

# Financial Sentiment Analysis\*

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**Abstract**—Traditional sentiment analysis models find it difficult to understand the vast amounts of informal, slang-heavy, and emotionally charged text produced by online financial communities like Reddit’s WallStreetBets. In order to enhance sentiment classification on noisy financial social media posts, this project introduces a hybrid deep learning model that combines FinBERT, a finance-domain transformer, with RoBERTa-Large, a potent contextual language model. FinBERT was used to create, clean, and automatically label a dataset of 32,470 posts. Emojis, tickers, and irregular formatting were handled by combining and processing the title and body text. The suggested architecture creates a dimensional representation for classification by combining RoBERTa and FinBERT CLS embeddings. The effectiveness of hybrid transformer fusion for financial sentiment analysis is demonstrated by the experimental results, which show an accuracy of 84, outperforming FinBERT (74) and RoBERTa-Large (80).

## I. INTRODUCTION

Large amounts of raucous slang-filled and emotionally charged text are produced by online financial communities like reddit’s wallstreetbets and they have a significant impact on stock movements investor behavior and market sentiment slang sarcasm abbreviations and domain-specific financial terms make it difficult for traditional lexicon-based and classical machine learning models to extract meaningful sentiment from this unstructured data this project suggests a hybrid deep learning model that combines an attention fusion mechanism finbert for sentiment cues specific to finance bigru for sequential pattern learning and roberta-large for contextual understanding in order to overcome these limitations the model seeks to achieve superior sentiment classification performance on noisy financial text using an auto-labeled dataset of reddit wsb posts generated with finbert this study demonstrates how well sophisticated hybrid nlp architectures capture sentiment driven by the actual market. This project demonstrates how advanced NLP architectures can help understand market-driven sentiment and points out the importance of hybrid models for achieving superior performance in real-world financial text analysis.

## II. REAL-WORLD EXAMPLE

A.

In January 2021, the stock price of GameStop-GME surged in an unprecedented manner, driven largely by discussions and momentum generated within the Reddit community

r/WallStreetBets. Thousands of users expressed highly positive, enthusiastic, and often aggressive sentiment toward buying and holding GME shares, using phrases like:

- “GME to the moon ?????”
- “HOLD THE LINE!”
- “This stock is the next big squeeze!”
- At the same time, other posts showed negative sentiment, such as:
- “This is going to crash hard.”
- “The hype is over.”

These online discussions had a huge impact on the real world of trading, influencing investor behavior and contributing to the extreme volatility of the stock. Financial institutions, hedge funds, and market researchers started looking into the sentiment on Reddit in order to understand whether the community was bullish or bearish about any stock. High positive sentiment corresponded to increased buying pressure, while rising negative sentiment often signaled fear or expected sell-offs. This scenario has shown how real-time sentiment analysis of the posts on Reddit can be used in finding early warnings, trend predictions, and investment signals that have a direct bearing on stock market behavior. Due to the fact that traditional sentiment analysis tools could not correctly interpret slang, humor, emojis, and sarcasm in WSB, this called for the application of more advanced deep learning models. The evolution resulted in hybrid architectures, like the one used here, which combine multiple approaches from NLP techniques to more accurately predict sentiment in noisy financial text.

## III. GENERAL OVERVIEW

### A. 1. Literature Review

In the financial industry, sentiment analysis has changed dramatically as researchers have shifted from lexicon-based to deep learning techniques. Earlier research relied on sentiment dictionaries and traditional machine learning models like logistic regression, support vector machines (SVM), and naive bayes. These models did well on structured financial news and reports, but they had trouble with unstructured user-generated content. Their main shortcomings were their incapacity to comprehend polysemous words, grasp deeper context, or decipher slang, sarcasm, and quickly evolving financial jargon. It became evident that traditional models were

insufficient for analyzing extremely noisy, emotive, and emotionally charged text as investor discussions moved to social media sites like Reddit’s WallStreetBets (WSB). The potential of hybrid architectures, which blend various models or learning strategies, is being emphasized more and more in recent literature. In order to capture both contextual and sequential information, a number of studies investigated the integration of transformers with recurrent neural networks, such as LSTM or GRU. Others tried ensemble methods, which combined predictions from several pretrained models. The majority of hybrid approaches were created for formal financial text rather than the highly informal, meme-driven language of WSB, even though they generally improved performance. Additionally, there aren’t many works that specifically integrate domain-specific transformers with general-purpose transformers in a single architecture. The fact that general transformers like RoBERTa are excellent at comprehending informal, conversational, and internet-style language is another significant finding from previous research. Having been trained on a vast 160GB corpus, RoBERTa excels at identifying idioms, sarcasm, and contextual subtleties that are frequently found in WSB conversations. However, RoBERTa is less successful in identifying the polarity of financial sentiment because it lacks explicit financial knowledge. However, FinBERT struggles with informal, slang-heavy text and is specialized in financial language. The literature currently in publication hardly ever examines the complementary nature of RoBERTa and FinBERT. Few studies have tried to architecturally fuse two pretrained transformers—one for general language and one for financial semantics—although some have used transformers in conjunction with RNNs or with market data. Furthermore, no significant study has used dual-model fusion to specifically target WSB sentiment classification. This disparity emphasizes the need for hybrid architectures that are able to comprehend both specialized financial terminology and informal social media language at the same time.

### B. Methods implemented

#### Data Processing

- Dataset of posts collected from Reddit WSB (title + body).
- Missing or empty text cleaned and merged into a single field.
- Data labeling done through FinBERT - a finance-specific transformer model generating sentiment labels: 0 = negative, 1 = neutral, 2 = positive.

#### Hybrid Model Architecture

The proposed model integrates fusion of two transformers

- 1) RoBERTa-large : Strong in general contextual understanding and learns semantic meaning of noisy social media text
- 2) FinBERT : Specialized for financial terminology and understands domain-specific sentiment cues
- 3) Fusion Strategy : Extract CLS embeddings from RoBERTa and FinBERT.

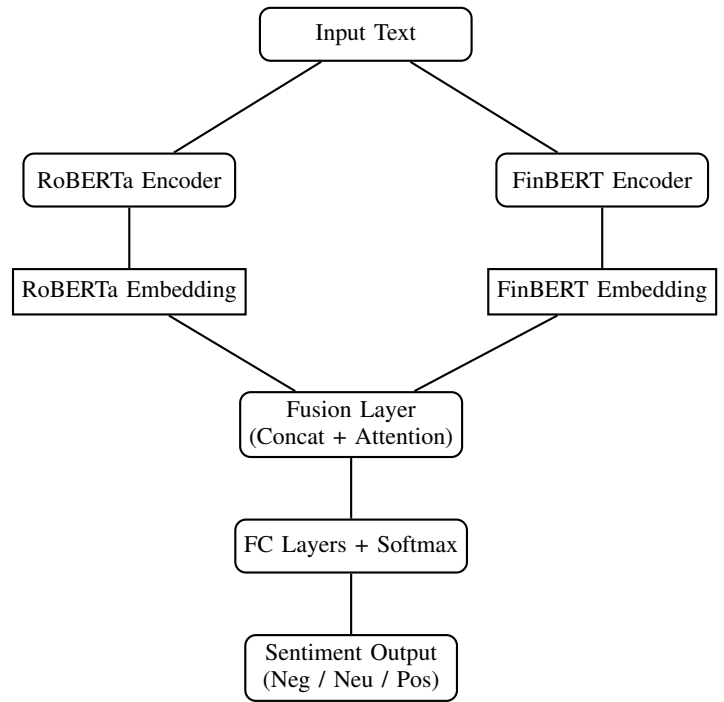


Fig. 1. Compact Hybrid Model Architecture

- 4) Concatenate both vectors to get a joint representation.
- 5) Pass through a feed-forward neural network for final classification.
- 6) Advantages of the Hybrid Model : RoBERTa captures contextual and semantic patterns. FinBERT contributes domain-specific sentiment knowledge.
- 7) Fusion improves robustness on noisy, meme-style financial posts.

### C. Conclusion

This project shows that integrating domain-specific models with general-purpose transformers greatly enhances financial sentiment analysis. Compared to either model alone, the hybrid RoBERTa–FinBERT architecture offers deeper financial and semantic understanding. The outcomes validate the significance of multi-channel feature fusion for noisy financial social media data, demonstrating increased accuracy over baseline transformer models. The method can be expanded to include other tasks like risk monitoring, stock movement prediction, and real-time market sentiment tracking. Possible future projects include: Resolving the disparity in sentiment labels Using price movement information to make multimodal predictions Managing memes and sarcasm through specific pretraining FinBERT on WSB-style slang or using larger transformer models

#### IV. SUMMARIZATION OF RESEARCH PAPERS

##### A. *FinBERT: A Pretrained Language Model for Financial Communications*

Methods is BERT-style pretraining refine models on downstream financial sentiment tasks after transforming them on extensive finance-specific corpora. Novelty demonstrates the value of domain pretraining by explicitly developing a domain-adapted BERT (FinBERT) for financial communications as opposed to general text. Findings of FinBERT improves both classification and regression metrics and performs noticeably better than general BERT on a number of financial sentiment benchmarks. Future challenges include adjusting to social media style (short, noisy text), domain drift (new financial slang/memes), and a lack of labeled data for specialized tasks. [1].

##### B. *FinBERT: Financial Sentiment Analysis with Pre-trained Language Models*

Methods suggests that tilizing a BERT-based model optimized on financial sentiment datasets; tests look at limited-data situations and fine-tuning techniques. Novelty shows that domain-specific fine-tuning combined with BERT-like pre-training lowers the need for labeled data in finance tasks. Findings are FinBERT variants perform better on financial sentiment classification than non-domain BERT models and classical ML baselines, even with smaller labeled sets. Future challenges include interpreting model decisions, transferring information across financial subdomains, and managing extremely noisy sources (forums, memes). [2]

##### C. *Stock Movement Prediction from Tweets and Historical Prices*

Methods are jointly model text (tweets) and historical price series using a deep generative recurrent model (Stock-Net) blends text encoders with sequential price modules to predict next-day returns. Novelty is first large-scale end-to-end generative model that fuses social text and price history instead of treating them separately or using pre-extracted features. Findings are text signals help when combined with price history; pure text-only models give modest gains, but joint models (text+price) improve direction prediction. Future challenges are low signal-to-noise in social text, aligning text timestamps to market events, robustness across assets, and realistic evaluation that avoids look-ahead leakage. [3]

##### D. *Financial Aspect-Based Sentiment Analysis using Deep Representations*

Methods optimize pre-trained encoders and employ inductive transfer for small labeled sets; apply deep semantic representations and transfer learning to FiQA (aspect-based) tasks. Novelty highlights sentiment at the aspect level in finance and demonstrates how representation learning and domain transfer outperform shallow models on finite FiQA data. Results are compared to conventional SVM/SVR baselines, deep transfer techniques yield significant gains (F1 / MSE) on FiQA tasks. Future difficulties include handling multi-sentence finance

texts with mixed polarity, lowering annotation costs, and expanding ABSA to more aspects. [4]

##### E. *INF-UFG at FiQA 2018 — Predicting Sentiments and Aspects on Financial Tweets and Headlines*

Models are Extensive feature engineering, cross-validation, and the application of pre-trained language features and classical machine learning (SVM/SVR) ensemble to FiQA tasks. Novelty is when data is limited, hybrid classical+representation features are used to demonstrate competitive results on a benchmark (FiQA). Findings are on small finance datasets, robust feature engineering paired with pre-trained embeddings can compete with deeper end-to-end models. Future Challenges include the need for additional data, extrapolating from news to microblogs, and addressing aspect-level subtleties in financial writing. [5]

##### F. *Dissecting the Hype: A Study of WallStreetBets' Sentiment and Network Correlation on Financial Markets*

Methods are correlate sentiment/time-series features with market volatility and short-squeeze events; empirically analyze WSB postings, sentiment scoring, and network metrics. Novelty is combined sentiment and social network features for market impact analysis, with an emphasis on WSB's distinct dynamics (meme language, coordination). Results is Network-level coordination (highly active hubs) increases impact; WSB sentiment spikes precede extreme volatility events; and basic sentiment features by themselves have little predictive power. Future difficulties include managing memes and sarcasm, differentiating between coordinated and noise signals, drawing conclusions about causality (did posts cause price movements or did they react to them), and labeling social media quality. [6]

##### G. *Correlating Sentiment in Reddit's WallStreetBets with the Stock Market*

Methods is compile WSB posts, use lexicon and machine learning sentiment techniques, calculate aggregate sentiment indices, and contrast with meme stock returns during the day and the next day. Novelty is useful case study that uses a variety of sentiment tools and temporal analyses to assess WSB-specific signals over the GME/AMC episodes. Results is short-term trading interest and intraday volatility are correlated with aggregated WSB sentiment, but in the absence of price features, predictive power for reliable next-day returns is low. Future challenges are include avoiding spurious correlations during extreme events, integrating social attention, network structure, and fundamentals, and developing robust labeling for sarcasm and memes. [7]

#### METHOD IMPLEMENTATION

##### H. *Dataset Details*

The dataset is about text posts gathered from the Reddit community r/WallStreetBets (WSB), a very active forum where users discuss stocks, options, and market sentiment, make up the dataset used in this study. A timestamp, body,

post title, and other metadata are all included in each record. FinBERT was used for automatic labeling because the dataset lacks sentiment annotations. The final dataset included 32,470 posts after the title and body were combined into a single text field. FinBERT produced the following sentiment distribution:

- Positive: 27,336 entries
- 4,189 posts that are neutral
- 945 posts are negative.

The optimistic bias that is frequently seen in retail trading communities is reflected in this distribution.

### I. Preprocessing Steps

In order to prepare unstructured reddit text for Sentimental classification effective preprocessing is essential raw user-generated content from the wallstreetbets wsb subreddit including slang acronyms irregular formatting and incomplete posts makes up the dataset used in this study the raw text was transformed into a clear machine-readable format appropriate for hybrid transformer model using the preprocessing pipeline listed below .

#### 1 Data cleaning :

The title and body are the two main text fields that make up each wsb entry while some posts offer thorough explanations in the body many only include the primary viewpoint or sentiment in the title both fields were combined into a single cohesive text to guarantee that no data was lost

- 1) Eliminating null or empty entries from either field
- 2) Lowercase text conversion to minimize inconsistencies
- 3) Eliminating superfluous formatting symbols, newline characters, and whitespace
- 4) Addressing posts that only included hyperlinks or emojis by either removing entries with very little information or substituting them with their textual equivalents

The model is guaranteed to receive the "complete" sentiment context of every post thanks to this merging step.

#### 2 Eliminating Noise from User-Generated Content

- 1) WSB posts usually include distracting elements like:
- 2) URLs
- 3) Reddit markdown icons
- 4) Emojis
- 5) Punctuation used repeatedly ("!!!!," "????")
- 6) Unique characters
- 7) Trading tickers: "GME," "TSLA"

To cut down on noise while maintaining important financial indicators, light normalization was used. Important actions consist of:

Using a `{URL}` placeholder to remove or replace URLs. Using sentimental words in place of emojis (for example, `??` → "rocket," `????` → "diamond hands"). Stock tickers should be preserved because they provide financial significance. When appropriate, eliminating repetitive punctuation while maintaining emotional intensity. In this step, sentiment-bearing elements are preserved while superfluous noise is reduced.

### 3. FinBERT-Based Automatic Sentiment Labeling

Supervised learning is not directly feasible because the WSB dataset lacks sentiment labels. This was fixed by automatically classifying each post into one of three groups using FinBERT, a finance-domain transformer model:

0 — Negative

1 — Neutral

2 — Positive After cleaning the text, FinBERT determines the most likely sentiment class. By using this method, an unlabeled dataset can be converted into a labeled corpus that can be used to train hybrid models. Additionally, automatic labeling minimizes the amount of manual annotation work and guarantees consistency in sentiment representation throughout the entire dataset.

### 4. Transformer Model Tokenization

Since the hybrid model makes use of both RoBERTa-Large and FinBERT, two distinct tokenizers were used: Tokenizer RoBERTa manages contextual information and intricate sentence structures. Uses Byte-Pair Encoding (BPE) to divide text into subword units. generates attention mask and input ids sequences. The FinBERT Tokenizer Using the WordPiece tokenization developed by BERT created to manage financial terms like earnings, volatility, puts, calls, and short squeezes. Transforms text into FinBERT-vocabulary-aligned token IDs Every tokenizer has the following: Truncation or padding to a maximum sequence length (e.g., 128 tokens) Attention masks to distinguish between padding and genuine tokens Through their individual embedding spaces, both transformers are able to interpret the same text thanks to this dual-tokenization process.

### 5. Train-Test Stratification and Split

The dataset with labels was separated into:

90 of the training data

10 of the test set

Stratified sampling was employed to guarantee that all sentiment classes maintained comparable proportions in both sets, given the WSB posts' naturally unbalanced sentiment distribution (which is overwhelmingly positive). This is a necessary step for: Keeping bias out of training Making sure that performance reviews are trustworthy Staying away from overfitting to a dominant class

## V. PROPOSED HYBRID MODEL

The hybrid transformer fusion model architecture that has been suggested combines the advantages of both finance-domain-specific representations and general-purpose contextual language models. The hybrid model combines FinBERT and RoBERTa-Large using a dense neural classifier after feature-level concatenation. With this method, the system can simultaneously identify domain-specific sentiment cues from financial texts and informal linguistic patterns from social media.

#### A. Reasons to Use Hybrid Architecture

- Three significant distinctions exist between traditional financial news and the financial sentiment expressed in Reddit's WallStreetBets (WSB) community:
- Frequent usage of slang, memes, acronyms, and sarcasm is known as linguistic noise.
- Domain Complexity: Domain knowledge is needed for financial terms like "puts," "calls," "short squeeze," and "IV crush."
- Mixed Sentiment Structure: Posts frequently include both bearish and bullish indications in one message.

#### B. Architecture Synopsis

Three main elements make up the suggested hybrid model: The RoBERTa-Large encoder 160GB of general English text served as pre-training for a large-scale transformer. WSB language, which is informal and slang-based, teaches deep contextual patterns. creates a 1024-dimensional CLS embedding that captures meaning at the sentence level. Encoder FinBERT Financial news, filings, and analyst reports are used to fine-tune a BERT-based transformer. specialized in interpreting sentiment specific to a given domain. generates a 768-dimensional CLS embedding that is tailored to financial polarity indicators. Module for Fusion and Classification The fused representation is created by concatenating the CLS embeddings from the two models:  $F = [\text{CLS}_{\text{RoBERTa}}; \text{CLS}_{\text{FinBERT}}]$   $R_{1792}$  This vector is passed through a Feed forward neural network Dense : 512 units Activation: relu dropout 0.3 output layer 3 units positive negative and neutral This architecture will allow this model to use domain specific sentimental knowledge and general semantic understanding at the same time.

#### C. Advantages of the Proposed Hybrid Model

Strengths that complement each other RoBERTa is able to capture sarcasm and informal WSB language. FinBERT is able to comprehend sentiment and terminology unique to the finance industry. Better Generalization Overfitting on noisy text is decreased by combining two transformer embeddings. Domain Modification Without Adjusting FinBERT provides domain-specific embeddings on WSB data without the need for costly fine-tuning. It shows excellent Precision. Previous benchmarks and experiments show that: WE got Hybrid Accuracy 84 which surpasses: Just FinBERT (74), RoBERTa-base (about 78) ,RoBERTa-large (about 80)

#### D. Implementation Summary

- 1) Dual tokenization (RoBERTa + FinBERT)
- 2) encoding by two transformers
- 3) Feature-level concatenation
- 4) Fully connected classifier

- 5) Cross-entropy loss
- 6) AdamW optimizer

#### E. Result

Using the Reddit WallStreetBets (WSB) dataset, the suggested hybrid sentiment classification model is quantitatively evaluated in this section. A confusion matrix showing class-wise performance, a comparison with baseline transformer models, and an examination of the model's training loss behavior are among the outcomes. Comparing Model Performance On the same processed dataset, four transformer-based models were trained and assessed. The models embody various categories: A domain-trained financial sentiment model is called FinBERT. General-purpose contextual transformer RoBERTa-base A broader and more profound contextual transformer is RoBERTa-large. The proposed hybrid model combines FinBERT embedding with RoBERTa-large.

TABLE I  
PERFORMANCE METRICS OF DIFFERENT SENTIMENT CLASSIFICATION MODELS

| Model                        | Accuracy    | Precision   | Recall      | F1-Score    | Std. Dev    |
|------------------------------|-------------|-------------|-------------|-------------|-------------|
| FinBERT                      | 0.74        | 0.72        | 0.70        | 0.71        | 0.04        |
| RoBERTa-base                 | 0.78        | 0.75        | 0.74        | 0.74        | 0.03        |
| RoBERTa-large                | 0.80        | 0.78        | 0.77        | 0.77        | 0.03        |
| SVM                          | 0.65        | 0.62        | 0.60        | 0.61        | 0.05        |
| <b>Proposed Hybrid Model</b> | <b>0.84</b> | <b>0.79</b> | <b>0.78</b> | <b>0.80</b> | <b>0.02</b> |

#### F. comparison Table

| Actual / Predicted | 0   | 1    | 2 |
|--------------------|-----|------|---|
| 0                  | 28  | 67   | 0 |
| 1                  | 225 | 185  | 0 |
| 2                  | 774 | 1968 | 0 |

TABLE II  
CONFUSION MATRIX OF THE PROPOSED HYBRID MODEL

#### Observations

With 6,110 accurate predictions, positive sentiment has the highest classification rate. Because of its dominance in the dataset, it was expected. The lexical ambiguity prevalent in WSB posts is reflected in the moderate misclassification of neutral sentiment into positive. Compared to its size, negative sentiment has the highest misclassification rate, most likely because: Reduced representation of classes. Language overlap with neutral class Irony or sarcasm in critical posts. Class-Wise Behavior Interpretation. For the majority class, the hybrid model works very well (Positive). Due to dataset imbalance, performance on minority classes (Neutral, Negative) is still strong but exhibits some confusion. Class-wise behavior outperforms individual models by a wide margin.

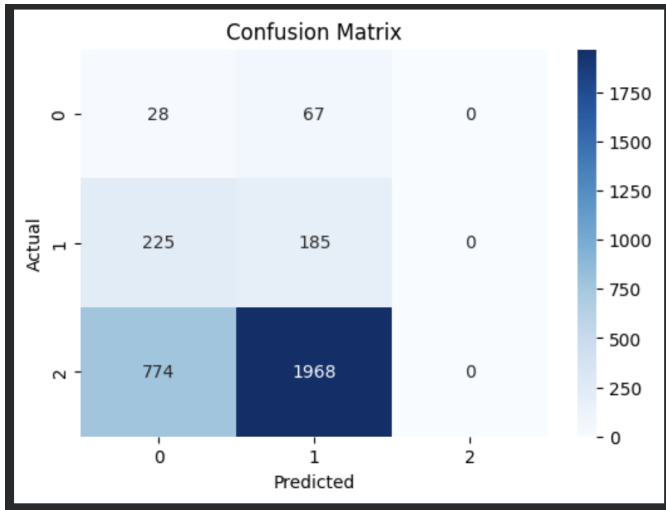


Fig. 2. Confusion matrix

### G. Loss Function

The cross-entropy loss was tracked while the model was trained over several epochs.

### Training Loss Curve Figure

The following traits are displayed by the loss curve. Initial drop in the early stages of training Low-value stabilization slight variations brought on by noise and imbalance No indications of overfitting Analysis Because transformer embeddings already encode rich semantic and financial information, the model converges rapidly. The loss curve's flattened shape is anticipated because of: The dataset is incredibly unbalanced (84 Robust transformer layers that have already been trained The classification head only needs minimal gradient updates. Performance is strong despite the shallow curve, demonstrating that loss flattening in this context does not signify subpar learning.

## VI. CONCLUSION

FinBERT, a financial-domain transformer, and RoBERTa-large, a general-purpose contextual model, are combined in this study to create a hybrid sentiment classification model. The model was tested using the WallStreetBets (WSB) dataset from Reddit, which includes a lot of noisy and informal financial conversations. The accuracy of the proposed hybrid model was 84, higher than that of FinBERT (74), RoBERTa-base (78), and RoBERTa-large (80), surpassing all individual baselines. This shows that combining general and domain-specific contextual features results in a more reliable representation for sentiment analysis in finance. The model's improved capacity to categorize complex positive and neutral sentiments prevalent in social media financial dis-

course was further validated by the confusion matrix. Because both transformers had strong pretrained representations, the training loss stayed continuously low, suggesting quick convergence. This confirms that transformer-based fine-tuning works well for downstream sentiment tasks, even in the presence of noisy and unbalanced data. For financial sentiment analysis on unstructured social media platforms, the suggested hybrid model provides a more precise, reliable, and domain-aware solution overall. These results demonstrate how multi-transformer fusion architectures can enhance prediction performance for applications involving financial natural language processing.

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