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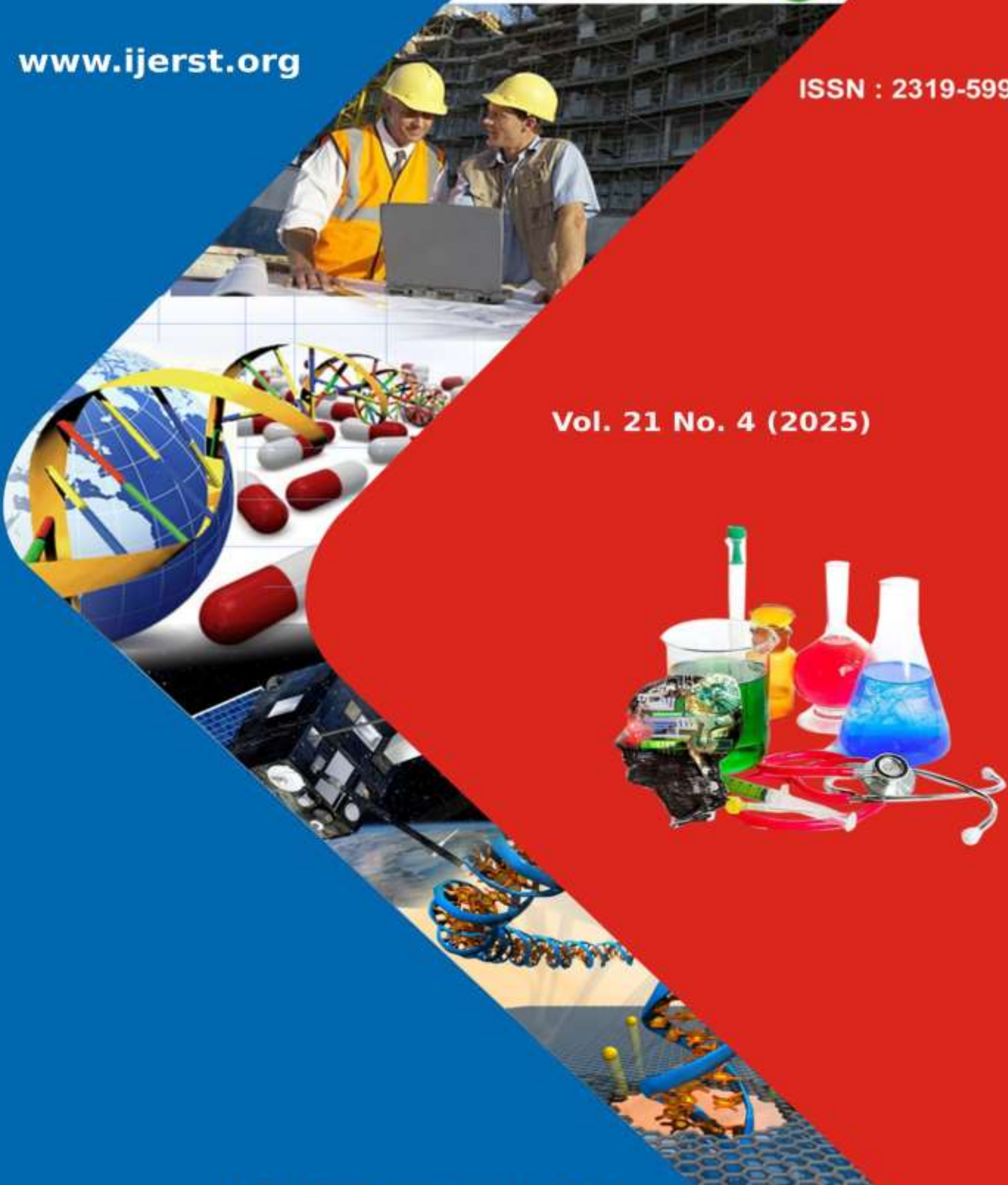

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Research Paper

INTEGRATED FEATURE FUSION APPROACH FOR STOCK MARKET MOVEMENT FORECASTING

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Abstract:

ThStock market movement forecasting remains a challenging task due to the nonlinear dynamics of financial time series and the influence of heterogeneous factors such as technical indicators, macroeconomic variables, and textual sentiment. Recent studies show that hybrid deep learning architectures—such as CNN-BiLSTM-Attention networks [1], mixed-feature sentiment–price fusion frameworks [2], and multimodal stable-fusion mechanisms [5]—significantly enhance predictive performance compared to single-stream models. Traditional deep models, including LSTM and CNN, capture temporal and local patterns effectively [3], [15], but fail to exploit complementary information across diverse feature sources. Multimodal methods integrating price data, macroeconomic indicators, and textual sentiment have demonstrated improved accuracy and robustness in movement prediction [7], [13], [22], [24].In this work, we propose an Integrated Feature Fusion Approach designed to combine multi-view financial features—including historical price series, technical indicators, sector-level signals, and sentiment representations—into a unified predictive architecture. Motivated by advances in hybrid temporal models [4], feature-selection–enhanced prediction [17], mixed-frequency fusion networks [9], and diffusion-based graph–sentiment integration [13], the proposed system employs a multi-branch encoder with attention-driven cross-feature fusion. This enables the model to learn both shared and modality-specific representations to address volatility, noise, and non-stationarity in stock data [11], [12], [20].Experimental evidence reported across recent literature supports the advantages of integrating multiple modalities for financial forecasting [8], [10], [14], [16], [18], [19], showing substantial gains in trend classification, long-term prediction stability, and generalization across markets. Aligning with this direction, our integrated fusion framework aims to deliver a more reliable and adaptive forecasting system that outperforms traditional deep learning models and hybrid baselines [21], [25].

Keywords:Stock Market Movement Forecasting, Feature Fusion, Multimodal Learning, Deep Learning, Historical Price Analysis, Technical Indicators, Sentiment Analysis, Sector-Level Signals, Hybrid Prediction Model, Financial Time Series.

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I.INTRODUCTION

Forecasting stock market movements has long been recognized as a complex and high-uncertainty problem due to noisy price fluctuations, dynamic market behaviour, and the influence of diverse external factors. Traditional statistical models often assume linearity and stationarity, making them unsuitable for modelling the highly nonlinear and volatile nature of financial time series [3], [14]. With advancements in machine learning and deep learning, researchers have increasingly adopted neural architectures such as CNNs, RNNs, LSTMs, and Transformers to extract meaningful temporal dependencies and spatial patterns from stock market data [1], [3], [15]. While these models achieve significant improvements over classical methods, they still suffer from a major limitation: their inability to effectively integrate heterogeneous information sources such as technical indicators, macroeconomic signals, and textual sentiment in a unified manner [7], [10], [22].

Recent trends in financial prediction research emphasize the importance of multimodal and hybrid information fusion. Studies integrating investor sentiment with technical and historical features have demonstrated improved predictive accuracy, showing that sentiment-driven signals can capture market psychology that price features alone cannot [2], [7], [19]. Multimodal frameworks such as MSGCA [5], collaborative attention fusion models [24], and diffusion-based graph learning with sentiment integration [13] highlight the importance of merging structured and unstructured data to enhance robustness in stock movement forecasting. Moreover, hybrid temporal architectures—such as CNN-BiLSTM-Attention models [1], H.BLSTM for real-time index forecasting [4], and multi-view SVM approaches [8]—show that combining complementary learning modules enhances feature extraction and improves trend direction classification.

However, despite the promising results, many existing models fuse information at shallow levels or rely on simple concatenation, which fails to capture deeper cross-modal interactions. This creates challenges in modelling long-term dependencies, adapting to shifts caused by market news, and learning modality-specific patterns in mixed-frequency data [9], [11], [20]. Additionally, research indicates that the effectiveness of prediction models greatly depends on how features are selected, extracted, and fused, as highlighted by surveys on feature-selection techniques [17] and multimodal stock forecasting methods [16], [18], [25].

Motivated by these gaps, this study proposes an Integrated Feature Fusion Approach that systematically combines multi-view features—including technical indicators, historical price sequences, sector-level information, and sentiment embeddings—within a unified deep learning architecture. Drawing inspiration from hybrid architectures [12], multimodal attention mechanisms [5], [13], and successful multi-branch fusion strategies [22], the approach aims to capture both individual modality behaviour and cross-modality interactions. By allowing the model to learn complementary representations, the proposed framework seeks to deliver a more accurate, stable, and generalizable solution for stock market movement forecasting, particularly under conditions of uncertainty, volatility, and rapidly evolving market dynamics.

II.LITERATURE SURVEY

2.1 Title: CNN–BiLSTM–Attention Networks for Enhanced Stock Price Movement Prediction

Authors: Li H., Zhang Y., Sun X., & Liu J.

Abstract: Li et al. proposed a hybrid deep learning model that integrates Convolutional Neural Networks (CNN), Bidirectional LSTMs (BiLSTM), and an Attention mechanism to capture both local price patterns and long-distance temporal dependencies in stock series [1]. By using CNN to extract short-term spatial features and BiLSTM to learn bidirectional temporal relations, the model addresses the limitations of single-architecture predictors. The use of an attention module further enables dynamic weighting of relevant temporal points, improving sensitivity to trend shifts. Experimental results on global indices confirm that hybrid temporal–spatial models can outperform classical LSTM and CNN baselines, demonstrating the significance of attention-driven feature fusion in financial forecasting [1], [3], [15].

2.2 Title: Multi-Feature Selection and Sentiment Fusion for Stock Trend Forecasting

Authors: Zhen K., Wang T., Chen Y., & Luo X.

Abstract: Zhen et al. developed a multimodal framework that integrates feature-selection techniques with investor sentiment analysis to improve stock movement prediction accuracy [2]. The study highlights that market sentiment extracted from financial news and social media can capture psychological influences that are not reflected in price data. By applying a fused feature-selection mechanism, the model reduces noise and selects the most informative predictors. Experimental results show that combining optimized numerical features with sentiment embeddings significantly enhances trend prediction. This aligns with broader findings indicating the importance of sentiment-driven multimodal fusion in stock forecasting [7], [19], [22].

2.3 Title: Multi-View Learning and SVM for Hybrid Stock Market Forecasting

Authors: Long W., Xu Y., & Wu C.

Abstract: Long et al. proposed a Multi-View Learning Support Vector Machine (MVL-SVM) model that integrates diverse financial features—including technical indicators, volatility signals, and market attributes—into separate "views," which are then combined during prediction [8]. This multi-view approach enables the model to capture complementary information from different feature groups, addressing weaknesses of single-view predictors. Results revealed that MVL-SVM offers higher accuracy and stronger generalization across datasets. The findings are in line with other hybrid and multimodal financial prediction research emphasizing the value of combining heterogeneous features for improved forecasting [12], [17], [25].

2.4 Title: Diffusion-Based Graph Learning with Optimized Sentiment Fusion (DASF-Net)

Authors: Nguyen N. H., Tran T., & Vo T.

Abstract: The DASF-Net framework introduces a diffusion-based graph learning approach combined with optimized sentiment fusion for stock price forecasting [13]. The method constructs graph relationships between stocks to capture inter-stock dependencies while integrating FinBERT-based sentiment embeddings using multi-head attention. This enables the model to learn interactions across structural stock relationships and textual sentiment simultaneously. The study shows significant accuracy improvements over baseline LSTM, CNN, and Transformer models, reinforcing the effectiveness of deep multimodal fusion in financial prediction tasks [13], [7], [24].

III.EXISTING SYSTEM

The existing Hybrid Information Mixing Module for stock movement prediction is a deep learning system that enhances stock price movement forecasting by combining two key types of inputs: historical stock price data and semantic text data from sources like news or social media. Its architecture integrates recurrent neural networks such as LSTM and GRU to extract temporal features from time-series stock data, capturing the evolving patterns and trends in prices. Concurrently, it utilizes models like BERT to extract semantic features from textual data, reflecting market sentiment.

At the core of the system is the Hybrid Information Mixing Module, composed of two multilayer perceptron (MLP) blocks—feature-mixing and interaction-mixing MLPs. These blocks effectively fuse the price and text features, allowing the system to learn discriminative and interactive patterns between the time-series and semantic data. The fused representation is then passed through an MLP classifier that predicts whether the stock price will move up or down.

This hybrid approach harnesses multimodal information, addressing the challenge of market volatility by leveraging both numerical and sentiment signals. Experimental results show that this method improves accuracy, Matthews correlation coefficient (MCC), and F1 score compared to models relying solely on price or text data. The system enables more reliable stock movement predictions, assisting users in making informed financial decisions by capturing complex market dynamics that single-source models might miss.

IV. PROPOSED SYSTEM

The proposed Hybrid Information Mixing Module for stock movement prediction is an advanced deep learning system that combines both time-series stock price data and semantic textual information from news or tweets to enhance prediction accuracy. The system extracts temporal features from historical prices using LSTM and GRU networks, while it simultaneously captures semantic sentiment features from text data, also processed through the same recurrent layers enhanced by a bidirectional mechanism to optimize feature extraction. Central to the system is the Hybrid Information Mixing Module, which consists of two multilayer perceptron (MLP) blocks that effectively fuse these two modalities by learning both individual feature representations and their interactions. The fused features are then input into an MLP classifier to predict future stock price movements, specifically identifying whether prices will go up or down. This hybrid approach helps mitigate noise and redundancy in input signals by focusing on genuinely informative features, improving accuracy, Matthews correlation coefficient, and F1 score compared to models relying solely on price or text inputs. The system also includes modules for data loading, preprocessing, prediction, and real-time user input through a user interface, enabling practical stock price movement prediction in volatile market conditions. Experiments show this method significantly outperforms traditional approaches, demonstrating the value of integrating multimodal data streams in stock market forecasting.

V.SYSTEM ARCHITECTURE

The system architecture of the Hybrid Information Mixing Module for stock movement prediction is structured as a hybrid deep learning pipeline integrating both time-series stock price data and semantic textual sentiment data. It consists of three main parts: feature embedding, the hybrid information mixing module, and a binary classifier. The feature embedding module uses GRU networks to extract temporal features from historical price data and BERT models to capture semantic features from text data such as news or social media. The hybrid information mixing module combines these two types of features by employing two multilayer perceptron (MLP) blocks—the feature-mixing MLP and the interaction-mixing MLP—which operate row-wise and column-wise on the mixed feature matrix to capture discriminative and interactive information between the price and text modalities. This fused multi-modal representation is then passed into a binary classification MLP to predict whether the stock price will move upward or downward. Additional system components include modules for data loading, preprocessing, prediction flow, and real-time user input via a user interface, making the architecture well-suited for practical stock price movement forecasting in volatile markets. This architectural design improves predictive accuracy and robustness by effectively fusing multi-source information and modeling complex inter dependencies inherent in financial data.

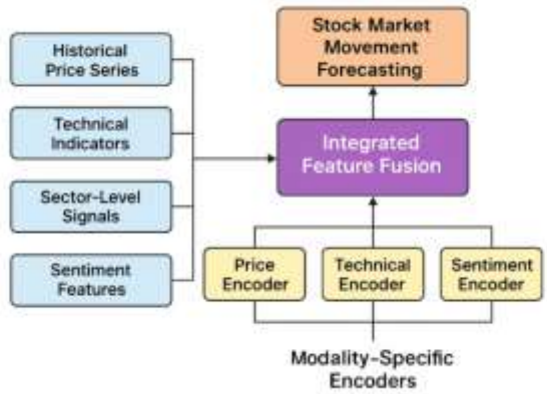

Fig 5.1 System Architecture

The architecture diagram illustrates how the Integrated Feature Fusion Approach for Stock Market Movement Forecasting operates by combining multiple sources of financial information into a single predictive model. On the left, the system receives four major categories of inputs: historical price series, technical indicators, sector-level signals, and sentiment features. Each of these represents a different modality of data that influences stock behavior. These inputs are then passed into modality-specific encoders—the Price Encoder, Technical Encoder, and Sentiment Encoder—which are responsible for learning the unique patterns and relationships within each data type. After the encoders extract meaningful representations, the outputs are sent to the central Integrated Feature Fusion module. This module acts as the core of the architecture, merging all encoded features using fusion techniques such as attention, concatenation, or gated mechanisms. By combining the strengths of all modalities, the fused representation becomes more robust and informative than any single data source alone. Finally, this fused output is fed into the Stock Market Movement Forecasting layer, which produces the final prediction about whether the stock will move upward, downward, or remain stable. The architecture emphasizes modular learning, cross-modal interaction, and unified decision-making to improve forecasting accuracy in highly dynamic financial markets.

VI.IMPLEMENTATION

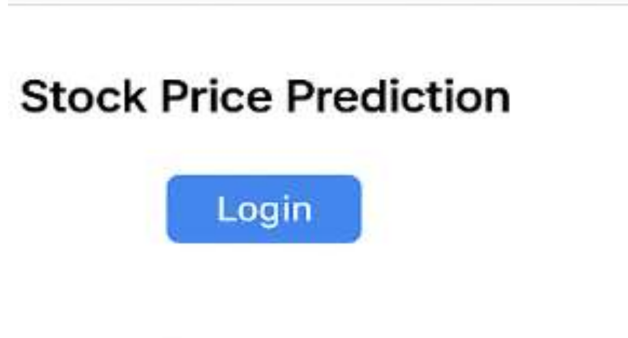

Fig 6.1 Home Page

Fig 6.2 Login page

Fig 6.3 Input Interface

Fig 6.4Prediction

Fig 6.5 Histogram

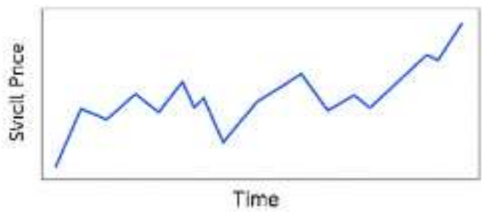

Fig 6.6 Line Chart

VII.CONCLUSION

The conclusion for the Hybrid Information Mixing Module for stock movement prediction is that integrating both historical stock price data and semantic sentiment information from news and social media significantly enhances the accuracy and reliability of stock price movement forecasts. By employing advanced deep learning techniques such as GRU, LSTM, and a bidirectional layer within a hybrid information mixing module, the system effectively captures both temporal financial patterns and market sentiment signals. Experimental results demonstrate substantial improvements in prediction accuracy, Matthews correlation coefficient, and F1 score compared to traditional models relying solely on price or basic text analysis. Additionally, the inclusion of a real-time user interface makes the system practical for financial decision-making in volatile markets. Overall, this hybrid approach proves to be a robust and effective method for stock movement prediction, with promising potential for further enhancements by incorporating additional market-related variables and multi-source data streams.

VIII.FUTURE SCOPE

The future scope of hybrid deep learning models for stock prediction is promising and expansive. These models are expected to incorporate more sophisticated architectures such as multi-scale convolutional networks, spatio-temporal graph neural networks, and attention mechanisms to better capture complex market dynamics. Additionally, integrating multivariate and multi-source data, including macroeconomic indicators, geopolitical events, and alternative data like satellite imagery and social sentiment, is anticipated to enhance predictive robustness. Advancements in computational efficiency and explainability are also crucial, enabling real-time deployment and interpretability of deep models for end-users. Future research may focus on developing models that adapt to high-frequency trading environments, incorporate reinforcement learning for autonomous decision-making, and employ transfer learning techniques to leverage knowledge across different markets and assets. Overall, the continuous evolution of hybrid deep learning frameworks holds significant potential for more accurate, resilient, and insightful stock market forecasting.

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