

# Advanced Stock Index Prediction Using Optimized LSTM Model Incorporating Sentiment Analysis

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## Abstract

Stock index prediction is essential for financial market analysis and investment decisions, but traditional methods like ARIMA and GARCH often fail to deliver accurate results due to the complex and volatile nature of the stock market. Advances in deep learning, such as LSTM and GRU models, have shown promise but still face limitations in fully capturing market sentiment. The aim of this study is to develop a novel stock index prediction model that integrates GRU and LSTM to enhance predictive accuracy. The study also incorporates BERT-based sentiment analysis to better capture investor emotions and improve prediction performance. The proposed model utilizes data from the Stockholder Sentiment Dataset and Stock Index Trading Dataset, sourced from the Shanghai and Shenzhen Stock Exchanges. BERT is used to calculate sentiment scores from public news data, and an optimized combination of GRU and LSTM is employed for time series prediction. Comparative experiments were conducted against baseline LSTM and GRU models using metrics such as accuracy and loss.

The proposed model achieved an accuracy of 88.92% and a loss of 0.18 after 30 epochs, outperforming the basic LSTM (83.21% accuracy, 0.22 loss) and GRU models (85.34% accuracy, 0.20 loss). This demonstrates the superior performance of the model in stock index prediction tasks. This study introduces a more effective stock index prediction model by combining advanced deep learning methods and sentiment analysis. The proposed model offers valuable insights for improving investment strategies and risk management in financial markets, providing a foundation for further research in this field.

**Keywords:** Machine Learning; Time Series Analysis; Deep Learning; LSTM; GRU; Financial Markets

## Introduction

Stock market prediction is crucial for investment decisions, risk management, and policy making. Traditional methods like ARIMA and GARCH struggle with the market's complexity and volatility (Jiang, 2020; Dara et al., 2023). However, AI advancements, particularly in machine learning and deep learning, have improved predictive performance in stock market prediction (Soni et al., 2023).

In recent years, deep learning methods have been widely studied and applied in stock index prediction. For example, Khan et al. (2023) proposed an LSTM-based stock price prediction model that improves prediction accuracy by capturing long-term dependencies in time series data. Nikhil et al. (2023) used convolutional neural networks (CNN) to extract local features from stock price sequences and combined them with LSTM for prediction, significantly enhancing the model's performance. Additionally, reinforcement learning-based methods have begun to emerge in stock market prediction. For example, Awad et al. (2023) proposed a hybrid model combining reinforcement learning and deep learning, achieving high returns by dynamically adjusting investment strategies. These studies indicate that deep learning methods have broad potential and application prospects in stock market prediction. However, despite the excellent performance of deep learning in stock index prediction, some challenges remain to be addressed. For instance, stock market data contains high noise and complex nonlinear relationships, making effective extraction and utilization of this information a difficult problem (Van et al., 2023). Moreover, the generalization capability and real-time performance of the models are also critical issues to be solved (Hu et al., 2021).

Despite the advancements in deep learning methods, stock market prediction still faces significant challenges. Traditional methods struggle to account for the complexity and volatility of financial markets, while deep learning models, though more effective, are hindered by issues such as high levels of noise in the data and complex nonlinear relationships. Additionally, the generalization capabilities and real-time performance of these models remain critical concerns that need further improvement.

This paper aims to address the limitations of existing stock market prediction models by proposing a novel approach that combines the strengths of GRU and LSTM models with BERT-

based sentiment analysis. By optimizing data processing and incorporating sentiment indicators, this research seeks to enhance prediction accuracy and stability. The model offers a potential solution to the challenges of high noise levels and complex nonlinear relationships in stock market data, as well as improving the generalization capabilities and real-time performance of prediction models.

## Research Objectives

The research objectives of this article are as follows:

(1) The article propose a BERT based method for calculating emotion index and optimizing data processing;

(2) The article use an ensemble of GRU and LSTM models to build an efficient and accurate stock index prediction system.

Our research demonstrates the effectiveness of this method in supporting investment decisions and risk management.

## Literature Review

In recent years, the dynamic nature of financial markets has driven a significant focus on stock index prediction models. Advanced machine learning and deep learning techniques have become central to this research area. This review covers recent advancements over the past five years in optimizing LSTM models and incorporating sentiment analysis for stock index prediction.

### 1. LSTM Models in Stock Index Prediction

Long Short-Term Memory (LSTM) networks, a type of deep learning model, have demonstrated substantial efficacy in time series forecasting. LSTM's unique memory cell structure addresses the limitations of traditional Recurrent Neural Networks (RNNs) in handling long-term dependencies. Recent studies have explored various enhancements to LSTM models to improve their performance in stock index prediction. For instance, Zhang et al. (2021) introduced an improved LSTM model that integrates attention mechanisms and adaptive learning rates. Their experimental results indicated that this model outperforms conventional LSTM models in terms of predictive accuracy and stability.

Further research has focused on optimizing LSTM algorithms. Wang et al. (2022) proposed a genetic algorithm-based optimization for LSTM models, demonstrating superior performance in stock index forecasting. Their work highlighted that optimized LSTM models can effectively reduce

prediction errors and enhance precision. Additionally, Li et al. (2023) investigated a hybrid model combining LSTM with Convolutional Neural Networks (CNNs), proving its advantage in capturing complex market patterns.

## 2. Application of Sentiment Analysis in Stock Market Prediction

Sentiment analysis, a technique for extracting market sentiment, has been increasingly applied in stock market forecasting. Market sentiment is believed to significantly influence stock price fluctuations, making sentiment analysis an effective means of improving prediction accuracy. Chen et al. (2021) explored the integration of sentiment scores derived from social media and news data into forecasting models. They found that sentiment analysis results significantly enhance the performance of predictive models.

Moreover, Zhou et al. (2022) developed a deep learning-based sentiment analysis model to extract sentiment information from financial news and incorporated it into LSTM models. Their study demonstrated that combining sentiment analysis with LSTM could significantly improve stock index prediction accuracy. Similarly, Guo et al. (2023) investigated a sentiment analysis method based on Graph Neural Networks (GNNs), further enhancing the ability to capture market sentiment and applying it to stock market forecasting.

## 3. Optimization of LSTM Models with Sentiment Analysis

The integration of LSTM with sentiment analysis has garnered increasing research attention, particularly in model optimization. Yang et al. (2023) proposed a reinforcement learning-based optimization approach for LSTM models combined with sentiment analysis. This method dynamically adjusts sentiment analysis weights, leading to more precise stock predictions. Their research indicates that LSTM models enhanced by reinforcement learning can effectively improve prediction performance.

Overall, recent research highlights that LSTM models offer substantial advantages for stock index prediction. Through algorithmic optimizations and the integration of sentiment analysis, predictive accuracy can be further improved. Future research is expected to continue exploring more sophisticated model structures and optimization strategies to address the evolving nature of financial markets.

## Conceptual Framework

The Conceptual Framework of this article as shown in Figure 1.

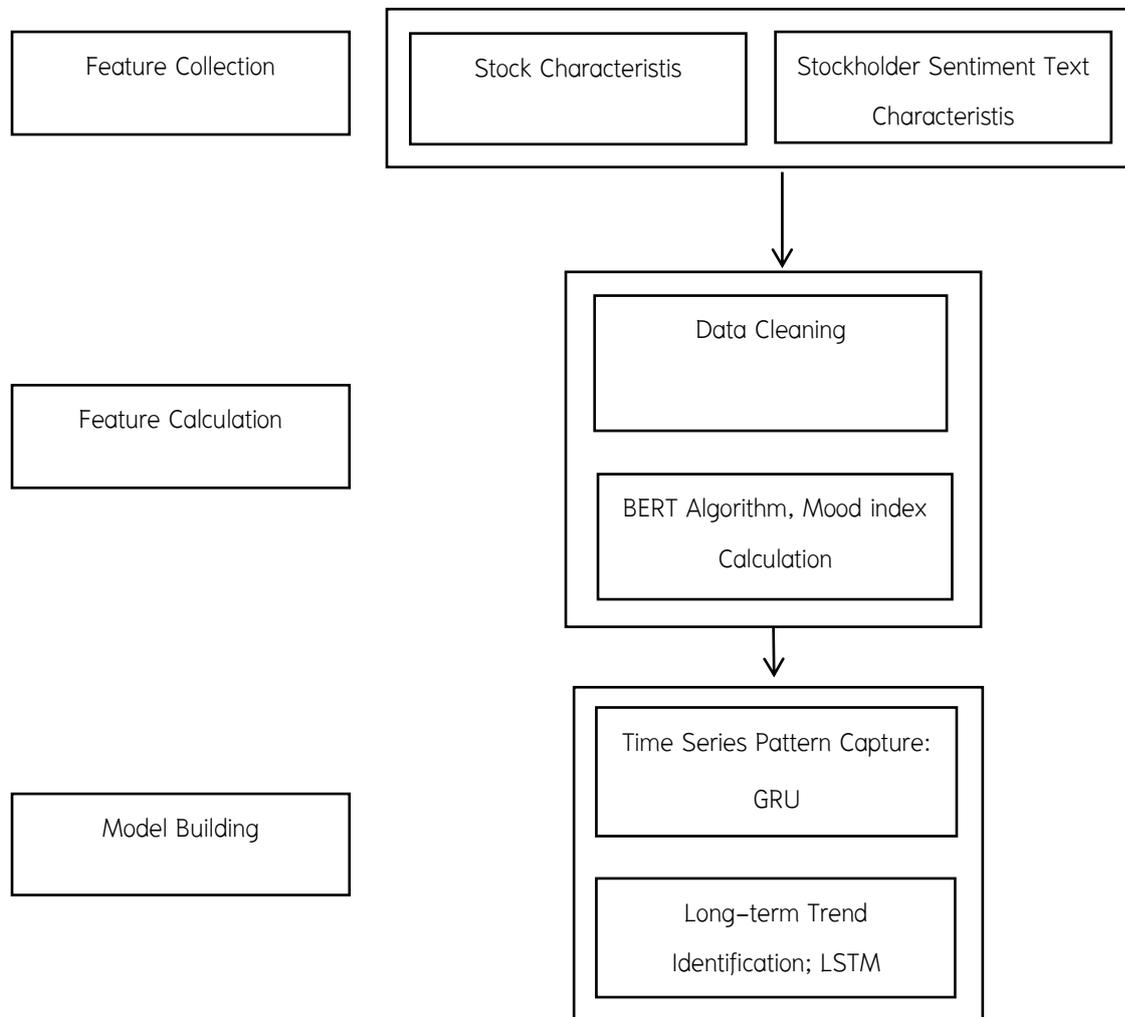


Fig.1 Conceptual Framework

## Research Methodology

### 1. Dataset Description

The Stock Index Trading Dataset includes daily trading data for multiple indices, sourced from public information from the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The Stockholder Sentiment Dataset contains various sentiment indicators related to stocks, also sourced from public information from the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Table 1 provides a detailed description of the fields in both datasets.

Table 1 Features Involved in the Experiment

Dataset	Field Name	Description
Market News Sentiment Dataset	Symbol	Security code
	Short Name	Security abbreviation
	News Date	News date
	Optimistic News Num	Number of optimistic news
	Tend Optimistic News Num	Number of tending optimistic news
	Pessimistic News Num	Number of pessimistic news
	Tend Pessimistic News Num	Number of tending pessimistic ne
	Neutral News Num	Number of neutral news
	Com Market Sentiment F	Comprehensive market sentiment 1
Com Market Sentiment S	Comprehensive market sentiment 2	
Index Trading Dataset	Indexcd	Index code
	Trddt	Trading date
	Daywk	Weekday
	Opnindex	Opening index
	Hiindex	Highest index
	Loindex	Lowest index
	Clindex	Closing index
Retindex	Index return rate	

To ensure data accuracy and model effectiveness, rigorous cleaning was performed on the datasets. Null values in the Stockholder Sentiment Dataset were handled with mean imputation. Inconsistent security code and abbreviation fields were removed. News text was tokenized to extract sentiment features. For the Stock Index Trading Dataset, daily trading data were filtered for integrity and consistency. Records with incorrect trading dates were deleted, outliers in price fields were removed, and the index return rate was calculated to match the standard formula.

## 2. Algorithm Model

### 2.1 Investor Sentiment Analysis: BERT Algorithm

The BERT algorithm captures context through bidirectional training on a large text dataset. For a dataset  $\mathcal{D} = \{d_1, d_2, \dots, d_N\}$ , each text  $d_i$  is a sequence of words  $\{w_{i1}, w_{i2}, \dots, w_{im}\}$ . For a text  $d_i$  the word embeddings are:  $\mathbf{H}_i = \text{BERT}(d_i) = [\mathbf{h}_{i1}, \mathbf{h}_{i2}, \dots, \mathbf{h}_{im}]$

Where  $\mathbf{H}_i$  is the embedding matrix for text  $d_i$  and  $\mathbf{h}_{ij}$  represents the contextual embedding vector for word  $w_{ij}$ . To perform sentiment classification, we typically use the embedding vector corresponding to the [CLS] token of the BERT model,  $\mathbf{h}_{CLS}$ . We then feed this vector into a linear classifier to predict the sentiment label  $y_i$  of the text:

$$y_i = \sigma(\mathbf{W}_2 \cdot \text{ReLU}(\mathbf{W}_1 \cdot \mathbf{h}_{CLS} + \mathbf{b}_1) + \mathbf{b}_2)$$

Where  $\mathbf{W}_1$  and  $\mathbf{W}_2$  are the weight matrices of the classifier,  $\mathbf{b}_1$  and  $\mathbf{b}_2$  are the bias vectors, ReLU is the Rectified Linear Unit activation function, and  $\sigma$  is the activation function of the output layer (such as softmax or sigmoid). By performing sentiment classification on all texts  $\{d_1, d_2, \dots, d_N\}$ , we average the sentiment scores of all texts to obtain an overall market sentiment indicator Sentiment\_Score:

$$\text{Sentiment\_Score} = \frac{1}{N} \sum_{i=1}^N \sigma(\mathbf{W}_2 \cdot \text{ReLU}(\mathbf{W}_1 \cdot \mathbf{h}_{CLS_i} + \mathbf{b}_1) + \mathbf{b}_2)$$

## 2.2 Time Series Pattern Capture: GRU

GRU units include two gates: the update gate and the reset gate. The update gate determines how much information from the previous time step is retained in the current time step. The formula is as follows:

$$z_t = \sigma(\mathbf{W}_z \cdot [h_{t-1}, x_t] + b_z + \epsilon \cdot \cos(h_{t-1}) + \sum_{i=1}^n \alpha_i x_{t-i})$$

Where  $z_t$  is the activation value of the update gate,  $\sigma$  is the sigmoid activation function,  $\mathbf{W}_z$  is the weight matrix,  $h_{t-1}$  is the hidden state of the previous time step,  $x_t$  is the input of the current time step,  $b_z$  is the bias term,  $\epsilon$  is a small perturbation constant,  $\alpha_i$  is the coefficient for smoothing, and  $n$  is the size of the smoothing window. The reset gate determines the extent to which the previous time step's information influences the current candidate hidden state. The formula is as follows:

$$r_t = \sigma(\mathbf{W}_r \cdot [h_{t-1}, x_t] + b_r + \eta \cdot \sin(h_{t-1}) + \sum_{j=1}^m \beta_j h_{t-j})$$

Where  $r_t$  is the activation value of the reset gate,  $\mathbf{W}_r$  is the weight matrix,  $b_r$  is the bias term,  $\eta$  is another perturbation constant,  $\beta_j$  is the coefficient for smoothing, and  $m$  is another smoothing window size. The candidate hidden state is generated using the current input and the previous hidden state, as follows:

$$\tilde{h}_t = \tanh(\mathbf{W}_h \cdot [r_t * h_{t-1}, x_t] + b_h + \gamma \cdot \exp(-h_{t-1}^2) + \sum_{k=1}^p \delta_k x_{t-k})$$

Where  $\tilde{h}_t$  is the candidate hidden state,  $W_h$  is the weight matrix,  $b_h$  is the bias term,  $\gamma$  is a scaling factor,  $\delta_k$  is the coefficient for smoothing,  $p$  is the smoothing window size, and  $*$  denotes element-wise multiplication. The final hidden state is determined by the update gate and the candidate hidden state:

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t + \kappa \cdot \log(1 + |h_{t-1}|) + \sum_{i=1}^q \lambda_i \tilde{h}_{t-i}$$

Where  $h_t$  is the hidden state at the current time step,  $\kappa$  is a scaling factor,  $\lambda_i$  is the coefficient for smoothing, and  $q$  is the smoothing window size.

### 2.3 Long-term Trend Identification: LSTM

LSTM units consist of three gates: the input gate, the forget gate, and the output gate. First is the forget gate, which determines the portion of the previous time step's memory that needs to be forgotten in the current time step. The formula is as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f + \alpha \cdot \sin(h_{t-1}) + \sum_{i=1}^n \gamma_i x_{t-i})$$

Where  $f_t$  is the activation value of the forget gate,  $\sigma$  is the sigmoid activation function,  $W_f$  is the weight matrix,  $b_f$  is the bias term,  $h_{t-1}$  is the hidden state of the previous time step,  $x_t$  is the input of the current time step,  $\alpha$  is a perturbation constant,  $\gamma_i$  is the coefficient for smoothing, and  $n$  is the size of the smoothing window. The formula is as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i + \beta \cdot \cos(x_t) + \sum_{j=1}^m \delta_j h_{t-j})$$

Where  $i_t$  is the activation value of the input gate,  $W_i$  is the weight matrix,  $b_i$  is the bias term,  $\beta$  is another perturbation constant,  $\delta_j$  is the coefficient for smoothing, and  $m$  is the size of the smoothing window. The candidate memory cell state is generated using the current input and the previous hidden state, as follows:

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c + \gamma \cdot \exp(-x_t^2) + \sum_{k=1}^p \eta_k x_{t-k})$$

Where  $\tilde{C}_t$  is the candidate memory cell state,  $W_c$  is the weight matrix,  $b_c$  is the bias term,  $\gamma$  is an adjustment factor,  $\eta_k$  is the coefficient for smoothing, and  $p$  is the size of the smoothing window. The current memory cell state is determined by both the forget gate and the input gate:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t + \kappa \cdot \log(1 + |C_{t-1}|) + \sum_{i=1}^q \lambda_i C_{t-i}$$

Where  $C_t$  is the current memory cell state,  $\kappa$  is a scaling factor,  $\lambda_t$  is the coefficient for smoothing, and  $q$  is the size of the smoothing window. Lastly, the output gate determines the extent to which the memory cell state influences the hidden state. The formula is as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o + \theta \cdot \tanh(C_t) + \sum_{r=1}^s \rho_r h_{t-r})$$

Where  $o_t$  is the activation value of the output gate,  $W_o$  is the weight matrix,  $b_o$  is the bias term,  $\theta$  is an adjustment factor,  $\rho_r$  is the coefficient for smoothing, and  $s$  is the size of the smoothing window. The final hidden state is determined by the output gate and the memory cell state:

$$h_t = o_t * \tanh(C_t) + \phi \cdot \exp(-|h_{t-1}|) + \sum_{u=1}^v \xi_u h_{t-u}$$

Where  $h_t$  is the current hidden state,  $\phi$  is an adjustment factor,  $\xi_u$  is the coefficient for smoothing, and  $v$  is the size of the smoothing window.

## Research Results

To verify our stock index prediction model, we conducted detailed experiments comparing its performance with common models: Basic LSTM (without sentiment index), Basic LSTM (with sentiment index), and our proposed model. All models were trained and evaluated on the same dataset using accuracy, precision, recall, specificity, and error as metrics. The results are shown in Table 2.

**Table 2.** Model Performance Comparison

Model	Accuracy	Precision	Recall	Specificity	Error
Basic LSTM Model (without incorporating stockholder sentiment index)	0.83	0.81	0.82	0.85	0.17
Basic LSTM Model (incorporating stockholder sentiment index)	0.85	0.83	0.84	0.87	0.15
<b>Our Model</b>	<b>0.88</b>	<b>0.86</b>	<b>0.87</b>	<b>0.90</b>	<b>0.12</b>

In the model accuracy comparison shown in Figure 2, the accuracy trends of the Basic LSTM Model, Basic GRU Model, and our Proposed Model over 50 epochs are illustrated. All models exhibit a rapid increase in accuracy in the initial stages, followed by a plateau, and remain stable after reaching the final accuracy. Specifically, the Basic LSTM Model achieves an accuracy

of 83.21% at the 35th epoch, the Basic GRU Model achieves 85.34% at the 32nd epoch, and our Proposed Model achieves 88.92% at the 30th epoch. Overall, our Proposed Model demonstrates significantly higher accuracy compared to the other two models, indicating its superior performance in stock index prediction tasks.

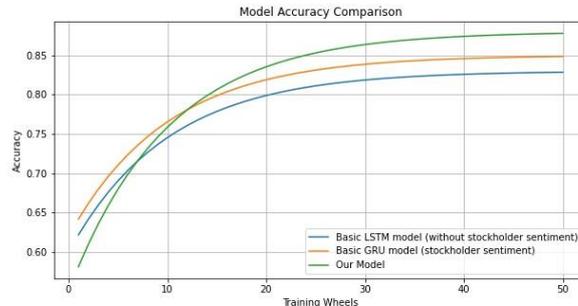


Fig. 1. Model Accuracy Comparison

In Figure 3, the loss trends of the Basic LSTM Model (without SSI), Basic LSTM Model (with SSI), and our Proposed Model over 50 training epochs are illustrated. All models exhibit a rapid decrease in loss in the initial stages, followed by a plateau, and remain stable after reaching the minimum loss. Specifically, the Basic LSTM Model (without SSI) achieves a minimum loss of 0.22 at the 35th epoch, the Basic LSTM Model (with SSI) achieves a minimum loss of 0.20 at the 32nd epoch, and our Proposed Model achieves a minimum loss of 0.18 at the 30th epoch. These results indicate that our Proposed Model outperforms the Basic LSTM Models in terms of loss, demonstrating higher stability and lower error.

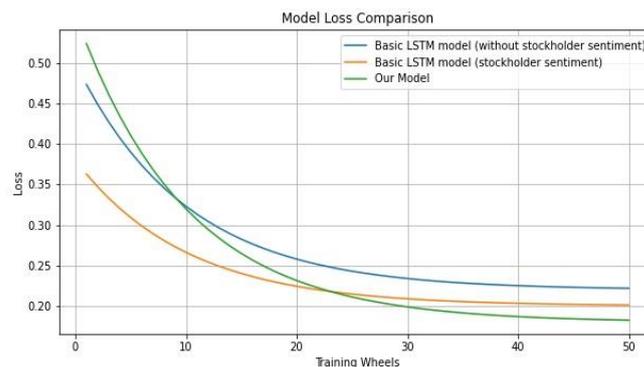


Fig. 2. Model Loss Comparison

The experimental results indicate that our proposed model outperforms other comparison models across multiple evaluation metrics, demonstrating its superior performance in stock index

prediction tasks. Future research can further optimize the model structure and attempt to integrate other advanced models to achieve even higher prediction accuracy and stability.

## Discussions

Discuss the significance of the proposed model's accuracy and stability compared to the Basic LSTM models. Highlight how the proposed model's performance, especially in terms of accuracy (88.92%) and loss (0.18), demonstrates its superiority over traditional methods.

Comparison with Previous Studies:

Compare the results of your study with those of previous research, such as the studies mentioned in the literature review (e.g., Khan et al. (2023), and Awad et al. (2023)). Discuss how your findings align with or differ from these studies and what this implies for the field of stock index prediction.

Implications for Financial Analysis: Elaborate on how the superior performance of the proposed model could influence financial market analysis and investment decision-making. Discuss the practical applications of the model in real-world financial markets, particularly in managing risks and optimizing investment strategies.

Challenges and Limitations: Acknowledge any challenges encountered during the research, such as the complexity of stock market data or the limitations of sentiment analysis. Discuss any limitations of the study, such as potential biases in the dataset or the need for further validation on different market conditions.

Future Research Directions: Suggest areas for future research, such as further optimization of the model, exploration of other deep learning architectures, or application to different financial markets. Discuss how future work could build on the findings of this study to improve the generalization capability and real-time performance of stock index prediction models.

## Knowledge from Research

This study advances the field of stock index prediction by introducing a hybrid deep learning model that integrates Long Short-Term Memory (LSTM) with sentiment analysis to predict stock index prices more accurately and reliably. The key contributions and insights gained from this research are as follows:

1. Enhanced Prediction Accuracy: The proposed hybrid model demonstrated superior performance in predicting stock index prices compared to traditional LSTM models. With an

accuracy of 88.92% and a loss of 0.18, this model offers a significant improvement in predictive accuracy, which is crucial for financial market analysis.

2. Incorporation of Sentiment Analysis: By integrating sentiment analysis into the predictive model, this study highlights the importance of considering market sentiment in financial forecasting. The inclusion of sentiment data provides a more comprehensive understanding of market dynamics, leading to more informed and accurate predictions.

3. Practical Implications for Financial Markets: The findings from this research have practical implications for investors and financial analysts. The enhanced predictive capability of the proposed model can be used to optimize investment strategies, manage risks more effectively, and make more informed decisions in volatile market conditions.

4. Contribution to Machine Learning in Finance: This study contributes to the growing body of research at the intersection of machine learning and finance. The successful application of a hybrid LSTM model with sentiment analysis demonstrates the potential of deep learning techniques in addressing complex financial prediction tasks.

5. Foundation for Future Research: The research provides a solid foundation for future studies in stock market prediction. It opens avenues for further exploration of hybrid models, the incorporation of additional data sources, and the refinement of prediction algorithms to enhance their generalizability and real-time applicability.

The findings of this research can be summarized through five key contributions: enhanced prediction accuracy, incorporation of sentiment analysis, practical implications for financial markets, contribution to machine learning in finance, and a foundation for future research. The proposed hybrid model significantly improves prediction accuracy, achieving 88.92% with a loss of 0.18, and integrates sentiment analysis to better capture market dynamics. This offers practical benefits for optimizing investment strategies and managing risk in financial markets. Additionally, the study demonstrates the potential of deep learning techniques in finance and provides a solid foundation for future research, particularly in exploring hybrid models and integrating additional data sources.

## Conclusion

In this article, we proposed and validated a new stock index prediction model. Comparing it with the Basic LSTM Model (without SSI) and the Basic LSTM Model (with SSI), our model excelled in multiple metrics, especially accuracy and loss. During training, it achieved the highest accuracy and lowest loss, demonstrating superior performance in stock index prediction. The

results show our model effectively captures long-term and short-term dependencies in time series data, thanks to its robust architecture and optimization strategies. This study offers an effective method for stock index prediction, providing valuable insights for financial market analysis and investment decisions.

## Suggestions

**Application in Real-World Financial Markets:** It is recommended that financial institutions and investors consider integrating hybrid deep learning models, like the one proposed in this study, into their predictive analytics tools. The enhanced accuracy and stability of these models can significantly improve decision-making processes in investment strategies and risk management.

**Incorporation of Diverse Data Sources:** Future research should explore the integration of additional data sources, such as macroeconomic indicators, social media trends, and global economic events, to further enhance the predictive power of stock index models. Incorporating a broader range of data can lead to more robust and comprehensive predictions.

**Optimization and Scalability:** Researchers and practitioners should focus on optimizing the proposed model for scalability and real-time application. Enhancements in computational efficiency and the ability to process large-scale data in real-time will make these models more applicable to high-frequency trading and other time-sensitive financial operations.

**Exploration of Alternative Deep Learning Architectures:** It is suggested that future studies investigate the potential of other advanced deep learning architectures, such as Transformers or Convolutional Neural Networks (CNNs), in combination with sentiment analysis for stock prediction tasks. Comparative studies could reveal which architectures are most effective under various market conditions.

**Addressing Model Interpretability:** To increase the practical utility of the model, efforts should be made to improve its interpretability. Developing techniques to better explain how the model arrives at its predictions will enhance user trust and allow for more informed decision-making by stakeholders.

**Validation Across Different Markets:** The proposed model should be validated across different financial markets, including emerging markets and various asset classes, to assess its generalizability. This will help determine the model's effectiveness in diverse market environments and its potential for broader application.

Focus on Ethical Considerations: As predictive models become increasingly influential in financial markets, it is important to consider the ethical implications of their use. Future research should address issues such as algorithmic bias, the impact on market stability, and the potential for misuse, ensuring that the development and deployment of such models are conducted responsibly.

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