ARTIFICIAL INTELLIGENCE IN STOCK MARKET PREDICTION: A COMPARATIVE STUDY OF TRADITIONAL MODELS VS. AI MODELS

A PROJECT STUDY SUBMITTED IN PARTIAL FULFILLMENT FOR THE REQUIREMENT OF THE POST-GRADUATE DIPLOMA IN MANAGEMENT (2024–26)

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INTRODUCTION

One of the most vital parts of any economy is the stock market, which acts as a conduit for saving money and directing it towards profitable ventures. For traders, investors, and politicians, forecasting changes in stock prices has long been a major concern. However, the stock market is marked by uncertainty and volatility, which are impacted by geopolitical developments, firm-specific factors, investor behaviour patterns, and macroeconomic variables.
A number of conventional models have been used over time to forecast the performance of the stock market. Financial forecasting has a solid basis thanks to models like the Capital Asset Pricing Model (CAPM) (Sharpe, 1964), the Efficient Market Hypothesis (EMH) (Fama, 1970), and time-series forecasting models like ARIMA (Box & Jenkins, 1976). The statistical presumptions of linearity, stationarity, and rational market behaviour are the foundation of these models. Although helpful, they frequently fall short in capturing the intricacies and nonlinear trends of actual stock markets.

The application of machine learning (ML) and artificial intelligence (AI) to stock market prediction has grown significantly during the last 20 years. AI models that have demonstrated significant success in capturing nonlinear dependencies, learning from large datasets, and adapting to dynamic settings include Random Forests (Breiman, 2001), Support Vector Machines, XGBoost, and Deep Learning frameworks like Long Short-Term Memory (LSTM) neural networks. For example, Patel et al. (2015) showed that ensemble machine learning models offer higher forecasting accuracy than traditional statistical models, while Fischer and Krauss (2018) discovered that LSTM networks perform better than logistic regression in predicting the S&P 500.

Even with these developments, there is still a lack of systematic comparison between contemporary AI-based financial models and classical models. Although AI seems promising, problems including interpretability, data overfitting, and the "black box" problem make it difficult for professional finance to use it (Guidotti et al., 2018). With an emphasis on predicted accuracy, dependability, and practical ramifications, this work attempts to perform a comparison analysis between the two paradigms.

In addition to comparing the effectiveness of AI and conventional models, this study will provide insight into how AI might change algorithmic trading, portfolio management, and investing strategies.

PROBLEM STATEMENT

Because of the market's volatility, nonlinearity, and susceptibility to world events, stock price prediction is intrinsically challenging. Although they have been around for a while, traditional models like CAPM and ARIMA have intrinsic drawbacks such the assumptions of linearity, stationarity, and rational expectations. When it comes to high-frequency trading or unstructured data like sentiment and news, these algorithms frequently fall short.
New opportunities have been made possible by artificial intelligence (AI). AI algorithms like Random Forests and LSTM networks can uncover hidden patterns by analysing vast amounts of structured and unstructured data. Although a number of studies emphasise AI's advantages, others warn against relying too much on it because of interpretability problems, moral dilemmas, and inconsistent results across datasets.
Therefore, the challenge is to methodically assess if AI-based models actually perform better than traditional models in a consistent and trustworthy way, as well as what market circumstances make this advantage significant. By doing a comparative analysis on Indian stock market data, our study fills this gap.

OBJECTIVES OF THE STUDY

1. To analyze the performance of traditional models such as CAPM, ARIMA, and Moving Average in stock market forecasting.
2. To apply AI-based models including Random Forest, XGBoost, and LSTM neural networks on the same dataset.
3. To compare the predictive accuracy of traditional and AI-based models using statistical error measures like RMSE, MAPE, and directional accuracy.
4. To evaluate the impact of incorporating behavioral and sentiment data into AI models for improving predictive performance.
5. To investigate interpretability challenges and ethical issues associated with AI in finance.
6. To derive practical implications for investors, traders, and financial institutions regarding the adoption of AI-driven forecasting models.

HYPOTHESIS

H0-1: There is no significant difference in predictive accuracy between traditional and AI-based models.

H0-2: AI-based models do not consistently outperform traditional forecasting models.

H1-1: AI-based models provide significantly superior predictive accuracy compared to traditional models.

REVIEW OF LITERATURE

Predicting the stock market has been extensively researched using both conventional and contemporary methods. The theoretical foundation for connecting risk and returns was developed by the Capital Asset Pricing Model (CAPM) (Sharpe, 1964) and the Efficient Market Hypothesis (Fama, 1970). However, their presumptions of linearity and rational behaviour left substantial gaps in real-world predictions. Although they struggled with market volatility, time-series models like ARIMA (Box & Jenkins, 1976) tried to capture previous price trends. By highlighting the shortcomings of linear models and the necessity of investigating alternatives, these classic works provide as inspiration for my research.

Subsequent studies that discovered trends in stock returns put the EMH to the test. Momentum techniques were proved by Jegadeesh and Titman (1993), indicating predictability in returns. Neural networks were first used in finance by White (1988), and Zhang (2003) shown that hybrid ARIMA-ANN models perform better than pure statistical ones. Because they show that markets are not totally efficient and that nonlinear approaches can provide better accuracy, these research serve as inspiration for my study.

This field was likewise shaped by the combination of behavioural elements and AI. Patel et al. (2015) shown that ensemble machine learning models performed better in Indian markets than individual approaches, while Bollen et al. (2011) demonstrated that sentiment on social media may forecast market movements. Similarly, Bao et al. (2017) and Chen et al. (2015) showed how deep learning techniques like LSTM are better at capturing sequential

dependencies. These motivate me to improve forecasting capabilities by fusing market data with cutting-edge AI algorithms.

AI's increasing significance is supported by more recent research. Gu, Kelly, and Xiu (2020) successfully used machine learning to asset pricing, whereas Fischer and Krauss (2018) validated LSTM's superior performance on the S&P 500. Meanwhile, Hoseinzade & Haratizadeh (2019) and Guidotti et al. (2018) warned against the dangers of overfitting and AI's black-box characteristics. These motivate me to consider AI's drawbacks and moral dilemmas in financial forecasting in addition to testing its accuracy.

In conclusion, research indicates that AI models continuously outperform traditional models in terms of predicted accuracy, even though the latter offer simplicity. This collection of work motivates me to directly compare traditional and AI models in order to connect theoretical underpinnings with contemporary applications.

RESEARCH METHODOLOGY

The present study is both exploratory and empirical in nature.

Data Collection: Secondary data will be obtained from NSE/BSE databases, Yahoo Finance, and Kaggle datasets. The dataset will cover the period 2015–2024 for the NIFTY50 index and selected large-cap companies across sectors such as banking, IT, and pharmaceuticals.

Models Used:

- Traditional: CAPM, ARIMA, Moving Average.
- AI: Random Forest, XGBoost, LSTM.

Tools & Software:

- Python (Scikit-learn, TensorFlow, Keras) for AI model development.
- MS Excel for preliminary analysis and visualization.

Evaluation Metrics:

- Root Mean Square Error (RMSE).
- Mean Absolute Percentage Error (MAPE).

- Directional Accuracy (upward/downward movement).
- Sharpe Ratio for portfolio backtesting.

Design: Both sets of models will be applied to the same dataset, followed by comparative analysis. Statistical tests will determine the significance of performance differences.

EXPECTED OUTCOME

This study will have important implications for researchers and practitioners in the field of mutual funds. They can develop deeper insights regarding the impact of corporate governance practices on mutual fund performance. After the literature review, it could be said that there is no single element of corporate governance that affects the performance of mutual funds; rather, there are multiple facets of corporate governance that affect the mutual fund performance. Good corporate governance creates investor confidence and goodwill for the company. In fact, various academic and non-academic researchers have proved that good corporate governance enhances firm valuation and boosts up the bottom line for the companies.

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