuracy: 0.9194 - precision_14: 0.9236 - recall_14: 0.9163 - val_loss: 1.6270 - val_accuracy:
0.5452 - val_precision_14: 0.5552 - val_recall_14: 0.5355 - lr: 0.0010
Epoch 5/30
114/114 [==============================] - 4s 31ms/step - loss: 0.1050 - accuracy: 0.9463 - precision_14: 0.9474 - recall_14: 0.9449 - val_loss: 1.7784 - val_accuracy:
0.5258 - val_precision_14: 0.5372 - val_recall_14: 0.5129 - lr: 1.0000e-04
Epoch 6/30
114/114 [==============================] - 3s 29ms/step - loss: 0.0979 - accuracy: 0.9498 - precision_14: 0.9497 - recall_14: 0.9485 - val_loss: 1.8097 - val_accuracy:
0.5290 - val_precision_14: 0.5236 - val_recall_14: 0.5000 - lr: 1.0000e-04
Epoch 7/30
114/114 [==============================] - 3s 29ms/step - loss: 0.0918 - accuracy: 0.9515 - precision_14: 0.9515 - recall_14: 0.9511 - val_loss: 1.8627 - val_accuracy:
0.5129 - val_precision_14: 0.5068 - val_recall_14: 0.4806 - lr: 1.0000e-05
Epoch 8/30
114/114 [==============================] - 3s 29ms/step - loss: 0.0907 - accuracy: 0.9529 - precision_14: 0.9537 - recall_14: 0.9524 - val_loss: 1.9017 - val_accuracy:
0.5097 - val_precision_14: 0.5034 - val_recall_14: 0.4806 - lr: 1.0000e-05

<keras.callbacks.History at 0x7f74801cd660>
```

Figure 9: Epochs of BERT.
Source: Authors, (2024).

Figure 9 depicts epochs of the BERT model, where the early stopping callback function plays a crucial role by monitoring the training and stopping it when progress levels off, which helps save computational resources. Then, the Adam optimizer comes into play, guiding parameter adjustments with a learning rate of 0.001 to ensure efficient convergence. The batch size is set at 20, determining how many pieces of data are processed in each step, an essential aspect of efficient training. Over 30 epochs, the model steadily improves its understanding of the data, refining its predictive abilities. Key performance metrics, including accuracy, precision, and recall, collectively shape the model's learning process and ultimately enhancing its proficiency in the assigned task.

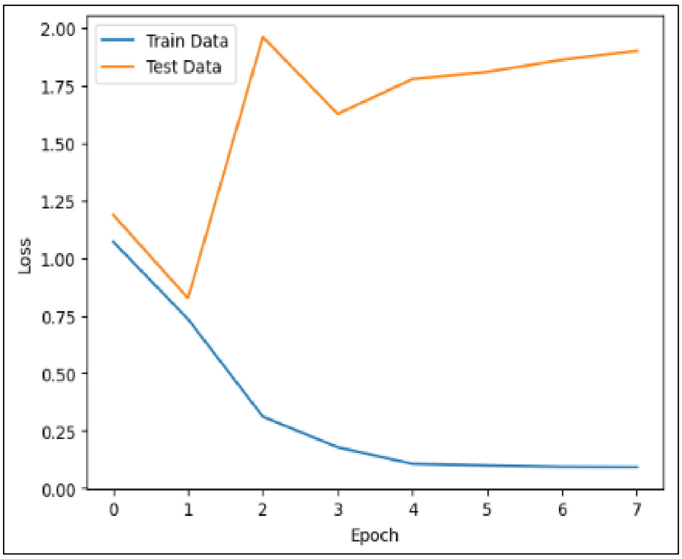

Figure 10: Graphical illustration of losses on the BERT model.
Source: Authors, (2024).

In Figure 10, a graphical representation illustrates the comparison of losses in the BERT model between the training and test datasets. The training set showed minimal loss, signifying efficient model learning and performance.

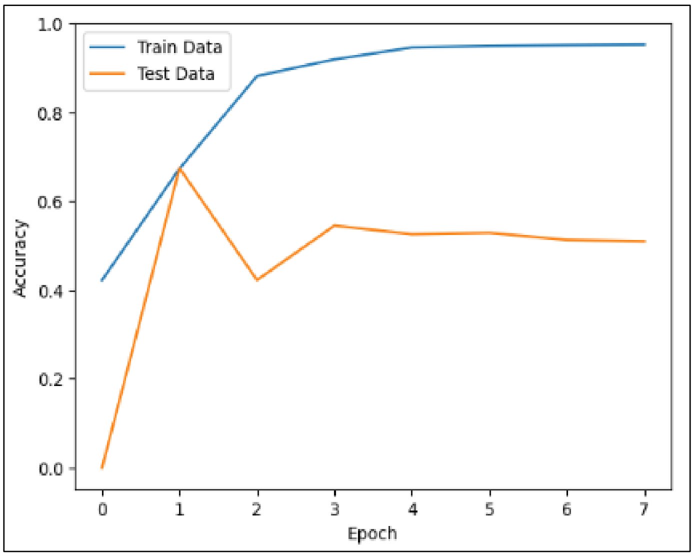

Figure 11: Graphical illustration of accuracy on the BERT model.
Source: Authors, (2023).

In Figure 11, a graphical representation illustrates the accuracy of the BERT model, differentiating between the training and test datasets. The training set demonstrated notably higher accuracy, emphasising the model's proficiency in learning from this dataset. This visual aid played a pivotal role in gauging the model's performance and highlighted the effectiveness of its training process, offering valuable insights for further refinement and application in real-world scenarios. Figure 12 presents a graphical representation comparing precision in the BERT model between the training and test datasets. The training set exhibited superior precision, signifying the model's effectiveness in correctly identifying specific classes. This visual assessment was crucial for evaluating the model's performance and ensuring its accuracy in practical applications.

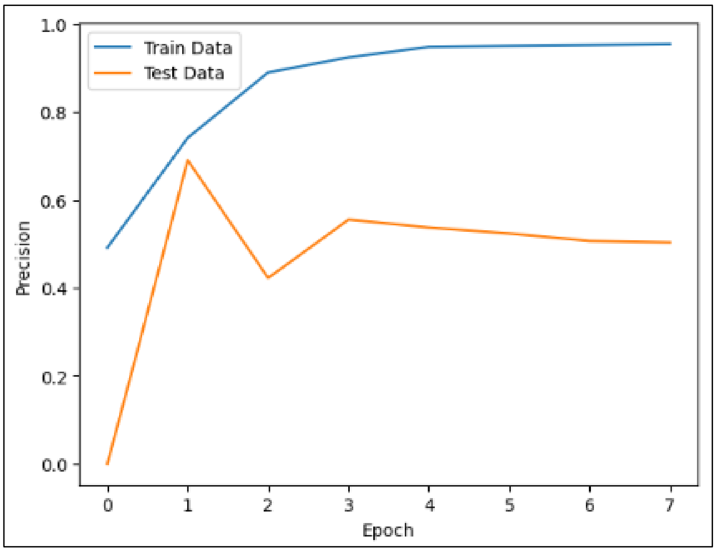

Figure 12: Graphical illustration of precision on the BERT model.
Source: Authors, (2024).

Figure 13 depicts a graphical representation that compares recall in the BERT model between the training and test datasets. The training set demonstrated superior recall, signifying the model's effectiveness in accurately identifying specific classes.

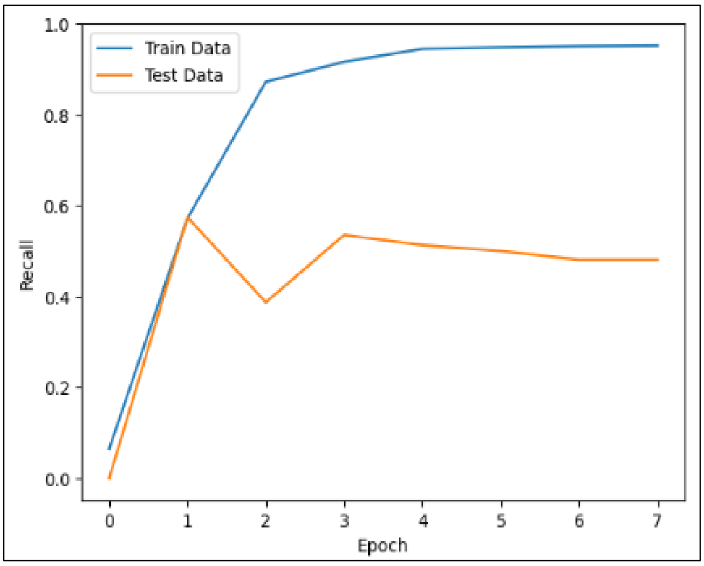

Figure 13: Graphical illustration of recall on the BERT model.
Source: Authors, (2024).

$$F1 - Score = \frac{2\ x\ P_{re}\ x\ R_{ec}}{P_{re} + R_{ec}} = \frac{2\ x\ 0.9537\ x\ 0.9524}{0.9537 + 0.9524} = 0.9532 \quad (1)$$

The study assessed the model's performance with several crucial metrics, revealing highly impressive results. An accuracy of 95.29% indicates the model's ability to make correct predictions in the financial sentiment analysis. The high precision of 95.37% highlights its capacity to precisely identify positive or negative sentiments. A recall of 95.24% suggests that the model effectively captures the most relevant information in the dataset. The minimal loss at 9.07% signifies minimal error in its predictions. The F1-score of 95.32% combines precision and recall, showcasing the model's balanced performance. These results affirm the model's effectiveness and reliability in financial sentiment analysis.

V. CONCLUSIONS

In conclusion, this study demonstrates the significance of using advanced natural language processing techniques, such as the BERT model to conduct sentiment analysis in financial markets. The model performed excellently, with 95.29% accuracy, 95.37% precision, and 95.24% recall. The model's robustness is further demonstrated by the model's low loss of 9.07%. The F1-score of 95.32% demonstrates the model's balanced precision and recall, indicating its ability to effectively classify sentiments. These results outperform several existing sentiment analysis algorithms, demonstrating the effectiveness of using deep learning techniques and the BERT model in financial sentiment research. This research not only advances sentiment analysis methodology, but it also provides financial practitioners with a strong tool for making informed choices based on sentiment insights. The BERT model's implementation tackles the complex nature of sentiments in financial texts, a vital feature that previous techniques sometimes ignore. The approach captures detailed links between words by exploiting bidirectional contextual embeddings, resulting in enhanced sentiment categorization. This study emphasises the importance of using advanced NLP techniques and modern algorithms like BERT in financial sentiment analysis, ultimately improving decision-making processes in the unstable environment of financial markets.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Najeem O. Adelakun, Adebisi A. Baale.
Methodology: Najeem O. Adelakun.
Investigation: Najeem O. Adelakun.
Discussion of results: Najeem O. Adelakun, Adebisi A. Baale.
Writing – Original Draft: Najeem O. Adelakun.
Writing – Review and Editing: Najeem O. Adelakun, Adebisi A. Baale.
Resources: Najeem O. Adelakun.
Supervision: Adebisi A. Baale.
Approval of the final text: Najeem O. Adelakun, Adebisi A. Baale.

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