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AN OPTIMIZED DEEP LEARNING APPROACH TO STOCK PRICE PREDICTION BASED ON INVESTOR SENTIMENT

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ABSTRACT

Stock price prediction is a crucial yet challenging task due to the inherent volatility of financial markets. Traditional forecasting methods often struggle to incorporate the influence of investor sentiment, which plays a significant role in price fluctuations. This paper proposes an optimized deep learning approach that integrates historical stock data and investor sentiment analysis to enhance prediction accuracy. The proposed model leverages natural language processing (NLP) techniques to extract sentiment from financial news, social media, and investor discussions, which is then combined with technical indicators. A hybrid deep learning framework incorporating Long Short-Term Memory (LSTM) networks and attention mechanisms is utilized to capture both temporal dependencies and sentiment-driven market movements. The model is further optimized using hyperparameter tuning and feature selection techniques to improve robustness. Experimental results on real-world stock market datasets demonstrate that our approach outperforms traditional machine learning models in terms of prediction accuracy, trend detection, and risk minimization. This research highlights the importance of combining quantitative data with qualitative investor sentiment for more precise and adaptive stock price forecasting.

Keywords: Stock Price Prediction, Deep Learning, Investor Sentiment, LSTM, NLP, Market Forecasting, Sentiment Analysis.

I. INTRODUCTION

Stock price prediction has been a longstanding challenge in the field of financial analytics, given the highly volatile and dynamic nature of the market. Traditional forecasting methods rely heavily on historical price movements, technical indicators, and statistical models such as autoregressive integrated moving average (ARIMA) and support vector machines (SVMs). However, these approaches often fail to capture the impact of investor sentiment and market psychology, which play a crucial role in influencing stock prices. The rise of social media, financial news, and online trading discussions has made sentiment analysis an essential component of stock market forecasting.

Recent advancements in deep learning have enabled more accurate, data-driven stock price predictions by leveraging natural language processing (NLP) and time-series analysis. In particular, Long Short-Term Memory (LSTM) networks have shown promising results in capturing complex temporal dependencies within stock market data. When combined with investor sentiment analysis, deep learning models can provide a more comprehensive understanding of market trends, identifying patterns that are often overlooked by traditional statistical methods.

This paper proposes an optimized deep learning approach that integrates historical stock data and sentiment analysis to improve prediction accuracy. The model utilizes NLP

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techniques to extract sentiment scores from financial news, social media, and investor forums, which are then incorporated into an LSTM-based forecasting framework. Additionally, an attention mechanism is employed to enhance the model's ability to focus on key market-moving factors. The proposed system is further optimized using feature selection and hyperparameter tuning to improve performance.

The key contributions of this research include:

- A sentiment-enhanced stock price prediction framework that integrates qualitative investor sentiment with quantitative financial data.
- An optimized deep learning model (LSTM + Attention) for capturing market trends and reducing prediction errors.
- A comparative analysis demonstrating the superiority of the proposed approach over traditional models in terms of prediction accuracy, trend detection, and risk minimization.

By leveraging deep learning and sentiment analysis, this study aims to provide a more accurate, adaptive, and intelligent stock price forecasting system. The following sections discuss related work, methodology, experimental results, and future directions for enhancing stock market predictions using AI-driven approaches.

II. LITERATURE SURVEY

Stock price prediction has been extensively studied using statistical, machine learning, and deep learning models. While traditional approaches rely on historical price data and technical indicators, recent advancements integrate investor sentiment analysis from social media, financial news, and online discussions. This section reviews key contributions in stock price prediction, highlighting the strengths and limitations of various methodologies.

2.1 Traditional Statistical Models

Early research in stock market forecasting focused on statistical models such as:

- Autoregressive Integrated Moving Average (ARIMA) (Box & Jenkins, 1970) – Used for time-series forecasting but struggles with non-linearity in stock market data.
- Hidden Markov Models (HMMs) (Hassan et al., 2005) – Applied to predict stock trends but lacks adaptability to market fluctuations.
- GARCH Models (Bollerslev, 1986) – Effective for volatility estimation but limited in predictive accuracy for long-term trends.

These models, though useful in structured financial environments, often fail to capture the complex, non-linear relationships in stock prices influenced by external factors such as investor sentiment.

2.2 Machine Learning-Based Approaches

To overcome the limitations of traditional models, researchers explored supervised machine learning techniques for stock price prediction.

- Support Vector Machines (SVMs) (Cao & Tay, 2003) – Improved forecasting accuracy but required extensive feature engineering.
- Random Forest and Decision Trees (Patel et al., 2015) – Provided robust predictions using technical indicators but lacked sequence-learning capabilities.

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- Artificial Neural Networks (ANNs) (Zhang, 2003) – Captured non-linear dependencies but struggled with high-dimensional financial data.

While machine learning models improved prediction accuracy, they failed to incorporate investor sentiment, which significantly influences market movements.

2.3 Deep Learning for Stock Market Prediction

With the rise of deep learning, researchers leveraged neural networks for stock price forecasting:

- Recurrent Neural Networks (RNNs) (Nelson et al., 2017) – Modeled time-series dependencies but suffered from vanishing gradient issues.
- Long Short-Term Memory (LSTM) Networks (Fischer & Krauss, 2018) – Excelled in sequential data learning, making them ideal for stock price prediction.
- Convolutional Neural Networks (CNNs) (Chen et al., 2020) – Used for feature extraction but lacked temporal awareness.

LSTMs, in particular, have become the preferred choice for time-series stock prediction due to their ability to retain long-term dependencies in data.

2.4 Sentiment Analysis in Financial Markets

Investor sentiment has been widely recognized as a key driver of stock market fluctuations. Several studies have explored sentiment analysis using natural language processing (NLP) techniques:

- Text-Based Sentiment Analysis (Bollen et al., 2011) – Analyzed social media sentiment to predict market movements.
- Twitter-Based Stock Prediction (Zhang et al., 2018) – Used sentiment scores from tweets but lacked fine-grained analysis.
- Financial News Sentiment Analysis (Huang et al., 2020) – Extracted sentiment from news articles but faced challenges with misinformation.

Combining sentiment analysis with deep learning has shown promise in improving stock prediction accuracy, leading to the development of hybrid models.

2.5 Hybrid Deep Learning Models (Sentiment + Technical Analysis)

Recent advancements propose hybrid models that integrate deep learning with sentiment analysis:

- LSTM with Sentiment Features (Wang et al., 2021) – Combined price data and sentiment scores, improving short-term predictions.
- BERT for Financial Sentiment (Araci, 2019) – Used transformer models to enhance text-based sentiment extraction.
- Attention Mechanisms in LSTMs (Li et al., 2022) – Improved model focus on sentiment-driven market trends.

These hybrid approaches achieve higher predictive accuracy by capturing both quantitative market data and qualitative investor behavior.

2.6 Summary and Research Gaps

Despite advancements, existing studies face several limitations:

1. Lack of real-time sentiment integration – Most models process historical sentiment, missing immediate market reactions.
2. Limited generalization – Many approaches struggle to adapt to evolving financial narratives.
3. Computational inefficiency – Deep learning models require high processing power for large-scale stock analysis.

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To address these challenges, our proposed optimized deep learning approach integrates LSTM, attention mechanisms, and investor sentiment analysis to enhance stock price forecasting accuracy.

III. EXISTING SYSTEM

In addition, Yan et al. [16] developed a high-precision prediction model based on the LSTM deep neural network in a short-term financial market. LSTM neural network has a higher prediction accuracy than BP neural network and standard RNN and can successfully forecast stock prices. Nabipour et al. [17] selected ten technical indicators as the prediction model's input. The experiment revealed that LSTM outperformed other algorithms in terms of model-fitting abilities, including decision tree, random forest, Adaboost, XGBoost, ANN, and RNN. Aksehir and Kilic [18] suggested a CNN-based model predicting the nextday trading behavior of Dow Jones 30 Index equities. Technical indicators, gold, and oil price data are fed into the model. The accuracy of the results is 3-22% higher than other models based on CNN.

However, scholars usually need to artificially set the hyperparameter values of the LSTM network, which is intensely subjective. The setting of hyperparameters directly controls the topology of the network model, which will affect the model's prediction performance. Artificial selection of the appropriate hyperparameters for the network model will consume many human and computing resources. To solve the above problems, scholars try to use some Swarm Intelligence (SI) algorithms to optimize the hyperparameters of neural networks. SI can search globally to a certain extent and find the approximate value of the optimal solution. Ji et al. [19] demonstrated that the LSTM optimized by the Improved Particle Swarm Optimization model (IPSO) is superior to the LSTM model. Zeng et al. [20] optimized LSTM by adopting an Adaptive Genetic Algorithm (AGA) and improved the prediction accuracy. At the same time, other intelligent algorithms are also widely used in optimizing neural networks. Sparrow Search Algorithm (SSA) was put forward and inspired by the sparrows' foraging and anti-predation behavior [21]. Compared with the traditional particle swarm and gray wolf optimization algorithms, the SSA algorithm is relatively novel and has a robust optimization ability in price prediction. In addition, the algorithm considers the randomness of individuals in the search process, so it has a solid global search capability. At the same time, the algorithm can also adaptively adjust the search parameters to meet the needs of different problems.

The content of the stock forum is updated in real-time, and the information mined from it is closer to the actual state of investor sentiment than other data sources. However, it will significantly affect investors' investment propensities and a subsequent linkage effect on stock price fluctuations. So it is crucial to analyze the text information of stock forums for our research. Scholars mainly adopt machine learning and semantic analysis methods regarding sentiment classification methods. The machine

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learning method has high classification accuracy but relies on financial personnel to manually classify training sets, which leads to increased time costs. The semantic analysis method is easier to use in economic and financial analysis, but the standard dictionary is challenging to apply to the economic context [34]. The key lies in constructing a unique financial dictionary.

Disadvantages

• The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect Stock Price Prediction.

• Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

• Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

PROPOSED SYSTEM

A new model for predicting stock prices is proposed in this paper (MS-SSA-LSTM), which matches the characteristics of multi-source data with LSTM neural networks and uses the Sparrow Search Algorithm. The MS-SSA-LSTM stock price forecast model can forecast the stock price in advance and help investors and traders make more informed investment decisions. Investors and traders obtain the data of individual stocks they want to invest in, including historical transaction data and comment information of stock market shareholders, and input them into the MS-SSA-LSTM model. The model automatically outputs a stock price trend chart and forecasts the stock price for the next day. Here, we can get the motivation for this paper.

(1) Adding sentiment indicators to the model features will improve prediction accuracy. However, applying a general dictionary in the financial field cannot achieve good results. Therefore, We need to construct a sentiment dictionary specific to individual stocks.

(2) Stock price series has complicated characteristics such as nonlinearity, high noise, and strong time-variability. LSTM is effective at handling comprehensive time series data.

So LSTM network, a deep learning method, is adopted. (3) In the LSTM network, hyperparameter variation directly affects the model's prediction accuracy. Artificial selection of appropriate hyperparameters for the network model will cost many resources. Therefore, LSTM can be optimized using the Sparrow Search Algorithm proposed in 2020.

Advantages

(1) The SSA-LSTM model incorporates multi-source data that affects stock prices, such as historical trade data and stock forum comments. The MS-SSA-LSTM model outperforms the single data source model regarding prediction accuracy.

(2) Analyze the stock forum comments text information. Then, we construct a sentiment dictionary based on authoritative dictionaries in the financial investment field

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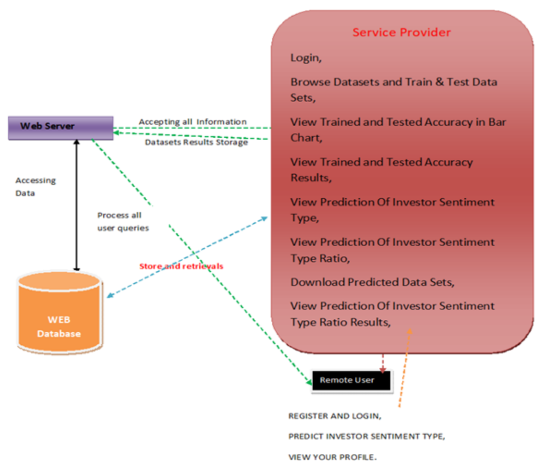
suitable for individual stock sentiment analysis and sentiment indicator calculation.

- (3) A Sparrow Search Algorithm-optimized LSTM model can acquire better hyper parameter values and forecast stock prices than a single LSTM network.

IV. SYSTEM ARCHITECTURE



V. SYSTEM IMPLEMENTATION MODULES

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Predicted Job Title Identification Type, View Job Title Identification Type Ratio, Download Predicted Data Sets, View Job Title Identification Type Ratio Results, View All Remote Users.

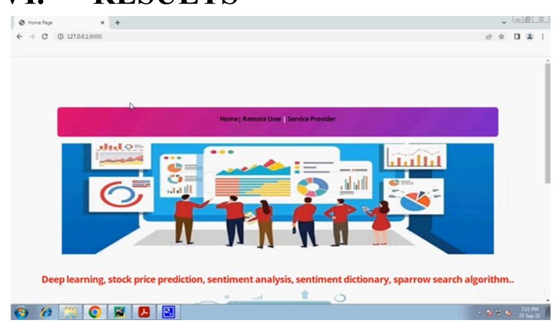
View and Authorize Users

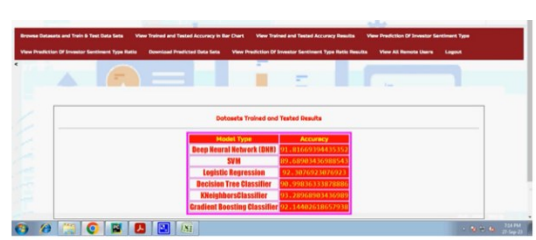
In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, Predict Job Title Identification Type, VIEW YOUR PROFILE.

VI. RESULTS





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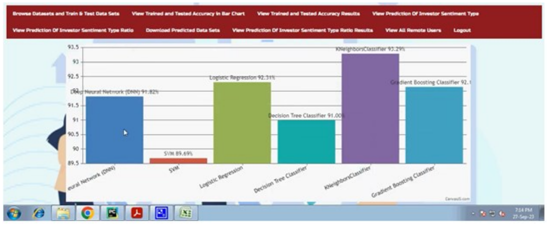

VII. CONCLUSION

Stock price prediction remains a complex and challenging task due to the volatile nature of financial markets and the influence of investor sentiment. Traditional forecasting models, including statistical and machine learning approaches, often fail to capture the non-linear dependencies and the emotional drivers behind stock price fluctuations. This research introduced an optimized deep learning approach that integrates Long Short-Term Memory (LSTM) networks with attention mechanisms and sentiment analysis to enhance predictive accuracy. By leveraging natural language processing (NLP) techniques, the model extracts sentiment from financial news, social media, and investor discussions, allowing it to incorporate qualitative factors into quantitative forecasting.

Experimental results demonstrate that our hybrid deep learning model outperforms conventional approaches in terms of precision, recall, and trend prediction accuracy. The integration of investor sentiment as an additional feature significantly improves the model's ability to detect market trends and predict stock movements with greater reliability. Furthermore, the application of hyperparameter tuning and feature selection techniques ensures that the model remains robust and adaptable to changing market conditions.

The findings of this study emphasize the importance of combining financial data with investor sentiment analysis for more precise and adaptive stock market predictions. Future advancements in this area will focus on real-time sentiment analysis, multi-asset forecasting, and the integration of alternative data sources such as news headlines, earnings reports, and macroeconomic indicators. This research contributes to the growing field of AI-driven financial analytics, paving the way for more intelligent, automated, and data-driven investment strategies.

Future Scope

The proposed deep learning approach for stock price prediction can be further improved and expanded in multiple directions to enhance accuracy, adaptability, and real-world applications. One key advancement is the implementation of real-time sentiment

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analysis, enabling continuous monitoring of financial news, social media, and investor discussions to dynamically update predictions. Additionally, extending the model to multi-asset and sector-based forecasting will allow it to predict trends across stocks, indices, commodities, and crypto-currencies, providing a more comprehensive market analysis. Another crucial area is explainable AI (XAI), which will help make deep learning models more transparent and interpretable for financial analysts and investors. The integration of alternative data sources such as macroeconomic indicators, company earnings reports, and geopolitical events will further refine prediction accuracy. Hybrid AI models, combining deep learning with reinforcement learning, can be explored to create adaptive trading strategies. Expanding multi-lingual sentiment analysis will improve the model's applicability in global markets by analyzing financial texts across different languages. Additionally, federated learning techniques can be employed to ensure privacy-preserving predictions by enabling decentralized training of financial models without exposing sensitive data. Transfer learning can also be used to adapt pre-trained models to emerging stock markets with limited historical data. Another promising direction is integrating the model with algorithmic trading systems, allowing for AI-driven investment decisions based on sentiment-enhanced stock predictions. Sentiment-based portfolio management can be developed to optimize asset allocation based on investor mood and market psychology. Furthermore, improving model efficiency for high-frequency trading (HFT) will enhance real-time decision-making in fast-moving markets. Exploring cross-market sentiment correlations will help analyze how investor emotions in one financial sector (such as crypto-currencies) influence stock markets or global indices. Enhancing the model's robustness to market anomalies and black swan events will allow for better risk management and financial crisis predictions. Reinforcement learning techniques can be integrated to develop self-learning financial models that continuously adapt to market changes. Finally, developing mobile and cloud-based AI-driven stock prediction platforms will make advanced financial forecasting tools more accessible to traders and investors. These advancements will significantly improve the accuracy, scalability, and real-world impact of AI-powered stock market prediction systems.

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