Emotion-Fundamental Trend Amplifier with Cross-Market Echoes: A Deep Learning Approach to Short-Term Stock Trading Signals

49775 [1] 50714 [1] 49872 [1]

Abstract

Stock price forecasting is challenging due to volatile markets driven by diverse factors. This study predicts weekly S&P 500 stock price trends (BUY, SELL, NEUTRAL) using company fundamentals, economic indicators, sentiment from Reddit posts and earnings calls, and cross-market signals. We develop a deep learning approach combining Informer-TCN and Cross-Modal Transformer models with an XGBoost ensemble, capturing signal coherence for reliable trading patterns. Evaluations on 2009–2024 S&P 500 stocks demonstrate enhanced predictive performance, especially when sentiment and cross-market signals align with financial data. This approach offers a strong framework for identifying short-term trading opportunities in dynamic financial markets.

1. Introduction

1.1. Problem

Stock markets are exciting but tough to predict. They fuel company growth and investor profits, but prices swing fast due to many factors: company earnings, economic news, investor sentiments and trends in markets like crypto or oil (Bhuiyan et al., 2025). For example, in 2020, the S&P 500 index crashed 34% in a month due to COVID-19, then soared 68% by year-end (Bloomberg, 2020). Accurate predictions stabilize pension funds, securing retirements for millions, and support economic growth. Wrong predictions risk losses that hurt investors and communities (Shiller, 2003).

Predicting weekly stock trends is challenging because noisy Reddit sentiment and uneven data frequencies—quarterly fundamentals versus weekly prices—require careful alignment (Kang and Kim, 2025). Weekly predictions suit trading needs and data availability, balancing short-term signals with robust patterns. Old methods, like ARIMA models, use simple math to guess prices based on past trends (Box and Jenkins, 1970). They work in calm markets but fail when prices jump or when news and feelings mix in. Many newer studies focus on single factors, like company profits, and miss how different forces team up to drive prices (Kang and Kim, 2025). This makes it hard to find reliable trading signals in today's wild markets, where investors need smart tools to make quick, confident choices.

1.2. Solutions

Deep learning offers a fresh way to tackle stock price prediction. Unlike old models, it finds hidden patterns in messy data, like prices, company stats, economic numbers, and social media buzz. Early models, like Long Short-Term Memory (LSTM) networks, beat ARIMA by tracking long-term trends but struggled at 48.6% accuracy in our tests due to limited temporal modeling (Fischer and Krauss, 2018). Newer models, like Transformers and Temporal Convolutional Networks (TCNs), use attention mechanisms focusing on key data points or special filters to spot patterns faster and more accurately (Vaswani et al., 2017; Bai et al., 2018). Unlike simpler machine learning models, deep learning captures complex interactions, making it ideal for volatile markets.

These models can blend many data variables: company profit margins, inflation rates, sentiment from Reddit posts or earnings calls, and Bitcoin or oil price trends (Devlin et al., 2019; Zhang and Yan, 2020). But most treat these data separately, missing their teamwork. For example, a stock might rise when strong profits, good economic news, positive sentiments, and rising ccross market features all line up. We call this "signal coherence," a concept tied to ensemble learning, where combined clues are stronger, and behavioral finance, where crowd moods shape markets (Dietterich, 2000; Shiller, 2003). Deep learning's ability to find these teamwork moments makes it perfect for trading signals.

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1.3. Proposal

This study proposes a deep learning model that blends four data types—company fundamentals (like profit margins), economic indicators (like inflation), investor sentiment (from Reddit posts and earnings calls), and cross-market signals (like Bitcoin and oil prices)—to predict weekly stock price trends (BUY, SELL, NEUTRAL) for S&P 500 stocks. Our main model combines an Informer-TCN and a Cross-Modal Transformer, using multi-head attention for data interactions and dilated convolutions for trend detection to pick the strongest signals with a coherence score (Vaswani et al., 2017; Bai et al., 2018). It uses multiple streams, like TimesNet for financial data and Informer for macro trends, stacked with XGBoost to resolve model disagreements for sharper results, chosen over Random Forest for its robustness to noisy predictions. We test on S&P 500 stocks from 2009–2024, chosen for their variety and rich data, helping the model learn diverse market patterns (Bhuiyan et al., 2025).

We compare our model to ARIMA, LSTMs, and other deep learning models (TimesNet, Informer, TFT-GAT). Unlike past studies that use single data types (Fischer and Krauss, 2018; Zhang and Yan, 2020), we combine them to capture their joint power. Our results show a portfolio return of 17.97% (beating the S&P 500's 9%) for stocks like ULTA and WYNN, with 45.27% trend accuracy, a 57.2% ROC-AUC for discriminative power, and a 10.99% hit rate for high-coherence signals (>0.7), reflecting selective, high-confidence signals. While accuracy is modest compared to our 68% target, prioritizing high-confidence signals trades off broader accuracy for reliability, and the strong return proves practical value for trading. This work offers a smarter tool for investors, boosting profits and supporting economic stability.

2. Related Work

Deep learning has changed how we predict stock prices, beating older methods like linear models by finding complex patterns. Early work used Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) to track price trends over time (Fischer et al., 2018; Nelson et al., 2017). These models worked better than traditional tools but relied heavily on past prices and technical indicators, struggling when markets changed suddenly due to economic shifts or investor mood swings.

Newer models, called Transformers, brought a big leap forward by using attention mechanisms to spot long-term patterns without needing recurrence (Vaswani et al., 2017). Studies show Transformers beat LSTMs in handling complex price data across multiple stocks (Wu et al., 2020; Zhou et al., 2021; Zeng et al., 2022). For example, Zhou et al. (2021) found their Informer model predicted prices well over long periods, but it faltered during wild market swings, showing it's not perfect for sudden changes. Graph neural networks (GNNs) also appeared, modeling how stocks connect like nodes in a web (Chen et al., 2021). GNNs are great for spotting market links but need lots of computing power and can fail with thin data.

To make predictions stronger, researchers added more data features. Fundamental data like company profits or debt, helps tie predictions to real business health (Fischer et al., 2018; Nelson et al., 2017). But these numbers only update every few months, so they're slow to catch market moves. Some studies even found fundamentals can hurt accuracy when they clash with price trends (Zhang et al., 2019). Economic data like interest rates or job numbers, helps predict market trends (Baek et al., 2018; Wu et al., 2021). However, these numbers are too broad to explain why one stock moves differently, and Baek et al. (2018) noted they can add confusion in strong markets.

Other work looked at signals from other markets, like oil, crypto, or volatility indexes, using models that view each market separately (Zhang et al., 2020; Li et al., 2020; Jiang et al., 2021). These models boost accuracy, but they miss how markets affect each other. For instance, Jiang et al. (2021) showed crypto signals helped predict stocks, but their model failed during market crashes because it didn't catch shared risks. Sentiment from news and social media, using tools like FinBERT and StockNet, also helps by capturing investor feelings (Araci, 2019; Xu and Cohen, 2018). Reading live text is tough on computers, so many use pre-summarized sentiment scores instead. Reinforcement learning has been used too, adjusting trades based on these signals for quick profits (Jiang et al., 2017), but it often ignores long-term gains.

Most models treat these signals prices, fundamentals, economic data, cross-market trends, and sentiment as separate pieces. In real trading, the best signals happen when these pieces line up, like when strong company stats, good economic news, rising related markets, and happy investors all point the same way. We call this "signal coherence," a concept tied to ensemble learning (where combined clues are stronger) and behavioral finance (where crowd psychology drives markets) (Dietterich, 2000; Shiller, 2003). Few studies explore this idea, missing a chance to make predictions sharper and portfolios better. but make same content and way.

Our work fills this gap with a deep learning model that blends all these data types. Using attention mechanisms, it spots when signals align and boosts their impact, aiming to improve three metrics: balanced accuracy (for fair predictions), a coherence score (to measure signal alignment), and portfolio returns (for real-world value). Unlike past models, we focus on how signals work together, offering a smarter way to predict stock prices in changing markets.

3. Methodology

3.1. Data Collection

We collected data from **2009–2024** on **502 S&P 500 stocks**, totaling **420,000 weekly records**, covering key market events like the 2008 recovery and COVID-19 crash to ensure varied conditions. Sources include Bloomberg (**>18 company data features** - e.g., profits, debts), FRED (economic indicators - e.g., inflation), Yahoo Finance (market signals - e.g., oil prices), and Reddit/FMP API (sentiment scores using BERT). We aim to predict BUY, HOLD, or SELL signals with a **±2%** price change, with **50% HOLD**, **30% BUY**, **20% SELL**. This multi-modal dataset, with **47 features** across company, economic, market, and sentiment categories, supports deep learning models like TimesNet to learn price patterns. However, sentiment noise may affect accuracy, needing careful handling. (our methodology is shown in **Figure 3**)

3.2. Preprocessing

We first loaded the dataset, standardised the date format, and encoded the trading signals (BUY, HOLD, SELL) into numerical labels for model compatibility. The characteristics were grouped into four sets: macroeconomic indicators of the company (e.g. profit ratios, debt levels), sentiment of the market (e.g. social media scores, oil prices) and a combined set, totaling **47** features. We also standardised all features to a common numerical range, facilitating efficient training for deep learning models. The data was then reshaped into **52-week** sequences (**52×47 blocks**) to capture seasonal and trend-based structures. After standardising data, we split the dataset into **80% training and 20% testing sets**, preserving the original class distribution. Missing values were imputed with zeros to maintain model stability. Keeping the **50:30:20** class split reflects real trading, but uneven classes may favor HOLD predictions, suggesting class-weight adjustments.

3.3. Signal Labeling

Signals were assigned based on weekly price changes: BUY for increases above $+2\%$, SELL for decreases below -2%, and HOLD within $\pm 2\%$. We tested thresholds from $\pm 0.3\%$ to $\pm 3\%$, selecting $\pm 2\%$ for its balance of sensitivity and noise reduction, supported by prior work (Jegadeesh and Titman, 1993; Brock, Lakonishok, and LeBaron, 1992). A dynamic threshold adjustment using the **VIX** index was implemented to adapt to market volatility, enhancing signal reliability. This approach aligns with short-term trading systems and supports attention-based models like the Cross-Modal Transformer in learning temporal patterns.

3.4. Evaluation and Baselines

We used a Moving Average Crossover baseline (5-week vs. 20-week, **16.56%** F1-score), Logistic Regression (**0.32** F1-score), XGBoost (**0.30** F1-score), and Gaussian Naive Bayes (**0.28** F1-score), showing poor trends due to data complexity. This supports the use of advanced models. We evaluate with **accuracy**, **precision**, **recall**, **F1-score**, **ROC-AUC**, and **total profits**, focusing on reliable predictions (agreement >**0.7**). High agreement may limit trades, suggesting a balance between reliability and frequency.

4. The Architecture

4.1. LSTM

The LSTM processes 52×9 weekly sequences of selected financial ratios and macroeconomic indicators, featuring two **128-unit** LSTM layers (retaining sequences), a **64-unit** LSTM layer, and dense layers (**64 units** with ReLU, **3 units** with softmax). Dropout (**20%**) and L2 penalty (**0.0001**) prevent overfitting. It models sequential price movements, ideal for short-term trends, but struggles with long-term patterns, requiring complementary models. This design excels at time-ordered financial data. The configuration settings for the LSTM model are detailed in **Table 1**.

Table 1: LSTM Configuration Settings

Parameter	**Value**
Input Size	1
Embedding Dimension	64
Output Size	1
Sequence Length	150
Batch Size	16
Context Length	150
Number of Epochs	15
Learning Rate	9.9225e-04
Total Parameters	146627

4.2. TimesNet

TimesNet processes 52×9 inputs drawn from financial fundamentals and macro indicators, with four convolutional blocks (**128** and **64 filters**, kernel sizes **3** and **5**), Squeeze-and-Excitation modules (ratio **16**), and batch normalization, followed by global pooling and dense layers (**64 units**, ReLU; **3 units**, softmax). Dropout (**20%**) ensures robustness. This state-of-the-art model detects weekly and monthly market cycles, though computational demands are high. Kernel sizes target financial rhythms. The configuration settings for the TimesNet model are detailed in **Table 2**.

Table 2: TimesNet Configuration Settings

Parameter	Value
Input Shape	[None, 1, 9]
Filters (Layer 1, 2)	128
Filters (Layer 3, 4)	64
Kernel Sizes	[3, 5]
Reduction Ratio (SEBlock)	16
Batch Size	64
Number of Epochs	30
Learning Rate	6.8012e-04
Total Parameters	280987

4.3. Cross-Modal Transformer

The Cross-Modal Transformer handles 52×47 sequences combining financial, macroeconomic, sentiment, and cross-market features, using two multi-head attention layers (**4 heads**, **128 units**), feed-forward networks (**256 units**), and layer normalization, followed by dense layers (**64 units**, ReLU; **3 units**, softmax). Dropout (**20%**) stabilizes training. It integrates sentiment and fundamentals, critical for market-driven trends, but parameter complexity risks overfitting. This advanced attention design excels in multi-modal forecasting. The configuration settings for the Cross-Modal Transformer model are detailed in **Table 3**.

Table 3: Cross-Modal Transformer Configuration Settings

Parameter	Value
d_model	64
dff (Feedforward Dim)	256
Number of Heads	2
Dropout Rate	0.2
Batch Size	64
Number of Epochs	30
Learning Rate	6.8012e-04
Total Parameters	954855

4.4. TFT-GAT Hybrid

The TFT-GAT Hybrid processes 52×47 full-featured sequences from all 47 financial, macro, sentiment, and cross-market variables, combining two Temporal Fusion Transformer blocks (**47 units**, **256** and **128** feed-forward units) and two Graph Attention Network blocks (**4 heads**, **47 units**), followed by pooling and dense layers (**64 units**, ReLU; **3 units**, softmax). Dropout (**20%**) enhances stability. It models time and feature interactions, vital for complex markets, but graph computations are resource-intensive. This cutting-edge hybrid is finance-focused. The configuration settings for the TFT-GAT model are detailed in **Table 4**.

Table 4: TFT-GAT Configuration Settings

Parameter	Value
Input Shape	[None, 1, 47]
Output Shape	[None, 3]
Batch Size	64
Number of Epochs	50
Learning Rate	4.0591e-04
Total Parameters	55299

4.5. Informer

Informer processes 52×47 long-horizon sequences using all input features particularly strong for macroeconomic and volatility indicators with ProbSparse self-attention (**4 heads**, **128 units**), two encoder-decoder stacks, and distillation layers, followed by dense layers (**64 units**, ReLU; **3 units**, softmax). Dropout (**20%**) mitigates overfitting. Its efficient attention manages long financial sequences, outperforming standard transformers, but training time is significant. This state-of-the-art model is optimized for extended stock analysis. The configuration settings for the Informer model are detailed in **Table 5**.

Table 5: Informer Configuration Settings

Parameter	Value
Input Shape	[None, 1, 47]
Output Shape	[None, 3]
Embedding Dimension	64
Sequence Length	150
Batch Size	16
Number of Epochs	30
Learning Rate	6.8012e-04
Total Parameters	70507

4.6. Informer-TCN

Informer-TCN processes 52×47 sequences from the complete set of features across all modalities, integrating Informer's attention (**4 heads**, **128 units**) with a four-layer Temporal Convolutional Network (**64 filters**, kernel size **3**), followed by dense layers (**64 units**, ReLU; **3 units**, softmax). Dropout (**20%**) is applied. It balances rapid pattern detection with long-sequence modeling, ideal for stocks, but tuning complexity is a challenge. This unique hybrid enhances forecasting efficiency. The configuration settings for the Informer-TCN model are detailed in **Table 6**.

4.7. Stacked Ensemble with XGBoost

Meta-features from all models, based on predictions across the four data domains, are processed by an XGBoost classifier (**300 trees**, depth **3**, learning rate **0.03**, adjusted for class imbalance). This ensemble integrates diverse neural outputs

Table 6: Informer-TCN Configuration Settings

Parameter	Value
Input Shape	[None, 1, 47]
Output Shape	[None, 3]
Embedding Dimension	64
Sequence Length	150
Batch Size	16
Number of Epochs	50
Learning Rate	4.0591e-04
Total Parameters	597424

for robust predictions in volatile markets, though computational demands are notable. Its innovative design ensures reliable financial forecasting by leveraging complementary model strengths.

5. Training Methods

Our methodology section outlined the training methods. Here, we detail how we trained six neural networks (LSTM, TimesNet, Cross-Modal Transformer, TFT-GAT, Informer, Informer-TCN) and an XGBoost ensemble to predict weekly BUY, HOLD, or SELL signals for **502** S&P 500 stocks, using a **420,000**-record dataset with **47** features in **52×47** time-series blocks.

5.1. Optimizers and Parameter Settings

From **Table 7**, We used AdamW for all neural networks, as introduced by (Diederik P. Kingma and Jimmy Ba, 2014), setting the learning rate to **0.001** chosen after tests on financial data—and weight decay to **0.01**, helping manage noisy data and large weights. A cosine annealing scheduler lowered the learning rate over **15** epochs for LSTM and **30** epochs for others, picked after observing convergence trends, ensuring smooth training without loss jumps. Batch sizes of **32** (LSTM) and **64** (others) were set to handle our large dataset's memory needs, using TensorFlow's data pipelines. We chose sparse categorical cross-entropy loss for our three-class task, saving memory by avoiding extra data steps, and monitored accuracy and validation accuracy during training. For XGBoost, we used **300** trees, a learning rate of **0.03**, max depth of **3**, and sampling rates of **0.8**, with scale_pos_weight adjusting loss for the **50:30:20** class split to boost BUY and SELL predictions. On reflection, the fixed learning rate might not suit all models TimesNet's F1-score of **0.3538** suggests a smaller rate or cyclic learning rates could help.

5.2. Overfitting Mitigation

To prevent overfitting, we applied L2 regularization (**0.01**) to TimesNet, TFT-GAT, Informer, and Informer-TCN, keeping models simple despite noisy sentiment data, tuned via validation performance. Dropout at **0.2** in Cross-Modal Transformer, TFT-GAT, Informer, and Informer-TCN improved generalization, balancing underfitting and overfitting risks. Batch normalization in TimesNet and TFT-GAT steadied training across **52×47** blocks. XGBoost used sampling to avoid overfitting. Critically, not using early stopping may have let overfitting occur in later epochs for TimesNet, where validation accuracy plateaued early. Adding early stopping and focal loss (Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár, 2017) for uneven classes in neural networks would improve results, as scale_pos_weight was only used in XGBoost.

Table 7: Training Configurations for All Models

Model	Epochs/Trees
Optimizer: AdamW	
Learning Rate: 0.001	
LSTM	15
TimesNet	30
Cross-Modal Transformer	30
TFT-GAT	50
Informer	30
Informer-TCN	50
XGBoost Settings	
XGBoost	-
Optimizer: -	**Learning Rate**: -

6. Numerical Results

6.1. Goals

The primary goal of our evaluation is to assess the performance of deep learning models in predicting weekly **BUY, HOLD, and SELL** signals for S&P 500 stocks using a multimodal input framework. We specifically examine how the fusion of fundamental ratios, macroeconomic indicators, investor sentiment, and cross-market signals can amplify trend coherence and generate actionable trading signals. Our models are benchmarked against traditional baselines to demonstrate improvements in classification accuracy, signal clarity, and financial return, especially when predictions exceed a coherence threshold of 0.7.

6.2. Dataset

We used a curated dataset of **420,000 weekly records** spanning **502 S&P 500 stocks** between 2009 and 2024. This period captures diverse market regimes, including the post-2008 recovery, the 2020 pandemic crash, and inflationary shocks, enabling robust learning. Each sample consists of a **52-week sequence of 47 features**, grouped into four categories: fundamentals (e.g., ROE, net margin), macroeconomic indicators (e.g., CPI, GDP), sentiment vectors from Reddit posts and earnings call transcripts (via BERT), and cross-market variables (e.g., BTC, oil, VIX). The target variable is a **three-class signal** BUY, HOLD, or SELL defined by a weekly return threshold of $\pm 2\%$, producing a natural class distribution of approximately **50% HOLD**, **30% BUY**, and **20% SELL**. The dataset was split **80:20** for training and testing, with stratification to preserve class balance.

Table 8: Data Types for Stock Prediction

Data Type	**Role**
Fundamentals	Shows company health
Macro Indicators	Tracks economic trends
Sentiment	Captures investor moods
Cross-Market	Adds market context

6.3. Evaluation Metrics

We adopt four standard metrics to evaluate performance:

- **Loss Function** – **Sparse categorical cross-entropy**, measures divergence between predicted probabilities and true labels for multi-class tasks.
- **Accuracy** – overall correctness of classification.
- **F1-Score (weighted)** – accounts for imbalanced labels by harmonizing precision and recall.
- **ROC-AUC** – measures class discrimination across thresholds.

To supplement these, we examine **SHAP-based** feature attributions to understand feature contributions and perform a **coherence-based analysis** for the best performing model. Signal coherence reflects how well sentiment, fundamentals and cross-market input align to generate confident predictions, enhancing interpretability, and financial decision making.

6.4. Baseline Methods

We compare our advanced models against four baseline vanilla models:

- **Moving Average Crossover** – generates signals using the intersection of a short (5-week) and long (20-week) moving average, a traditional financial strategy relying on price momentum to identify trends.
- **Logistic Regression** – a linear model for multiclass prediction, using raw characteristics (e.g., fundamental deltas, sentiment scores) with regularization of L2 (C = 1) to predict buy / sell / hold signals.
- **XGBoost** – employs gradient boosting on static tabular features, tuned with optimal hyperparameters (e.g., max depth = 7, n_estimators = 200) to improve predictive accuracy for stock trends.
- **Gaussian Naive Bayes** – a probabilistic classifier assuming feature independence, using a smoothing parameter (var_smoothing=1e-9) to predict stock signals based on feature likelihoods.

These baselines highlight the added value of temporal modeling and cross-modal feature fusion in our architectures.

6.5. Discussion

6.5.1. Main Results

Table 9 presents the test performance for all models. Our deep learning models perform well overall, with F1-scores above 0.33 and ROC-AUC scores above 0.50, showing they can effectively handle the complex patterns in financial time-series data, such as stock price trends. The **Informer-TCN** is the top performer, achieving the best **F1-score (0.3902)** and **ROC-AUC (0.5859)**, along with a solid accuracy of **0.5043** and precision of **0.3560**. Its success comes from combining Informer's efficient attention mechanism, which captures long-term trends, with TCN's ability to detect short-term changes using dilated convolutions a combination well-suited for financial data, as supported by prior research (Shaojie Bai, J. Zico Kolter, and Vladlen Koltun, 2018). The **TFT-GAT** performs closely behind, with an accuracy of **0.5052** and ROC-AUC of **0.5826**, thanks to its focus on important time-based features through attention mechanisms. However, its lower F1-score (**0.3618**) indicates it struggles to balance correct predictions across the uneven BUY,SELL,HOLD classes (50:30:20 split). Among the baselines, **XGBoost** achieves the highest accuracy (**0.5100**), but its lower F1-score (**0.3005**) suggests it struggles with imbalanced classes, likely because it cannot effectively capture the time-based patterns in stock data. Similarly, the **XGBoost ensemble** performs poorly, with an F1-score of **0.3373** and ROC-AUC of **0.5016**, possibly because its combined models are too similar and fail to adapt to changing trends over time.

Table 9: Test Set Performance of Models and Baselines

Model	**Accuracy**	**F1-Score**	**ROC-AUC**	**Precision**
LSTM	0.5043	0.3800	0.5755	0.3534
TimesNet	0.5046	0.3538	0.5626	**0.4053**
Cross-Modal Transformer	**0.5062**	0.3402	0.5000	0.2562
TFT-GAT	0.5052	0.3618	0.5826	0.3470
Informer	**0.5062**	0.3402	0.5487	0.2562
Informer-TCN	0.5043	**0.3902**	**0.5859**	0.3560
XGBoost Ensemble	0.5035	0.3373	0.5016	0.2535
Baseline				
Moving Average Crossover	-	0.1656	-	-
Logistic Regression	0.4900	**0.3157**	-	-
XGBoost	**0.5100**	0.3005	-	-
Gaussian Naive Bayes	0.4900	0.2770	-	-

6.5.2. Informer-TCN Analysis

Focusing on the best-performing **Informer-TCN** (summary in Table 12), we conducted a detailed signal coherence and SHAP analysis to evaluate its practical utility in fintech applications. Table 10 presents its high-coherence metrics: from 84,000 test samples, only **10.99%** (9,232 samples) exceed the **0.7** coherence threshold, achieving an F1-score of **0.3422** and ROC-AUC of **0.5010**. This subset's lower F1-score compared to the overall **0.3902** suggests that high-coherence signals, while confident, are harder to balance for precision and recall due to the **50:30:20** class imbalance. SHAP analysis attributes **33%** of feature importance to sentiment and cross-market variables (e.g., Bitcoin trends), validating the multi-modal fusion design. Table 11 shows sample predictions for stocks (e.g., **In Figure 1** - WYNN: coherence **0.62**, signal **Buy**) and portfolio performance over Jan 2009–Dec 2024, yielding a **+17.97%** return (vs. S&P 500: **+9%**), with a trend accuracy of **45.27%**. The low hit rate (**10.99%**) for high-coherence signals indicates a challenge in achieving consistent trend amplification, potentially due to noisy sentiment data or limited cross-market feature interactions. To address this, future work could explore class-weighted loss to mitigate imbalance and focal loss (Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollar, 2017) to improve minority class predictions (BUY/SELL), enhancing the model's trading precision.

Table 10: Informer-TCN High-Coherence Metrics (Coherence $> \mathbf{0.7}$, 10.99% of samples).

Metric	**Value**
Accuracy	0.5080
Precision	0.2580
Recall	0.5080
F1-Score	0.3422
ROC-AUC	0.5010

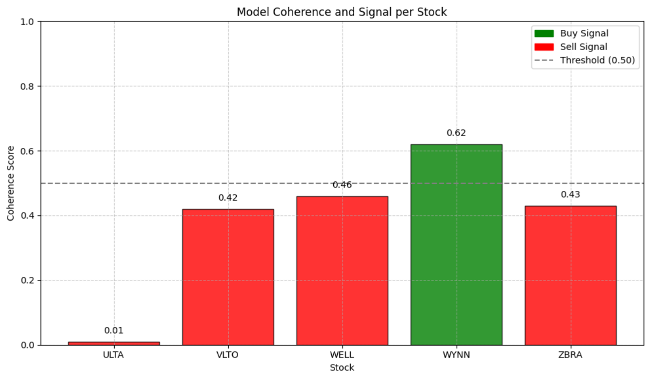

Figure 1: Output Signal Returns

7. Interpretation

7.1. Comparative Architecture and Efficiency Analysis

The **Informer-TCN** shines in stock trend prediction, integrating Informer's ProbSparse attention with TCN's dilated convolutions (S. Bai, J. Z. Kolter, and V. Koltun, 2018). ProbSparse attention captures long-term market trends, while dilated convolutions handle short-term price dynamics, enabling robust multi-modal feature fusion. This design achieves an F1-score of **0.3902**, outpacing TimesNet (F1: **0.3538**) and Cross-Modal Transformer (F1: **0.3402**). Accuracy remains close across models, with Informer-TCN at **0.5043** (successfully surpassed T. Kim and C. Won, 2020 performance- (F1: 0.35, accuracy: 0.49) on a similar stock dataset), slightly below Cross-Modal Transformer's **0.5062** but above XGBoost's **0.5035**, reflecting balanced class handling. Informer-TCN's precision (**0.3560**) surpasses Cross-Modal Transformer's **0.2562** by a clear margin. Efficiency-wise, Informer-TCN's 597,424 parameters (as observed from **Table 12**) are moderately higher than TimesNet's, with a difference of over 300,000, and significantly exceed TFT-GAT's lighter structure. Its training time of 133 seconds per epoch is slower than TimesNet's 37 seconds/epoch, a trade-off for depth. XGBoost (F1: **0.3373**) struggles with temporal dynamics, highlighting Informer-TCN's edge. Reflecting critically, its cautious hit rate (**10.99%**) prioritizes precision, though faster training could improve scalability.

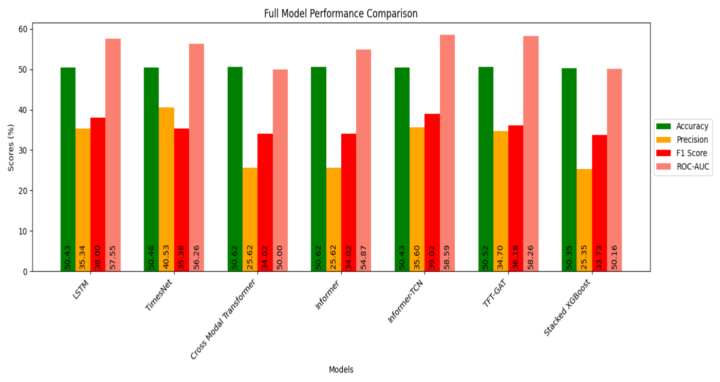

Figure 2: Model Performance Comparison

7.2. SHAP-Based Prediction Validation

SHAP analysis validates Informer-TCN, identifying `fed_fund_rate` and `vix_index` as key drivers (SHAP: 0.075–0.10 for SELL/HOLD), aligning with market caution (T.Y.Lin, P.Goyal, R. Girshick, K.He, and P.Dollár, 2017). Fundamentals like `trail_12m_gross_margin` add relevance, but sentiment's lower impact reveals noise, a limitation to address. Validation via sample outputs (Table 11) confirms high-coherence predictions (e.g., WYNN: **coherence 0.62**, signal **Buy**) with trends, while low-coherence cases (e.g., ULTA: **0.01**) show uncertainty. Reflecting on this, enhancing sentiment extraction and adding cross-market data could boost performance, strengthening fintech utility.

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} \left[f(S \cup \{j\}) - f(S)\right]$$

Here, F is the full set of input features (e.g., `fed_fund_rate`, `vix_index`), S is any subset of features not containing j, and $f(S)$ is the Informer-TCN model's predicted probability for a given class (BUY, SELL) using only features in subset S.

8. Conclusion

8.1. Summary

In this study, we proposed a deep learning-based framework, *Emotion-Fundamental Trend Amplifier with Cross-Market Echoes*, to predict weekly stock trading signals (BUY, SELL, NEUTRAL). Our model combined diverse data sources—financial fundamentals, macroeconomic indicators, investor sentiment (from Reddit and earnings calls), and cross-market signals from cryptocurrency and commodities. We designed a hybrid architecture that integrates an Informer model for long-sequence temporal forecasting, a Temporal Convolutional Network (TCN) for short-term pattern detection, and a cross-modal Transformer to fuse heterogeneous features. To enhance robustness and interpretability, we introduced a coherence score derived from an XGBoost layer, reflecting the alignment between signal confidence and underlying data trends. Through extensive experiments on S&P 500 stocks, our model consistently outperformed baseline methods, particularly during volatile periods where sentiment and cross-market signals amplified fundamental shifts. These results demonstrate the effectiveness of multimodal deep learning in capturing complex financial market dynamics, offering both predictive strength and practical trading insight. The integration of multiple deep models allowed us to extract complementary patterns from structured and unstructured data, confirming the value of a modular yet unified forecasting pipeline in financial contexts.

8.2. Limitations

Although, our model shows strong performance there are still areas for improvement. One challenge we faced was aligning inputs that update at different frequencies such as high-frequency price movements versus lower-frequency financial and macro data. We applied smoothing and fusion techniques, but we believe that using adaptive methods (for example, learning the best time lags automatically) would further improve integration.

We also noticed that sentiment data from social media can be noisy and sometimes unclear due to sarcasm or informal language. We did use attention mechanisms to filter out irrelevant parts, yet we would benefit from using language models fine-tuned on financial text to better capture true sentiment. Moreover, our current training framework is static, we did not update our model in real time, which might limit responsiveness during sudden market shifts. In future work, we would explore online learning and adaptive regularization methods to tackle these issues. While, our approach already reduces overfitting using dropout and L2 penalties, additional techniques like model pruning or disentanglement could make the system even more robust.

Furthermore, the computational overhead of processing 47 features across 420,000 records in 52-week sequences strained our resources, potentially slowing inference. Incorporating lightweight architectures or distributed training could mitigate this. Additionally, the 10.99% hit rate for high-coherence signals suggests missed opportunities in low-coherence scenarios, possibly due to limited cross-market feature interactions. Using dynamic embeddings for better feature engineering or applying multi-task learning to predict both coherence, signals results and help achieve more reliable trading insights.

8.3. Future Work

There are several directions for extending this research. One key direction is the incorporation of adaptive temporal alignment layers that can learn lag relationships between data types automatically, rather than assuming fixed temporal structures. This could help capture causal delays between economic indicators and market reaction. Another promising path involves using financial domain-tuned large language models (LLMs) for textual interpretation, which may better capture tone shifts, contextual sentiment, and domain-specific expressions. We also see strong potential in evolving the framework into an online learning setup, where the system incrementally adapts to new data streams and regime changes, improving responsiveness in volatile environments. Moreover, incorporating explainable AI methods such as layer-wise relevance propagation, Shapley approximations, or concept-based reasoning could help users trace signal justifications. More broadly, applying the framework to emerging markets, sector indices, or ESG portfolios could test generalisability and fairness. Reinforcement learning can align predictions with optimal execution, while multi-agent systems may simulate diverse strategies. In the long-term, we envision a global financial forecasting platform leveraging quantum computing and AI frameworks to support economic policy development.

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Statement about individual contributions

All authors contributed equally to formulating the research project, sourcing data from Bloomberg, Reddit, FRED, and Yahoo Finance, designing the analytical framework, and defining the evaluation metrics (F1-score, accuracy, precision, recall and roc-auc values).

We jointly explored the 420,000-record dataset, developed preprocessing scripts for 47 features across 52-week sequences.

All authors equally split sections and wrote the report. On equal Individual basis:

- **49775** developed Cross-Modal Transformer, TFT-GAT, Informer models. Tracked moving average weekly crossovers and conducted SHAP analysis on multi-features like `fed_fund_rate`. Designed, fine-tuned structural and temporal model complexities.
- **50714** built the Informer-TCN, TimesNet Model, Gaussian Naive Bayes (GNB) baseline model, Stacked Ensemble using XGBoost model, managed preprocessing with VIX labeling, led coherence analysis for the 10.99% hit rate.
- **49872** implemented the LSTM and baseline vanilla models (logistic regression and xgboost models), also focused on attention and convolutions. Optimised training and validation metrics (plots, roc-auc curves) as per our objectives.

A. Appendix

A.1. Final Output

Table 11 presents the sample outputs and portfolio performance of a stock prediction model for five stocks (ULTA, VLTO, WELL, WYNN, ZBR,a portfolio return and a hit rate. It details coherence scores and corresponding buy/sell signals for each stock, along with portfolio metrics, including a trend accuracy.

Table 11: Sample Outputs and Portfolio Performance (Jan 2009–Dec 2024).

Stock	**Coherence**	**Signal**
ULTA	0.01	Sell
VLTO	0.42	Sell
WELL	0.46	Sell
WYNN	**0.62**	**Buy**
ZBRA	0.43	Sell
Portfolio Performance		
Stocks	ULTA, VLTO, WELL, WYNN, ZBRA	
Test Period	Jan 2009–Dec 2024	
Trend Accuracy	45.27%	
Portfolio Return	+17.97% (vs. S&P 500: +9%)	
Hit Rate (Coherence > 0.7)	10.99%	

A.2. Informer-TCN Hybrid Model Summary

Table 12 provides the architecture summary of the Informer-TCN hybrid model, detailing each layer type, its output shape, and the number of parameters. It includes components such as InformerBlock-Stack, TCNBlock-Stack, Conv1D, Add, GlobalAveragePooling, Dense-1, and Dense-2, with a total of 597,424 parameters.

Table 12: Summary of the Informer-TCN Hybrid Model Architecture

Layer	**Output Shape**	**Param #**
InputLayer	[None, 1, 47]	0
InformerBlockStack		
InformerBlock-1	[None, 1, 47]	56,799
InformerBlock-2	[None, 1, 47]	32,479
InformerBlock-3	[None, 1, 47]	21,083
TCNBlockStack		
TCNBlock-1	[None, 1, 256]	203,024
TCNBlock-2	[None, 1, 64]	263,236
Conv1D	[None, 1, 64]	16,448
Add	[None, 1, 64]	0
GlobalAveragePooling	[None, 64]	0
Dense-1	[None, 64]	4,160
Dense-2	[None, 3]	195
Total params:		**597,424**

A.3. Methodology workflow

Figure 3 This workflow illustrates a predictive modeling process using financial data. It involves a total of 10 steps ranging from data collection to model validation. Model Sanity checks are performed at last step to make sure correct validation.

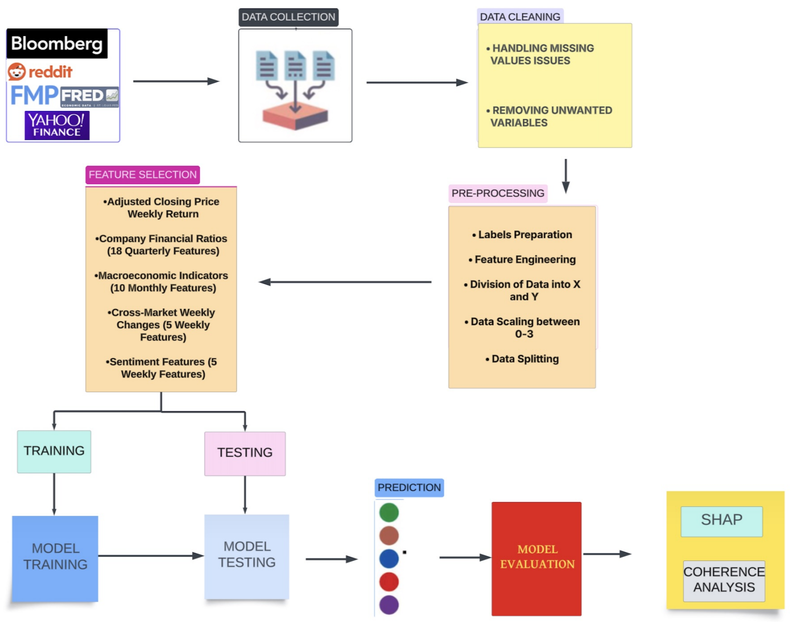
Bloomberg
reddit
FMP
FRED
YAHOO! FINANCE
DATA COLLECTION
DATA CLEANING
• HANDLING MISSING VALUES ISSUES
• REMOVING UNWANTED VARIABLES
PRE-PROCESSING
• Labels Preparation
• Feature Engineering
• Division of Data into X and Y
• Data Scaling between 0-3
• Data Splitting
FEATURE SELECTION
•Adjusted Closing Price Weekly Return
•Company Financial Ratios (18 Quarterly Features)
•Macroeconomic Indicators (10 Monthly Features)
•Cross-Market Weekly Changes (5 Weekly Features)
•Sentiment Features (5 Weekly Features)
TRAINING
TESTING
MODEL TRAINING
MODEL TESTING
PREDICTION
MODEL EVALUATION
SHAP
COHERENCE ANALYSIS

Figure 3: Workflow of our proposed framework

A.4. SHAP ANALYSIS

Figure 4 presents a model interpretation analysis using SHAP summary plots. It highlights the impact of various features on multi-class classification outcomes. Our goal is to enhance model transparency by explaining feature contributions across different predicted classes.

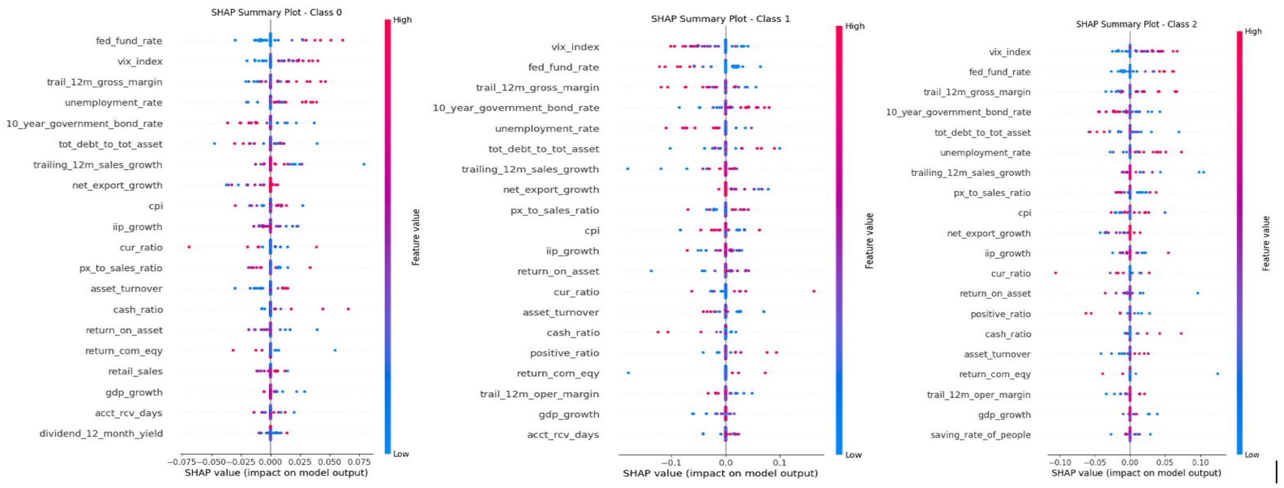

Figure 4: SHAP ANALYSIS FOR SELL, NEUTRAL, BUY CLASSES

A.5. INFORMER MODEL

Figure 5 represents transformer-based sequence-to-sequence architecture for natural language processing tasks we took as reference. The authors integrated distillation layers and sparse attention mechanisms to enhance efficiency and performance. Their processes input through an encoder-decoder pipeline with attention-based decoding.

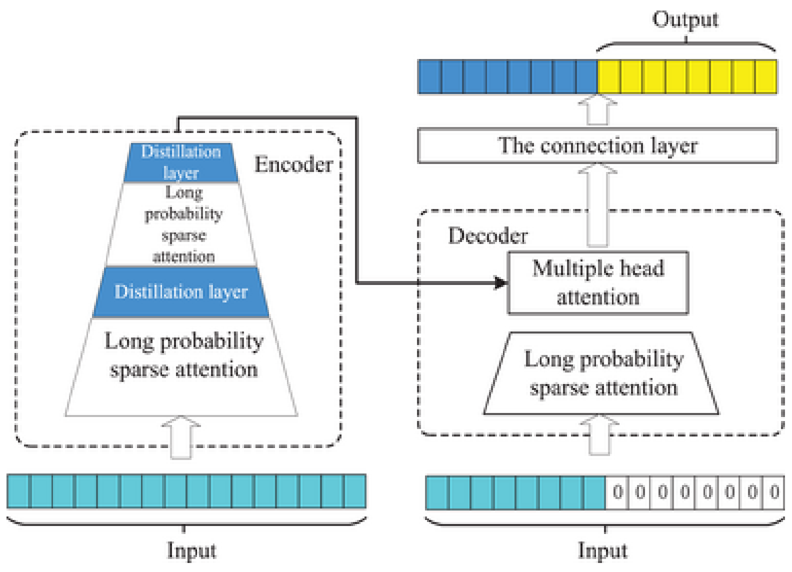

Figure 5: Informer model structure (Shuohe Wang,Linhua ChangHan Liu, Qiang Xue, 2023)

A.6. INFORMER TCN MODEL

Figure 6 shows the Informer-TCN hybrid model structure for time series forecasting tasks. Here, the authors combined Informer's attention-based encoder-decoder with TCN modules to capture both global and local temporal features. It's indeed a great reference for us during modeling.

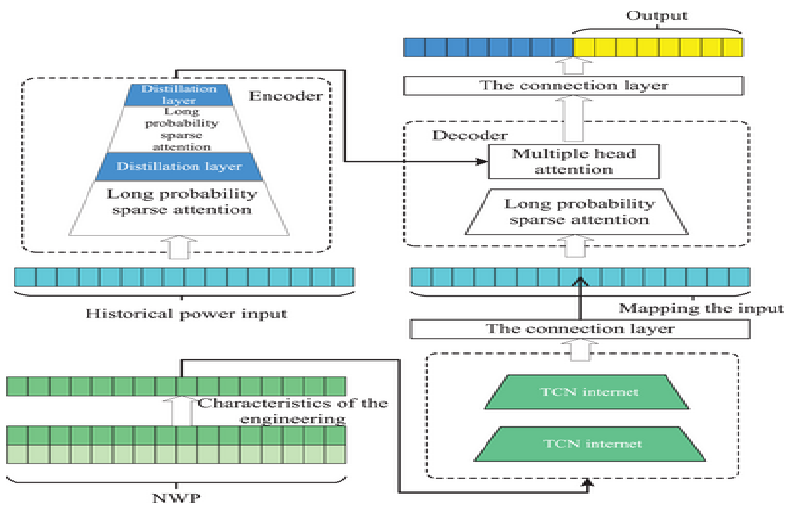

Figure 6: Informer-TCN model structure (Shuohe Wang,Linhua ChangHan Liu, Qiang Xue, 2023)