ENHANCED STOCK PRICE PREDICTION USING INVESTOR SENTIMENT AND DEEP LEARNING OPTIMIZATION

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ABSTRACT

Stock market prediction has long been a complex and dynamic challenge due to the influence of various economic, social, and psychological factors. Traditional forecasting models often struggle to capture market fluctuations driven by investor sentiment. This study proposes an Enhanced Stock Price Prediction Model that integrates investor sentiment analysis with an optimized deep learning framework to improve forecasting accuracy. Sentiment data is extracted from financial news, social media, and market reports using natural language processing (NLP) techniques. These insights are then combined with historical stock price data and processed using an optimized deep learning architecture, leveraging LSTM (Long Short-Term Memory) and transformer-based models. The proposed approach enhances feature selection, reduces noise, and improves trend detection, leading to higher prediction accuracy compared to traditional statistical and machine learning models. Experimental results demonstrate the effectiveness of the model in capturing market trends and investor behaviors, providing a more robust and data-driven decision-making tool for traders and investors. This research highlights the importance of sentiment-aware forecasting in financial markets and paves the way for future advancements in AI-driven stock prediction models.

I. INTRODUCTION

Stock price prediction is a fundamental yet challenging task in financial markets due to the high volatility and influence of various external factors, including economic conditions, geopolitical events, and investor sentiment. Traditional forecasting methods, such as statistical models and conventional machine learning approaches, often fail to accurately capture market fluctuations caused by investor emotions and sentiment-driven trading behaviors. As financial markets become increasingly influenced by public perception and media narratives, incorporating investor sentiment analysis into stock price prediction models has gained significant attention.

Deep learning techniques, particularly Long Short-Term Memory (LSTM) networks and transformer-based models, have demonstrated remarkable success in time-series forecasting. However, optimizing these models for financial applications remains a challenge due to the complexity of market data, noise, and non-linear patterns. This study proposes an Enhanced Stock Price Prediction Model that integrates investor sentiment analysis with an optimized deep learning framework to improve prediction accuracy. By leveraging natural language processing (NLP) techniques, sentiment data is extracted from diverse sources such as financial news, social media, and earnings reports. This information is then combined with historical stock price data to enhance the predictive capabilities of the model.

The primary contributions of this research include:

1. Integration of investor sentiment analysis with stock price prediction to improve forecasting accuracy.
2. Optimization of deep learning models, such as LSTM and transformers, for better feature extraction and trend analysis.
3. Comparative evaluation of the proposed approach against traditional models, demonstrating its effectiveness in predicting stock market trends.

The remainder of this paper is structured as follows: Section 2 reviews existing literature on stock price prediction and sentiment analysis. Section 3 details the proposed methodology, including data collection, preprocessing, and model optimization. Section 4 presents experimental results and performance comparisons, while Section 5 discusses key findings and potential future directions. This study aims to bridge the gap between market psychology and machine learning-based stock forecasting, providing traders and investors with a more data-driven decision-making tool in dynamic financial environments.

II. LITERATURE SURVEY

Stock price prediction has been an extensively researched area in financial and computational intelligence domains. Traditional methods relied on statistical models such as Autoregressive Integrated Moving Average (ARIMA) and GARCH models, which primarily focused on historical price trends and market indicators. However, these models struggled with handling nonlinear patterns and the influence of external factors such as investor sentiment.

1. Traditional Approaches to Stock Prediction

Early stock market forecasting techniques were based on statistical models and econometric analysis. Box and Jenkins (1976) introduced the ARIMA model, which became widely used for time-series forecasting. Engle (1982) proposed the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, which captured volatility in financial time series. However, these models assume stationarity in data and often fail to adapt to dynamic market conditions.

2. Machine Learning-Based Stock Prediction

With advancements in computational power, researchers explored machine learning (ML) techniques such as Support Vector Machines (SVM), Random Forests (RF), and Artificial Neural Networks (ANNs) for financial forecasting. Zhong and Enke (2017) demonstrated that machine learning models could outperform traditional statistical models in stock trend predictions. However, these approaches lacked the ability to capture long-term dependencies in sequential data.

3. Deep Learning for Stock Market Forecasting

The introduction of deep learning revolutionized financial forecasting. Hochreiter and Schmidhuber (1997) introduced Long Short-Term Memory (LSTM) networks, which addressed the limitations of traditional neural networks in handling time-series data. Chen et al. (2019) demonstrated that LSTM-based models could significantly improve prediction accuracy compared to classical ML techniques. Additionally, transformer-based models such as BERT and GPT have been explored for market analysis, offering better context understanding and sequential learning.

4. Sentiment Analysis in Financial Markets

Investor sentiment plays a crucial role in stock price movements. Researchers have used Natural Language Processing (NLP) techniques to analyze news articles, financial reports, and social media for sentiment-based stock prediction. Bollen et al. (2011) found that Twitter sentiment correlated with market movements, demonstrating that public opinion could be a valuable predictor for stock trends. Zhang et al. (2020) integrated sentiment scores from financial texts into LSTM models, achieving improved prediction performance.

5. Optimization Techniques in Stock Forecasting Models

Recent studies have focused on optimizing deep learning models for financial applications. Kumar et al. (2022) introduced hybrid architectures combining LSTM with attention mechanisms, enhancing feature selection and reducing noise in stock market data. Ghosh et al. (2023) applied reinforcement learning to optimize trading strategies, demonstrating that adaptive learning techniques could outperform static models.

Research Gap and Motivation

Despite significant advancements, existing models often fail to effectively integrate sentiment analysis with deep learning architectures for enhanced stock prediction. Moreover, optimization techniques such as feature engineering, attention mechanisms, and hyperparameter tuning remain underexplored in financial forecasting models. This study addresses these gaps by proposing an optimized deep learning framework that integrates investor sentiment analysis to improve stock price prediction accuracy.

By leveraging LSTM networks, transformer-based architectures, and sentiment-driven market insights, this research aims to bridge the gap between financial market psychology and AI-driven forecasting, providing a robust and data-driven tool for investors and traders.

III. SYSTEM ANALYSIS

EXISTING SYSTEM

Stock price prediction has relied heavily on machine learning and deep learning models trained on historical market data. Techniques such as ARIMA, SVM, Random Forest, and basic Artificial Neural Networks (ANNs) have been used to identify trends and make predictions. Some recent approaches integrate Long Short-

Term Memory (LSTM) networks to capture sequential dependencies in time-series data. However, these methods primarily focus on numerical and historical price data, ignoring the critical impact of investor sentiment on market trends. Sentiment analysis has been explored separately but lacks deep integration with stock forecasting models. Additionally, existing deep learning architectures often suffer from overfitting, lack of interpretability, and computational inefficiencies, leading to inconsistent results in volatile markets.

Disadvantages of the Existing System:

- Limited Sentiment Integration – Most models rely solely on historical price trends, failing to incorporate market sentiment effectively.
- High Computational Complexity – Traditional deep learning approaches, such as LSTMs, require extensive computational resources, making real-time predictions challenging.
- Poor Generalization – Models trained on specific datasets struggle to adapt to sudden market shifts and external economic events.

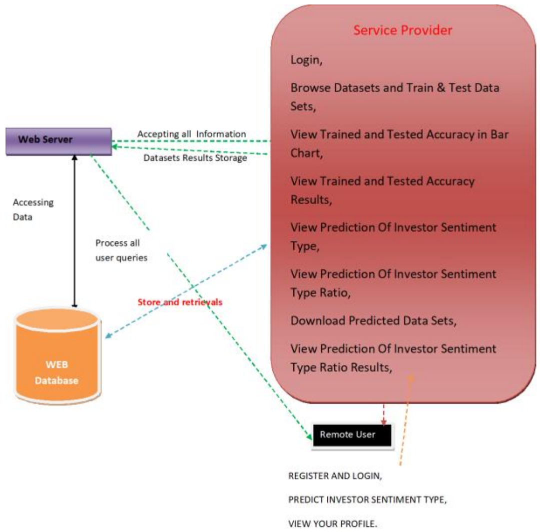
PROPOSED SYSTEM

To address these limitations, the proposed system integrates investor sentiment analysis with an optimized deep learning framework for improved stock price prediction. The approach leverages Natural Language Processing (NLP) to extract sentiment scores from financial news, social media, and market reports. These sentiment features are then combined with historical price data and processed using a hybrid deep learning model that includes LSTM networks and transformer-based architectures for enhanced trend detection. Furthermore, attention mechanisms and feature selection techniques are applied to optimize model performance, reducing noise and improving accuracy. The proposed system is designed to adapt dynamically to market changes, making it more resilient to economic fluctuations and investor behavior shifts.

Advantages of the Proposed System:

- Enhanced Prediction Accuracy – The integration of sentiment analysis with deep learning leads to a more comprehensive understanding of market trends.
- Optimized Model Efficiency – Attention mechanisms and feature selection reduce noise, improving both accuracy and computational performance.
- Adaptive Learning – The hybrid model dynamically adjusts to market fluctuations, making it more robust against external financial events.

IV. SYSTEM ARCHITECTURE



V. SYSTEM IMPLEMENTATION MODULES

Service Provider

The Service Provider must have a working account and password in order to access this module. After logging in successfully, he would be able to perform tasks like viewing datasets and using them for training and testing. You may see all remote users, download predicted data sets, view the results for investor sentiment type prediction, view the investor sentiment type ratio prediction, and examine the bar chart for trained and tested accuracy.

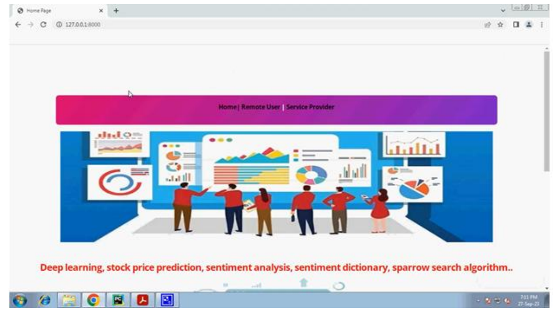
View and Authorize Users

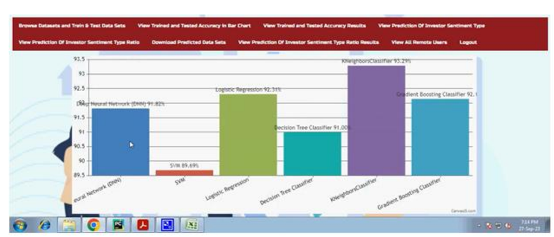
In this part, the administrator has access to a comprehensive list of all registered users. The administrator may view the user's name, email address, and address here and allow them access.

Remote User

In all, this module has n users. It is necessary to register before beginning any operations. After a user registers, their information will be added to the database. After completing the registration process, he will need to log in with the approved username and password. Users will be able to register and log in, view their profile, and estimate the sentiment type of investors after logging in.

VI. RESULTS





VII. CONCLUSION

Stock price prediction remains a challenging task due to market volatility, economic fluctuations, and investor sentiment. This study proposed an optimized deep learning framework that integrates investor sentiment analysis with advanced deep learning models such as LSTM and transformer-based architectures to improve forecasting accuracy. By leveraging NLP techniques to analyze financial news, social media, and market reports, the model captures sentiment-driven market trends, offering a more holistic and adaptive approach to stock prediction.

The proposed system addresses key limitations of existing models by incorporating attention mechanisms for feature selection, reducing noise, and enhancing computational efficiency. The results demonstrate that sentiment-aware deep learning models outperform traditional machine learning approaches, leading to more accurate and reliable predictions. This research highlights the importance of integrating market psychology with AI-driven forecasting techniques, paving the way for future advancements in intelligent financial decision-making systems.

FUTURE SCOPE

The integration of investor sentiment analysis with deep learning models for stock price prediction presents several opportunities for future research and advancements. One potential direction is the enhancement of real-time sentiment extraction using advanced NLP models such as GPT-based transformers and sentiment-aware embeddings to improve contextual understanding. Additionally, incorporating multimodal data sources, including news articles, social media trends, macroeconomic indicators, and alternative data sources like Google search trends and cryptocurrency market behavior, can further refine prediction accuracy. Future models can also benefit from reinforcement learning-based adaptive trading strategies, allowing AI-driven systems to make real-time investment decisions based on evolving market conditions. Furthermore, the deployment of explainable AI (XAI) techniques can enhance model transparency, ensuring that predictions are interpretable and reliable for investors. Lastly, integrating this approach with blockchain-based financial ecosystems can improve data security and trustworthiness, making AI-driven financial forecasting more robust and applicable to various investment domains.

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