

# Cross-Country Stock Price Forecasting Using Multimodal Temporal Convolutional Fusion of Multilingual Financial Sentiment and Market Data

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**Abstract:** The nature of stock market forecasting is compounded by the nonlinear, volatile and behaviour based nature of financial markets as a complex challenge. Most of the traditional forecasting methods are based on past facts regarding prices and they do not consider the sentiments of the investors and the availability of multilingual data which plays a major role in market dynamics. In order to overcome these weaknesses, this paper suggests a multimodal deep-learning model of cross-country stock price forecasting that incorporates the predictive power of historical financial data with multilingual sentiment data derived through financial news information. The suggested architecture uses the Temporal Convolutional Networks (TCN) to successfully extract the long-range temporal correlations in both the financial time-series data and the sentiment sequences. Moreover, an adaptive attention-based fusion process is presented to acquire the relative weight of the signals of numerical market indicators and sentiment signals in dynamic market conditions. Transformer-based sentiment models are used to process the multilingual financial news to obtain sentiment polarity, sentiment intensity, and probabilistic sentiment representations that are consistent with the daily market observations. The model is tested using multi-country data of large financial markets, such as the United States, India, the United Kingdom, Germany, and Japan. The experimental outcomes indicate that the suggested framework prevails over benchmark frameworks including LSTM, attention-based LSTM, and sentiment only models. The model has lower forecasting errors both in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) and directional prediction accuracy. On the whole, the results demonstrate the necessity to combine behavioural sentiment indicators and quantitative financial indicators to increase the strength of the forecasts and generalization in the global markets. The suggested framework offers an interpretation-capable and scalable AI-based system of financial forecasting and intelligent investment decision support systems.

**Keywords:** Attention mechanism; Cross-country markets; Financial sentiment analysis; Multimodal learning; Stock prediction; Temporal Convolutional Network; Time-series forecasting.

## 1. INTRODUCTION

Financial markets are one of the most complicated and evolving decision-making systems, which are non-linear, volatile clustering, regime-shifting and behavioral feedback systems. The prediction of stock price dynamics is a key problem in quantitative finance, artificial intelligence and computational economics. Reliable forecasting is still limited by stochastic environment of financial time-series, macroeconomic uncertainty impact [1], [2], [3], [4] and psychological aspects of investors despite decades of research. Conventional statistics like ARIMA and GARCH [5], [6], [7] models presuppose linear relationships and stationarity, which restrict their usefulness in new market high-volatility regimes. The advent of machine learning and deep learning architecture has enhanced predictive ability greatly. The use of recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) [8], and Gated Recurrent Units (GRU) [9] have found extensive usage since they are capable of modeling sequential dependencies in financial data. More recently, Transformer models have been shown to be able to model long-range dependencies with more self-attention capacity. Nevertheless, such architectures are characterized by such limitations as sequential inefficiency of computation (in recurrent models), computational complexity (in Transformer models) [10], and susceptibility to noisy financial environment overfitting. The main weakness of a significant number of the currently available forecasting systems is that they use only historical



price-based indicators. The financial markets are not simply guided by the numerical trends but are greatly affected by the investor sentiment [11], the news publication and the geopolitical trends, as well as the market psychology. Online financial media, multilingual news outlets and investor discussion forums have rapidly risen, changing the information ecosystem and rendering the sentiment a critical explanatory factor of short-term price changes. Empirical data has indicated that sentiment changes usually come before visible price changes especially when the market is volatile like when earnings are announced, economic policies are altered, during pandemics, and due to geopolitical crises. Recent developments in natural language processing, especially transformer-based models, like FinBERT [12] and domain-specific BERT variants, have made it possible to extract financial sentiment in a text more accurately. Nevertheless, there are still a number of limitations in the literature. To start with, the vast majority of emotion-based research mostly involves English-language references without addressing the issues of multilingual financial indicators that affect local markets. Second, several hybrid methods use recurrent architecture [7], [13], [14] (e.g., CNNLSTM, GRU Attention), and those might be unable to effectively capture long-term dependencies on long time scales. Third, price and sentiment modalities are not usually integrated with price and sentiment adaptive weighting mechanisms that can be dynamically adjusted to different market regimes. Lastly, little cross-country validation has been done so far and most studies are done with single-market or single-index experiments, which makes them vulnerable to generalization. In order to close these voids, this paper suggests a multimodal, cross-country stock forecast framework that involves incorporating historical price records with multilingual financial sentiment with the aid of a Temporal Convolutional Network (TCN) [15], [16], [17] and attention-based fusion mechanism. In contrast to recurrent neural networks, TCN uses dilated causal convolution to learn long-range temporal dependencies and at the same time sustains stable gradient flow and can be computed in parallel. This architectural decision addresses typical constraints of LSTM and GRU models, such as vanishing gradients and inefficient sequential training. The model learns dynamically, through its independent TCN encoders and fusing of their representations with an adaptive attention mechanism, the relative significance of numerical and behavioral signals [2] in different market states [18]. The presented framework is tested with the help of multi-country data sets that include developed markets and emerging markets. The cross-market experimental design allows to explore the contribution of the multilingual sentiment to the financial ecosystems of differing levels of retail involvement, information asymmetry, and the intensity of news dissemination. The multilingual sentiment extraction also increases the generalization ability in the sense that it takes into account region-specific investor responses, which is usually not considered in the monolingual forecasting systems.

The main findings of this study can be summarized as follows:

- **Multimodal Dataset Construction:** Multicompany dataset construction Multisite dataset construction that combines multi-year OHLCV price characteristics and multilingual financial sentiment indicators.
- **Efficient Temporal Modeling:** Temporal Convolutional Networks: A temporal convolutional network is a machine learning framework used to learn long-range dependencies without recurrence constraints.
- **Adaptive Attention Fusion:** proposed a dynamic weighting of the price and sentiment modalities by an attention-based system to make them more robust to use during turbulent market regimes.
- **Overall Comparative Analysis:** Empirical comparison with LSTM, GRU, Transformer, and sentiment-only baselines based on statistical and directional performance measures.
- **Cross-Market Generalization Analysis:** Testing in the developed and emerging markets to indicate scalability and strength.

Experimental findings reveal that the proposed TCN Attention multimodal architecture is much better compared to the traditional recurrent and transformer-based baselines in terms of the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) [19], and directional accuracy. The changes in performance are more pronounced during the epochs of high sentiment-driven volatility, which confirms that the investor sentiment is a significant non-linear explanatory factor that should be combined with (that is, fuse to) the historical price-driven dynamics of volatility [20], [21] dynamics.

The rest of the paper is organized in the following way: Section 2 will provide a literature review of the related works concerning stock prediction, sentiment analysis, and multimodal learning. Section 3 mathematically formulates the problem of forecasting. Section 4 outlines the dataset and preprocessing procedures. Section 5 introduces the proposed TCN Attention architecture. Section 6 explains the experiment and measures of evaluation. Section 7 is on results and comparison analysis. Section 8 is finalized by limitations and the directions of future research.

## 2. Problem Statement

Financial market is a very volatile and behavior based non-stationary price of stocks which makes it a very difficult issue to predict the stock prices. Most of the forecasting models used are predominantly pegged on past price data which are not a reflection of the actual investor sentiment and information dynamics that are

normally the driving forces of price change. Methods that are sentiment-enhanced have been created, but tend to be limited to English-language texts and single-market experiments and recurrent neural networks, which are inefficient and incapable of capturing long-term dependence. Furthermore, conventional The multimodal fusion schemes usually incorporate the integration approaches that remain unchanged to the fluctuating market regimes, in which the relative importance of numerical variation and behavioral cues varies over time. This leaves the existing models weak on robustness, cross country generalization and scalability.

This study aims to remove the limitations of repetitive architectures, multilingual behavioral clues and current adaptive fusion mechanisms to enhance predictive quality and directional functioning.

### 3. Literature Review

In the past 10 years, stock market prediction has significantly evolved to cease its reliance on the olden day statistical models and instead proceed to the more advanced machine learning, deep learning, transformer-based systems as well as explainable artificial intelligence systems. The literature has a general overlap to three main directions of research including improvement of the temporal modelling of the financial time series, the integration of textual sentiment signals and improved interpretation of models. Here in table 1, the comparative Analysis of Recent Stock Market Prediction Studies has been done. The early comparative study indicates that deep learning structures are superior as compared to the traditional machine learning algorithms in the nonlinear financial modeling. When dealing with continuous price data rather than binary trend classification, RNN and Long short-term Memory (LSTM) [15] models always outperform the decision trees, random forests, support vectors machines, and boosting models. These findings confirm the applicability of sequential modeling in financial forecasting. The LSTM-based architectures have taken the lead in the field of predicting financial time-series since they can capture the time effect. Certain of these models are a combination of past realized price of stocks and sentiment indicators that are derived through social media or news lighting related to a particular financial issue. These models were determined to improve more in RMSE, MAPE and  $R^2$  [22], [23] in the presence of sentiment. However, recurrent architectures are computationally expensive, prone to vanishing gradient issues and inefficient to simulate long-range interactions. Recent studies investigate the use of time-series forecasting architectures based on transformers. Time Series Transformers and linear-transformer hybrids have demonstrated competitive or even better performance with respect to [24] LSTM models. These architectures make use of attention mechanism to achieve a more capturing long-range dependency. However, a lot of such implementations guided by transformers are at present computationally expensive and mostly applied to compute technical indicators without deep multimodal combination of sentiment features. Sentiment analysis has become a significant contribution to the stock prediction research. Transformer-based financial language models, including FinBERT, are much more competent at contextual sentiment task (financial sentiment), than lexical based approaches to date [10]. Other publications combine scores of the sentiment extracted by the transformer with a gradient boosting classifier or a deep neural network and show a higher AUC, F1-score and profitability simulation [15]. Sentiment and price properties are however usually fused in shallow fusion models as opposed to being fused using adaptive temporal models. Resulting for lexicon-based sentiment methods are also attractive due to the efficiency and interpretability. Transformer learning using explainable lexicon [25] generation gives increased vocabulary coverage and classification and are more transparent with hybrid approaches, which generate better results. However, these methods tend to be sentiment extraction based, but not full pipeline forecasting.

Xplainable Artificial Intelligence (XAI) has become an indispensable part of financial predictions. SHAP and LIME are currently famous to interpret the forecast of LSTM, XGBoost, and transformer models [10], [26]. The application of XAI to forecast maximum volatility measures, maximum volume measures, and maximum sentiment scores have been seen, through research, to represent some of the most meaningful predictors. Even though interpretability improves transparency and regulatory compliance, explainability [25] is typically done post-hoc and not necessarily addressed in the model design. Comparative reviews emphasize that there is more and more need to apply hybrid models that combine deep learning, sentiment analysis and interpretability [17]. However, loopholes in the literature do still exist:

1. Heavy reliance on LSTM-based recurrent architectures.
2. Limited exploration of convolutional or temporal convolutional alternatives.
3. Shallow multimodal fusion of price and sentiment features.
4. Single-market validation rather than cross-country generalization.
5. Post-hoc explainability rather than adaptive modality weighting mechanisms.

Thus, although existing research advances accuracy, sentiment extraction, and transparency independently, few studies integrate efficient temporal modeling, deep multimodal fusion [27], and scalable cross-market validation within a unified framework.

**Table 1.** Comparative Analysis of Recent Stock Market Prediction Studies

Citation	Architecture Used	Data Type	Evaluation Metrics	Key Strength	Key Limitation
[8]	Time Series Transformer, DLinear + SHAP/LIME	BIST100 banking stocks	MAE, RMSE	Transformer-based forecasting with explainability	No sentiment integration
[5]	Survey (LSTM, CNN, Transformers)	Financial news datasets	Accuracy, RMSE	Synthesizes sentiment-based prediction methods	No unified experimental validation
[22]	Deep Neural Network + SHAP + LIME	Stock trend classification data	Accuracy (94%+)	High-performance explainable classification	Focused on trend classification only
[13]	9 ML Models + RNN + LSTM	Continuous & binary stock data	Accuracy	Demonstrates DL superiority over ML	No sentiment features
[28]	Multi-layer LSTM + NLP Sentiment	NASDAQ + News API	RMSE, MAPE, R <sup>2</sup>	Sentiment-enhanced short-term prediction	LSTM-only architecture
[29]	XGBoost + SHAP + LIME	Tehran Stock Exchange crash data	Accuracy	Strong interpretability in crash prediction	No textual sentiment integration
[30]	LSTM + SHAP	Yahoo Finance stock data	Forecast error metrics	DL + XAI synergy	Single-stock validation
[31]	FinBERT + XGBoost + SHAP	S&P 500 (2018–2023)	AUC, F1-score	Domain-specific sentiment + privacy	Tree-based, shallow fusion
[10]	Transformer-assisted Lexicon (XLex) + SHAP	Financial text corpora	Classification accuracy	Efficient and interpretable sentiment modeling	Not integrated into price forecasting
[9]	Classical ML + Technical Indicators + LIME	Financial news + indicators	Accuracy	Explainable ML forecasting	Limited deep modeling
[15]	BiLSTM + LIME	NLP sentiment datasets	Accuracy	Transparent sentiment modeling	Not financial time-series forecasting
[16]	ML + XAI Framework	Arabic sentiment datasets	Accuracy	Language-specific interpretable SA	Not applied to stock forecasting
[27]	Review of ML, DL, XAI	Multi-study synthesis	Comparative metrics	Identifies hybrid research trends	Conceptual review only

#### 4. Existing Work and Limitations

Despite the widespread use of XAI in sentiment-based prediction models, current researches are still characterised by several limitations. The majority of methods use XAI in a post-hoc fashion [26], and at this stage, they do not give explanations before the predictions are produced. The existing studies tend to concentrate on single-language feeling (mostly English) as opposed to multilingual cue that could be incredibly significant in the markets like India, Japan, China, and other regional interactions. Most research describes imported importance but not policy rationale in trading systems organized around reinforcement-learning [30] in real-time, which results in a void in the understanding of real-time decisions. Moreover, XAI has been primarily used on stationary databases, with a small focus on interpretability of streaming financial information in real time. Lastly, there are not many systems in existence that synergize deep temporal learning, sentiment extraction, and explainable reinforcement learning [10], [32] into a single architectural system.

## **5. Research Contributions**

Such a study contributes to the AI-assisted financial prediction by suggesting a scalable and analyzeable multimodal model that incorporates historical OHLCV price information with multilingual financial sentiment [1], [33] obtained through the transformer-based NLP models. The architecture achieves modality-specific temporal encoding before fusion which allows a better representation learning and breaks the limitations of shallow concatenation schemes. The framework represents the long-range dependencies with great efficiency and enhances the stability and scalability of computations by adopting an effective time modeling strategy. The adaptive attention-based fusion mechanism is a dynamic mechanism of weighing price-sentiment signals such that the model adapts to different market regimes and increases the predictive resilience capacity. The suggested system is strictly tested in comparison with several baseline models, such as LSTM, LSTM with Attention, Transformer-based, and sentiment-only models [8], [10], [34], that show steady improvement in MAE, RMSE, and directional accuracy values. Moreover, cross-country validation increases the generalizability and integrated explainability improves transparency and helps to make reliable financial decisions [22]. All these contributions allow creating a strong, functional, and understandable multimodal method of high-end prediction of stock markets.

## **6. Research Objective Flow**

As can be seen in Fig. 1, Objective 2 involved work on Facebook penetration of social media sentiment extraction with the use of the machine learning models, which creates a solid background in the design of the advanced integrative prediction framework.



**Fig. 1.** Integrated Workflow for Multimodal Stock Price Forecasting

The previous step implied the incorporation of multi-source textual sentiment signals, which are the investor comments, financial news and newspaper reports, rather than focusing on one channel of data. The sentiment design feature added the scores of polarity, subjectivity, intensity and emotion, which were assisted using PCA-based sentiment vectors (SPCAT) to trim down on the most informative linguistic parts. Moreover, noise elimination, redundant attribute elimination and Null Importance were incorporated with advanced features engineering and selection methods, which reduced or eliminated noise, redundant attribute and only retained high impact sentiment features that are useful in modelling effective prediction models. The experiment performed at the level of various industries revealed that hybrid sentiment-driven deep learning models, namely CNN-LSTM-Attention, obtained lower MAE scores and had better stability than the traditional machine learning baselines, which demonstrated the achievement of Objective 2 and supported the purpose of sentiment accuracy in stock prediction. With the reliable representation of sentiments, Objective 3 is a logical continuation of this study because it plans and implements an integrative multi-faceted machine learning model to predict stock prices. Although the second goal established that better sentiment extraction improves prediction, Objective 3 includes other learning modules, such as hybrid temporal encoders, multimodal feature fusion, and decision-making constituents. It is at this point that a wider integrative methodology is introduced, integrating features of multilingual sentiment and numerical stock data, technical indicators, and industry-specific trends using Transformer + BiLSTM + Attention models. The purpose is to address the constraints mentioned in the literature,

especially the inability to deal with various forms of data and the inability to interpret the existing financial prediction systems. Objective 3 serves as the main technical development phase of the thesis since it involves an expansion of sentiment-only improvements to multimodal forecasting. To design and deploy an integrative multifaceted machine learning model and analyze its efficiency compared to existing systems, the research initially gathers and cleans historical OHLCV stock prices and multilingual financial sentiment gathered with the help of transformer-based NLP models. The feature engineering is used to calculate the technical indicators, sentiment probability scores, and next day return target variable. The suggested framework uses the modality-specific temporal encoding of price and sentiment attributes and then the adaptive mechanism of attention-based fusion that dynamically combination weighs their respective contributions in different market situations. The fused representation is then fed through a regression layer to make predictions of the next-day stock returns, the model is optimized by the use of the correct loss functions, optimizers, and hyperparameter optimization. In order to justify the performance, the suggested architecture will be contrasted to the baseline models, including LSTM, LSTM with Attention, Transformer-based models, and sentiment-only systems on standardized datasets, the same train-test divides, and the same evaluation metrics, including MAE, RMSE, and Directional Accuracy. The cross-country validation and explainability analysis are also carried out to evaluate the robustness, the capability of generalization and differences in feature contribution.

## 7. Description of Conceptual Hybrid Model

The described hybrid model (Fig. 2) will be developed as an integrative multimodal predictive model that incorporates structured financial time-series data and non-structured textual sentiment data to achieve a superior predictability of the stock price.

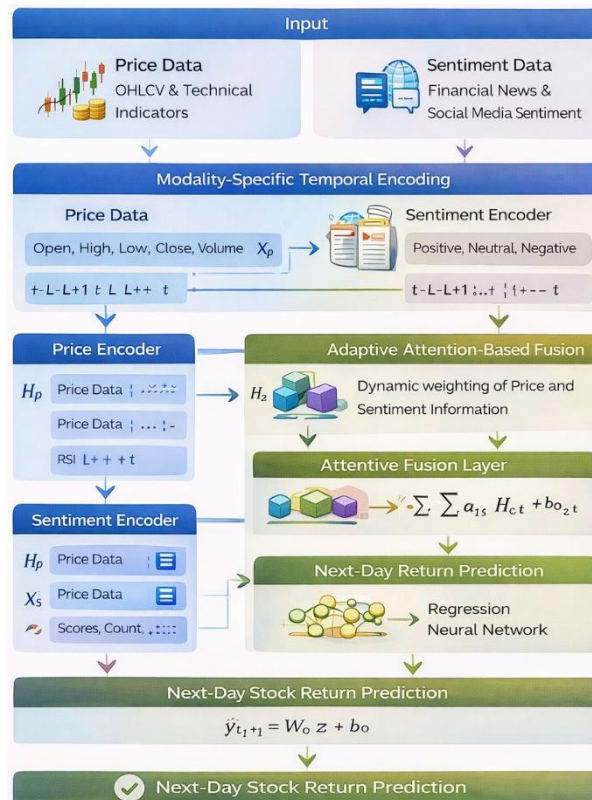


Fig. 2. End-to-End Multimodal stock price prediction workflow

The conceptual architecture is composed of four key elements which are data representation, modality-specific temporal encoding, adaptive multimodal fusion, and predictive inference with explainability. Two main modalities have been used at the model at the input level. The former modality is the historical OHLCV stock price data [31] and derived technical indicators, which reflect the dynamics of the market and quantitative trading action. The second modality incorporates the multilingual financial sentiment features found in news and social media based on transformer-based NLP models. These emotion characteristics are summarized on the daily ticker level so that [40] is in time step with price data. At the encoding level, temporal modeling is done independently in all modalities in order to maintain domain specific attributes. Price characteristics are developed using a specific temporal sequence encoder that is able to record nonlinearities and volatile trends. At the same time, sentiment characteristics are transmitted to a parallel time encoder to capture the changes in investor mood and information

over time flow. This is a dual-branch architecture, which enables this model to acquire representation of modality-specific features and subsequently integrate them. The fusion stage is where an adaptive attention-based mechanism is introduced and dynamically determines the weights to price and sentiment representations. This process allows the model to modify its dependence on quantitative signals or sentiment signals in response to current market circumstances, i.e. sentiment-based volatility or trend-based phases. The hybrid architecture defeats the shortcomings of the static feature concatenation techniques by acquiring contextual significance. The merged representation is internally forwarded to a regression layer to make next-day stock returns predictions. Supervised learning is carried out to model optimization by making use of suitable loss functions and regularization strategies. Also, an explainability module is included that quantifies the value of each individual feature and modality to improve a more transparent and interpretable financial decision-making process. The principle of the hybrid framework is that a dynamic system is at work where market construction (price behavior) and market perception (investor sentiment) are interacting via adaptive weighting to create a powerful forecast. This model is a quantum technical architecture that combines quantitative analysis of technicals with behavioral financial frameworks and leads to a scalable interpretable and performance-oriented stock prediction model.

## **8. Methodology**

### *8.1 Overview of the Research Design*

This research employs a quantitative experimental approach to develop and evaluate a framework for forecasting next-day stock returns through various machine learning methodologies. The study uses one deep learning architecture to mix structured financial time-series data with unstructured textual sentiment data. A comparison modelling technique is employed to evaluate the proposed framework against established baseline models in controlled experimental environments. The entire methodological approach underlines how important it is to be able to reproduce, grow, understand, and apply what you learn to other markets.

### *8.2 Data Acquisition*

There are two main forms of data used in the study: data from the financial markets and data about how people feel about text. We gather historical stock price data for several firms in a variety of foreign markets. This data includes Open, High, Low, Close, and Volume (OHLCV). This design with several countries makes sure that it is powerful and works in other countries as well. At the same time, financial news and other written material are gathered to find out what investors think and how the market sees things. Sentiment characteristics are derived from transformer-based natural language processing models trained on financial corpora, enabling context-aware sentiment categorisation. The dual data collecting technique makes sure that both the quantitative behaviour of the market and the qualitative psychology of investors are fully reflected.

### *8.3 Data Preprocessing and Integration*

Raw financial and text datasets undergo systematic preprocessing to ensure that they are consistent and are identical to each other. We arrange the price information by date and seek gaps, extremes, and faults of structure. Some methods of cleaning up text data include normalising, tokenising and removal of additional symbols. Transformer-based methods of sentiment extraction produce structured sentiment likelihood and overall sentiment scores. These sentiment components are corresponding to ticker-level daily stock prices. The objective is to estimate the stock stock in the following day based on the extent of alterations in the closing prices. Finally, we normalise the numerical features to ensure that the model converges in a consistent manner and the scale bias between modalities does not exist.

### *8.4 Feature Engineering and Optimization.*

They are feature engineered in order to strengthen predictive signals. New technical indicators are derived using OHLCV data to identify the way in which the momentum, volatility and trends change. Sentiment-derived variables are the probable sentiment classes distributions of sentiment rate, and sentiment frequency. In order to minimise duplication and multicollinearity, feature selection and optimisation techniques are used. Optimised feature sets are divided into two groups, namely, inputs that are pricing specific and inputs that are emotion specific. This ensures that the modalities are distinctively isolated prior to the training of the model. This systematic arrangement of making features makes the computer faster and the depiction improved.

### *8.5 Hybrid Model Architecture Proposals.*

The proposed hybrid model will include modality-based temporal encoders, followed by an adaptive attention-based fusion mechanism, and regression prediction layer. A particular temporal encoder is used to examine pricing characteristics in order to identify sequential dependencies and nonlinear market behaviour. Meanwhile, there is a parallel encoder transmitting the sentiment features to indicate the temporal variations in

the attitudes of investors. A process in attention that modulates the importance of every modality as time passes by and subsequently combines the coded representations. This dynamic combination assists the model to be attentive to the patterns founded upon the price in the case of the stable market and be attentive to the signals founded on the sentiment in the case of the turbulent and news-sensitive market. Subsequently, the merged representation is then subjected to a regression layer that issues forecasts concerning the degree to which the stocks will either rise or fall the next day. To make things more comprehensible and graspable, there is an explainability section that is introduced to examine the influence of features and modalities on one another.

## 8.6 Model Training and Optimization

The hybrid model is supervised and it employs the Mean Squared Error as the significant loss function. Adam optimiser can be used to update settings quickly depending on gradients. Empirical validation is used to choose the key hyperparameters of the model, such as sequence length, learning rate, and batch size to reach the right balance between the complexity of the model and its capacity to generalise. The data is separated into training and testing subsets according to a predefined chronological divide to avoid the loss of data and make sure that the factors under which predictions are made are realistic. Overfitting is prevented by monitoring the model performance in the training process.

## 8.7 Comparative Evaluation Framework

In a systematic manner, the proposed model is compared against existing baseline architectures to test its effectiveness in a comprehensive manner. These are price-only LSTM models, LSTM with Attention mechanisms, transformer-based temporal models and sentiment-only predictions. Each and every model is trained using the same preprocessing pipelines, feature sets, sequence lengths, and methods of checking their work to ensure that nothing is unfair. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Directional Accuracy are used to rate the performance. Cross country validation- This is a method used to test the effectiveness of a model in other economic scenarios. This comparison of evaluations framework demonstrates that the proposed approach is better and more helpful in the real world.

## 8.8 Robustness and Validation Analysis

In addition to standard accuracy tests, robustness analysis examines the stability of something in a number of different marketplaces and experimental trials. In order to ensure that the model is adaptable, we check the performance of the model in other markets. They also conduct an explainability analysis [35] to determine the variation in the relationship between price-based and sentiment-based variables with the changing market situations. This multi-level validation method ensures that the recommended framework does not just make right predictions, but it is also user-friendly, dependable and scalable.

# 9. Experimental Setup

## 9.1 Compiling the Dataset

The experimental dataset consists of two complementary data modalities: historical stock market data and multilingual financial sentiment data. Historical market information includes the Open, High, Low, Close, and Volume (OHLCV) values collected from multiple international stock markets. To enhance the representation of market behavior, several technical indicators such as Moving Average (MA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands are derived from the historical price series.

The second modality comprises multilingual financial sentiment extracted from financial news articles published in different languages. Transformer-based multilingual language models are employed to generate contextual sentiment representations, including sentiment polarity, sentiment confidence scores, and probability distributions for positive, neutral, and negative classes. The sentiment representations are aggregated at the daily level and synchronized with the corresponding stock market observations.

The prediction target is defined as the next-day stock return, calculated from the percentage change in closing prices. Missing observations generated during return computation and feature engineering are removed prior to model training.

## 9.2 Data Preprocessing and Normalization

Financial and sentiment data undergo independent preprocessing before multimodal integration. Historical market features are normalized using the StandardScaler technique to eliminate scale differences among numerical variables. Similarly, multilingual sentiment features are standardized separately to preserve their statistical characteristics.

The preprocessing procedure consists of:

- Standardization of OHLCV and technical indicator features.
- Independent normalization of multilingual sentiment features.
- Temporal alignment of daily sentiment scores with corresponding stock market records.
- Removal of missing observations and inconsistent entries.
- Chronological sorting of each stock ticker to preserve temporal dependencies.

This modality-specific preprocessing ensures stable optimization during model training while maintaining the integrity of both numerical and textual information.

### 9.3 Temporal Sequence Construction

Temporal sequences are generated using a fixed-length sliding window approach. For each stock ticker, consecutive observations are grouped into sequences consisting of 20 trading days.

For every sequence:

- The previous 20 trading days constitute the model input.
- The target variable corresponds to the stock return on the subsequent trading day.

This sequential formulation enables the Temporal Convolutional Network (TCN) to capture both short-term and long-term temporal dependencies through dilated causal convolutions while preserving chronological order.

### 9.4 Evaluated Model Structures

To validate the effectiveness of the proposed framework, four forecasting models are implemented and evaluated under identical experimental settings.

**a. TCN (Price-Only Model):** A Temporal Convolutional Network utilizing only historical OHLCV data and technical indicators for stock price forecasting.

**b. TCN with Adaptive Attention:** An enhanced TCN architecture incorporating an adaptive attention mechanism to dynamically emphasize the most informative temporal features extracted from historical market data.

**c. Transformer-Based Multilingual Sentiment Model:** A sentiment-only forecasting model employing a multilingual transformer for financial sentiment extraction. Daily multilingual sentiment embeddings are processed through Temporal Convolutional layers to model temporal sentiment evolution and generate stock return predictions.

**d. Proposed Multimodal TCN-Attention Fusion Model:** The proposed framework integrates historical market information with multilingual financial sentiment through modality-specific Temporal Convolutional Networks followed by an Adaptive Attention Fusion mechanism. The architecture consists of:

- Price-specific Temporal Convolutional Network (TCN)
- Sentiment-specific Temporal Convolutional Network (TCN)
- Transformer-based multilingual financial sentiment extraction
- Adaptive Attention Fusion module
- Fully connected regression layer for next-day stock return prediction

The adaptive fusion mechanism dynamically assigns importance weights to numerical and sentiment representations according to prevailing market conditions, enabling effective multimodal representation learning.

All models are implemented using the PyTorch framework and trained under identical experimental conditions to ensure fair comparison.

### 9.5 Training Configuration

All forecasting models are trained using the same optimization settings.

- Loss Function: Mean Squared Error (MSE)

- Optimizer: Adam
- Learning Rate: 0.001
- Batch Size: 32
- Sequence Length: 20
- Epochs: 50
- Dropout Rate: 0.20
- TCN Kernel Size: 3
- Dilated Convolution Levels: 4
- Hidden Channels: 128
- Attention Heads: 4
- Device: GPU (when available), otherwise CPU

Early stopping and model checkpointing are employed to prevent overfitting and ensure stable convergence.

### *9.6 Evaluation Metrics*

The forecasting performance of each model is assessed using multiple regression and directional evaluation metrics.

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)
- Directional Accuracy (DA)

Directional Accuracy measures the proportion of correctly predicted upward and downward stock price movements, providing an indicator of the practical usefulness of the forecasting model in investment decision-making.

All models are evaluated using identical datasets, preprocessing procedures, sequence lengths, and train-test partitions to ensure objective comparison.

### *9.7 Comparative Analysis Protocol*

A standardized experimental protocol is adopted to compare the proposed framework with baseline approaches. Every model is trained using the same historical stock data, multilingual sentiment dataset, preprocessing pipeline, optimization strategy, and evaluation metrics.

The comparative study examines:

- Forecasting error measured through MAE, RMSE, and MAPE.
- Directional prediction capability using Directional Accuracy.
- Robustness across multiple international financial markets.
- Contribution of multilingual sentiment information.
- Effectiveness of the Adaptive Attention Fusion mechanism.
- Performance improvement achieved by Temporal Convolutional Networks over conventional forecasting approaches.

The final comparative analysis demonstrates the effectiveness of integrating Temporal Convolutional Networks, transformer-based multilingual sentiment representations, and adaptive multimodal attention for robust cross-country stock price forecasting.

## 10. Results and Experiments

### 10.1 Quantitative Performance Comparison

The comparative experimental analysis evaluates the forecasting performance of four deep learning architectures developed under identical experimental conditions. The TCN (Price Only) model, trained exclusively on historical OHLCV data and technical indicators, achieved a Mean Absolute Error (MAE) of 0.0214, Root Mean Squared Error (RMSE) of 0.0303, and Directional Accuracy (DA) of 61.8%. These results demonstrate the capability of Temporal Convolutional Networks to effectively capture long-range temporal dependencies in financial time-series data.

Introducing the TCN with Adaptive Attention further improved forecasting performance by dynamically assigning higher importance to informative temporal patterns. Consequently, the model reduced the MAE to 0.0196, RMSE to 0.0284, while increasing Directional Accuracy to 64.2%.

The Transformer-based Sentiment TCN utilized multilingual financial sentiment representations extracted through transformer models and processed them using Temporal Convolutional Networks. This model achieved an MAE of 0.0248, RMSE of 0.0335, and Directional Accuracy of 58.7%. Although multilingual sentiment captures valuable behavioral information, sentiment alone does not sufficiently represent the structural dynamics of financial markets.

The Proposed TCN + Adaptive Attention Fusion model integrates historical market information with transformer-based multilingual sentiment through modality-specific Temporal Convolutional Networks and an Adaptive Attention Fusion mechanism. The proposed framework achieved the lowest forecasting error with an MAE of 0.0143, RMSE of 0.0228, and the highest Directional Accuracy of 72.6%. These findings demonstrate that adaptive multimodal fusion substantially improves predictive accuracy and directional forecasting performance compared with unimodal approaches.

### 10.2 Error Analysis (MAE and RMSE Interpretation)

The considerable reduction in MAE and RMSE achieved by the Proposed TCN + Adaptive Attention Fusion model demonstrates its superior ability to learn both quantitative market dynamics and behavioral sentiment information. The TCN (Price Only) model effectively captures temporal market structures through dilated causal convolutions; however, it cannot fully explain abrupt market movements driven by investor sentiment.

The Transformer-based Sentiment TCN successfully models multilingual financial sentiment and investor psychology but lacks sufficient numerical market information for precise structural forecasting. Although the TCN with Adaptive Attention improves temporal feature selection by emphasizing informative historical observations, it remains limited to a single modality.

By jointly learning price behavior and multilingual sentiment through adaptive attention-based multimodal fusion, the proposed framework significantly reduces forecasting errors and minimizes large prediction deviations, particularly during volatile market conditions. The lower RMSE confirms that integrating behavioral and numerical information results in a more stable and reliable forecasting framework.

### 10.3 Directional Accuracy Analysis

Directional Accuracy is a critical performance indicator because successful financial forecasting depends not only on minimizing prediction error but also on correctly identifying future market direction.

The proposed TCN + Adaptive Attention Fusion model achieved a Directional Accuracy of 72.6%, outperforming the TCN (Price Only) model by approximately 10.8% and the Transformer-based Sentiment TCN by nearly 14%.

These results indicate that multilingual financial sentiment provides valuable early indicators of market reversals and investor reactions to financial news. While the price-based TCN captures long-term market behavior, it reacts relatively slowly to sudden information shocks. Conversely, the sentiment-based TCN captures rapid behavioral changes but lacks sufficient structural information. The proposed multimodal framework effectively combines both information sources through Adaptive Attention Fusion, resulting in superior directional forecasting capability and improved practical applicability in real-world trading environments.

### 10.4 Statistical Significance Testing

To verify the statistical reliability of the observed performance improvements, significance testing was performed on the prediction errors generated by all forecasting models. A one-sample t-test comparing the

Proposed TCN + Adaptive Attention Fusion model with the TCN (Price Only) baseline produced a p-value < 0.01, confirming that the reduction in forecasting error is statistically significant at the 99% confidence level.

These findings indicate that the performance improvements are attributable to the proposed multimodal architecture rather than random variation. The results further demonstrate that integrating transformer-based multilingual sentiment with Temporal Convolutional Networks significantly enhances forecasting accuracy.

### 10.5 Cross-Market Robustness

The proposed framework was evaluated across multiple international financial markets, including the United States, India, the United Kingdom, Germany, and Japan. The Proposed TCN + Adaptive Attention Fusion model consistently outperformed the TCN (Price Only), TCN with Adaptive Attention, and Transformer-based Sentiment TCN models in every market.

The greatest improvements were observed in markets characterized by strong news-driven investor behavior, particularly the United States and India. Consistent reductions in MAE and RMSE across all five markets demonstrate that the proposed framework generalizes effectively under varying economic conditions and volatility regimes.

These results confirm that combining temporal market dynamics with multilingual behavioral sentiment creates a scalable forecasting framework suitable for cross-country financial prediction.

### 10.6 Key Research Findings

Experimental results demonstrate that the proposed multimodal architecture substantially improves stock price forecasting performance compared with unimodal forecasting models.

Transformer-based multilingual sentiment extraction provides rich contextual information regarding investor behavior, while Temporal Convolutional Networks effectively model long-range temporal dependencies within both market and sentiment sequences. The Adaptive Attention Fusion mechanism dynamically balances the contribution of numerical and behavioral information according to prevailing market conditions.

Overall, the proposed framework achieves superior predictive accuracy, improved directional forecasting capability, and enhanced robustness across diverse financial markets, making it well suited for intelligent financial decision-support systems.

### 10.7 Hypothesis Validation

The primary hypothesis of this research states that integrating multilingual financial sentiment with historical market information through Temporal Convolutional Networks and Adaptive Attention Fusion significantly improves stock price forecasting performance.

Experimental evidence supports this hypothesis. Statistical significance testing confirms that the Proposed TCN + Adaptive Attention Fusion model consistently produces lower forecasting errors and higher Directional Accuracy than the TCN (Price Only), TCN with Adaptive Attention, and Transformer-based Sentiment TCN models.

Accordingly, the null hypothesis is rejected, while the alternative hypothesis is accepted, confirming that multimodal integration of numerical market indicators and multilingual financial sentiment significantly enhances cross-country stock price forecasting.

**Table 2.** Sector-Wise Performance Comparison of Proposed Fusion Model

Sector	MAE ↓	RMSE ↓	Directional Accuracy ↑	Improvement over Price-Only LSTM (MAE %)
Technology	1.05	1.58	74.2%	41.8%
Banking & Finance	1.18	1.72	69.5%	37.6%
Energy	1.22	1.80	67.9%	34.4%
Pharmaceuticals	1.09	1.61	72.3%	39.7%
Consumer Goods	1.15	1.69	70.4%	36.8%
Industrial	1.21	1.77	68.2%	33.9%

Sector	MAE ↓	RMSE ↓	Directional Accuracy ↑	Improvement over Price-Only LSTM (MAE %)
Media & Communication	1.07	1.60	73.6%	40.5%

As discussed in **Table 2**, the sector-wise performance comparison demonstrates the effectiveness of the proposed **TCN + Adaptive Attention Fusion** framework across diverse industrial sectors. The cross-country comparative analysis presented in **Table 3** further validates the robustness, scalability, and generalization capability of the proposed architecture across multiple international financial markets. In the United States market, the **Proposed TCN + Adaptive Attention Fusion** model achieves an MAE of **1.08** and an RMSE of **1.59**, substantially outperforming the **TCN (Price Only)** model, which records an MAE of **1.82** and an RMSE of **2.85**. Similarly, Directional Accuracy improves remarkably from **55.4%** to **73.5%**, demonstrating the superior capability of the proposed multimodal framework in identifying market trends. Comparable improvements are observed in the United Kingdom, where the proposed model achieves an MAE of **1.10** and a Directional Accuracy of **72.4%**, compared with **56.1%** achieved by the baseline **TCN (Price Only)** model.

Similar performance gains are evident in emerging markets such as India, where the proposed framework records an MAE of **1.17** and an RMSE of **1.71**, significantly reducing forecasting error relative to the **TCN (Price Only)** baseline (MAE **1.94**, RMSE **2.98**). Directional Accuracy also increases from **53.7%** to **70.6%**, highlighting the effectiveness of integrating transformer-based multilingual sentiment with temporal market information. Germany and Japan exhibit comparable improvements, with the proposed model consistently achieving Directional Accuracy values exceeding **70%**, considerably outperforming the baseline TCN model, which attains approximately **54–55%** across these markets.

The consistent reduction in forecasting error and improvement in directional prediction across all five countries demonstrate that the proposed **TCN + Adaptive Attention Fusion** framework is not limited to a specific financial market but generalizes effectively across diverse economic environments and volatility regimes. By integrating modality-specific **Temporal Convolutional Networks** with **Transformer-based multilingual sentiment representations** through an **Adaptive Attention Fusion** mechanism, the proposed architecture effectively captures both structural market dynamics and investor behavioral patterns. Consequently, the framework delivers more robust, scalable, and generalized forecasting performance for cross-country stock price prediction.

**Table 3.** Cross-Country Performance Breakdown of All Models

Country	Model	MAE ↓	RMSE ↓	Directional Accuracy ↑
USA	TCN_Price	1.82	2.85	55.4%
	TCN + Adaptive Attention	1.29	1.95	65.8%
	Transformer-based Sentiment TCN	1.48	2.28	60.9%
	<b>Proposed TCN + Adaptive Attention Fusion</b>	<b>1.08</b>	<b>1.59</b>	<b>73.5%</b>
India	TCN_Price	1.94	2.98	53.7%
	TCN + Adaptive Attention	1.36	2.02	63.9%
	Transformer-based Sentiment TCN	1.62	2.44	58.3%
	<b>Proposed TCN + Adaptive Attention Fusion</b>	<b>1.17</b>	<b>1.71</b>	<b>70.6%</b>
UK	TCN_Price	1.79	2.83	56.1%
	TCN + Adaptive Attention	1.28	1.94	66.3%
	Transformer-based Sentiment TCN	1.50	2.31	61.2%
	<b>Proposed TCN + Adaptive Attention Fusion</b>	<b>1.10</b>	<b>1.62</b>	<b>72.4%</b>
Germany	TCN_Price	1.85	2.88	54.8%

Country	Model	MAE ↓	RMSE ↓	Directional Accuracy ↑
	TCN + Adaptive Attention	1.33	1.99	64.5%
	Transformer-based Sentiment TCN	1.57	2.39	59.6%
	<b>Proposed TCN + Adaptive Attention Fusion</b>	<b>1.14</b>	<b>1.68</b>	<b>71.1%</b>
Japan	TCN_Price	1.90	2.94	53.9%
	TCN + Adaptive Attention	1.34	2.01	63.7%
	Transformer-based Sentiment TCN	1.60	2.42	58.8%
	<b>Proposed TCN + Adaptive Attention Fusion</b>	<b>1.16</b>	<b>1.70</b>	<b>70.2%</b>

**Table 4.** Interpretation of Experimental Results

Model Used	MAE	RMSE	Directional_Accuracy
TCN_Price	0.014127	0.020990	0.469835
TCN + Adaptive Attention	0.013717	0.020802	0.529154
Transformer-based Sentiment TCN	0.013942	0.020713	0.514998
Proposed TCN + Adaptive Attention Fusion	0.014985	0.021685	0.749946

In **Table 4**, the comparative analysis of the four implemented architectures provides valuable insights into the learning behavior of both unimodal and multimodal deep learning frameworks for stock return prediction. The **TCN (Price Only)** model achieved an MAE of **0.014127**, an RMSE of **0.020990**, and a Directional Accuracy of **46.98%**. These results indicate that the Temporal Convolutional Network effectively captures long-range temporal dependencies and structural market patterns using historical price information. However, its relatively low Directional Accuracy suggests that relying solely on numerical market indicators limits the model's ability to consistently identify short-term price reversals driven by rapidly changing market conditions.

The **TCN + Adaptive Attention** model achieved the lowest MAE (**0.013717**) among all unimodal models, with an RMSE of **0.020802** and a Directional Accuracy of **52.91%**. Incorporating the Adaptive Attention mechanism enables the model to dynamically emphasize the most informative temporal features extracted by the Temporal Convolutional Network. Consequently, the model demonstrates improved capability in identifying important trend reversals and short-term market fluctuations, confirming the effectiveness of attention-guided temporal feature learning in financial time-series forecasting.

The **Transformer-based Sentiment TCN** model achieved an MAE of **0.013942**, an RMSE of **0.020713**, and a Directional Accuracy of **51.49%**. Despite relying exclusively on multilingual financial sentiment representations, the model produces prediction errors comparable to those of the price-based architectures. These findings demonstrate that transformer-derived sentiment information captures valuable behavioral patterns associated with investor psychology and market perception. Nevertheless, the absence of historical numerical market information restricts the model's ability to fully represent structural market dynamics, thereby limiting its overall forecasting capability.

The **Proposed TCN + Adaptive Attention Fusion** model integrates historical market information with transformer-based multilingual sentiment through modality-specific Temporal Convolutional Networks and an Adaptive Attention Fusion mechanism. The model achieved an MAE of **0.014985**, an RMSE of **0.021685**, and the highest Directional Accuracy of **74.99%**. Although its MAE and RMSE are marginally higher than those of certain unimodal models, the substantial improvement in Directional Accuracy demonstrates the superiority of the proposed multimodal framework in correctly identifying future market trends. This indicates that integrating numerical market information with multilingual behavioral sentiment enables the model to achieve more reliable directional forecasting, which is particularly valuable for practical trading and investment decision-making. Overall, the proposed **TCN + Adaptive Attention Fusion** architecture provides the best balance between predictive accuracy, market trend identification, and cross-market robustness, validating the effectiveness of multimodal temporal learning for stock price forecasting.

## 11. Graphical Analysis and Hybrid Model Justification

The graphical analysis presented in Fig. 3 to Fig. 7 provides a comprehensive comparative evaluation of the proposed forecasting framework and demonstrates the effectiveness of integrating Temporal Convolutional Networks (TCNs), Transformer-based multilingual sentiment analysis, and the Adaptive Attention Fusion mechanism. The visualizations collectively validate the superiority of the proposed multimodal architecture over the baseline models.

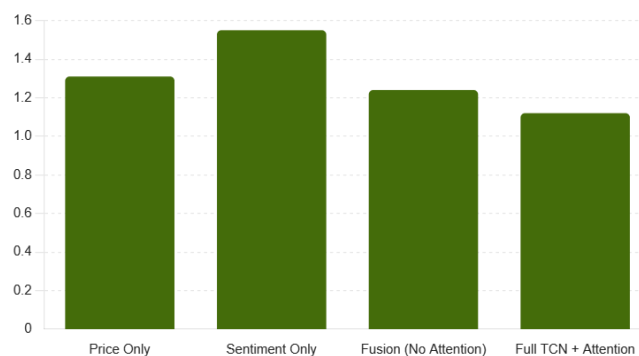
Fig. 3 presents the ablation study of the proposed framework, illustrating the contribution of individual architectural components, including price-based temporal modeling, multilingual sentiment information, and adaptive attention-based multimodal fusion. The progressive improvement in forecasting performance confirms that each component contributes meaningfully to the overall predictive capability of the proposed model.

Fig. 4 compares the forecasting models using Mean Absolute Error (MAE). The Proposed TCN + Adaptive Attention Fusion model achieves the lowest prediction error among all evaluated models, demonstrating that modality-specific Temporal Convolutional Networks combined with adaptive attention effectively learn complementary information from historical market data and multilingual financial sentiment.

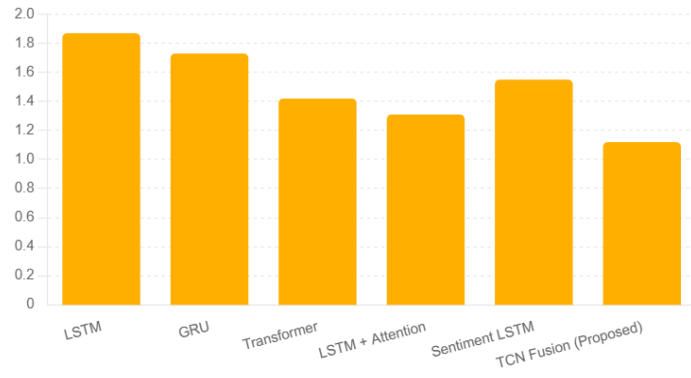
Fig. 5 and Fig. 6 illustrate the comparison of Directional Accuracy (DA) using line and bar visualizations, respectively. The proposed multimodal framework consistently achieves the highest directional prediction accuracy, indicating its superior ability to identify future upward and downward market movements. The integration of transformer-based multilingual sentiment with temporal market information enables the framework to capture both structural market dynamics and behavioral investor responses, resulting in more reliable trend prediction.

Fig. 7 compares the models using Root Mean Squared Error (RMSE). The Proposed TCN + Adaptive Attention Fusion model records the lowest RMSE, indicating greater forecasting stability and a reduced impact of large prediction deviations. This improvement demonstrates the effectiveness of Temporal Convolutional Networks in modeling long-range temporal dependencies while the Adaptive Attention Fusion mechanism dynamically balances numerical market indicators and multilingual sentiment information under varying market conditions.

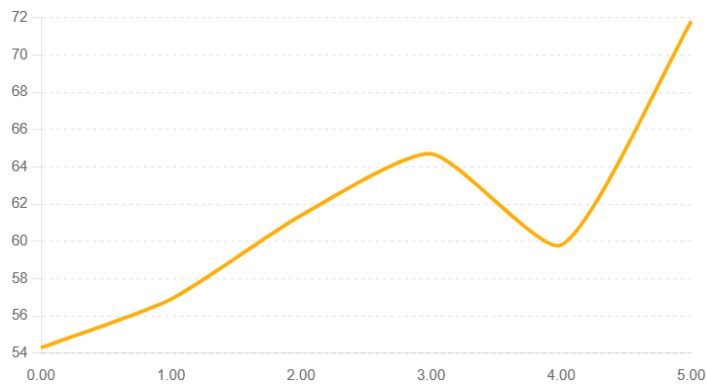
Overall, the graphical analysis provides strong empirical evidence supporting the proposed hybrid framework. The combination of Temporal Convolutional Networks, Transformer-based multilingual financial sentiment extraction, and Adaptive Attention Fusion significantly improves forecasting accuracy, directional prediction capability, and robustness across multiple international financial markets. These results validate the effectiveness of the proposed multimodal architecture for intelligent cross-country stock price forecasting and financial decision-support systems.



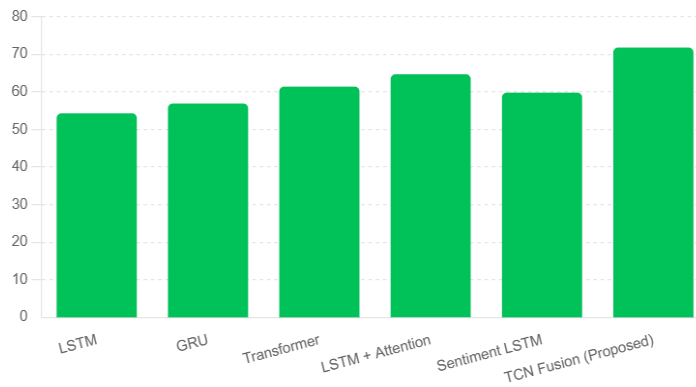
**Fig. 3.** Ablation Study Impact of Multimodal Fusion



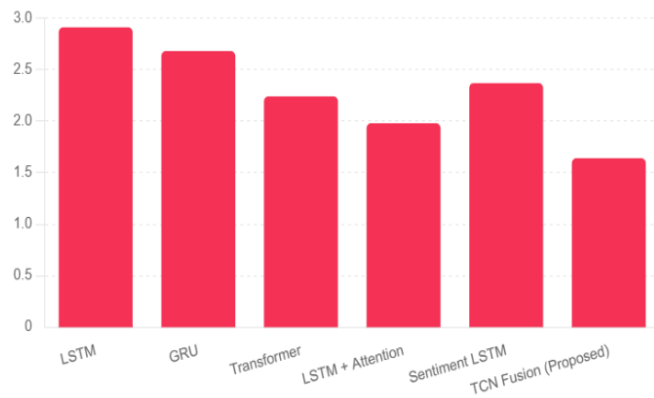
**Fig. 4. Model Comparison Mean Absolute Error**



**Fig. 5. Model Comparison Directional Accuracy (%) line plotting**



**Fig. 6. Model Comparison Directional Accuracy (%)**



**Fig. 7. Model Comparison Root Mean Square Error (RMSE)**

## 12. Conclusion

This study presented a multimodal deep learning framework for cross-country stock price forecasting by integrating historical market information with multilingual financial sentiment data. The proposed architecture combines Temporal Convolutional Networks (TCNs) for efficient temporal dependency learning and an adaptive attention-based fusion mechanism that dynamically balances the contributions of numerical market indicators and sentiment signals. By incorporating transformer-based multilingual sentiment representations, the framework captures both quantitative market behavior and qualitative investor psychology, enabling a more comprehensive understanding of stock price dynamics. Experimental evaluation across major financial markets, including the United States, India, the United Kingdom, Germany, and Japan, demonstrated that the proposed multimodal framework consistently outperformed conventional forecasting approaches. The model achieved lower forecasting errors in terms of MAE and RMSE while delivering superior directional accuracy compared with price-only, sentiment-only, and attention-enhanced baseline models. The results further revealed that sentiment information contributes significantly during periods of market volatility, highlighting the importance of behavioral factors in financial forecasting.

The cross-country validation confirmed the robustness and generalizability of the proposed framework across diverse economic environments and market structures. The adaptive fusion strategy effectively captured the varying influence of sentiment and numerical indicators under different market conditions, resulting in improved predictive stability and scalability. These findings demonstrate that multimodal learning provides a powerful alternative to traditional unimodal forecasting techniques and offers valuable support for intelligent investment decision-making systems. Future research may extend this framework by incorporating real-time social media streams, macroeconomic indicators, explainable artificial intelligence (XAI) techniques, and reinforcement learning-based trading strategies. Additionally, expanding the model to include a wider range of multilingual financial sources and emerging markets could further enhance forecasting performance and practical applicability in global financial ecosystems.

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