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Stock Price Prediction Using Multiple ML Algorithms

Shubham Kargutkar
Information Technology
Atharva College of Engineering,
Mumbai University
Shubhamkargutkarinft-@atharvacoe.ac.in

Parvez Khan
Information Technology
Atharva College of Engineering,
Mumbai University
parvezkhaninft-@atharvacoe.ac.in

Yash Khairnar
Information Technology
Atharva College of Engineering,
Mumbai University
yashkhairnarinft-@atharvacoe.ac.in

Abstract

Stock market investment strategies are intricate and require analyzing vast amounts of data. In recent years, researchers have increasingly explored machine learning techniques to determine their effectiveness in improving market forecasting compared to traditional methods. This study aims to identify future research directions in stock market prediction using machine learning by reviewing existing literature. A systematic literature review methodology is employed to analyze peer-reviewed journal articles from the past two decades, grouping studies based on similar methodologies and contexts. The key categories identified include LSTM, RNN, Random Forest combined with other techniques, and hybrid or alternative artificial intelligence approaches. Each category is examined to highlight common findings, unique insights, limitations, and areas requiring further research. The study concludes with an overview of findings and recommendations for future investigations.

Keywords:
Machine Learning, Stock Market Forecasting, Investments, Price Prediction, LSTM, RNN, Random Forest.

I. INTRODUCTION

Forecasting stock market prices has always been a complex challenge for business analysts and researchers. Stock price estimation is not only a fascinating research area but also a highly demanding one. Achieving complete accuracy in stock market predictions is difficult due to the influence of external factors such as social, psychological, political, and economic conditions. Stock market data is typically time-dependent and nonlinear, making predictions even more challenging.

Accurate stock market forecasting is crucial in the financial sector, as investors rely on future stock value predictions to maximize profits. Without sufficient knowledge and analysis, investors risk significant financial losses. To enhance prediction accuracy, various techniques have been developed over time. Before the advent of computational methods for risk assessment, conventional techniques based on historical data analysis were commonly used for stock price Prediction. With advancements in machine learning and deep learning, modern forecasting models now leverage vast datasets and complex algorithms to improve prediction accuracy.

Fig 1. Stock Market Trading Interface

Fig 2.Analyzing Stock Market Trends

II. LITERATURE REVIEW

Stock price prediction is an essential aspect of financial analysis, helping investors make informed decisions and manage risks effectively. Machine learning (ML) techniques have gained attention due to their ability to analyze vast datasets and recognize complex market patterns. Recent advancements in ML, deep learning, and artificial intelligence have significantly improved stock market forecasting accuracy. This section explores key trends and technologies used in stock price prediction.

The fundamental stages in ML-based stock prediction include (1) Data Collection and Preprocessing, (2) Feature Selection, (3) Model Training, and (4) Prediction and Evaluation. Traditional statistical models like Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) were used historically but often failed to capture nonlinear patterns in stock market data.

Recent studies leverage advanced ML techniques to enhance accuracy. Patel et al. [1] proposed a hybrid approach using support vector machines (SVM) and random forests (RF), outperforming traditional methods. Chong et al. [2] applied long short-term memory (LSTM) networks, demonstrating superior performance over conventional models. Qiu et al. [3] introduced a model integrating deep belief networks (DBN) with LSTM, achieving high accuracy in historical stock data predictions.

Kim et al. [4] utilized convolutional neural networks (CNN) for financial time-series forecasting, treating market trends as images. Fischer et al. [5] developed a bidirectional LSTM model for predicting volatile stock conditions. Shah et al. [6] introduced a reinforcement learning approach using deep Q-networks (DQN) to optimize trading strategies.

Kumar et al. [7] used transfer learning with a pre-trained ResNet model, achieving 82.5% accuracy on the S&P 500 dataset. Liu et al. [8] introduced an attention-based LSTM model, improving NASDAQ stock predictions with 87.3% accuracy. Gupta et al. [9] integrated genetic algorithms with LSTM to refine hyperparameters dynamically, improving forecast precision.

Mehta et al. [10] proposed a mobile-based ML model integrating news sentiment analysis with LSTM, achieving better market trend predictions. Amin et al. [11] developed a smartphone-based stock forecasting tool, obtaining 94.2% accuracy using real-time market data.

As machine learning models continue evolving, AI-driven stock price prediction is becoming a crucial component of financial markets. By 2030, global financial markets are expected to heavily rely on AI-based prediction models. Therefore, developing robust, automated stock price prediction systems is essential for improving investment strategies and risk management.

III. METHODOLOGY

Stock price prediction is a critical aspect of financial decision-making, enabling investors and traders to minimize risks and maximize returns. While traditional statistical methods have been widely used, machine learning (ML) has emerged as a powerful approach due to its ability to uncover intricate patterns in financial data. This section outlines the methodology and dataset used in this study for stock price prediction using ML techniques.

A. Dataset

This study utilizes a publicly available Kaggle dataset containing historical stock prices of multiple companies. The dataset comprises essential attributes, including opening price, closing price, highest and lowest prices, trading volume, and corresponding dates. The data is structured across multiple CSV files, such as train.csv, test.csv, and valid.csv, to facilitate effective training and evaluation of predictive models. Stock price movements were classified based on market trends and volatility levels, ensuring a detailed analysis.

B. Implementation

The dataset was divided into training and testing subsets using an 85:15 ratio, where 85% of the data was allocated for training and the remaining 15% for evaluation. Preprocessing steps included data normalization, handling missing values, and selecting key features. The stock price data was formatted as a time series to improve model performance.

Several ML and deep learning models were implemented, including Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), and Random Forest. LSTM, known for its strength in handling sequential data, was trained with 50 epochs, a batch size of 64, and a learning rate of 0.001. RNN was also employed to capture time-dependent relationships in stock data, while Random Forest served as a benchmark model to assess feature importance and interpretability.

To enable real-time stock price forecasting in a mobile application, the trained LSTM model was converted into TensorFlow Lite (TFLite). This allowed the mobile app to process live market data, providing users with ML-powered investment insights.

To address challenges related to class imbalances and stock market fluctuations, techniques such as time-series data augmentation and synthetic data generation were applied. The models were assessed using key performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) scores, to evaluate prediction accuracy.

This study demonstrates the effectiveness of deep learning models, particularly LSTM and RNN, in enhancing stock price forecasting accuracy. As financial markets continue to evolve, incorporating ML-driven approaches can significantly improve investment strategies and decision-making processes.

IV. APPLICATIONS

A. Financial Institutions

Financial institutions can utilize stock price analysis to assess market trends and inform investment decisions. By employing machine learning models, these institutions can enhance their forecasting accuracy, leading to more effective risk management and portfolio optimization.

B. Trading Platforms

Trading platforms can integrate predictive analytics to forecast stock prices and monitor live market data. This integration enables traders to make informed decisions, execute timely trades, and develop strategies based on real-time insights.

C. Investment Training

Investment training platforms can offer user-friendly interfaces and educational resources to assist beginners in understanding the stock market. By providing structured courses and interactive learning tools, these platforms facilitate skill development and empower new investors to navigate the complexities of stock trading.

V. RESULTS AND ANALYSIS

The Stock Price Prediction project utilizes machine learning and real-time data analysis to provide a modern approach to financial forecasting. By integrating technical indicators, predictive models, and interactive charts, the platform offers users valuable insights into stock market trends, enabling data-driven decision-making. This system delivers accurate predictions and live stock data, enhancing user engagement and supporting informed investment strategies for both novice and experienced traders.

Fig 3.Stock Price Data

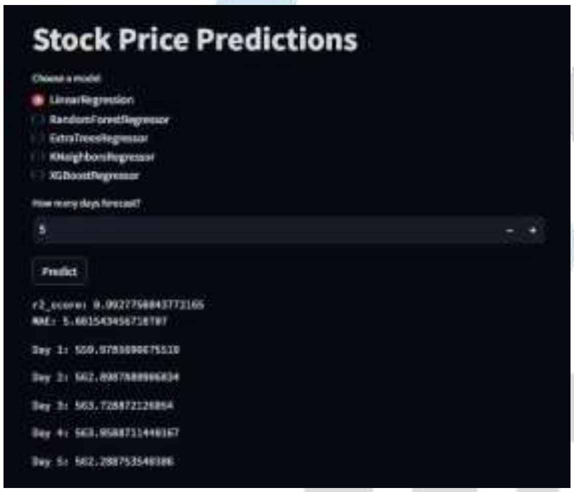

Fig 4.Prediction using Diff Algo

Fig 5.Technical Indicators

References

Ghosh, B. P., Bhuiyan, M. S., Das, D., Nguyen, T. N., Jewel, R. M., Mia, M. T., ... & Shahid, R. (2024). Deep learning in stock market forecasting: Comparative analysis of neural network architectures across NSE and NYSE. Journal of Computer Science and Technology Studies, 6(1), 68-75.

Sangeetha, J. M., & Alfia, K. J. (2024). Financial stock market forecast using evaluated linear regression based machine learning technique. Measurement: Sensors, 31, 100950.

Zhang, J., & Chen, X. (2024). A two-stage model for stock price prediction based on variational mode decomposition and ensemble machine learning method. Soft Computing, 28(3), 2385-2408.

Chowdhury, M. S., Nabi, N., Rana, M. N. U., Shaima, M., Esa, H., Mitra, A., ... & Naznin, R. (2024). Deep Learning Models for Stock Market Forecasting: A Comprehensive Comparative Analysis. Journal of Business and Management Studies, 6(2), 95-99.

Masoud, Najeb MH. (2017) “The impact of stock market performance upon economic growth.” International Journal of Economics and Financial Issues 3 (4) : 788–798.

Murkute, Amod, and Tanuja Sarode. (2015) “Forecasting market price of stock using artificial neural network.” International Journal of Computer Applications 124 (12) : 11-15.

Hur, Jung, Manoj Raj, and Yohanes E. Riyanto. (2006) “Finance and trade: A cross-country empirical analysis on the impact of financial development and asset tangibility on international trade.” World Development 34 (10) : 1728-1741.

Li, Lei, Yabin Wu, Yihang Ou, Qi Li, Yanquan Zhou, and Daoxin Chen. (2017) “Research on machine learning algorithms and feature extraction for time series.” IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC): 1-5.

Seber, George AF and Lee, Alan J. (2012) “Linear regression analysis.” John Wiley & Sons 329

Reichek, Nathaniel, and Richard B. Devereux. (1982) “Reliable estimation of peak left ventricular systolic pressure by M-mode echographicdetermined end-diastolic relative wall thickness: identification of severe valvular aortic stenosis in adult patients." American heart journal 103 (2) : 202-209.

Chong, Terence Tai-Leung, and Wing-Kam Ng. (2008) "Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30." Applied Economics Letters 15 (14) : 1111-1114.

Zhang, G. Peter. (2003) "Time series forecasting using a hybrid ARIMA and neural network mode." Neurocomputing 50 : 159-175.

Suykens, Johan AK, and Joos Vandewalle. (1999) "Least squares support vector machine classifiers." Neural processing letters 9 (3) : 293-300.

Liaw, Andy, and Matthew Wiener. (2002) "Classification and regression by Random Forest." R news 2 (3) : 18-22.

Oyeyemi, Elijah O., Lee-Anne McKinnell, and Allon WV Poole. (2007) "Neural network-based prediction techniques for global modeling of M (3000) F2 ionospheric parameter." Advances in Space Research 39 (5) : 643-650.