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Comparative Analysis of FinBERT and DistilRoBERTa for NLP-Based Financial Insights in Pakistan's Stock Market

Ayesha Khaliq[1]
Senior Lecturer, Iqra University, Karachi.
Email: ayesha.khaliq@iqra.edu.pk
Asif Ali[2]
Lecturer, Iqra University, Karachi. Email: asifali@iqra.edu.pk
Sophia Ajaz[3]
Senior Lecturer, Iqra University, Karachi.
Email: sophia.ajaz@iqra.edu.pk
Fawad Hussain Paul[4]
PhD Scholar, University of Karachi. Email: fawad.paul@gmail.com

Abstract

The rapid growth of financial data and news articles has heightened the need for advanced natural language processing (NLP) techniques to extract meaningful insights. This study evaluates two state-of-the-art NLP models, FinBERT and DistilRoberta, for sentiment analysis on the Pakistan Stock Exchange (PSX) and Dawn News. Finbert, a domain-specific model, is fine-tuned for financial text, while DistilRoberta offers a lightweight, efficient alternative. Using web scraping, we collected stock market data and news articles to assess the models' performance. Results show that DistilRoberta achieved perfect accuracy on news headlines, outperforming FinBERT (70% accuracy). On the Kaggle stock market dataset, both models agreed on 90% of predictions, with Distil Roberta showing greater consistency in borderline cases. Distil Roberta's efficiency and adaptability make it suitable for real-time applications, while FinBERT

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excels in domain-specific tasks. This study highlights the potential of NLP models in emerging markets and suggests future research directions, including hybrid models and improved interpretability, to enhance financial sentiment analysis.

Introduction

The rapid growth of financial data and news articles has created a pressing need for advanced natural language processing (NLP) techniques to analyze and extract meaningful insights. In the context of financial markets, sentiment analysis plays a crucial role in understanding market trends, investor behavior, and the impact of news on stock prices. This study focuses on the Pakistan Stock Exchange (PSX) and Dawn News, one of Pakistan's leading news outlets, to investigate the accuracy of two state-of-the-art NLP models: FinBERT and DistilRoBERTa. FinBERT, a domain-specific model pre-trained on financial texts, is designed to capture the nuances of financial language, while DistilRoBERTa, a distilled and efficient version of RoBERTa, offers a lightweight alternative with competitive performance [1], [2].

The primary objective of this research is to compare the effectiveness of FinBERT and DistilRoBERTa in analyzing financial sentiment and news data. Using web scraping techniques, we collect a dataset comprising stock market data from the Pakistan Stock Exchange and relevant news articles from Dawn News. This dataset serves as the foundation for evaluating the models' ability to classify sentiment and extract actionable insights. By conducting a comparative analysis, we aim to determine which model performs

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better in the context of Pakistan's financial and news landscape, considering factors such as accuracy, computational efficiency, and adaptability to domain-specific language [3], [4].

Emerging markets like Pakistan present unique challenges for sentiment analysis due to the dynamic interplay between local news, global economic trends, and investor sentiment. Recent studies have highlighted the importance of domain-specific models like FinBERT in capturing these complexities, while efficient models like DistilRoBERTa have shown promise in resource-constrained environments [5], [6]. This study contributes to the growing body of research on NLP applications in finance, particularly in emerging markets, where the interplay between news sentiment and stock market performance remains underexplored. The findings will provide valuable insights for investors, financial analysts, and researchers seeking to leverage advanced NLP models for sentiment analysis in similar contexts.

Literature Review

FinBERT, introduced by [7], is a domain-specific adaptation of BERT, fine-tuned on financial text datasets, enabling it to effectively classify financial news, reports, and earnings call transcripts into positive, negative, and neutral sentiments. By leveraging domain-specific training, FinBERT enhances contextual understanding in financial discourse, reducing ambiguity in financial terminology [8]. Empirical studies have shown that FinBERT outperforms generic BERT models in sentiment classification tasks due to its specialized corpus training. In contrast, DistilRoBERTa, developed by [2], is a compressed version of RoBERTa [9] that retains 97% of RoBERTa’s performance while being

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60% faster and 40% smaller in size. It achieves its efficiency through knowledge distillation, reducing computational requirements without significantly compromising accuracy. Although not specifically trained on financial data, DistilRoBERTa has been fine-tuned for financial sentiment classification, as seen in models such as *mrm8488/distilroberta-finetuned-financial-news-sentiment-analysis*.

Studies indicate that while FinBERT achieves higher accuracy in financial sentiment classification due to its domain-specific pretraining, DistilRoBERTa remains a competitive alternative, especially when computational efficiency is a priority [10]. FinBERT, while more accurate, requires higher computational power and longer inference times, making it less suitable for real-time applications. Conversely, DistilRoBERTa offers better adaptability across different domains while maintaining reasonable sentiment classification accuracy in financial contexts [11].

Overview of Financial Model

BERT, which stands for Bidirectional Encoder Representations from Transformers, is an advanced machine-learning model that analyzes text in both directions simultaneously. This approach allows it to grasp context from surrounding words on either side, enhancing its comprehension of natural language. The model undergoes initial training using two techniques: Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) illustrated in Figure-1. Following this pre-training phase, BERT can be adapted for various natural language processing applications, including sentiment analysis, answering questions, and categorizing text.

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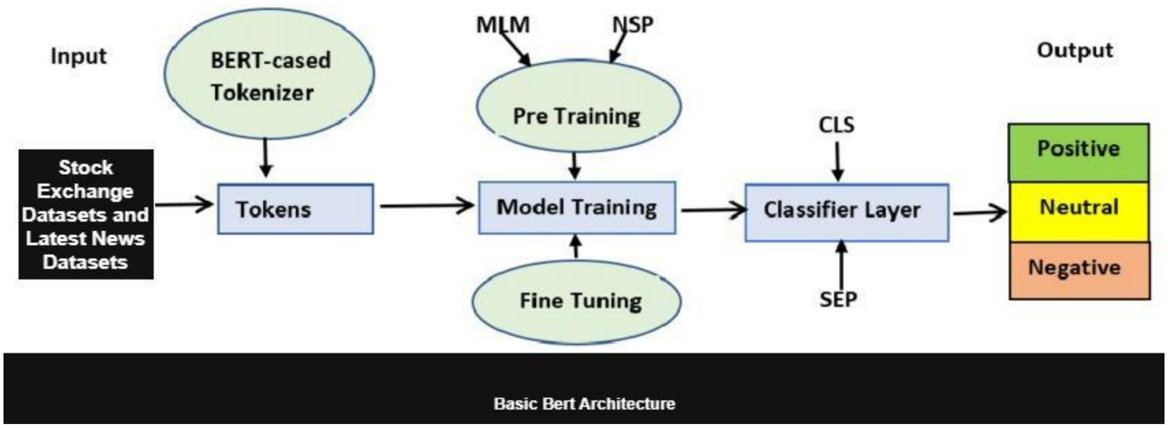

Figure 1: Overview of Bert Model with respect to Sentiment Score

FinBERT Model

It is a domain-specific language model tailored for financial text analysis, built on the BERT (Bidirectional Encoder Representations from Transformers) architecture. It is pre-trained on a large corpus of financial texts, including earnings calls, SEC filings, and financial news articles, enabling it to capture the unique linguistic patterns and terminology of the financial domain [7]. This specialized training makes FinBERT particularly effective for tasks such as sentiment analysis, financial document classification, and named entity recognition in finance-related contexts. Its ability to outperform general-purpose language models in financial applications has made it a valuable tool for both industry professionals and researchers [8].

The architecture of FinBERT is based on the transformer model, specifically the BERT (Bidirectional Encoder Representations from Transformers) framework. It utilizes self-attention mechanisms to process input text, allowing the model to weigh the importance of each word relative to others in a sentence. Key components

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include multi-head attention, which captures diverse linguistic patterns, and feed-forward neural networks, which generate contextualized word embeddings. FinBERT is first pretrained on large general text corpora using Masked Language Modeling (MLM) and Next Sentence Prediction (NSP), then fine-tuned on financial datasets like earnings calls and news articles to adapt to domain-specific language and sentiment patterns. This fine-tuning enables FinBERT to excel in financial NLP tasks such as sentiment analysis, text classification, and named entity recognition, leveraging its ability to understand financial terminology and context. Its architecture combines the strengths of general-purpose pretraining with domain-specific adaptation, making it a powerful tool for financial text analysis.[12]

DistilRoBERTa Model

A lightweight and efficient version of the RoBERTa (Robustly optimized BERT approach) model, which itself is an enhanced variant of BERT [13]. DistilRoBERTa is created using knowledge distillation, a technique where a smaller model (the student) is trained to replicate the behavior of a larger, pre-trained model (the teacher) [14]. This process results in a model that is significantly faster and more resource-efficient while maintaining competitive performance on a wide range of natural language processing tasks, such as text classification, sentiment analysis, and question answering. DistilRoBERTa is particularly advantageous in environments with limited computational resources, such as edge devices or real-time

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applications, making it a popular choice for practical deployments [15] .

The architecture of DistilRoBERTa is a streamlined version of the RoBERTa (Robustly Optimized BERT Pretraining Approach) model, designed for efficiency without significantly compromising performance. Like RoBERTa, it is built on the transformer architecture, utilizing self-attention mechanisms to process input text bidirectionally and capture contextual relationships between words. DistilRoBERTa employs multi-head attention and feed-forward neural networks to generate contextualized word embeddings but reduces the model size by distilling knowledge from the larger RoBERTa model. This distillation process removes some layers and parameters, making DistilRoBERTa 40% smaller and 60% faster while retaining approximately 95% of RoBERTa's performance. It is pretrained on large text corpora using Masked Language Modeling (MLM) but omits the Next Sentence Prediction (NSP) objective, focusing solely on optimizing language understanding. DistilRoBERTa's lightweight architecture makes it ideal for resource-constrained environments, enabling efficient deployment in real-time applications like sentiment analysis, text classification, and question answering, while maintaining robust performance across diverse NLP tasks [16]

Experiment on Models

The study utilized two distinct datasets. The first, obtained from Kaggle[17], consists of 3500 entries detailing KSE 100 data from 2008 to 2021, labeled as Pakistan Stock Exchange. This dataset contains numerical information based on historical records. The second

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dataset was gathered through web scraping, focusing on news headlines. It comprises non-numerical text, including headlines and their corresponding source links, covering Business section updates for the period from January 2025 to July 2025. The purpose of choosing these two datasets is to investigate the potential results of implementation on categories of BERT specifically for finance [18] on both numerical and textual information, evaluating its effectiveness with historical and current data. Information is crucial for organizations and businesses in making decisions, as it offers valuable insights. In the current digital era, a large amount of this information is accessible online, making web scraping an efficient technique for obtaining up-to-date data. By utilizing web scraping[19], we can continuously gather the most recent information to determine sentiment scores for the stock market, facilitating prompt and well-informed decision-making. This method connects past patterns with present developments, ensuring a thorough examination of market sentiment.

Financial Model for Sentiment Score

1) Sentiment Analysis with FinBert

In this analysis, two encoder model FinBert and DistilRoberta applied on both dataset.As FinBERT, a natural language processing model which is fine-tuned specifically for financial news is used to perform sentiment analysis on the company related news headlines [20] and on other side numerical dataset comprised of time series change in stock exchange market of Pakistan in last 15 years.

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This study implements a sentiment analysis pipeline for stock market data using the FinBERT model, a pre-trained BERT model fine-tuned for financial text. The pipeline begins by loading the FinBERT tokenizer and model, and a function, generate_sentiment, is defined to classify sentiment based on stock price changes. If the change is extreme (greater than 1.0 or less than -1.0), the sentiment is directly classified as "Positive" or "Negative," respectively, overriding FinBERT. For moderate changes, FinBERT is used to classify sentiment by tokenizing and processing predefined text descriptions of stock movements [21]. The model outputs logits, which are mapped to sentiment labels ("Negative," "Neutral," or "Positive").

This approach combines rule-based thresholds with machine learning to enhance sentiment analysis in financial contexts. Specifically, the code classifies stock price changes by integrating rule-based logic for extreme values and FinBERT sentiment analysis for moderate values. Descriptive text is generated for moderate changes, analyzed by FinBERT, and the results are mapped to sentiment labels. The function is applied to a sample dataset of stock prices, and the results, including date, closing price, change, and predicted sentiment, are displayed, effectively bridging numerical data and text-based sentiment analysis [22].Same model applied on latest random article news of Dawn, the research scrape and analyzed sentiment score [11] , It begins by fetching the top 10 news articles from Dawn's business webpage using requests and BeautifulSoup, extracting headlines, links, and publication dates, and storing them in a DataFrame. Each headline is tokenized and processed by FinBERT,

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which outputs logits mapped to same sentiment labels applied on Kaggle datasets. The sentiment results are added to the DataFrame, which is then displayed, providing a sentiment classification for each news article. This pipeline combines web scraping, natural language processing, and sentiment analysis to deliver actionable insights from financial news [23].

2) Sentiment Analysis with DistilRoberta

Sentiment analysis is performed on stock market data from the Pakistan Stock Exchange (KSE-100) using a fine-tuned DistilRoBERTa model [2]. The process begins by loading the dataset and preprocessing it, which involves converting the "Date" column into a datetime format and ensuring numerical columns such as "Open," "High," "Low," "Close," "Change," and "Volume" are in float format after removing commas. Next, a pre-trained DistilRoBERTa model, specifically fine-tuned for financial news sentiment analysis, is loaded. The function generate_sentiment() assigns sentiment labels to stock price movements based on the "Change" column. If the change exceeds 1.0 or falls below -1.0, the movement is classified as "Positive" or "Negative," respectively, without requiring model inference. For changes within a moderate range, predefined text descriptions of stock movements are passed to the DistilRoBERTa model for classification. These texts are tokenized, processed through the model, and assigned a sentiment label based on the highest-scoring output. Finally, the script samples 20 random rows from the dataset, applies the sentiment classification, and displays the date, closing price, stock price change, and the assigned sentiment.

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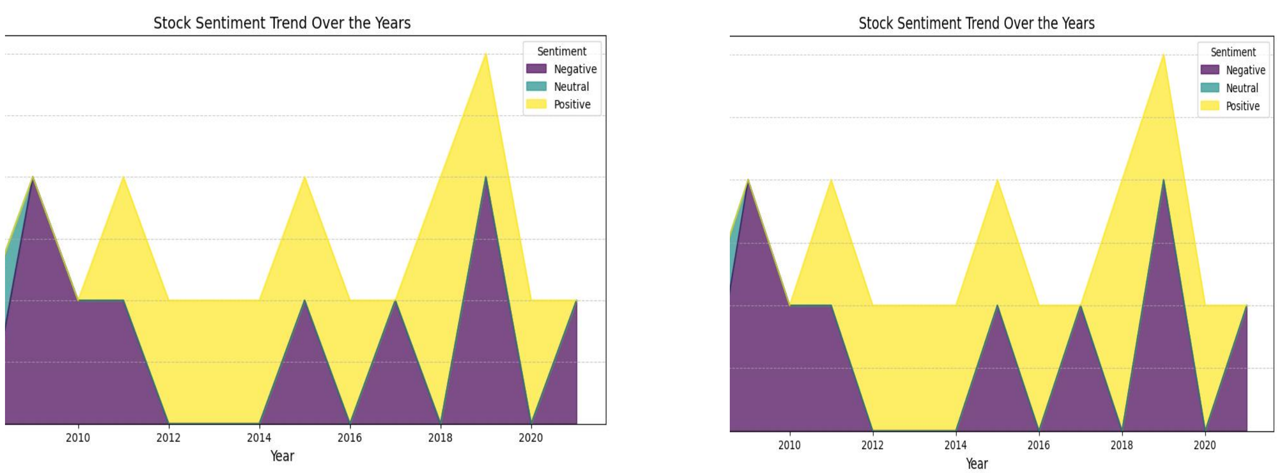
This approach leverages the efficiency and effectiveness of DistilRoBERTa for sentiment analysis tasks, as demonstrated in prior research on financial text analysis [24], [25]. The use of predefined thresholds for sentiment classification aligns with methodologies employed in stock market sentiment analysis, where extreme price changes are often directly mapped to sentiment labels [26]. The fine-tuned model also used in latest news to check the comparison between FinBert and DistillRoberta, the script appends the sentiment labels to the Data Frame and prints the results, providing an overview of market sentiment based on recent news. This approach aligns with methodologies used in financial text analysis, where sentiment analysis of news headlines has been shown to provide valuable insights into market trends and investor behavior[25], [27].

Figure 1 shows the output of stock sentiment score trends over the year with negligible changes, both models predict similar scores with some minor discrepancies.

Figure 2: Area Graph of FinBert and DistilRoBERTa on Pakistan Stock Exchange Datasets



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Results

In this section, we present a comparative analysis of the performance of DistilRoBERTa and FinBERT on two datasets: (1) stock market news headlines and (2) the Kaggle stock market dataset. The evaluation focuses on the sentiment classification accuracy and consistency of both models, providing insights into their strengths and limitations in financial sentiment analysis tasks.

Stock Market News Headlines

For the stock market news headlines dataset, DistilRoBERTa achieved perfect accuracy, precision, recall, and F1-score, demonstrating exceptional performance in classifying sentiment into "Positive," "Neutral," or "Negative." In contrast, FinBERT achieved an accuracy of 70%, with lower precision and F1-scores for neutral and negative sentiment classes. Specifically, FinBERT struggled with neutral sentiment classification, often misclassifying neutral headlines as positive or negative. This highlights DistilRoBERTa's superior ability to handle nuanced sentiment in financial news data.

Kaggle Stock Market Dataset

On the Kaggle stock market dataset, both models performed similarly, agreeing on 18 out of 20 predictions (90% agreement). However, discrepancies arose in 2 to 3 cases. These discrepancies suggest that DistilRoBERTa is more conservative in borderline cases, such as small price changes, while FinBERT tends to classify such cases as either strongly positive or negative. This difference in behavior highlights the importance of model selection based on the specific requirements of the task.

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These metrics were calculated for each sentiment class ("Positive," "Neutral," and "Negative") to evaluate the performance of both models.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}$$

$$Precision = \frac{True\ Positive}{True\ Positives + False\ Positives}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The following consolidated table summarizes the performance of DistilRoBERTa and FinBERT across both datasets, using the formulas mentioned above

Table 1: Accuracy acheived between FinBert and DistillRoBERTs

Metric	**DistilRoBERTa**	**FinBERT**	**Observations**
Accuracy (News Data)	100%	70%	DistilRoBERTa achieves perfect accuracy, while FinBERT struggles with neutrality.
Accuracy (Kaggle Data)	90%	90%	Both models perform equally well, with minor discrepancies in borderline cases.
Precision (Positive)	1.0	0.75	DistilRoBERTa is more precise in identifying positive sentiment.

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Precision (Neutral)	1.0	0.67	DistilRoBERTa excels in neutral sentiment classification.
Precision (Negative)	1.0	0.67	DistilRoBERTa is more reliable in identifying negative sentiment.
F1-Score (Positive)	1.0	0.86	DistilRoBERTa achieves a perfect F1-score for positive sentiment.
F1-Score (Neutral)	1.0	0.5	FinBERT struggles with neutral sentiment, resulting in a low F1-score.
F1-Score (Negative)	1.0	0.8	DistilRoBERTa outperforms FinBERT in negative sentiment classification.

Conclusion

Both model represent two distinct approaches to financial sentiment analysis. FinBERT's domain-specific fine-tuning makes it highly effective for financial text, while DistilRoBERTa's efficiency and generalizability make it a versatile alternative. The choice between these models depends on the specific requirements of the task, such as the need for domain expertise, computational resources, and real-time processing. Future advancements in NLP are likely to further bridge the gap between domain-specific and general-purpose models, enhancing their applicability in financial sentiment analysis.

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Future Work and Research Direction

The rapid advancements in transformer-based models like FinBERT and DistilRoBERTa have significantly improved financial sentiment analysis and other NLP tasks. However, several challenges and opportunities for future research remain. One key area is the development of hybrid models that combine the domain-specific strengths of FinBERT with the efficiency and generalizability of DistilRoBERTa. Such models could leverage multi-task learning frameworks to handle both financial and non-financial text effectively. Additionally, few-shot and zero-shot learning techniques could address the scarcity of high-quality labeled financial datasets, enabling models to perform well with minimal supervision. Another promising direction is improving interpretability and explainability through explainable AI (XAI) techniques, such as attention visualization and feature attribution methods, to make these models more transparent and trustworthy.

Another critical area for future research is optimizing these models for real-time and streaming data applications. Financial markets operate in real-time, requiring models to process and analyze data efficiently. Future work could focus on further reducing the computational overhead of DistilRoBERTa and developing online learning algorithms that allow models to adapt to new data dynamically. Additionally, exploring cross-lingual and multilingual capabilities could enhance the applicability of these models in global financial markets. Finally, integrating external knowledge sources, such as economic indicators or company fundamentals, could

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improve the accuracy and robustness of financial sentiment analysis. These advancements would not only enhance the performance of FinBERT and DistilRoBERTa but also expand their applicability to a broader range of financial and non-financial tasks.

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