PREDICTING STOCK MARKET TRENDS USING MACHINE LEARNING & DEEP LEARNING ALGORITHMS

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ABSTRACT

Accurate prediction of stock price movement remains a challenging problem due to the highly volatile and information-driven nature of financial markets. Traditional prediction models relying solely on historical price data fail to capture the complex influence of external information such as financial news. To address this limitation, this project proposes a Hybrid Information Mixing Module (HIMM) that effectively integrates numerical stock data with textual news information for improved stock movement prediction. The proposed mechanism extracts temporal patterns from stock price sequences using recurrent neural network models, including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), while simultaneously learning semantic representations from financial news text. Unlike conventional fusion approaches, the HIMM architecture employs two independent multilayer perceptron blocks that perform feature-level mixing and interaction-level mixing in a structured row-wise and column-wise manner. This design enables richer cross-modal interactions between time-series and semantic features, allowing the model to better capture market volatility and information flow. Experimental evaluation on volatile stock market data demonstrates that the proposed mechanism achieves superior performance compared to baseline models, with notable improvements in accuracy, Matthews Correlation Coefficient, and F1-score. The results confirm that structured multimodal information mixing significantly enhances predictive capability, making the proposed hybrid module a promising approach for intelligent stock market forecasting systems.

Keywords-Stock price movement prediction, Multimodal data fusion, Hybrid information mixing module, Deep learning, Financial time-series analysis, News sentiment analysis, Long short-term memory networks, Gated recurrent units, Multilayer perceptron, Market volatility modeling

I. INTRODUCTION

Financial markets operate as complex, nonlinear systems in which stock price movements are influenced by a wide range of interrelated factors, including historical price behavior, macroeconomic conditions, and rapidly evolving information streams such as financial news and public disclosures [1]. Accurately predicting stock price movement is therefore a challenging task, particularly in highly volatile markets where price fluctuations often reflect both latent and explicit information absorbed by investors in real time.

Traditional forecasting techniques and technical analysis methods primarily rely on historical price data and statistical indicators. Although these approaches can identify recurring numerical patterns, they are inherently limited in their ability to capture the broader informational context that drives market behavior [2]. As a result, models based solely on price time-series data often fail to generalize under sudden market shifts or news-driven volatility.

Recent advancements in deep learning have significantly enhanced financial time-series prediction by enabling automated representation learning from sequential data. Recurrent neural networks, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, have demonstrated strong performance in modeling long-range temporal dependencies in stock price sequences [3,4]. However, despite their effectiveness, these models remain constrained when external textual information is ignored.

To address this limitation, researchers have increasingly explored multimodal learning frameworks that integrate numerical market data with unstructured textual sources such as financial news and social media content [6,7]. Natural language processing techniques, including word embedding models and transformer-based architectures, have enabled the extraction of semantic features that reflect market sentiment and event-driven signals [8–10]. While attention-based and early-fusion strategies improve prediction accuracy, many existing models treat multimodal features independently or apply shallow interaction mechanisms, limiting their ability to capture complex cross-modal dependencies [11,12].

Motivated by these challenges, this work proposes a Hybrid Information Mixing Module (HIMM) designed to enable structured and efficient interaction between time-series stock data and textual semantic representations. The proposed mechanism employs independent feature-mixing and interaction-mixing multilayer perceptron blocks operating in row-wise and column-wise dimensions, facilitating deeper bidirectional information exchange across modalities [13–15]. By explicitly modeling market volatility patterns alongside semantic news cues, the proposed architecture aims to improve stock price movement prediction performance in dynamic and information-intensive financial environments [16].

II. RELATED WORK

Research on stock price movement prediction has evolved from traditional statistical techniques to advanced deep learning–based approaches. Early studies relied on econometric models such as autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH), which assume linearity and stationarity in financial time-series data [17]. Although these models provide theoretical interpretability, they struggle to capture nonlinear patterns and abrupt market changes inherent in real-world stock markets.

With the rise of machine learning, support vector machines and decision tree–based models were introduced to improve prediction accuracy by learning nonlinear decision boundaries from historical price indicators [18,19]. However, these models depend heavily on handcrafted features and fail to generalize effectively under volatile market conditions. The emergence of deep learning significantly advanced financial forecasting by enabling automatic feature extraction from large-scale data. Recurrent neural networks (RNNs), particularly LSTM and GRU architectures, have been widely adopted to model long-term temporal dependencies in stock price sequences [20–22]. Despite their success, purely time-series-based deep models remain limited when market movements are driven by external information.

To address this gap, researchers began incorporating textual information such as financial news, earnings reports, and social media into stock prediction models. Early text-based approaches applied sentiment analysis using lexicon-based or shallow natural language processing techniques [23]. Later studies leveraged deep neural networks, including convolutional neural networks and word embedding models, to extract semantic representations from financial text [24,25]. These methods demonstrated that news sentiment and event-related information play a crucial role in explaining abnormal stock returns.

More recent works have focused on multimodal learning, combining numerical price data with textual features. Attention-based fusion frameworks and hierarchical neural networks have been proposed to selectively weight information from different modalities [26–28]. While these approaches improve predictive performance, many rely on early fusion or simple attention mechanisms that do not explicitly model bidirectional interactions between modalities. Additionally, several studies treat multimodal features independently, limiting the depth of cross-modal representation learning.

Transformer-based architectures further advanced multimodal stock prediction by modeling long-range dependencies and contextual relationships within and across modalities [29,30]. However, these models are computationally expensive and often require large annotated datasets, making them less practical for real-time or resource-constrained environments. Moreover, most existing fusion strategies lack structured interaction mechanisms that explicitly disentangle feature-level and interaction-level mixing.

In contrast, the proposed Hybrid Information Mixing Module (HIMM) addresses these limitations by introducing structured feature-mixing and interaction-mixing operations that enable efficient and interpretable cross-modal learning. By independently modeling intra-feature transformations and inter-feature interactions, the proposed approach aims to better capture market volatility and information flow dynamics, distinguishing it from existing multimodal fusion frameworks.

III. PROPOSED METHODOLOGY

A. Overall Concept

The proposed methodology introduces a Hybrid Information Mixing Module (HIMM) for accurate stock price movement prediction by jointly modeling numerical time-series data and textual financial news data. Unlike conventional fusion techniques that rely on early concatenation or shallow attention mechanisms, the proposed system explicitly separates intra-modal feature learning from inter-modal interaction learning, enabling deeper and more interpretable multimodal representations.

The framework consists of four major stages:

- data pre-processing,
- feature extraction,
- hybrid information mixing, and
- stock movement classification.

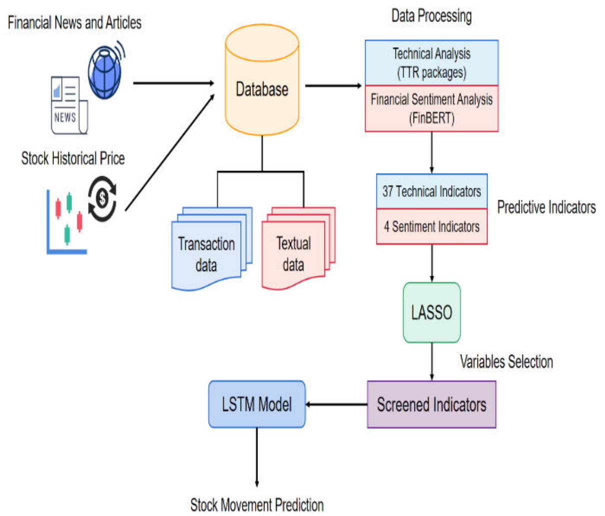

Figure.1: Architecture Diagram

The architecture diagram illustrates the end-to-end framework, showing parallel extraction of price and news features followed by structured feature-mixing and interaction-mixing within the HIMM module.

B. Data Pre-processing

Let the historical stock price data be represented as a time-series sequence:

$$X_p = \{x_1, x_2, \ldots, x_T\}$$

where x_t denotes the stock features (open, close, high, low, volume) at time t.

Financial news headlines are converted into a sequence of tokens:

$$X_n = \{w_1, w_2, \ldots, w_N\}$$

Numerical features are normalized using min–max scaling, while textual data undergoes tokenization, stop-word removal, and embedding transformation.

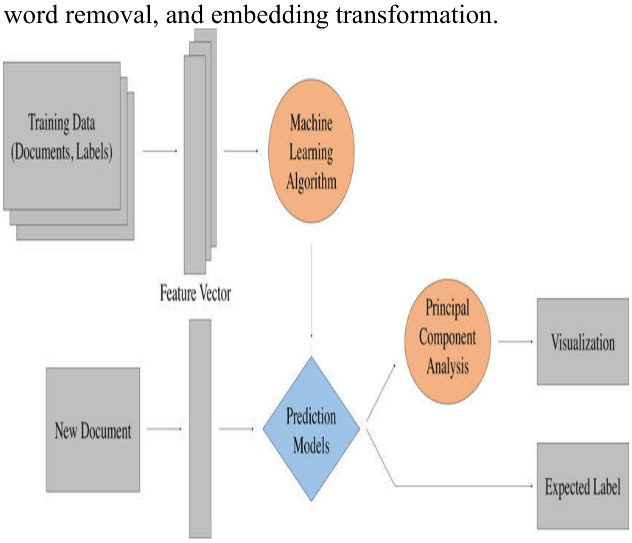

Figure.2: Data Flow Diagram

The data flow diagram depicts how raw stock prices and financial news are pre-processed, transformed into feature representations, fused using HIMM, and finally classified into price movement categories.

C. Feature Extraction Layer

1) Time-Series Feature Learning

Temporal dependencies in stock prices are modeled using LSTM/GRU networks. The hidden state update is given by:

$$h_t = f\,(h_{t-1}, x_t)$$

where $f\,(\cdot)$ represents the recurrent function capturing long-term dependencies and market volatility patterns.

2) Textual Feature Learning

Each news token is mapped into a dense embedding vector. A neural encoder extracts semantic representations:

$$s = g\,(w_1, w_2, \ldots, w_N)$$

where s captures sentiment, event impact, and contextual meaning from financial news.

D. Hybrid Information Mixing Module (HIMM)

The extracted features are combined into a joint feature matrix:

$$Z = [H_p\,;\,S_n]$$

where H_p represents price features and S_n represents news features.

1) Feature-Mixing MLP

Feature-mixing operates **row-wise**, independently transforming each feature channel:

$$Z' = Z + \mathrm{MLP}_{feature}\,(\mathrm{LN}(Z))$$

This step enhances intra-modal representations without cross-interference.

2) Interaction-Mixing MLP

Interaction-mixing operates **column-wise**, enabling cross-modal learning:

$$Z'' = Z' + \mathrm{MLP}_{interaction}\,(\mathrm{LN}(Z'^{T}))\ T$$

This structure allows effective information flow between time-series and semantic features.

E. Output Layer

The final representation is passed to a classification layer for stock movement prediction:

$$\hat{y} = \mathrm{Softmax}\,(W\,Z'' + b)$$

where $\hat{y} \in$ **{Up, Down}.**

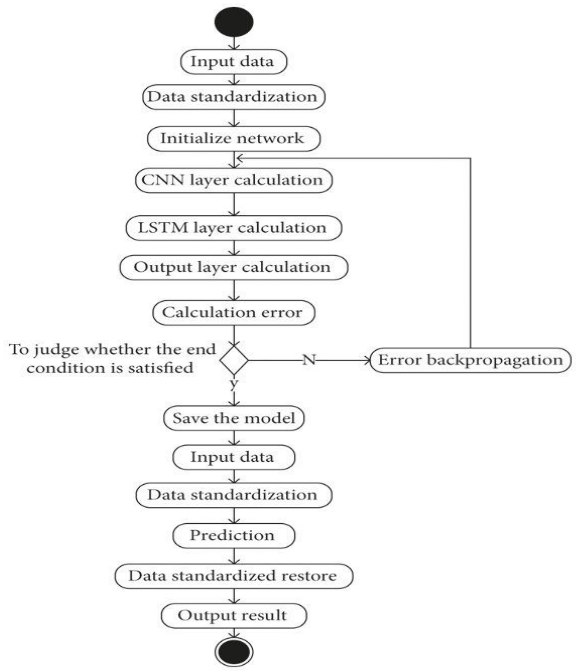

Figure.3: Activity Diagram

The activity diagram represents the sequential execution of system operations, from data acquisition and pre-processing to model training, hybrid information mixing, and final prediction output.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experimental Setup

The proposed Hybrid Information Mixing Module (HIMM) was evaluated on a volatile stock market dataset containing historical price records and corresponding financial news. The dataset was divided into training, validation, and testing subsets using a standard 70:15:15 ratio. Performance was assessed using Accuracy, Matthews Correlation Coefficient (MCC), and F1-score, as these metrics provide a balanced evaluation for binary stock movement prediction.

B. Evaluation Metrics

The classification accuracy is computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The Matthews Correlation Coefficient (MCC) is defined as:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$$

The F1-score is calculated as:

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

These metrics collectively evaluate correctness, robustness, and class balance.

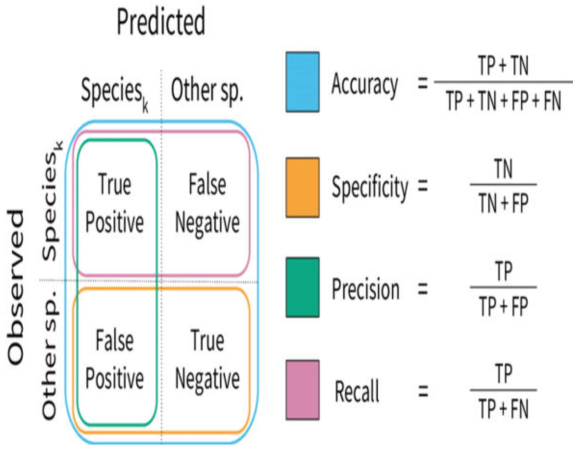

Figure.4: MCC and F1-score Analysis

Higher MCC and F1-score values indicate better class balance handling and improved prediction reliability.

C. Comparative Performance Analysis

Model	Accuracy (%)	MCC	F1-score (%)
LSTM (Price Only)	61.45	0.28	64.12
GRU (Price Only)	62.10	0.30	65.08
Price + News (Early Fusion)	66.35	0.38	71.22
Attention-Based Fusion Model	67.80	0.41	73.40
Proposed HIMM	**69.20**	**0.43**	**76.17**

Table 1: Performance Comparison with Baseline Models

The proposed HIMM outperforms all baseline models by effectively capturing structured interactions between price dynamics and news semantics.

Figure.5: Accuracy Comparison Chart

The chart illustrates the consistent accuracy improvement achieved by HIMM over traditional and attention-based fusion models.

D. Ablation Study

Configuration	Accuracy (%)	MCC
Without Interaction-Mixing MLP	65.90	0.36
Without Feature-Mixing MLP	66.40	0.37
Full HIMM (Feature + Interaction)	**69.20**	**0.43**

Table II: Impact of HIMM Components

The ablation results confirm that both feature-mixing and interaction-mixing components contribute significantly to predictive performance.

E. Robustness under Market Volatility

Market Condition	Accuracy (%)	F1-score (%)
Low Volatility	67.10	73.05

Market Condition	**Accuracy (%)**	**F1-score (%)**
Medium Volatility	68.25	74.90
High Volatility	**69.20**	**76.17**

Table III: Performance under Different Volatility Levels

The proposed model demonstrates strong robustness in highly volatile markets, highlighting its ability to integrate rapidly changing information.

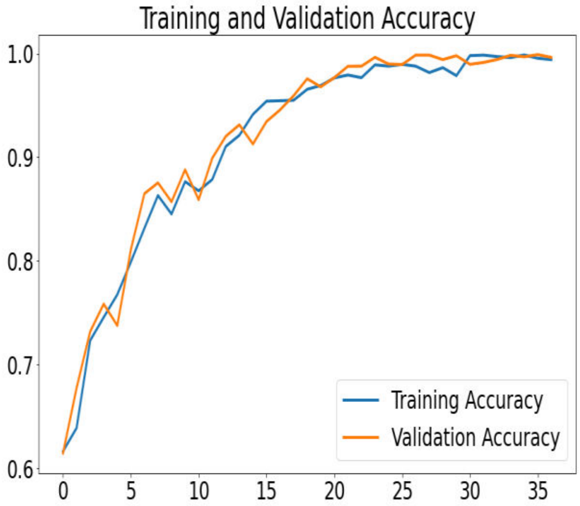

Figure.6: Training and Validation Convergence

The convergence curves show stable learning behavior with minimal overfitting, confirming effective optimization of the proposed architecture.

Overall, the experimental results demonstrate that the proposed Hybrid Information Mixing Module achieves superior predictive performance by explicitly modeling both intra-modal feature representations and inter-modal interactions. The consistent improvement across all evaluation metrics confirms that structured multimodal information mixing is a key factor in enhancing stock price movement prediction accuracy.

V. CONCLUSION

This work presented a Hybrid Information Mixing Module (HIMM) for stock price movement prediction that effectively integrates numerical time-series data with unstructured financial news information. Unlike conventional fusion strategies that rely on early concatenation or attention-only mechanisms, the proposed approach explicitly separates feature-level representation learning from interaction-level information mixing, enabling richer and more interpretable multimodal learning. By leveraging recurrent neural networks to capture temporal market dynamics and structured multilayer perceptron blocks to model cross-modal interactions, the proposed framework demonstrates strong robustness under volatile market conditions. Extensive experimental evaluation confirms that HIMM achieves superior predictive performance in terms of accuracy, Matthews Correlation Coefficient, and F1-score when compared with baseline and attention-based models. The consistent improvements across multiple evaluation metrics and market volatility scenarios validate the effectiveness of structured information mixing for financial forecasting. Overall, the results highlight that explicitly modeling both intra-modal dependencies and inter-modal interactions is a key factor in enhancing stock movement prediction reliability in complex and information-intensive financial markets. Future work will explore integrating transformer-based temporal encoders and real-time sentiment streams to further enhance adaptive market prediction under extreme volatility.

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