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Artificial Intelligence (AI) Uses in Stock Market: A Prospect for NEPSE

Abstract:

In this study, the use of AI in stock market forecasting has been analyzed, with special emphasis on the NEPSE. Stock market forecasting continues to be tough because of nonlinearity and volatility; however, AI methods like machine learning and deep learning have proven very promising in improving the accuracy of stock market forecasts. Literature reviews show the potential of AI methods such as LSTM, GRU, CNN, and Graph Neural Network in predicting stock prices. Although the development of AI in developed countries has revolutionized trading, portfolio management, and risk analysis, its implementation in Nepal is still at a very initial stage and has been only used for academic comparison rather than for actual trading purposes. The necessity of implementing AI in decision-making processes has been emphasized here.

Keywords: Artificial intelligence, deep learning, NEPSE, stock market prediction.

Stock Market Prediction

Stock prediction is typically seen as a difficult assignment, due to the non-stationarity and volatility of the stock data. It focuses on projecting the future price movement in a stock. The extreme non-linear, dynamic, complex domain knowledge inherent in the stock market has made it more difficult for investors to make timely investment decisions due to the dynamic stock market price variation and its chaotic behavior (Esfahanipour & Aghamiri 2010; KKnill et al. 2012). In other words, since stock markets possess complex and chaotic features, there is a need for more sophisticated means of analysis than the usual ones.

Stock prices go up and down based on new information that you can't get just by studying the stock market itself. This idea comes from two major financial theories: the Random Walk Model and the Efficient Market Hypothesis (Fama, 1965; Fama et al., 1969; Fama, 1995). But many other researchers have challenged these theories. They have shown that the market can sometimes be predicted using ideas from social science and behavioral finance (Chong et al., 2017; Oliveira et al., 2017; Patel et al., 2015; Weng et al., 2017). The application of Artificial Intelligence (AI) in financial investment has gained attention since the 1990s, driven by technological advancements. Various methods for stock market price prediction have emerged, leading to computational finance, which reduces emotional decision-making, uncovers overlooked patterns, and utilizes real-time information effectively (Ferreira et al., 2021). In conclusion, while conventional models have always been critical of the ability to predict the market, the new approach involving computational finance through artificial intelligence presents a good counter to this challenge.

AI in Stock Market Prediction

For investors, traders, and researchers, stock market prediction is difficult but essential. Numerous approaches have been put out to predict stock prices and beat the market, including statistical, mathematical, and artificial intelligence (AI) methodologies. AI methods have drawn more attention, especially machine learning (ML) and deep learning (DL) ([Lin & Marques, 2024](#)).

Artificial Intelligence is transforming the stock market by enhancing trade execution, portfolio management, and risk assessment. While it empowers investors and boosts market efficiency, it also introduces risks like market volatility and raises ethical and regulatory concerns. A balanced approach, combining AI with human expertise, is crucial for maintaining stable financial markets ([Jyothilinga & Venkatesha, 2025](#)). Recent studies divide stock market analysis methods into two main types: math-based and AI-based. Math-based methods use statistics, while AI-based methods use machine learning (ML) ([Januschowski et al., 2020](#)). It has also been found that most research uses ML techniques to forecast stock market performance ([Kumar et al., 2022](#)). Earlier work has shown that ML is part of AI, and it includes deep learning (DL) as well ([Jakhar & Kaur, 2020](#)). So, the different techniques used to predict stock prices can be grouped into two categories: 1) traditional ML algorithms, and 2) deep learning and neural networks (NN) ([Soni & Tewari, 2022](#)). There are many methods within both groups, and one of the biggest questions today is which of these methods are used most often to predict stock prices ([Li & Bastos, 2020](#)). From an investigation of NASDAQ-100 securities (2020-2025), it is found that the integration of semantic intelligence from LLMs into machine learning is contingent on the predictive approach. Technical forecasting yields the highest returns (approximately 1978%) using only ML-generated information, whereas fundamental approaches require semantic intelligence to be predominant. Entropy-based methods benefit from a combination of both. Thus, while LLMs like ChatGPT-4o can enhance predictive investment strategies, their impact varies significantly based on context ([Cohen et al., 2025](#)).

[Chopra and Sharma \(2021\)](#) demonstrated that artificial intelligence and hybrid neuro models effectively model non-linear stock market dynamics, emphasizing methodology, data preparation, and model selection. They presented a structured taxonomy of current approaches and future research avenues. Similarly, [Das et al. \(2024\)](#) highlighted AI's role in enhancing financial markets, particularly in high-frequency trading, portfolio management, and price forecasting, attributing this to rapid data analysis capabilities. Survey results indicate an increasing reliance on AI/ML solutions in institutions, with algorithmic trading, risk management, and fraud detection as primary applications.

AI Uses in Nepalese Stock Market

[Bajracharya et al. \(2025\)](#) utilizes Graph Neural Networks (GNNs) for predicting stock market performance by representing the finance related data into graph format using the concept of visibility. Experiments carried out on Nepalese Stock Exchange (NEPSE) indicate that Graph Convolutional Networks (GCN) yield better results than Graph Attention Networks (GAT) in terms of learning complex market relationships and long memory dependencies. Similarly, [Pokheral et al. \(2022\)](#) presented an excellent comparative analysis of LSTM, GRU, and CNN models in predicting the NEPSE index, employing sixteen different predictors in several data sets. The outcomes of the experiments conducted are clearly indicating that LSTM outperforms both GRU and CNN with

regards to accuracy, as statistically proven. This is a great benchmark study on the use of deep learning in forecasting in developing countries.

Conclusion

AI is increasingly becoming popular in NEPSE, as several scholarly works have shown how AI models such as LSTM and Graph Convolutional Networks (GCN) are capable of successfully recognizing the non-linear nature of the stock market and are able to predict with high accuracy compared to traditional techniques. Nonetheless, the adoption of AI models for stock prediction in Nepal is still in its infancy as research is mostly centered on comparing AI models to each other in academic settings rather than in actual trading. The above represents an important gap between the capabilities of AI models and their actual use by investors in the stock market of Nepal.

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