Sentiment Analysis of Financial News using Transformer-based Model

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Problem Statement

The state of the market has a big influence on stock prices and investment decisions in the quick-paced world of finance. To make informed decisions, investors, analysts, and companies must analyze sentiment in financial news. Traditional sentiment analysis techniques frequently have trouble interpreting financial language because it is context-dependent and nuanced. Transformer-based models, like BERT, have demonstrated an amazing capacity to extract sentiment and context from text. We can create a system that offers more accurate sentiment analysis by applying these models to financial news. This system can then be used for automated trading, risk management, and financial forecasting.
This research aims to overcome the shortcomings of conventional methods by putting in place a Transformer-based sentiment analysis model. Better insights and forecasts can be obtained by this model's ability to distinguish between the sentiments expressed in intricate, nuanced financial statements thanks to BERT's contextual understanding. Financial institutions can use such a model to improve their trading algorithms, quickly spot market trends, and make better investment decisions.

Keywords: Financial sentiment analysis, Transformer-based models, BERT, Automated trading, Financial forecasting

I. Significance of the Work

1. **Enhanced Sentiment Accuracy:** This work significantly improves the accuracy of financial sentiment analysis by leveraging BERT's contextual understanding. Unlike traditional methods, BERT can capture the nuanced and context-dependent nature of financial language, providing more reliable insights into market trends and sentiments.

2. **Real-time Market Insights:** With the ability to process and analyze large volumes of financial news in real time, the model offers crucial insights for investors and institutions. This enables quicker identification of market shifts, enhancing decision-making for automated trading and risk management.

3. **Improved Forecasting Precision:** By analyzing complex financial statements with greater accuracy, the model contributes to more precise financial forecasting. It supports more informed investment decisions, allowing financial institutions to fine-tune their trading algorithms and respond proactively to market changes.

4. **Broad Financial Applications:** The model's adaptability makes it valuable across various financial applications, from sentiment-based trading to risk assessment. By accurately interpreting financial news, it helps institutions enhance their market strategies, identify emerging opportunities, and mitigate potential risks in a dynamic financial landscape.

In conclusion, this work demonstrates the potential of Transformer-based models, particularly BERT, in transforming financial sentiment analysis. By overcoming the limitations of traditional approaches, the model offers more accurate insights, aiding automated trading, risk management, and financial forecasting. Its ability to process context-rich, nuanced financial data positions it as a powerful tool for improving decision-making and enhancing overall market strategies in the financial sector.

II. Dataset Used

The model is trained and assessed using the Twitter Financial News Sentiment Dataset. This dataset is made up of a selection of Twitter-sourced financial news headlines that have been labelled as "positive," "negative," or "neutral." It is composed of 12424 entries, each of which is a headline and a sentiment label. The dataset offers a wide variety of financial news, reflecting market swings and sentiment trends. Training a strong sentiment analysis model that can effectively generalize to new, untested data requires this diversity.

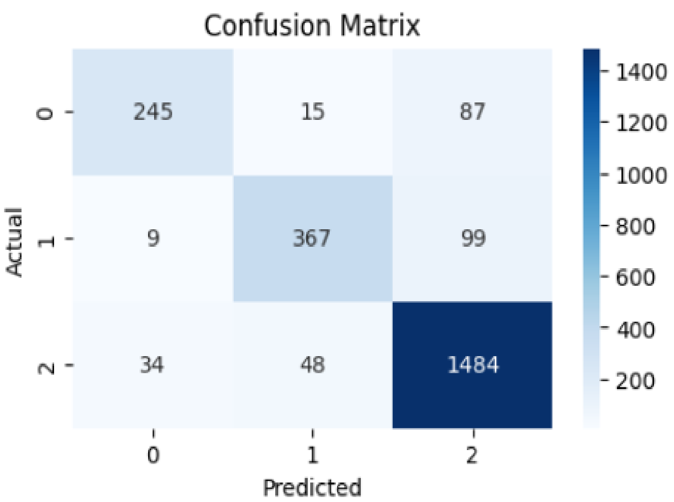
Because it captures sentiment from the market in real time as it is expressed on Twitter—a platform where news breaks quickly—this dataset is especially valuable. In contrast to conventional news articles, tweets frequently use financial slang, jargon, and abbreviations, which poses a special difficulty for natural language processing algorithms. The structure of the dataset provides context, which can be essential for comprehending market reactions, by including not only sentiment labels but also the time and source of each tweet. Furthermore, the dataset goes beyond general-purpose sentiment analysis datasets because of its focus on financial news, which makes it a great resource for creating models that can comprehend and analyze the unique language and sentiment of the financial industry.

III. METHODOLOGY

The proposed methodology utilizes a Transformer-based BERT model for sentiment analysis of financial news. The text is tokenized using the BERT tokenizer, and labels are encoded using `LabelEncoder`. The model is trained using the Adam optimizer with sparse categorical cross-entropy loss, and the learning rate is adjusted using a custom schedule. Early stopping and model checkpoint callbacks are employed to prevent overfitting, ensuring generalization. Training is conducted on datasets split into training and validation sets, with performance monitored using classification metrics such as accuracy, confusion matrix, and ROC curve. The model's ability to capture contextual meaning is leveraged to improve sentiment classification accuracy.

IV. RESULTS

The proposed methodology achieved a classification accuracy of 88% on the validation set, surpassing traditional sentiment analysis methods. This demonstrates the effectiveness of the Transformer-based approach in financial news sentiment classification.



The confusion matrix illustrates a strong ratio of true positives and true negatives, highlighting the model's effectiveness in distinguishing between different classes.

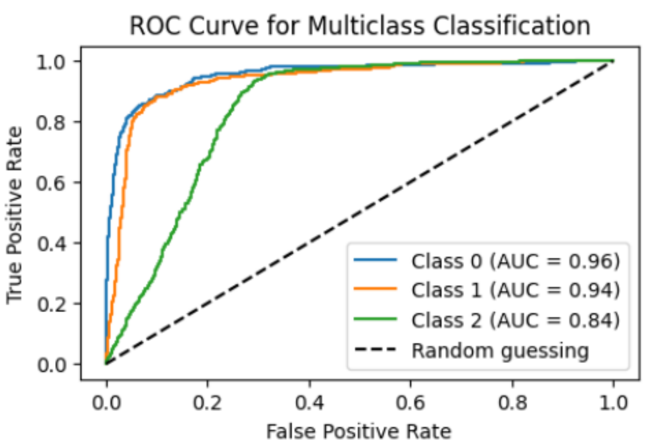


Fig. 1

Fig 1 explains the ROC curve and AUC of the model.

ROC (Receiver Operating Characteristic) curve visually represents the trade-off between true positive rate and false positive rate for the classification model.

AUC (Area Under the Curve) quantifies the overall performance providing a single value that summarizes the model's ability to distinguish between classes based on the ROC curve.

	Bearish [0]	Bullish [1]	Neutral [2]
Precision	0.85	0.85	0.89
Recall	0.71	0.77	0.95
F1 Score	0.77	0.81	0.92
Support	347	475	1566

Table 1

Table 1 shows the Classification Report of the model.

IV. CONCLUSION

In summary, the proposed approach offers an effective automated method for sentiment analysis of financial news. By leveraging Transformer-based models like BERT, this technique improves both the accuracy and contextual understanding of sentiment classification. This advancement benefits financial analysts and decision-makers by providing more precise insights into market trends. Future work could explore deploying this model in real-world financial applications to evaluate its practical impact and scalability.