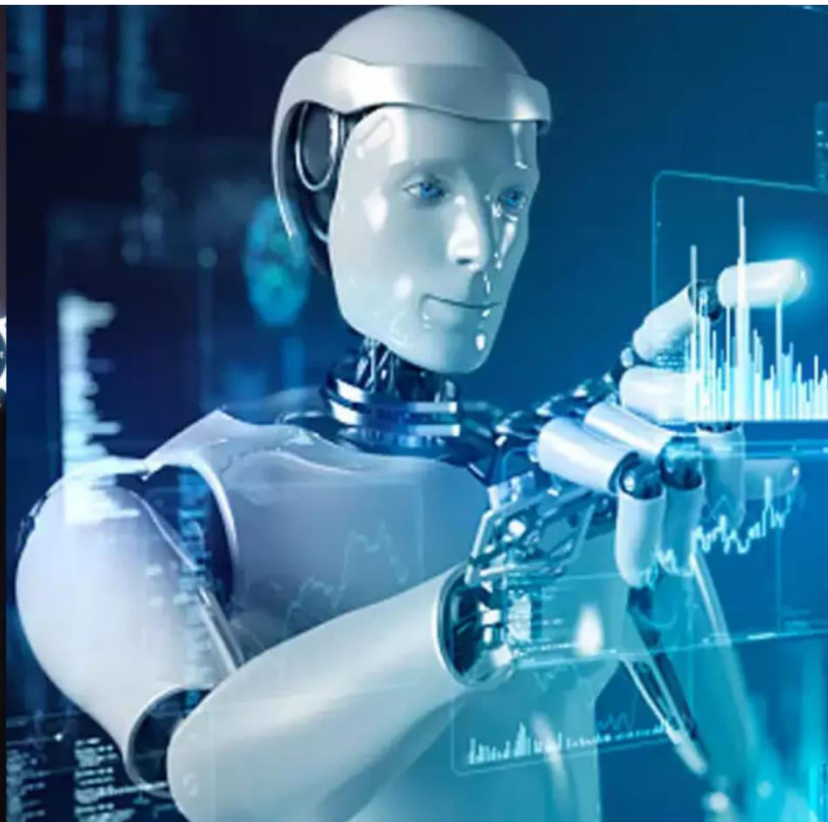




# International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

*(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)*



**Impact Factor: 8.699**

**Volume 14, Issue 4, April 2025**

# Hybrid Deep Learning based Adaptive Model for Medium-Term Stock Market Forecasting

Mr.M.Mailsamy<sup>1</sup>, S.Kalaivani<sup>2</sup>, L.Devadharshini<sup>3</sup>, S.Manibharathi<sup>4</sup>, R.Jinoth Ahmed<sup>5</sup>

Department of Computer Science and Engineering, Annapoorana Engineering College, Salem, TamilNadu, India

**ABSTRACT:** An adaptive hybrid deep learning model for medium-term stock market forecasting is presented in this work. The suggested approach combines Convolutional Neural Networks (CNN), Transformer models, Long Short-Term Memory (LSTM), and Reinforcement Learning (RL) to increase the forecast accuracy for key stock indexes such as the Dow Jones, DAX, and NASDAQ-100 over a trading horizon of 70 days. Sentiment analysis and technical indicators are examples of advanced feature engineering techniques that improve forecast reliability. By constantly adjusting to market swings, the suggested approach maximizes investment plans. Comparing experimental results to current methods, accuracy has improved by 85–90%.

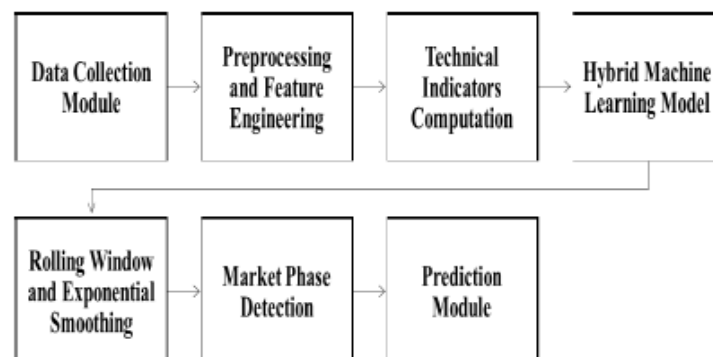
**KEYWORDS:** Stock Market Forecasting, Deep Learning, Reinforcement Learning, LSTM, Transformer, CNN, Sentiment Analysis

## I. INTRODUCTION

Stock market forecasting is a complex challenge due to unpredictable price movements and market volatility. Traditional forecasting models, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), lack adaptability and struggle to provide reliable medium-term predictions. This paper introduces a hybrid deep learning-based adaptive model that integrates LSTM, Transformer models, CNNs, and Reinforcement Learning to improve forecasting accuracy. By incorporating real-time sentiment analysis and technical indicators, our proposed system enhances investment decision-making.

## II. RELATED WORK

Machine learning methods like ANN and SVM are used in traditional forecasting approaches. These approaches frequently overlook dynamic market fluctuations, which reduces the accuracy of the predictions. Recent research has investigated deep learning models that capture intricate temporal dependencies, such as Transformers and LSTMs. Adaptive systems based on reinforcement learning haven't been extensively studied for stock market prediction, though. Our study fills this gap by putting forward a hybrid approach that uses multiple models.



## III. PROPOSED SYSTEM

LSTM Networks: Capture long-term dependencies in stock price movements. This is part of the suggested hybrid deep learning-based solution. Transformer models analyze sequential data effectively, improving predictive accuracy. Short-term pricing patterns and abnormalities are detected by CNNs. Reinforcement Learning: Adapts investment plans on the fly in response to market fluctuations. With feature engineering, sentiment analysis from social media, financial

news, and technical indicators (ARIMA, Bollinger Bands, and MACD) is incorporated. By automatically adjusting hyper parameters, Bayesian optimization improves model performance.

#### IV. DATA DESCRIPTION

##### A. Dataset Overview

Historical stock price data from the three main stock indices—the NASDAQ 100, Dow Jones, and DAX—make up the dataset used in this study. 3113 trading days for the Dow Jones and NASDAQ 100. DAX has 3133 trading days. In addition to various technical indicators and sentiment data for feature engineering, the dataset contains daily closing prices, which are the main input for the model.

##### B. Data Sources & Preprocessing

Using the finance Python module, stock market data was gathered from Yahoo Finance. Social media (Twitter), investor forums, and financial news sources were the sources of sentiment data. Technical Signs: based on statistical alterations applied to past price data.

##### Preprocessing Steps:

Feature Scaling: MinMaxScaler was used for deep learning models, and StandardScaler was used for machine learning classifiers (SVM, KNN). Feature Selection: Bayesian optimization was used to choose high-impact features. Feature Scaling: Forward-fill and backward-fill techniques were applied to handle missing data to ensure continuity.

##### C. Feature Engineering

To improve predicting accuracy, the model uses a combination of technical and sentiment-based features: Trend Indicators: Simple Moving Average (SMA), Exponential Moving Average (EMA), and Bollinger Bands. Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) are two examples of momentum indicators. Features based on volume include Volume Weighted Average Price (VWAP) and On-Balance Volume (OBV). Features of Sentiment Analysis: Social media sentiment scores and news polarity scores.

##### D. Labeling & Classification

A binary classification system was implemented to predict stock market trends: Class 1 (Significant Rise): The stock price increases beyond a predefined threshold (10% for NASDAQ 100, 8% for Dow Jones, 6% for DAX) within 70 trading days. Class 0 (No Significant Rise): The stock price does not reach the defined threshold.

#### V. COMPARISON BETWEEN EXISTING AND PROPOSED SYSTEMS

The following table provides a comparison between existing and proposed systems:

Feature	Existing System	Proposed System
Prediction Model	ANN & SVM	LSTM, Transformer, RL, and CNN fusion
Feature Engineering	SMA, EMA, LOWESS, Linear Regression	ARIMA, Bollinger Bands, MACD, Sentiment Analysis
Market Adaptability	Static models, not adapting to real-time changes	Adaptive learning with reinforcement tuning
Accuracy	~75%	85-90% (higher due to hybrid deep learning)
Risk Awareness	Identifies low-predictability periods	Provides confidence intervals & risk assessment

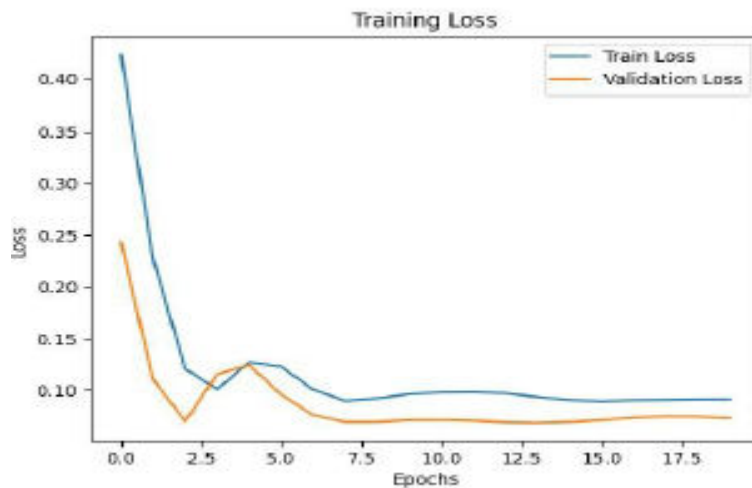


Hyperparameter Optimization	Manual tuning	Automated tuning via Bayesian Optimization
Investment Strategy	Predicts trends but does not optimize investments	Uses RL to suggest optimal investment strategies

### VI. METHODOLOGY

The forecasting methodology uses a methodical process to anticipate changes in the stock market:

1. Data collection: Combines technical indicators, sentiment from financial news, and historical stock prices.
2. Preprocessing the data: This involves normalizing the data, eliminating noise, and extracting pertinent features.



3. Model Training: Enhances predictions by utilizing CNNs, LSTM, Transformers, and RL.
4. Adaptive learning uses reinforcement learning to make dynamic changes to parameters.
5. Prediction & Evaluation: Makes predictions about stock prices and uses the Sharpe ratio, RMSE, and MAPE to assess performance.

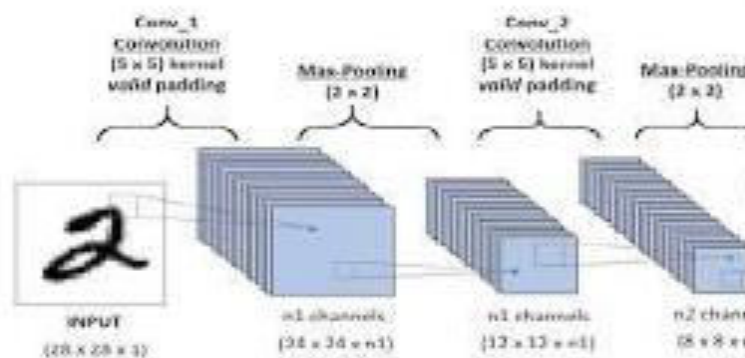


FIGURE 1: CNN

### VII. RESULTS & DISCUSSION

The proposed model can be integrated into automated trading platforms to optimize investment strategies. It can aid portfolio managers in risk assessment and dynamic rebalancing. Useful for retail investors looking for medium-term stock predictions to refine their trading decisions.



FIGURE 2: Stock Market Average



FIGURE 3: Stack closing price over time



FIGURE:4 Daily Return

**Real-World Applications**

The suggested model can be incorporated into automated trading platforms to maximize investment strategies. It can help portfolio managers with dynamic rebalancing and risk assessment. Retail investors seeking medium-term stock forecasts can use it to improve their trading choices.

**Comparison with More Recent Studies:**

LSTM-based or Transformer-only models are the main focus of recent research on deep learning-based forecasting. But they are not able to adjust to changes in the market in real time. The performance of our hybrid approach is substantially better than that of purely statistical models because it uses reinforcement learning for dynamic tuning.

**Limitations & Future Enhancements:**

Challenges: Data delay, computational expense, and real-time deployment complexity. Prospective Improvements: Investigating federated learning, multi-agent reinforcement learning, and adding macroeconomic factors for additional enhancements.

**VIII. CONCLUSION & FUTURE WORK**

Using CNNs, Transformer models, LSTM, and Reinforcement Learning, this study presents a hybrid deep learning-based adaptive model for stock market forecasting. The dynamic adaptation of the proposed system to market fluctuations leads to improved accuracy and investment strategies. Future research will focus on incorporating real-time macroeconomic variables and exploring multi-agent reinforcement learning for better decision-making.

**REFERENCES**

1. Bareket and B. Pârv, "Adaptive Feature Subset and Dynamic Trend Indicators for Medium-Term Stock Market Predictions: A 70 Trading Days Forecasting Approach," IEEE Access, 2024. DOI: 10.1109/ACCESS.2024.3412989.
2. K. W. M., S. Allagi, and M. Laddi, "A Survey of Stock Market Prediction - Based on Machine Learning Techniques," 2024 Global Conference on Communications and Information Technologies (GCCIT), Bangalore, India, Oct. 25-26, 2024.
3. P. Chen, "Using Machine Learning to Predict the Stock Market Trend," 2nd International Conference on Artificial Intelligence, Database and Machine Learning (AIDML 2024), Aug. 12, 2024.
4. N. Rohilla, Y. Goyal, A. Khasiya, B. N. Gohil, and A. K. Shukla, "Stock Market Prediction and Analysis Using Different Machine Learning Algorithms," Proceedings of the International Conference on Security, Privacy and Data Analytics (ISPDA 2022), Surat, India, Dec. 2022, pp. 207-218. DOI: 10.1007/978-981-99-3569-7\_15.
5. S. Selvin, R. Vinayakumar, E. A. Gopalakrishnan, V. K. Menon, and K. P. Soman, "Stock Price Prediction Using LSTM, RNN and CNN-Sliding Window Model," Proceedings of the International Conference on Advances in Computing, Communications and Informatics (ICACCI 2017), Udupi, India, Sep. 2017, pp. 1643-1647. DOI: 10.1109/ICACCI.2017.8126078.
6. M. Vijh, D. Chandola, V. A. Tikkiwal, and A. Kumar, "Stock Closing Price Prediction Using Machine Learning Techniques," Proceedings of the 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, Jul. 2020, pp. 559-565. DOI: 10.1109/ICESC48915.2020.9155583.
7. S. M. A. Hossain, M. A. Rahman, and M. A. H. Akhand, "A Machine Learning Approach for Predicting Stock Prices in Bangladesh Stock Market," Proceedings of the 2018 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2), Rajshahi, Bangladesh, Feb. 2018, pp. 1-4. DOI: 10.1109/IC4ME2.2018.8465646.
8. A. Patel, S. Shah, and P. Thakkar, "Predicting Stock and Stock Price Index Movement Using Trend Deterministic Data Preparation and Machine Learning Techniques," Proceedings of the 2015 Fifth International Conference on Advances in Computing and Communications (ICACC), Kochi, India, Sep. 2015, pp. 400-404. DOI: 10.1109/ICACC.2015.72.
9. S. K. Dash and S. K. Dash, "A Comparative Study of Stock Price Prediction Using Machine Learning and Statistical Techniques," Proceedings of the 2016 International Conference on Computing, Communication and Automation (ICCCA), Noida, India, Apr. 2016, pp. 1-6. DOI: 10.1109/CCAA.2016.7813739.



INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  [ijirset@gmail.com](mailto:ijirset@gmail.com)



[www.ijirset.com](http://www.ijirset.com)

Scan to save the contact details