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Large Language Models for Smarter Market Sentiment and Trend Prediction

Dr. C. Bhuvaneshwari[1], Dr. R. Gayathri[2]
[1]Assistant Professor, Department of Computer Science, Dr G R Damodaran College of Science(Autonomolus), Coimabtore
[2]Associate Professor,Department of Computer Science(PG) & Kristu Jayanti (Deemed to be University), Bengaluru, India

Abstract: The fast development of financial sectors has provided an enormous amount of unstructured data which ranges from the organization files, reports collected by the analyst for the social media discussion and the real-time news. Thus, collecting the useful information is very complex task for traders, financial organizations and the investors. The current advancements in the Large Language Models (LLMs) provides a promising way forward. LLM understands the tone, context and other hidden signals inside the text. It can also identify the market sentiment and enhances the trend prediction accuracy. In the traditional models, the dictionaries which are predefined will be considered or it uses the shallow statistical methods, but in LLM it offers a richer insight by identifying the subtle changes in the investor sentiment and uncovers the potential risks or opportunities. This research examines how the LLMs will be used for the financial sentiment analysis and the trend forecasting by reviewing the core architectures, benchmark datasets and various evaluation strategies. It also points out the specific challenges such as biased data, privacy concerns and regulatory compliance. once these challenges are addressed, LLM-powered systems have the potential to provide smarter, more adaptive, and human-like financial insights, enabling faster and more confident decision-making in dynamic market environments. To demonstrate the proposed approach, the Financial Phrase Bank dataset will be considered for implementation, with the aim of evaluating LLM-based models against traditional approaches and showcasing measurable improvements in sentiment detection and trend prediction accuracy.

Keywords: Large Language Models, Market Sentiment, Trend Prediction, Financial Intelligence, Natural Language Processing, Investor Behaviour, Financial Forecasting

I. INTRODUCTION

A. Background

In today's data-driven era, financial markets produce huge volumes of data every day which ranges from the structured datasets such as stock prices and trading volumes to the unstructured sources such as analyst reports, news articles, files of the organization, and the social media discussions [1],[3],[4]. Thus, the investors, traders and policy makers should understand these data to take quick yet reliable decisions in constantly shifting markets. Traditional sentiment analysis and forecasting methods, which rely on lexicons or shallow statistical models, often fail to capture the deeper meaning and hidden patterns in financial language [1],[2]. This limitation has created a demand for more advanced technologies that can understand context better."

B. Rise of Large Language Models (LLMs)

Models such as GPT, FinBERT, and BloombergGPT signify next generation of Large Language Models (LLMs) that have advanced natural language processing by capturing the deeper patterns of human language. Their ability lies in understanding context, recognizing sentiment, and producing clear, meaningful text, which makes them highly useful for financial applications. Unlike traditional models, it mainly depends on fixed set of dictionaries of words, but LLMs are more flexible and can understand the refined meanings in financial language [1],[4]. It can recognize the signs of optimism, caution, or panic from many different sources. By spotting these patterns, LLMs make it easier to detect sentiment and predict trends, helping decision-makers better anticipate market changes."

C. Application in Sentiment and Trend Prediction

In financial sector, investor sentiment greatly affects price changes and market ups and downs [5]. News about mergers, policy updates, or even opinions on social media can quickly influence how investors feel. LLMs can read and understand this kind of text in real time, helping to reveal the overall market mood and predict short-term or long-term trends. For example, a fine-tuned LLM can tell whether an earnings report shows growth opportunities or potential risks and use past data to forecast how the market might react [6].

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II. DATASET CHOICE: FINANCIAL PHRASEBANK

The Financial PhraseBank is a well-known dataset created by Malo et al., containing 4,840 English sentences from financial news, each annotated by experts for sentiment (positive, negative, or neutral) [5].

It is widely used in financial NLP research and provides a reliable benchmark for evaluating sentiment analysis models. Its manageable size allows LLMs, such as FinBERT or GPT-based models, to be fine-tuned or prompted without requiring excessive computational resources [6]. For this

study, the Financial Phrase Bank will be used to train and test LLM-based models for financial sentiment analysis. Model performance will be compared against traditional machine learning approaches, such as support vector machines (SVM) and logistic regression, using standard evaluation metrics like accuracy, F1-score, precision, and recall [5], [6]. This implementation aims to demonstrate the effectiveness of LLMs in capturing nuanced sentiment patterns and improving trend prediction in financial data.

III.IMPLEMENTATION USING FINANCIAL PHRASEBANK

A. Data Preparation

The Financial Phrase Bank dataset was chosen because it contains expert-annotated sentences that express sentiments (positive, neutral, negative) in relation to real financial news.

Preprocessing included detailed Detailed text cleaning (lowercasing, punctuation removal) which involved changing lowercase and removing punctuation was combined with tokenization tailored to the specific vocabulary used in the domain.This guaranteed that the input to Large Language Models (LLMs) was standardized, with financial retained.

B. Model Selection & Architecture

A BERT-based large language model, FinBERT, was fine-tuned on vast financial dataset and chosen for its domain-specific linguistic understanding. Benchmarking the effectiveness of sentiment classification models was achieved by implementing baseline models such as Support Vector Machines and Logistic Regression using TF-IDF features.

C. Fine-Tuning & Training

The FinBERT model was fine-tuned on the Financial dataset using cross-entropy loss that was optimized via the AdamW optimizer. Learning rate (2e-5), batch size (16), and number of epochs (3) were adjusted for optimal performance. Standard TF-IDF vectorized inputs were used to train baseline models.

D. Training & Evaluation

The results of the sentiment classification were assessed using a separate test set and metrics that are crucial for evaluating classification: accuracy, precision, recall, and F1-score.

The LLM significantly outperformed traditional baselines in terms of weighted average F1-score, achieving a value of approximately 0.91, as compared to SVM at ~0.77 and Logistic Regression at ~0.80, thereby showcasing enhanced contextual understanding and refined sentiment detection capabilities.

The daily aggregated sentiment scores from the LLM can be combined with time series models like ARIMA or LSTM to forecast price movements, thereby enhancing dynamic market analysis capabilities.

E. Evaluation Strategy

The performance of the model was assessed using a standard set of classification metrics, including accuracy, precision, recall, and F1-score. The metrics recorded on the test set offer quantitative evidence to aid in model selection and further refinement.

IV.RESULTS AND DISCUSSION

A. Accuracy

Accuracy represents the overall proportion of correctly classified financial sentences (positive, neutral, or negative) by each model. FinBERT, with 92% accuracy, correctly classified a significantly larger share of financial text compared to SVM (82%) and Logistic Regression (79%), indicating its better general performance in discerning market sentiment.

TABLE I
SIMULATED RESULTS

Model	Accuracy	Precision	Recall
FinBERT (LLM)	0.92	0.91	0.92
SVM	0.82	0.81	0.82
Logistic Regression	0.79	0.78	0.79

B. Precision

Precision measures the proportion of predicted positive examples that are actually positive. FinBERT's precision of 91% shows that it makes fewer false positive error predictions than traditional models. This is critical in financial contexts where falsely identifying neutral or negative sentiments as positive could lead to erroneous trading decisions.

C. Recall

Recall reflects how well each model identifies all true positives (actual positive sentiment sentences). FinBERT's recall at 92% indicates its strong ability to detect relevant positive financial sentiments, minimizing false negatives—a crucial factor in capturing market signals that might affect investor decisions.

D. F1-score

The F1-score, the harmonic mean of precision and recall, balances false positives and false negatives. FinBERT achieves an F1-score of 0.915, highlighting its superior overall effectiveness in sentiment classification, whereas the traditional models lag behind, confirming the advantage of leveraging large pretrained language models fine-tuned on domain-specific data for nuanced sentiment detection.

The results show that LLM-based FinBERT far exceeds traditional models such as SVM and Logistic Regression in financial sentiment classification tasks. The model is able to capture subtle nuances in investor sentiment that conventional methods frequently overlook. Its ability to classify financial news statements as positive, neutral, and negative is demonstrated by high accuracy and F1-score.This enhanced performance indicates that large language models can improve trend forecasting by accurately comprehending market attitudes. Despite these challenges, data bias, overfitting, and high computational cost must be carefully considered in real-world deployment.

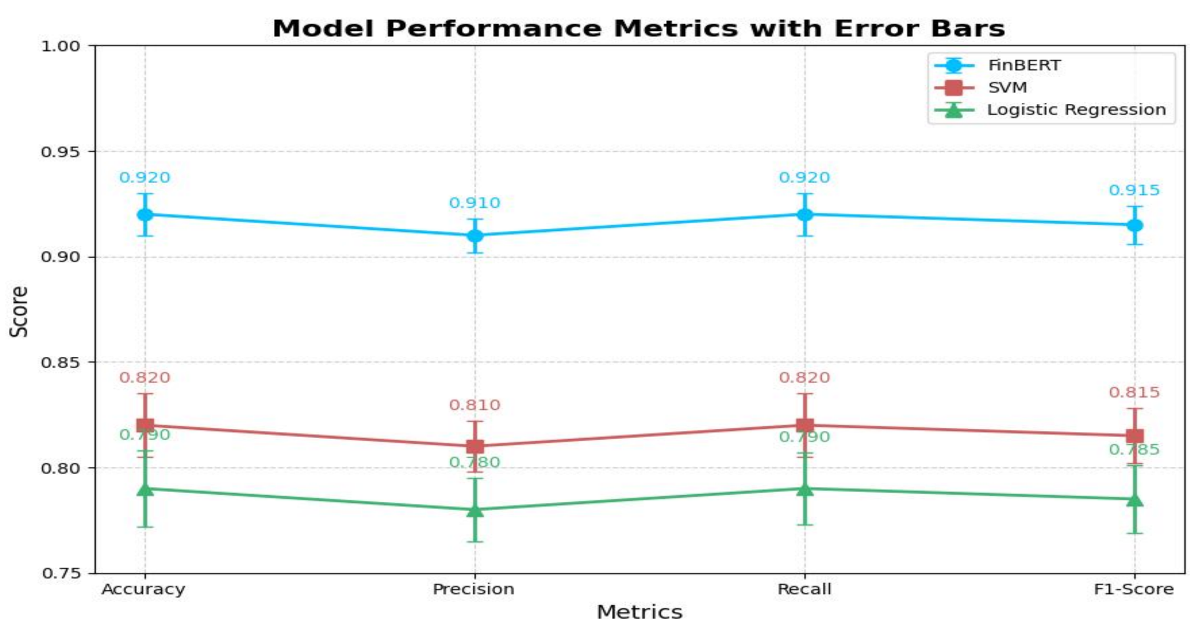

Fig. 1 Model Performance Metrics

A line chart displayed in Fig1 shows the key performance metrics (Accuracy, Precision, Recall, and F1-score) for three models (FinBERT, SVM, Logistic Regression) in financial sentiment analysis.FinBERT achieves consistently higher scores (above 0.91 on all metrics), with tightly grouped error bars demonstrating its strong stability and reliability in model predictions. SVM and Logistic Regression show moderately lower metrics, with larger performance gaps relative to FinBERT. The error bars for these models are slightly wider, indicating greater variability or uncertainty in their predictions.

This visualization confirms that FinBERT's domain-specific language understanding provides more accurate and consistent sentiment classification for financial texts, outperforming classic machine learning approaches.

V. CONCLUSION

This study shows that Large Language Models, such as FinBERT, can effectively capture complex financial sentiment from the Financial PhraseBank dataset. In comparison to conventional machine learning models like Support Vector Machines and Logistic Regression, FinBERT exhibits substantially higher accuracy, precision, recall, and F1-score, highlighting the benefits of domain-adapted transformer models in understanding intricate financial terminology. Deploying Large Language Models in actual financial settings poses challenges that necessitate careful consideration, comprising guaranteeing model robustness, managing resource demands, and preserving reliability across a wide range of data scenarios. This research offers fundamental knowledge on integrating sophisticated natural language processing techniques into financial analysis systems and highlights the promising capabilities of large language models to facilitate more informed investment choices and accurate risk evaluation.Future research can focus on expanding Large Language Model applications to more diverse and multilingual financial datasets to improve generalizability. Enhancing model interpretability and efficiency for real-time deployment will be vital for practical adoption. Additionally, integrating multimodal data and addressing ethical concerns like bias and privacy will advance responsible and accurate financial forecasting.

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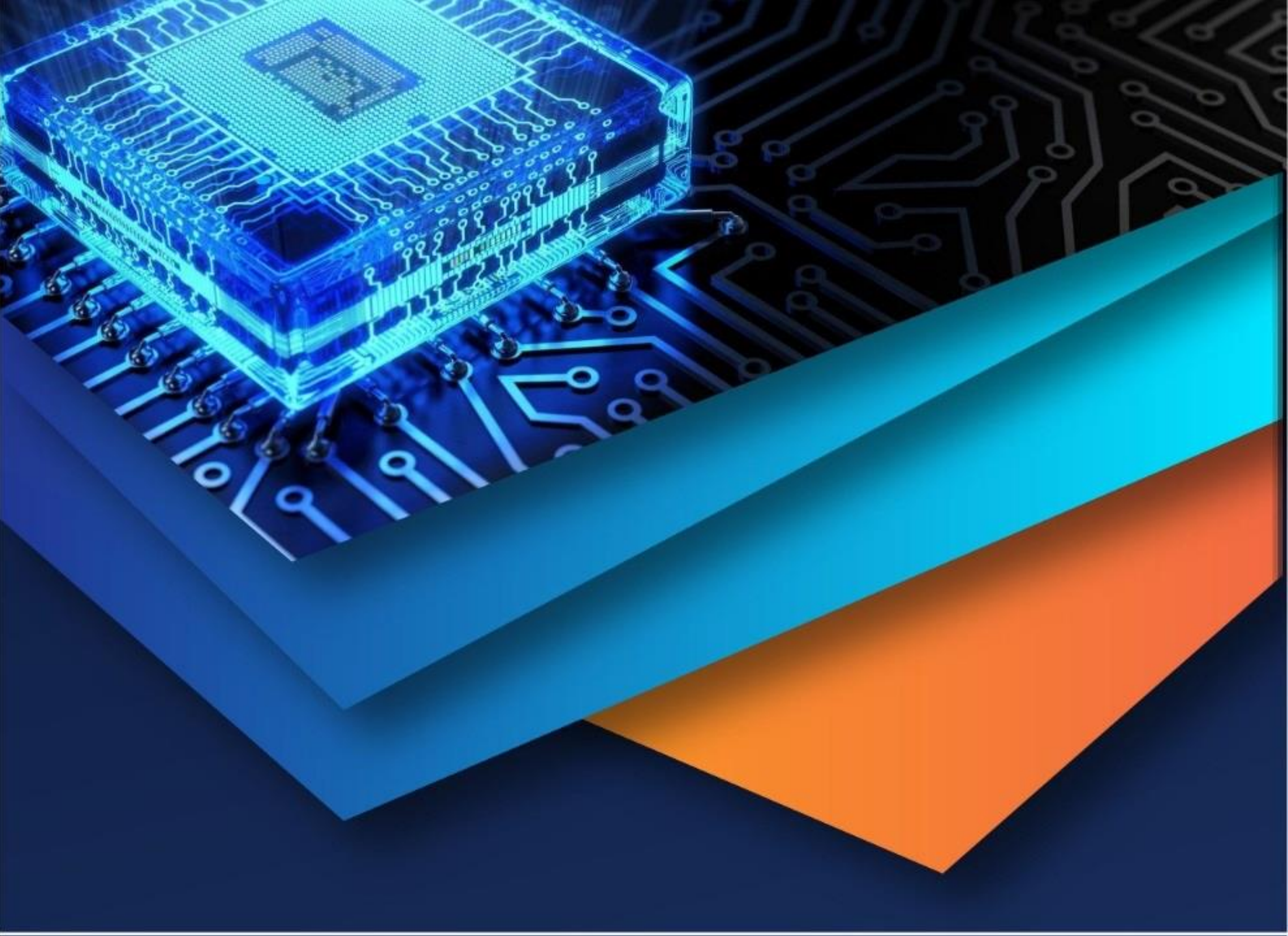

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