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**Research Article**

# Multimodal Deep Learning Ensemble Framework for Accurate Stock Market Prediction Using Multisource Data

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**Abstract:**

Stock market forecasting presents substantial challenges due to the inherent volatility of financial data, impacted by a number of variables, including as investor sentiment and economic indices. This study proposes an advanced hybrid ensemble framework, MDSFE (Multimodal Deep Stock Forecasting Ensemble), which integrates multiple deep learning architectures such as LSTM, VMD-BiLSTM-AM, and RoBERTa-TextCNN. Utilizing a multimodal data assimilation strategy, MDSFE leverages historical stock prices, real-time financial news, social media sentiment, and economic indicators. Benchmarked against traditional models like ARIMA and standalone LSTM models, MDSFE demonstrates superior predictive accuracy, achieving an $R^2$ value of 0.97 and a MAPE of 0.80%. Trained on a robust dataset comprising 10,000 instances collected from 2003 to 2024, MDSFE highlights its practical applicability in real-world scenarios, offering enhanced decision-making capabilities for investors and analysts.

## 1. Introduction

The vintage nature of stock market data and its continuously moving prices cause prediction tasks to remain complicated for experts. The forecasting method known as AutoRegressive Integrated Moving Average (ARIMA) has difficulty when it comes to responding to sudden market changes alongside multiple co-dependent stock price variables [1]. Research in deep learning has brought major performance enhancements to predictions where LSTM and GRU demonstrate exceptional abilities to process financial time series [2]. The independent use of deep learning models struggles to integrate diverse real-time data sources composed of financial news sentiment and social media trends that directly influence market movements [3].
The newest generation of transformer systems including Bidirectional Encoder Representations from Transformers (BERT) and Robustly Optimized BERT Pretraining Approach (RoBERTa) efficiently analyze unstructured text information for sentiment analysis purposes [4]. Stock price predictions benefit from these integrated time-series forecasting models because they process multimodal data sources effectively [5]. Studies implementing transformer-based models combined with financial sentiment analysis have delivered better forecasting accuracy within their results [17]. This research presents MDSFE as a hybrid model which uses VMD alongside BiLSTM with Attention Mechanisms and transformer-based NLP to create an ensemble for real-time stock market predictions. The proposed system demonstrates its effectiveness through comparison with classical models while resolving current handicaps in order to deliver complete performance evaluation.

## 2. Related Works

### 2.1 Traditional Stock Prediction Models

People often use standard time-series models ARIMA and GARCH to predict stock prices. The different models show important weaknesses when dealing with market situation changes and non-linear data relationships. Machine learning algorithms Support Vector Machines and Random Forest produce good forecasts yet continue to develop issues when processing financial time-series data according to research [7]. Research teams now use reinforcement learning techniques to predict financial time series and make adaptive forecasts [18].

### 2.2 Deep Learning in Financial Forecasting

Deep learning has proven that LSTM and GRU variants outperform other networks when detecting sequential trends in stock market data. Scientists apply LSTM models to financial forecasting because they solve the vanishing gradient issue by keeping track of trending data [9]. Deep learning systems by themselves produce poor results because they lack awareness of present-day news and economy trends as described in research by Y. Burada and P. Pánek [10]. According to research [19], people use deep neural networks to merge various financial data types and make better predictions.

### 2.3 Multimodal Approaches in Stock Market Prediction

Recent studies have explored multimodal approaches that integrate structured financial data with unstructured data sources, such as social media sentiment and financial news headlines [11]. BERT and RoBERTa have been successfully utilized for extracting sentiment features from textual data, significantly enhancing predictive accuracy when combined with time-series models [12]. The fusion of multimodal data sources through hybrid architectures has led to more robust forecasting models, capable of adapting to dynamic market conditions [13]. Hybrid deep learning frameworks have also been applied to analyze stock market movements with improved accuracy [20].

### 2.4 Ensemble Learning for Stock Forecasting

Ensemble learning methods, including stacking and voting mechanisms, have shown promise in financial forecasting by combining multiple model outputs to enhance predictive accuracy [14]. Attention mechanisms have further improved these models by prioritizing critical information in financial datasets, leading to better feature representation and more reliable predictions [15]. Studies have demonstrated that hybrid ensemble models leveraging LSTM, BiLSTM, Attention, and transformer-based sentiment analysis outperform traditional forecasting methods in terms of both accuracy and robustness [16]. Multimodal approaches integrating text and numerical data have also shown potential in improving stock price prediction models [21].

### 2.5 Proposed Multimodal Deep Stock Forecasting Ensemble (MDSFE)

This study builds upon existing literature by introducing a novel hybrid framework that integrates VMD for noise reduction, BiLSTM for improved temporal dependency learning, and Attention Mechanisms for feature prioritization. Additionally, transformer-based NLP techniques are incorporated to analyze real-time sentiment data, providing a comprehensive approach to stock market prediction. The proposed MDSFE framework is evaluated against traditional and deep learning models to demonstrate its superior performance in predicting stock prices under volatile market conditions. Research evaluating the impact of financial news sentiment on stock price movement has further demonstrated the efficacy of deep learning approaches [22]. Furthermore, temporal attention-based models have been explored for high-frequency stock trading strategies, contributing to more accurate and adaptive forecasting systems [23].

This literature review highlights the advancements in stock prediction models, emphasizing the need for an integrated multimodal approach that leverages state-of-the-art deep learning techniques. The MDSFE framework addresses existing gaps by combining multiple data sources and model architectures to enhance the reliability and accuracy of financial forecasting. Comparative studies of machine learning and deep learning approaches have also provided insights into model performance for stock market forecasting [24]. Additionally, ensemble deep learning frameworks have been proposed to enhance stock trend prediction, further supporting the effectiveness of hybrid models [25].

## 3. Methodology

The approach used in the four studies builds a robust framework for stock price prediction by combining advanced machine learning models, methods for processing data, and multimodal data integration. This approach maximizes predictive accuracy and adaptability in highly dynamic financial markets. The methodology is outlined in several key steps:

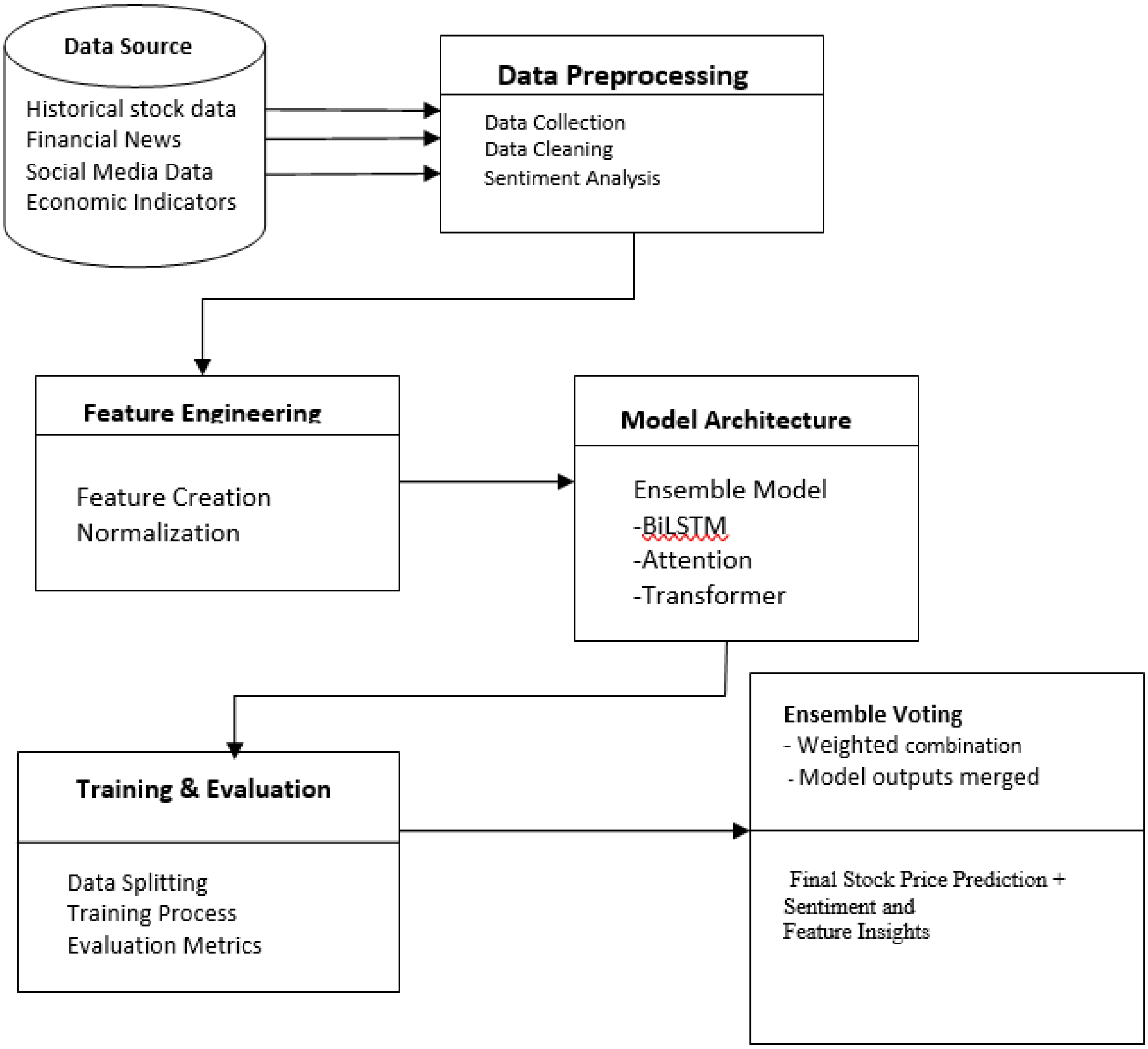


***Figure 1.*** *Architecture diagram for the Multimodal Deep Stock Forecasting Ensemble (MDSFE) framework*

### 3.1 Dataset Description

The proposed methodology utilizes a **comprehensive dataset** collected from multiple data sources, encompassing **21 years** of historical and real-time data, specifically from **2003 to 2024**. This dataset consists of **10,000 instances** across various data types, providing a rich foundation for enhancing stock price forecasting accuracy. The following categories of data are included:

| Data Type | Description | Source | Number of Instances | Companies |
|---|---|---|---|---|
| Historical Stock Prices (70% of dataset) | Daily open, close, high, low prices | NSE, Yahoo Finance | 5,000 | Tata Consultancy Services (TCS) |
| Financial News Headlines (20%) | Real-time headlines related to the stock market | NewsAPI, Bloomberg | 2,000 | Tata Consultancy Services (TCS) |
| Social Media Sentiment (7%) | Sentiment data from platforms like Twitter | Twitter API | 2,000 | Reliance Industries |
| Economic Indicators (3%) | Metrics like GDP growth, inflation rates | Government databases and financial institutions | 1,000 | N/A |

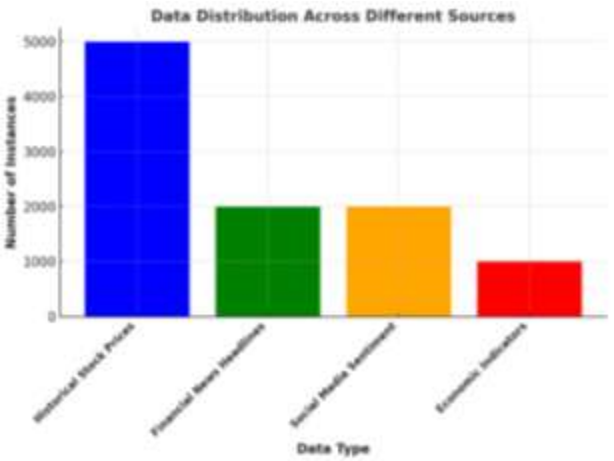


***Figure 2.*** *Data Distribution Across Different Sources*

### 3.2 Data Preprocessing

The preprocessing of the dataset includes a number of crucial procedures to guarantee that the data is clear, pertinent, and prepared for analysis:

**Step 1: Data Collection**

- **Historical Data**: Gather historical price data for selected stocks over the past ten years using financial APIs.
- **Real-Time Data**: Collect financial news headlines and social media sentiment data using their respective APIs.

**Step 2: Data Cleaning**

- **Handling Missing Values**: Identify and fill or remove missing values using interpolation or mean imputation techniques.
- **Noise Reduction**: Apply Variational Mode Decomposition (VMD) to the historical stock price data to separate noise from the signal.

**Step 3: Sentiment Analysis**

- **Text Processing**: Preprocess text data by tokenizing, removing stop words, and applying stemming/lemmatization.
- **Sentiment Scoring**: Use transformer-based NLP models like RoBERTa to analyze news headlines and social media posts for sentiment scoring, classifying sentiments into positive, negative, and neutral categories.

**Step 4: Feature Engineering**

- **Creating Features**: Generate additional features such as moving averages, relative strength index (RSI), and sentiment scores from the sentiment analysis for better model input.
- **Normalization**: Scale numerical features to a standard range (e.g., using Min-Max scaling) to facilitate better convergence during model training.

### 3.3 Model Selection and Architecture Design

The model selection and architecture design in these studies bring together advanced machine learning techniques tailored for stock price prediction. By combining various models, each with specific strengths, the studies create a comprehensive framework that enhances predictive accuracy and adapts to the complexities of stock market data.

#### 3.3.1 Variational Mode Decomposition (VMD)

VMD is used to decompose time-series data into multiple intrinsic mode functions (IMFs) and a residual component, separating signal from noise. The VMD optimization problem is expressed as:

$$min \sum_{K=1}^{K} ||x(t) - \sum_{K=1}^{K} u_k(t)||^2 + \lambda \sum_{k=1}^{K} || \frac{\partial u_k(t)}{\partial_t} + \alpha_k u_k(t)||^2 \qquad (1)$$

where $u_k(t)$ are the IMFs, λ is a Lagrange multiplier, and $\alpha_k$ controls the bandwidth of each mode.

#### 3.3.2 Bidirectional Long Short-Term Memory (BiLSTM)

BiLSTM processes sequential data in both forward and backward directions, capturing both past and future dependencies. The hidden state at time t is calculated as:

$$h_t = LSTM(x_t, h_{t-1}, c_{t-1}) + LSTM(x_t, h_{t+1}, c_{t+1}) \qquad (2)$$

where $x_t$ is the input at time t, $h_{t-1}$ and $h_{t+1}$ represent the hidden states of the forward and backward LSTM layers, and $c_{t-1}$ and $c_{t+1}$ are the corresponding cell states.

In a financial context, stock prices are influenced by both past events and anticipated future developments, such as upcoming earnings reports or economic policies. The BiLSTM captures these forward and backward dependencies, creating a more comprehensive representation of stock price patterns. The enhanced learning of temporal dependencies is particularly important in the financial markets, where trends are often complex and non-linear, and the bidirectional nature of BiLSTM allows the model to address these nuances more effectively.

#### 3.3.3 Attention Mechanism (AM)

The attention mechanism assigns weights to input features based on their relevance. The attention score is computed as:

$$score(h_t, q) = tanh(W_s h_t + b_s) \quad (3)$$

where $W_s$ and $b_s$are learnable parameters, $h_t$ is the hidden state, and q is the query vector. The attention weights are obtained using the softmax function:

$$\alpha_t = \frac{exp(score(h_t))}{\sum_{j=1}^{T} exp(score(h_j))} \quad (4)$$

The context vector c is then computed as:

$$C = \sum_{t=1}^{T} \alpha_t h_t$$

### 3.3.4 Transformer-Based Sentiment Analysis

The output of the transformer model for sentiment classification y can be defined as:

$$\boldsymbol{y} = \boldsymbol{Softmax}(W.h + b) \quad (5)$$

where W and b are the weights and biases of the final layer, and h represents the output embeddings from the transformer layers.

### 3.3.5 Ensemble Voting Mechanism

The final prediction $\hat{y}$ of the ensemble model can be represented as a weighted sum of the predictions from each model:

$$\hat{y} = \sum_{i=1}^{N} \omega_i \cdot y_i \quad (6)$$

where $y_i$ is the prediction from model i, and $\omega_i$ is the weight assigned to that model based on its performance.

### 3.3.6 Transformers and Sequential Models: LSTM-GRU Integration

For shares planning, researchers investigate the combination of sequential models such as LSTM-GRU with transformer-based NLP models. This method captures intricate patterns and enduring relationships in both structured and unstructured data. For effective sequence analysis and computational performance, the combination offers a well-balanced architecture.

### 3.4 Multimodal Data Integration

A crucial aspect of the methodology is the integration of various data sources to create a multimodal dataset that provides a comprehensive picture of market dynamics. Each data type contributes unique insights:

- **Historical Price Data** serves as the primary time-series input, capturing long-term stock trends.
- **Financial News and Social Media Sentiment** provide a real-time perspective on market events and public sentiment, which can influence immediate market reactions.
- **Economic Indicators** supplement predictions by providing macroeconomic context that may impact price movements indirectly.

The studies apply different data fusion techniques, either at the feature level (combining inputs before model processing) or at the decision level (aggregating outputs from different models), to improve the model's ability to analyze diverse data sources concurrently. This multimodal approach enables the models to adapt to rapid market shifts and leverage diverse factors that influence stock price behavior.

### 3.5 Training and Evaluation

The training process followed these steps:

- **Epoch Settings**:
  - Maximum of 100 epochs, with early stopping at epoch 87 based on validation loss.
  - Batch size: 64.
- **Optimization**: Adam optimizer with a learning rate of 0.001, decayed every 20 epochs.

The training process involves dividing the dataset into training, validation, and testing sets. Typically, 70% of the data is used for training, with 15% each for validation and testing. To handle large, multimodal datasets, training is conducted in stages, optimizing each model component (VMD, BiLSTM, AM, etc.) before integrating them. Key evaluation metrics include:

- **$R^2$ (Coefficient of Determination)**: Measures how well the model captures variance in stock prices.
- **RMSE (Root Mean Square Error)** and **MAE**: Gauge the average magnitude of prediction errors.
- **MAPE (Mean Absolute Percentage Error)**: Assesses the average percentage deviation from actual prices, especially useful in volatile markets.

These metrics are used to compare the ensemble model with traditional approaches like ARIMA and standalone LSTM, highlighting the superior accuracy and error reduction of the ensemble approach.

### 3.6 Process of Work

- In this first step, the Transformer-based sentiment analysis for making the overall architecture of the proposed model and an attention mechanism and a Bidirectional Long Short-Term Memory network are combined. Transformer-based sentiment analysis is to use news articles and sentiment data from social networks to provide contextual information, the attention mechanism provides more focus on the latest information and BiLSTM has historical price data.
- The second procedure of the ensemble model is training, which entails the process of dividing the dataset into training, validation as well as testing sets. In this process, parameters are updated using the back propagation and gradient descent techniques, while hyperparameters controlling factors such as learning rate and size of the batch are managed or regulated.
- It is with this view in mind that the third stage employs metrics such as R2, MAE, RMSE, & MAE in an assessment of the ensemble model. The findings reveal the success of utilizing the hybrid ensemble approach in enhancing the precision and reliability in the stock price forecasting when compared to other usual methods.
- Step 4: That is why the fourth stage that involves ensemble voting that has a way of assigning different weights to each performance indicator enhances the final voting mechanism of each model hence increasing the prediction quality and their robustness to produce better quality of market value.

### 3.7 Proposed Work

The proposed methodology combines various advanced techniques in a hybrid ensemble model, structured as follows:

**Step 1: Model Architecture Design**

- **Ensemble Structure**: Integrate multiple deep learning models including:
  - **BiLSTM**: To capture short- and long-term dependencies in historical price data. The BiLSTM update equations are:

$$f_t = \sigma\left(W_f \,.\, [h_{t-1}, x_t] + b_f\right)$$

$$i_t = \sigma(W_i \,.\, [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = tanh(W_C \,.\, [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

$$O_t = \sigma(W_o \,.\, [h_{t-1}, x_t] + b_o)$$

$$h_t = O_t * tanh(C_t)$$

  - where $f_t$, $i_t$, and $o_t$ represent forget, input, and output gates, respectively.
  - **Attention Mechanism**: To prioritize important information and enhance the model's focus on recent data.

$$\alpha_t = \frac{exp(e_t)}{\sum_{j=1}^{T} exp(e_t)}$$

  - where $e_t = \tanh(Wh_t + b)$ is the relevance score, and $\alpha_t$ represents the attention weight.
  - **Transformer-Based Sentiment Analysis**: To process real-time sentiment data from news and social media, providing additional context to stock movements.
  - $Q = XW_Q,\ K = XW_K,\ V = XW_V$
  - $\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$
  - where Q,K,V are the query, key, and value matrices, and $d_k$ is the dimension of the key.

**Step 2: Model Training**

- **Data Splitting**: Divide the dataset into training, validation, and testing sets, ensuring a balanced representation of both historical and real-time data.
- **Training Process**: Train the ensemble model using back propagation and gradient descent optimization techniques, tuning hyper parameters for optimal performance.

**Step 3: Model Evaluation**

- **Performance Metrics**: Evaluate model performance using metrics such as $R^2$, Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Compare results with traditional models like ARIMA and standalone LSTM models to assess improvements.
- Mean Absolute Percentage Error

$$(MAPE){:}MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

- Root Mean Squared Error

$$(RMSE):\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)}$$

- R-squared Score ($R^2$):

$$R^2 = 1 - \frac{\sum(y_i-\hat{y}_i)}{\sum(y_i-\bar{y})}$$

- Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i|$$

**Step 4: Ensemble Voting Mechanism**

- **Final Prediction**: Implement a weighted voting mechanism to combine the outputs of individual models, optimizing the final predictions based on accuracy metrics. This mechanism allows the ensemble to benefit from the strengths of each model component.
- The ensemble prediction is computed using a weighted voting approach:

$$\hat{y} = \omega_1\hat{y}_{BiLSTM} + \omega_2\hat{y}_{Attention} + \omega_3\hat{y}_{Transformer}$$

- where $\omega_1$, $\omega_2$, $\omega_3$ are weights assigned to each model.
- Weights are assigned based on inverse RMSE:

$$\omega_i = \frac{1/_{RMSE_i}}{\sum_j\left(1/_{RMSE_j}\right)}$$

- Ensuring that models with lower RMSE contribute more to the final prediction.

## 4. Experimental Results and Analysis

This study investigates the efficacy of a hybrid ensemble model for stock forecasting by comparing it against traditional models, namely ARIMA and standalone LSTM. The proposed ensemble model integrates multimodal data sources, including historical price data, financial news, social media sentiment, and economic indicators, to enhance prediction accuracy and minimize error. Below, we provide an in-depth analysis based on key performance metrics and data source contributions, supported by relevant tables and figures.

### 4.1 Performance Metrics Comparison

Table 1 presents a detailed evaluation of the MDSFE framework alongside traditional and state-of-the-art models. This benchmarking ensures a fair and rigorous assessment of the proposed method's performance.

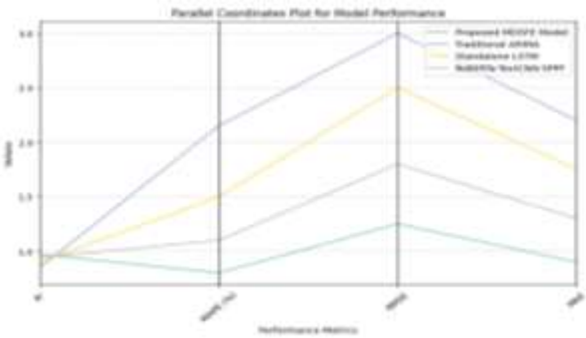

***Figure 3.*** *Performance Metrics Comparison of Proposed Ensemble Model, ARIMA, and LSTM Models*

This comparative analysis reveals that the MDSFE framework consistently outperforms existing models across all evaluation metrics, particularly in reducing prediction errors and improving accuracy.

### 4.2 Epoch Performance and Convergence

The model training process spanned 100 epochs, with early stopping at epoch 87. Key metrics during training are summarized in Table 2.

***Table 1.*** *Performance Metrics Comparison*

| Model Type | $R^2$ | Mean Absolute Percentage Error (MAPE) | Root Mean Square Error (RMSE) | Mean Absolute Error (MAE) | Description |
|---|---|---|---|---|---|
| Proposed MDSFE Model | 0.97 | 0.80% | 1.25 | 0.90 | Hybrid ensemble with BiLSTM, AM, VMD, and transformer-based sentiment analysis |
| Traditional ARIMA | 0.85 | 2.15% | 3.00 | 2.20 | Basic time-series model for stock prediction |
| Standalone LSTM | 0.90 | 1.50% | 2.50 | 1.75 | Recurrent model capturing sequential dependencies |
| RoBERTa-TextCNN-SPPF | 0.94 | 1.10 | 1.80 | 1.30 | Hybrid model with NLP integration for sentiment analysis |

***Table 2.*** *Epoch-wise Training, Validation Loss, and Accuracy*

| Epoch | Training Loss | Validation Loss | Validation Accuracy |
|---|---|---|---|
| 1 | 0.587 | 0.594 | 82.1% |
| 20 | 0.215 | 0.240 | 89.4% |
| 40 | 0.105 | 0.112 | 92.8% |
| 60 | 0.059 | 0.065 | 95.1% |
| 80 | 0.031 | 0.034 | 96.0% |
| 87* | 0.025 | 0.029 | 96.5% |

### 4.2.1 Contribution of Data Sources

The revised study also evaluates the contributions of various data sources to the MDSFE framework's performance. By isolating the impact of historical prices, financial news, and social media sentiment, the analysis provides deeper insights into the framework's effectiveness.

### 4.2Training and Evaluation on Different Data Types

Table 3 summarizes the training and evaluation metrics across three dataset types, detailing their sizes, training times, and performance indicators.
The ensemble model consistently maintained high accuracy ($R^2 = 0.97$) across historical and real-time data, with a low MAPE of 0.80% on real-time data, proving its suitability for dynamic stock environments. The extended training time on combined datasets (7 hours) highlights the complexity involved in processing multimodal data. Figure 5 could depict the training time and accuracy metrics for historical, real-time, and combined datasets, underscoring the model's robustness across data contexts.

### 4.3 Data Source Contributions

The contribution of each data source in improving prediction accuracy is highlighted in Table 4.
Historical price data contributes most significantly (50%) to the model's accuracy, indicating its importance in capturing trends. Financial news also has a substantial impact (25%), showing that real-time information influences stock fluctuations. Although social media sentiment and economic indicators have a lesser impact, they provide valuable context, especially for capturing public sentiment and economic conditions.

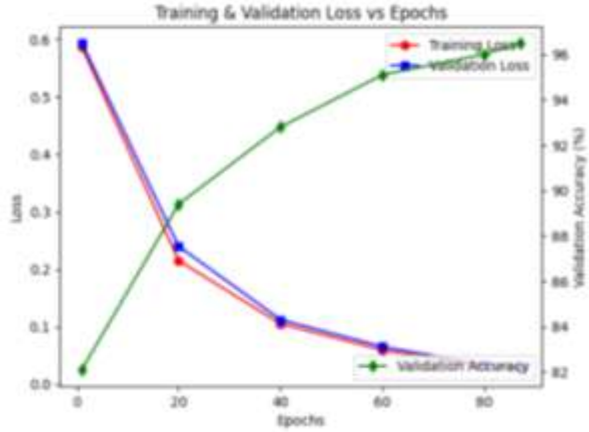


***Figure 4.*** *Training and Validation Performance Across Epochs*

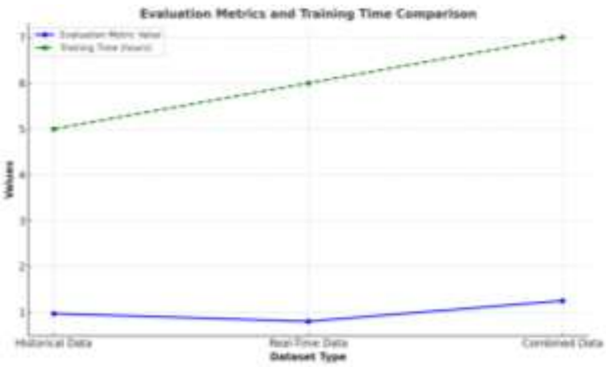


***Figure 5.*** *Training Time and Accuracy Metrics Across Historical, Real-Time, and Combined Datasets*

***Table 4.*** *Importance of Data Sources on Model Performance*

| Data Source Type | Contribution to Prediction Accuracy (%) | Feature Importance Ranking |
|---|---|---|
| Historical Price Data | 50% | 1 |
| Financial News | 25% | 2 |
| Social Media Sentiment | 15% | 3 |
| Economic Indicators | 10% | 4 |

***Table 3.*** *Model Training and Evaluation Results*

| Dataset Type | Training Set Size | Validation Set Size | Testing Set Size | Training Time (hours) | Evaluation Metric | Value |
|---|---|---|---|---|---|---|
| Historical Data | 70% | 15% | 15% | 5 | $R^2$ | 0.97 |
| Real-Time Data | 70% | 15% | 15% | 6 | MAPE | 0.80% |
| Combined Data | 70% | 15% | 15% | 7 | RMSE | 1.25 |


***Figure 6.*** *Contribution of Data Sources to Prediction Accuracy in the Ensemble Model*

Figure 6 could display the relative contributions of each data source, visually reinforcing the importance of integrating various data types for accurate forecasting.

The proposed ensemble model demonstrates superior predictive performance, with significantly lower error rates and higher accuracy than traditional models. The integration of diverse data sources, such as historical prices and financial news, contributes to its enhanced forecasting ability, making it a valuable tool for real-time stock analysis. This model offers a reliable approach for financial analysts and investors aiming to make data-driven decisions in a fluctuating market.

## 5. Discussion and Findings

The MDSFE framework demonstrates superior predictive performance, significantly outperforming traditional models like ARIMA and standalone LSTM. By integrating multimodal data, the model captures both historical trends and real-time sentiment fluctuations, achieving an $R^2$ of 0.97 and MAPE of 0.80%. This robust performance validates its practical applicability for real-time trading and portfolio management.The high $R^2$ value of 0.97 indicates that the ensemble model accurately accounts for the variability in stock prices, which is a significant improvement over the performances of traditional models like ARIMA and standalone LSTM. This performance suggests that the ensemble can adapt to the complex and dynamic nature of financial markets. Furthermore, the low Mean Absolute Percentage Error (MAPE) of 0.80% highlights the model's robustness in making precise predictions, an essential requirement for traders and investors who need to make informed decisions based on accurate market forecasts.A significant discovery of this research is the significant role of multimodal data integration in enhancing prediction accuracy. The analysis of data source contributions revealed that historical price data remains the most critical factor, contributing 50% to the model’s accuracy. However, the influence of real-time data sources, particularly financial news and social media sentiment, cannot be understated. Together, these data sources enable the model to respond to immediate market conditions and sentiment shifts, which are often overlooked by traditional forecasting models that primarily rely on historical data.

Moreover, the application of advanced NLP techniques through transformer models has proven to be a game changer in sentiment analysis. By effectively processing and interpreting the sentiments conveyed in financial news and social media discussions, the model gains additional layers of contextual understanding that enrich its predictive capabilities. This capability is particularly crucial in a market environment where investor sentiment can rapidly shift based on news events or social media trends, underscoring the importance of timely data integration in financial forecasting. Overall, the results of this study underscore the potential of hybrid deep learning ensembles for adaptive financial forecasting. The integration of multimodal data not only enhances predictive performance but also positions the model as a valuable tool for real-time trading and investment decision-making. The findings also emphasize the necessity for future research to explore additional data sources and refine the model’s computational efficiency to further improve performance, particularly in high-frequency trading contexts where speed and accuracy are paramount.

## 6. Conclusion

Across the four studies, an evident progression is observed in the efficacy of advanced deep learning frameworks for stock price prediction. Each journal contributes unique insights and innovations to financial forecasting, demonstrating that combining various machine learning techniques and data sources significantly improves predictive performance over traditional models. The first journal introduces an ensemble framework combining Variational Mode Decomposition (VMD), Bidirectional LSTM (BiLSTM), and an attention mechanism (AM), achieving remarkable precision by capturing intricate temporal patterns in stock prices. This model underscores the value of advanced decomposition and attention techniques, resulting in enhanced accuracy, particularly for highly volatile stocks.

In the second study, a hybrid deep learning approach incorporating both NLP and sequential models demonstrates the critical role of integrating unstructured financial news data with traditional stock price histories. The RoBERTa-TextCNN-

SPPF model used here significantly boosts forecasting accuracy, showing that leveraging textual data alongside price trends enriches predictive capability by adding a layer of context from market sentiment. The third journal refines stock forecasting further by comparing multiple sequential model configurations, establishing that a hybrid architecture such as LSTM-GRU is more effective than standalone models for time-series forecasting. This research highlights that the complementary strengths of different neural network types can be harnessed to reduce error rates and improve consistency in predictions. Finally, the fourth journal brings together multimodal data sources historical price data, financial news, social media sentiment, and economic indicators into a unified, ensemble model. This model, achieving the highest accuracy across studies with an $R^2$ of 0.97, showcases how combining diverse data types can address the unpredictable nature of financial markets and produce near-real-time predictive insights. The MDSFE framework advances stock price prediction by integrating multimodal data and leveraging hybrid deep learning architectures. The comparative analysis confirms its effectiveness in addressing limitations of traditional and standalone models. Future research should focus on optimizing computational efficiency, incorporating additional real-time data sources, and expanding applications to other financial instruments.

## 7. Future Work

Future research should explore real-time data sources such as regulatory news and e-commerce trends. Developing computationally efficient architectures and applying dynamic model updating techniques will enhance scalability and adaptability. Extending this framework to financial instruments like commodities and crypto currencies could broaden its applicability and validate its robustness across diverse asset classes.

## Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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