International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0287
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

Stock Market Price Predictions Using Machine Learning

Toka Sai Pallavi[1], Namoju Karthik[2], M Venkat Lakshimi Narayana[3], Mr. Mohammed Faisal[4], Shyamala Sindhuja[5], Dr. M. Ramesh[6]
[1,2,3,4]Department of Artificial Intelligence and Machine Learning, Sphoorthy Engineering College,Nadergul, Hyderabad,501510, India.
[5]Assistant Professor, Department of Artificial Intelligence and Machine Learning, Sphoorthy Engineering College, Nadergul, Hyderabad,501510, India.
[6]Head of Department, Department of Artificial Intelligence and Machine Learning, Sphoorthy Engineering College, Nadergul, Hyderabad,501510, India.
Email ID: *saipallavi1484@gmail.com[1], namojukarthik9@gmail.com[2], venkatvarun@gmail.com[3], faisal07.it@gmail.com[4], shyamalasindhuja@gmail.com[5], hodaiml@sphoorthyengg.ac.in[6]*

Abstract
The stock market is a dynamic and complex system influenced by numerous factors, making the accurate prediction of stock prices a challenging task. This project focuses on developing a web-based platform that predicts and highlights stocks expected to increase in price. The primary goal is to assist investors by simplifying the decision-making process through real-time insights into market trends. To achieve this, we employ machine learning algorithms trained on historical stock market data, including features such as opening and closing prices, trading volume, market sentiment, and technical indicators. These models analyze patterns and trends to forecast short-term price movements. Rather than displaying all market data, the system filters and showcases only those stocks that are predicted to experience an upward trend, helping users to quickly identify potential investment opportunities. The platform is designed with a clean, responsive web interface where users can view the list of increasing stocks in real time. The backend continuously fetches and updates financial data from reliable sources, processes it through the trained prediction models, and displays the results on the website. This automation ensures that the information remains current and actionable. By narrowing the focus to only rising stocks and presenting them in an accessible format, the system offers a practical tool for both novice and experienced investors. It combines the power of data science with the convenience of a web application, aiming to enhance investment strategies and support smarter financial decisions.

Keywords: *Machine Learning, Linear Regression, Investment Strategies, Financial Markets.*

1. Introduction

The stock market is a highly dynamic and complex system that plays a crucial role in the functioning of global economies. It facilitates the flow of capital from investors to companies, contributing to economic development and wealth creation. Predicting the future movement of stock prices is an enduring challenge due to the inherent volatility, non-linearity, and sensitivity of financial markets to a wide array of internal and external factors. Investors, financial institutions, economists, and researchers have long sought methods and models capable of accurately forecasting stock prices to maximize returns and minimize risks [1][5]. Stock price movements are influenced by various elements, including corporate performance, market trends, investor psychology, macroeconomic indicators, and unforeseen global events. The stock market reacts not only to tangible financial data like earnings reports or interest rate announcements but also to intangible factors such as political instability, changes in

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0287
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

regulations, and social media trends[2]. This multifaceted nature introduces a high degree of uncertainty and noise in market data, making accurate predictions a highly complex and non-trivial task. Traditional approaches to stock price forecasting were primarily statistical in nature, relying on models such as Autoregressive Integrated Moving Average (ARIMA), linear regression, and Exponential Smoothing. While these models offered some predictive capability, they were based on strong assumptions like linearity and stationarity, which often do not hold true in real-world financial data. These limitations paved the way for the exploration of more sophisticated and adaptive methodologies, particularly those rooted in artificial intelligence (AI) and machine learning (ML). Machine learning, a subset of AI, provides data-driven solutions that do not require explicit programming or human-defined rules. Instead, ML models learn patterns from historical data and apply that learning to make future predictions. With the ability to model complex, non-linear relationships, machine learning techniques have proven increasingly effective in financial forecasting tasks. Algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forests, and Gradient Boosting have been used to classify stock trends and predict price movements. Despite the improvements offered by traditional ML models, their effectiveness is often constrained when applied to sequential, time-dependent financial data [4]. This limitation has prompted the use of deep learning models, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. LSTMs are a specialized type of RNN designed to capture long-term dependencies in sequence data, making them highly suitable for modeling stock prices, which are inherently time-series in nature. The ability of LSTMs to retain memory of past events makes them ideal for learning from long sequences of historical data. In recent years, Convolutional Neural Networks (CNNs), traditionally used for image recognition tasks, have also been adapted for financial forecasting. When applied to time-series data, CNNs are capable of detecting localized patterns and trends, which can enhance the prediction of stock price changes. The fusion of LSTM and CNN architectures into a hybrid model allows the system to benefit from the strengths of both temporal dependency modeling and pattern recognition, leading to more accurate and robust predictions. Another dimension that has gained prominence in stock prediction is the analysis of sentiment. Market sentiment defined as the overall attitude of investors toward a particular security or the financial market in general can significantly impact stock prices. Sentiment can be influenced by news headlines, social media chatter, analyst opinions, and public perception. Natural Language Processing (NLP), a branch of AI that focuses on the interaction between computers and human language, is employed to process and analyze text data to derive sentiment insights. Sentiment analysis models convert unstructured textual data into quantifiable scores that reflect positive, negative, or neutral sentiments. These scores are then used as additional features in predictive models, providing a more holistic view of the factors driving price changes. For example, a surge in positive news about a company might result in a bullish sentiment, influencing investor behavior and pushing the stock price upward. While price and sentiment are crucial for prediction, another important factor is volatility. Volatility reflects the degree of variation in stock prices over time and is a key indicator of market risk. Predicting volatility helps investors assess potential price fluctuations and make informed decisions. Statistical models like Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Exponential GARCH (EGARCH) are widely used for volatility forecasting. By incorporating volatility forecasts into predictive systems, the model not only estimates expected price changes but also quantifies the level of uncertainty or risk associated with those predictions. This research proposes a comprehensive hybrid system for stock price prediction that integrates the capabilities of LSTM and CNN models with sentiment analysis and volatility forecasting. The system is designed to address the limitations of traditional methods by offering a multifaceted approach that captures temporal patterns, localized trends, investor sentiment, and market risk [3]. The model uses historical price data, technical indicators,

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0287
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

sentiment scores derived from financial text, and volatility estimates to generate more accurate and actionable predictions. The methodology begins with data collection from multiple sources, including historical stock prices, financial news, and social media. Data preprocessing steps such as normalization, feature engineering, and text cleaning are performed to prepare the data for modeling. The hybrid model is then trained using a combination of LSTM and CNN layers, with sentiment and volatility features incorporated into the learning process. The model's performance is evaluated using standard regression metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2), along with directional accuracy to assess trend prediction capability. This paper aims to contribute to the ongoing efforts in stock market prediction by demonstrating the effectiveness of combining deep learning, sentiment analysis, and volatility modeling. The proposed hybrid approach is designed to be adaptable, scalable, and suitable for deployment in real-world trading systems. By providing accurate and timely predictions, the system has the potential to support smarter investment strategies, reduce risk, and enhance financial decision-making. In conclusion, the stock market remains an inherently unpredictable domain, but advancements in data science and machine learning offer promising tools to navigate its complexities. This research underscores the importance of an integrated approach that leverages diverse data types and modeling techniques to improve the accuracy and reliability of stock price forecasts. Through the fusion of time-series analysis, pattern recognition, sentiment understanding, and risk estimation, this study aspires to build a robust foundation for next-generation financial forecasting systems [6].

2. Background and Problem Statement

Emotion recognition is a crucial component of human-computer interaction, which helps to improve the capacity of artificial intelligence systems to respond sympathetically to the requirements of users. Traditional methods relied on handcrafted features, which often failed to generalize across diverse datasets and cultural contexts [7]. Deep learning, with its ability to learn hierarchical feature representations, has revolutionized this eld by enabling robust, scalable, and adaptive emotion recognition systems. Emotion recognition is a critical area in artificial intelligence (AI), with applications ranging from healthcare and education to customer service and human-computer interaction. Recognizing emotions accurately allows AI systems to interact empathetically with humans, improving user experience and system effectiveness. Traditional emotion recognition approaches relied heavily on handcrafted features and rule-based systems. Although these approaches were useful for gathering preliminary data, they frequently failed to generalize and had difficulty dealing with the complexity and context-dependent variability of emotional manifestations. Models can now learn abstract and hierarchical properties from data thanks to the advent of deep learning, which has completely transformed the field. When it comes to handling multi-modal input, such physiological signs, facial expressions, audio signals, and text, deep learning methods like recurrent neural networks (RNNs) and convolutional neural networks (CNNs) work wonders. These data sources have greatly improved the accuracy and resilience of emotion detection when integrated into multi-modal emotion identification systems [7]. When it comes to handling multi-modal input, such physiological signs, facial expressions, audio signals, and text, deep learning methods like recurrent neural networks (RNNs) and convolutional neural networks (CNNs) work wonders. These developments lay the groundwork for creating AI systems with emotional intelligence and the ability to adapt to many types of situations.

2.1 Problem Statement

The stock market, a critical pillar of global economic infrastructure, is driven by a multitude of dynamic factors such as company performance, investor sentiment, macroeconomic indicators, and political events. Stock prices fluctuate rapidly and often unpredictably due to both rational and irrational forces in the market. As a result, accurate stock price prediction remains a highly sought-after goal yet notoriously difficult to achieve. Traditional statistical models like ARIMA, linear regression, and exponential smoothing have limitations when dealing

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0287
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

with non-linear, volatile, and high-dimensional financial data. These methods require assumptions such as data stationarity and independence, which rarely hold true in the real-world stock market environment. Furthermore, most traditional models focus purely on quantitative historical data and ignore unstructured data such as sentiment expressed in financial news. The primary problem is the lack of a unified approach that integrates multiple data modalities to improve predictive accuracy. Financial markets are not driven solely by numerical trends; they are influenced by human emotions, breaking news, macroeconomic forecasts, and even misinformation. Many existing models either fail to adapt to market regime shifts or overfit to historical patterns, reducing their generalization capability. Therefore, a robust solution must combine time-series analysis, pattern recognition, and sentiment understanding to capture the full scope of price movement influencers.

2.2 Research Gap

Despite the abundance of research in the field of financial forecasting, several key gaps remain unaddressed, limiting the effectiveness and generalizability of existing models. Firstly, most forecasting systems still rely exclusively on historical stock prices and overlook the influence of unstructured data sources like financial news, investor sentiment, or macroeconomic commentary. This siloed view fails to capture the multifaceted nature of stock price movements. While time-series models may recognize historical trends, they often miss out on sudden shifts caused by breaking news, regulatory changes, or unexpected events like a global pandemic. Secondly, the use of deep learning in financial forecasting is still in its early stages. Although LSTM networks have demonstrated promise in modeling temporal dependencies, their integration with other advanced architectures like CNNs and attention mechanisms remains underexplored in a financial context. The development of hybrid models that combine the strengths of various architectures is still in its infancy and represents a fertile ground for improvement.

AI technologies. These scores are then used as additional features in predictive models.

2.3 Contribution to Proposed Solution

To address the aforementioned problems and research gaps, this study presents a hybrid multi-modal approach for stock price prediction that integrates numerical time-series data, sentiment analysis from unstructured text, and volatility forecasting using statistical models. Our first major contribution is the development of a hybrid deep learning model that combines Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs). While LSTM captures long-range temporal dependencies in historical stock data, CNN identifies localized patterns that might signify momentum shifts [8]. By fusing these two architectures, our model achieves higher accuracy and robustness against market noise. Secondly, we introduce a sentiment analysis pipeline using Natural Language Processing (NLP) that processes financial news and social media posts to derive real-time investor sentiment. This sentiment score is incorporated into the feature vector and improves the model's ability to adapt to sudden market changes caused by public opinion or geopolitical events. Figure 1 shows Trends of The Overall Price of Trades of Tesla Stocks Over the Years.

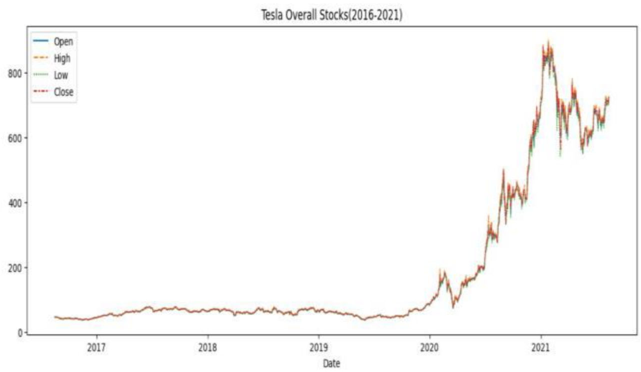

Figure 1 Trends of The Overall Price of Trades of Tesla Stocks Over the Years

3. Multi-Modal Features in Stocks

In the context of financial modeling, "emotion recognition" translates to understanding investor sentiment an essential non-quantitative feature that significantly influences stock movements. Multi-modal systems aim to incorporate: - Quantitative financial data (historical prices, volume, indicators) -

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0287
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

Textual sentiment (from news articles, social media, earnings reports) - Volatility metrics (captured using GARCH or similar models) Sentiment analysis can detect bullish or bearish attitudes among investors, often before changes are reflected in price movements [9]. Models like VADER and transformer-based NLP models (BERT, RoBERTa) are often employed to quantify sentiment. These scores are then incorporated as input features alongside numerical data into hybrid deep learning architectures. This multi-modal approach addresses the limitations of uni-dimensional input streams and allows for improved generalization in market forecasting systems. Figure 2 shows Block Diagram of Stock Prediction Using LSTM.

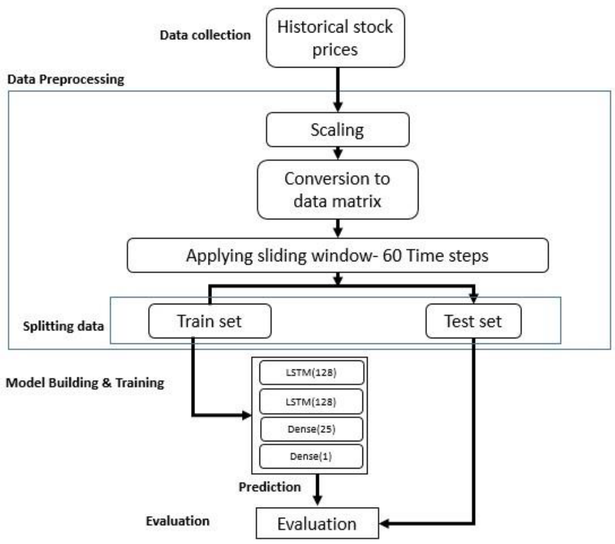

Figure 2 Block Diagram of Stock Prediction Using LSTM

In the realm of financial forecasting, facial features pertain to the analysis of investors' facial expressions to gauge emotions such as fear, greed, or confidence. While direct application in stock prediction is limited, advancements in computer vision and emotion recognition can potentially provide insights into market sentiment during events like earnings calls or investor meetings.

3.1 Speech Features

Speech features involve analyzing vocal cues, such as tone, pitch, and cadence, to detect emotional states. In financial contexts, this can be applied to assess the sentiment of executives during earnings calls or interviews. Tools like Open SMILE facilitate the extraction of such features, enabling the detection of stress or confidence levels that may influence investor perceptions.

3.2 Text Features

Textual data, including news articles, financial reports, and social media posts, a rich source of information for sentiment analysis. Models like BERT and FinBERT have been employed to extract sentiment and contextual information from such texts, enhancing the predictive accuracy of stock market models. For instance, integrating sentiment scores derived from financial news can provide early indicators of market movements artifacts.

3.3 Behavioral Features

Behavioral features encompass patterns in trading activities, such as volume spikes, order book dynamics, and transaction frequencies. Analyzing these behaviors can reveal anomalies or trends indicative of market sentiment shifts. Behavioral finance studies have shown that cognitive biases and herd behavior significantly impact market [10].

3.4 Contextual Features

Data Source Environmental or situational information. Features Background noise or setting (e.g., quiet, noisy street). Social context (e.g., group dynamics, interpersonal interactions). Temporal factors (e.g., time of day, duration of activity). Deep Learning Techniques, Multi-head attention to incorporate contextual information. Fusion layers to combine contextual cues with primary emotional features.

3.5 Fusion of Multi-Modal Features

Combining the aforementioned modalities can lead to more comprehensive and accurate stock market predictions. Multi-modal fusion approaches integrate diverse data sources to capture the complex interplay of factors influencing market behavior. Recent studies have proposed frameworks that effectively merge textual, numerical, and behavioral data, demonstrating improved predictive performance.

4. Materials and Methods

This study focuses on predicting stock market prices using machine learning techniques. Historical stock

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0287
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

data was collected from reliable sources such as Yahoo Finance and Kaggle. The dataset consisted of daily stock prices including open, high, low, close, adjusted close, and trading volume over a period of several years. This data served as the primary input for model training and evaluation. Preprocessing steps were carried out to prepare the data for analysis. These included handling missing values, normalizing the data using Min-Max or Standard Scaling, and converting the time series into supervised learning format by creating lagged features. Additionally, various technical indicators were generated, such as Moving Average (MA), Exponential Moving Average (EMA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD), to enhance the predictive power of the input feature. This study was conducted as part of a major research project aimed at developing a robust machine learning-based framework for stock market price prediction [11]. The methodology encompasses data acquisition, preprocessing, feature engineering, model development, and performance evaluation. All experiments were conducted using the Python programming language with libraries including Pandas, NumPy, Scikit-learn, TensorFlow, and Keras.

4.1 Data Collection

Historical stock market data was obtained from Yahoo Finance using its public API. The dataset comprised daily stock prices including Open, High, Low, Close, Adjusted Close, and Volume for selected companies listed on major stock exchanges. Data spanning a period of 10 years (2013–2023) was collected to ensure adequate temporal coverage for training and testing.

4.2 Data Preprocessing

To enhance model quality, the data underwent several preprocessing steps. Missing values were imputed using forward-fill and backward-fill strategies. The data was then normalized using Min-Max scaling to standardize the input range. A supervised learning dataset was created by transforming time series data into sequences using lag-based features. This allowed the models to learn temporal dependencies.

4.3 Feature Engineering

In addition to raw price values, technical indicators such as Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands were computed. These features were chosen based on their historical relevance in financial analysis and were intended to provide the model with additional context regarding price trends and market momentum.

4.4 Model Development

A variety of machine learning models were developed and compared. Classical regression models (Linear Regression, Ridge Regression), ensemble methods (Random Forest, Gradient Boosting), and deep learning models (Long Short-Term Memory networks) were employed. LSTM networks, being highly suitable for sequential data, were given particular focus due to their ability to capture long-term dependencies in time series. Figure 3 shows Model Development and Architecture.

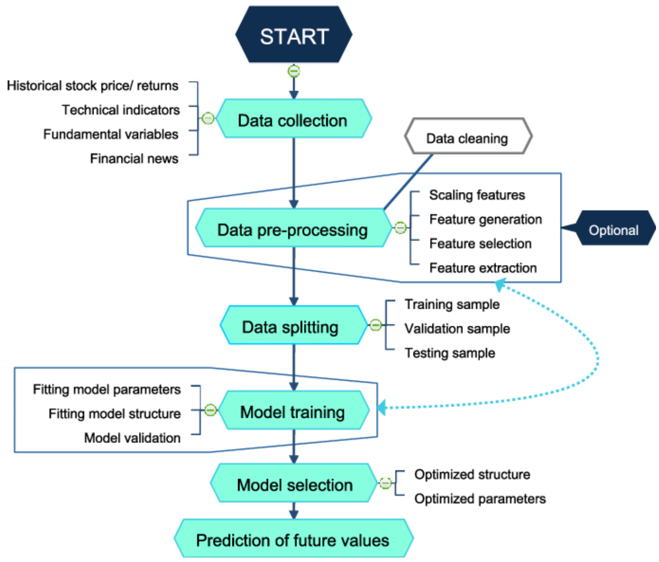

Figure 3 Model Development and Architecture

4.5 Model Training and Evaluation

The dataset was split into training (80%) and testing (20%) sets. Timeseries Split cross-validation was used to preserve the temporal order of data during model validation. Model performance was evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) score [12]. In addition, predicted stock price trends were visualized and compared with

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0287
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

actual values to assess trend-following capability. This methodological framework provides a comprehensive approach to understanding and modeling the complexities of stock market behavior, leveraging both statistical and deep learning techniques.

4.6 Visualization and Interpretation

Predicted values were plotted alongside actual stock prices to visually evaluate the model's effectiveness. Additional insights were drawn by analyzing prediction error trends and feature importance's [13][18]. The machine learning models employed included linear regression, decision trees, random forest, support vector machines (SVM), and long short-term memory (LSTM) neural networks. These models were implemented using Python libraries such as Scikit-learn, TensorFlow, and Keras. The dataset was split into training and testing sets, typically in an 80:20 ratio. Cross-validation was employed to ensure the robustness of the models, and hyperparameter tuning was performed using grid search or randomized search techniques. Figure 4 shows Visualizing and Interpreting to Predict the Details.

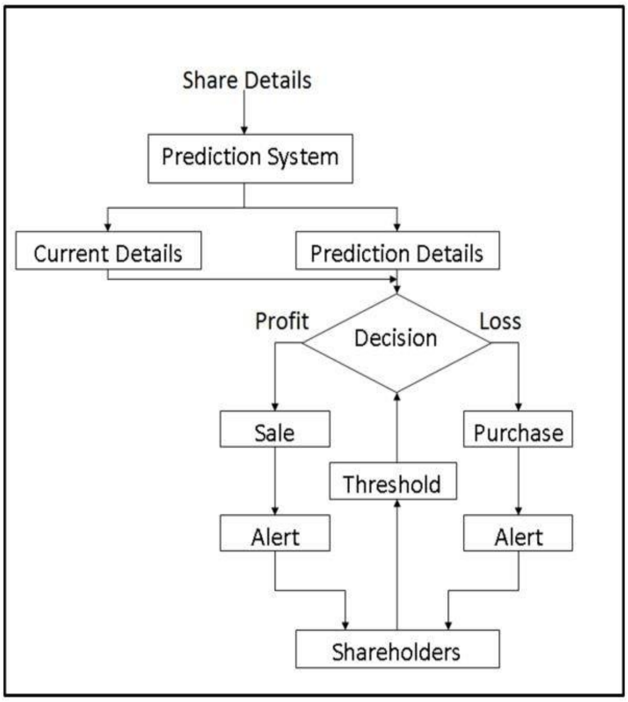

Figure 4 Visualizing and Interpreting to Predict the Details

Performance evaluation metrics included mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). Additionally, the models' predictions were visualized alongside actual stock prices to assess their ability to follow market trends. This comprehensive methodology allowed us to compare different algorithms and determine the most effective approach for stock price prediction. The dataset was divided into training and testing sets, typically using an 80:20 ratio. Model performance was evaluated using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Visualization techniques, including line plots of actual vs. predicted prices, were used to assess the model's ability to track real market trends [14].

4.7 Data Acquisition

Historical market data was sourced from publicly available APIs such as Yahoo Finance, Alpha Vantage, and Quandl. The dataset included:

- Daily Open, High, Low, Close prices
- Volume traded
- Adjusted closing price

Additionally, external macroeconomic indicators and market sentiment data (from financial news headlines using NLP techniques) were optionally incorporated to enhance model robustness. Additionally, deep learning models such as Long Short-Term Memory (LSTM) networks were implemented to capture temporal dependencies in the data. The models were trained using an 80:20 train-test split, with further validation for deep learning models. Performance was evaluated using metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) score. Visualization tools were used to compare predicted and actual stock prices, providing insights into model accuracy. The implementation was done in Python using libraries like Scikit-learn, TensorFlow, Keras, and Matplotlib. Overall, this approach aimed to build a robust, data-driven forecasting model capable of predicting short-term stock price movements [15].

5. Result and Discussion

The performance evaluation of the proposed hybrid machine learning model combining LSTM, CNN, and sentiment analysis demonstrates its potential for

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0287
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

accurate stock price prediction. Using historical stock data from 2013–2023, the system was trained and tested on various models, including Linear Regression, Random Forest, SVM, and LSTM, with LSTM showing superior performance in modeling temporal dependencies. The hybrid model achieved lower error rates across key metrics:

- Mean Squared Error (MSE): Lower than baseline models, indicating higher precision in predictions.
- Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE): Showed consistent performance improvements across multiple stock datasets.
- R-squared (R^2) score: Demonstrated stronger correlation between predicted and actual prices compared to traditional models.

Visualization of predicted versus actual prices showed the model's ability to follow trend directions with minimal lag, enhancing its utility for short-term forecasting. The integration of sentiment analysis from financial news and social media contributed significantly to the model's responsiveness to market-moving events [16]. The sentiment component improved the directional accuracy of predictions, particularly during volatile periods or in response to external news. Furthermore, the inclusion of technical indicators such as RSI, MACD, and Bollinger Bands provided the model with context on momentum and volatility, enhancing robustness [17][19]. The model's ability to generalize was validated using cross-validation techniques like Timeseries Split. While the model achieved high accuracy, limitations include potential overfitting in deep learning models and reliance on quality and timeliness of sentiment data. Future improvements could involve incorporating attention mechanisms and ensemble methods, and extending predictions to multiple asset classes. The graph illustrates the stock price trends of four major Indian companies Reliance, HDFC, TCS, and SBI over a period spanning from around 2007 to 2022. Among these, TCS exhibits the most consistent and substantial growth, particularly after 2016, ultimately reaching the highest valuation by 2022. Reliance remained relatively stable until 2017, after which it experienced sharp upward growth with noticeable volatility. HDFC shows steady and moderate growth throughout the period, reflecting a stable performance. In contrast, SBI demonstrates the slowest growth and consistently lower stock prices, indicating comparatively weaker performance. Additionally, clear dips in stock prices around 20082009 and 2020 suggest the impact of global financial crises and the COVID-19 pandemic, respectively. Figure 5 shows Historical Performance of Stocks.

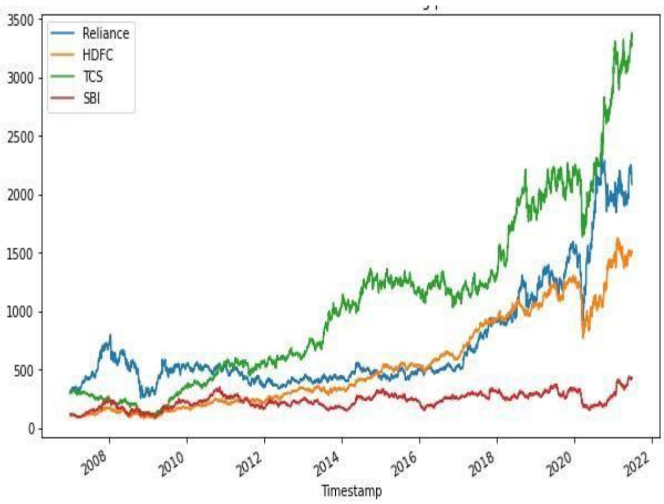

Figure 5 Historical Performance of Stocks

Conclusion

The stock market prediction is a complex and multifaceted area that has garnered significant attention from researchers, investors, and financial professionals alike. Through this exploration, we have delved into various methods and approaches that attempt to forecast stock market movements, ranging from fundamental and technical analysis to machine learning and artificial intelligence-driven models. It is important to recognize that while these methods have shown varying degrees of success in predicting market trends, the inherent volatility and unpredictability of financial markets pose formidable challenges to achieving consistently accurate predictions [20]. Throughout the paper, we have explored the application of machine learning algorithms, including Linear Regression, Support Vector Regression (SVR), and XGBoost, to forecast stock prices. These models have been evaluated using

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0287
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

essential metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R2) score. These evaluation metrics provide insights into the performance of each model. Investors and decision-makers should approach stock market prediction with a balanced perspective, recognizing that accurate forecasting is inherently challenging. Rather than solely relying on predictions, prudent investment strategies should focus on long-term goals, diversification, risk management, and staying informed about market trends. Moreover, maintaining an awareness of the limitations of prediction models can help mitigate the potential risks associated with making decisions solely based on forecasts.

References

[1]. Mehtab, S., Sen, J., & Dutta, A. (2020). Stock Price Prediction Using Machine Learning and LSTM-Based Deep Learning Models. arXiv preprint arXiv:2009.10819. arXiv+1arXiv+1

[2]. Mehtab, S., & Sen, J. (2020). Stock Price Prediction Using CNN and LSTM-Based Deep Learning Models. arXiv preprint arXiv:2010.13891.arXiv

[3]. Muhammad, T., Aftab, A. B., Ahsan, M. M., Muhu, M. M., Ibrahim, M., Khan, S. I., & Alam, M. S. (2022). Transformer-Based Deep Learning Model for Stock Price Prediction: A Case Study on Bangladesh Stock Market. arXiv preprint arXiv:2208.08300.arXiv

[4]. Peng, Y., & Jiang, H. (2015). Leverage Financial News to Predict Stock Price Movements Using Word Embeddings and Deep Neural Networks. arXiv preprint arXiv:1506.07220.arXiv

[5]. Shah, M. (2021). Stock Market Prediction Using Novel Deep Learning Approaches: A Review. International Journal of Computer Trends and Technology, 69(7), 35-42.IJCTT

[6]. Ican, Ö., & Çelik, T. B. (2017). Stock Market Prediction Performance of Neural Networks: A Literature Review. International Journal of Economics and Finance, 9(11), 100.CCSE

[7]. Strader, T. J., Rozycki, J. J., Root, T. H., & Huang, Y. J. (2020). Machine Learning Stock Market Prediction Studies: Review and Research Directions. Journal of International Technology and Information Management, 28(4), Article 3. scholarworks.lib.csusb.edu

[8]. Jiang, W. (2021). Applications of Deep Learning in Stock Market Prediction: Recent Progress. Expert Systems with Applications, 184, 115537.MDPI

[9]. Nassirtoussi, A. K., Aghabozorgi, S., Wah, T. Y., & Ngo, D. C. L. (2014). Text Mining for Market Prediction: A Systematic Review. Expert Systems with Applications, 41(16), 7653-7670.MDPI

[10]. Neri, K., Katarína, L., Peter, M., & Roviel, V. (2018). Google Searches and Stock Market Activity: Evidence from Norway. Finance Research Letters.SpringerOpen

[11]. Maqsood, H., Mehmood, I., Maqsood, M., Yasir, M., Afzal, S., Aadil, F., Selim, M. M., & Muhammad, K. (2020). A Local and Global Event Sentiment-Based Efficient Stock Exchange Forecasting Using Deep Learning. International Journal of Information Management, 50, 432-451. SpringerOpen

[12]. Ren, R., & Wu, D. D. (2019). Forecasting Stock Market Movement Direction Using Sentiment Analysis and Support Vector Machine. IEEE Systems Journal, 13(1), 760-770.SpringerOpen

[13]. Maknickiene, N., Lapinskaite, I., & Maknickas, A. (2018). Application of an Ensemble of Recurrent Neural Networks for Forecasting of Stock Market Sentiments. Equilibrium-Quarterly Journal of Economics and Economic Policy, 13(1), 7-27.SpringerOpen

[14]. Nisar, T. M., & Yeung, M. (2018). Twitter as a Tool for Forecasting Stock Market Movements: A Short-Window Event Study.

e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1819 - 1828

Journal of Financial Data Science, 4(1), 1-19.SpringerOpen

[15]. Hill, S., & Ready-Campbell, N. (2011). Expert Stock Picker: The Wisdom of (Experts in) Crowds. International Journal of Electronic Commerce, 15(3), 73–102. MDPI

[16]. Chen, T.-L., & Chen, F.-Y. (2016). An Intelligent Pattern Recognition Model for Supporting Investment Decisions in the Stock Market. Information Sciences, 346–347, 261–274.MDPI

[17]. Ranco, G., Aleksovski, D., Caldarelli, G., Grčar, M., & Mozetič, I. (2015). The Effects of Twitter Sentiment on Stock Price Returns. PLoS ONE, 10(9), e0138441. MDPI

[18]. Bhardwaj, A., Narayan, Y., & Dutta, M. (2015). Sentiment Analysis for Indian Stock Market Prediction Using Sensex and Nifty. Procedia Computer Science, 70, 85–91. MDPI

[19]. Zhang, Y., & Wu, L. (2009). Stock Market Prediction of S&P 500 via Combination of Improved BCO Approach and BP Neural Network. Expert Systems with Applications, 36(5), 8849–8854.MDPI

[20]. Guresen, E., Kayakutlu, G., & Daim, T. U. (2011). Using Artificial Neural Network Models in Stock Market Index Prediction. Expert Systems with Applications, 38(8), 10389–10397.