National Stock Index Prediction Using ANN and Python Programming

Dr. Suresh Sundaradasu, B.Tech, M.Tech, Ph.D, HOD of CSE department, suresh.hod@gmail.com

Balusu Sri Sai Sudha (22JD1D5801), M. Tech scholar, sudhabalusu147@gmail.com
Department of CSE

ELURU COLLEGE OF ENGINEERING AND TECHNOLOGY, Approved by AICTE-NEW DELHI & Affiliated to JNTU-KAKINADA Duggirala(V), Pedavegi(M), Eluru - 534007

ABSTRACT

This paper presents a real-time intelligent system for forecasting short-term trends in the Indian stock market, specifically for key NSE indices such as NIFTY and BANKNIFTY. The project uses Artificial Neural Networks (ANN) developed in Python to analyse historical intraday data obtained from Yahoo Finance and integrate it with real-time feeds via Angel One SmartAPI. The model predicts trend direction (UP/DOWN) and offers actionable BUY/SELL recommendations every 5 minutes during market hours.

By combining historical market data obtained from Yahoo Finance with real-time price feeds from the Angel One SmartAPI, the technique enables the continuous and dynamic forecasting of stock movements. The algorithm is designed to look at a string of stock prices from the past in order to predict whether the price will go up or down in the future. The input data must be optimized and standardized for ANN-based learning, and a structured pretreatment pipeline ensures this.

Practical information such as current price trends, average high/low comparisons, and potential buy/sell opportunities are shown with forecasts that are developed and presented

practically quickly. By updating its forecasts every few minutes according to fresh input data, the system runs at regular intervals, much like a true trading decision-support tool. The system's modular design and flexibility make it easy to add support for other stocks or indexes.

This research demonstrates the practical usage of neural networks in financial forecasting and the creation of prediction models via the combining of historical and real-time data streams. Not only that, but the research lays the groundwork for even more advanced models, such as LSTM or hybrid deep learning approaches, to be developed in the future.

I. INTRODUCTION

1.1 A Summary of the Stock Market:

The stock market is crucial to the functioning of the contemporary economy since it enables the exchange of shares from publicly listed companies. As an indicator of a nation's economic well-being, it shows how confident investors are. In India, the National Stock Exchange (NSE) is a major hub for trading stocks. Investor actions, company results, geopolitical developments, and economic statistics are all factors that add to the market's inherent volatility. This unpredictability has put a lot of focus

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on the art of market movement forecasting. It is common practice to utilize stock indexes such as the NIFTY50 and BANKNIFTY to track the overall market performance or the performance of certain industries. However, conventional statistical models often miss the mark when it comes to financial data due to its complexity and volatility.

1.2 The Value of Predictive Models

Knowledgeable stock price forecasts, even if just approximate, would be a boon to institutional and individual investors alike. Due to the inherent complexity of financial markets, perfect forecasts are hard to produce. However, inorder to guide investment decisions, it is essential to identify potential upward or negative trends. Therefore, predictive models are decision-making tools that traders may use to their advantage to increase profits and minimize losses. Artificial neural networks (ANNs) are a powerful tool for modelling time-series data and a deep learning technique in general. Compared to traditional linear models, artificial neural networks (ANNs) are more suited to the ever-changing and often-unpredictable stock market analysis due to their ability to learn and represent complex nonlinear correlations.

II. RELATED WORK

2.1 Summary of Methods for Stock Prediction

Stock market forecasting has long piqued the attention of academics and professionals alike due to the difficulty and potential reward of doing so. Several statistical methods, including linear regression, ARIMA models, and moving averages, formed the backbone of the first methods. Since these tactics assume linear correlations, they usually function well when the market is steady. Their prediction power, however, diminishes when applied to non-linear, real-world market data that is very variable. In response to this limitation, more complex

approaches have evolved, most notably in the fields of deep learning and machine learning.

2.2 Using Machine Learning to Predict Financial Events

Machine learning (ML) has made financial forecasting more easier and more precise. We have used techniques such as decision trees, support vector machines (SVM), k-nearest neighbours (KNN), and random forests to uncover complex patterns and trends in stock market data.

These models learn from previous input-output pairings and then use that knowledge to generate predictions on new data. The great generalizability of ML models across several datasets is one of its main advantages. People may still struggle with time-series forecasting due to their weak recall of sequential connections. Even while ML offers certain benefits over traditional statistics, deep learning models have more room to manoeuvre when it comes to making predictions about the future.

2.3 Traditional Methods vs. Deep Learning

Learning hierarchical representations and handling enormous volumes of data have both been revolutionized by deep learning. A number of models have shown potential in handling financial time-series data. These models include Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). Unlike conventional models, which depend on artificially generated features, deep learning can automatically identify meaningful patterns in raw data. In instance, ANN models may mimic non-linear relationships and adjust to various financial information. Long Short-Term Memory (LSTM) networks and other recurrent models may enhance prediction accuracy for time-dependent tasks like market forecasting by storing prior values. In general, deep learning methods outperform other

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approaches in terms of adaptability and accuracy of predictions.

III. SYSTEM MODEL

3.1 SYSTEM ARCHITECTURE

National Stock Index Prediction Using LSTM Neural Networks and Python Programming

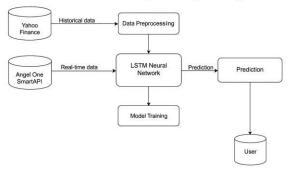


Figure 1. Architecture of the proposed stock prediction system using ANN.

IV. RESULTS AND DISCUSSIONS

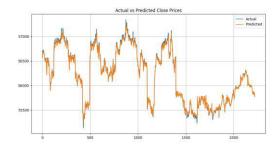


Figure 2. Graph showing actual vs predicted NIFTY close prices using the ANN model.

```
10:15 [NIFTY] Live: ₹22,325.75

→ Predicted: ₹22,348.20 | Trend:

□ UP

10:20 [NIFTY] Live: ₹22,342.00

→ Predicted: ₹22,318.55 | Trend:
□ DOWN

10:25 [NIFTY] Live: ₹22,326.00

→ Predicted: ₹22,335.65 | Trend:
□ UP

10:30 [NIFTY] Live: ₹22,346.80

→ Predicted: ₹22,334.25 | Trend:
□ DOWN
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Figure 3. Real-time prediction output displaying live NIFTY price, model forecast, and trend direction.

V. CONCLUSION

5.1 Summary of Work

A trustworthy, modular system capable of predicting short-term market trends for key NSE indices was the goal of the NSE Stock Prediction Project, which used artificial neural networks (ANN).

The project successfully integrated Yahoo

Finance's historical data with Angel One SmartAPI's real-time price feeds to provide a comprehensive prediction solution.

Python and its data science tools were used for data pipeline construction, model training, and result visualization. The program was able to generate predictions every five minutes during live market hours and offered buy, sell, and hold recommendations based on historical high and low criteria. The architecture's modularization was vital since it ensured scalability and reuse.

5.2 Major Outcomes

A full-stack machine learning pipeline, including data acquisition, preprocessing, training, and prediction, was built in Python.

The project's real-time interface with Angel One SmartAPI allowed effective modelling of real-time market activity.

Short-term predictions made by the ANN model, which was trained using price history, were accurate in most test cases. Practical suggestions (BUY, SELL, or HOLD) were generated by comparing prices rationally. The user has the option to choose from many indexes, such as NIFTY, BANKNIFTY, FINNIFTY, NIFTYIT, etc., and get results tailored to each index.

5.3 Limitations:

The effort has proven fruitful, yet it is not without its limitations:

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- Compared to LSTM or Transformer-based models, ANN models may struggle to capture complicated temporal connections.
- It does not yet allow for analysis at the stock level and only supports a limited selection of NSE indexes. Factors beyond the control of the forecast logic, such as news events or macroeconomic indices, are not considered as potential market influences.
- During times of low trade volume or strong volatility, performance and accuracy might change. Users without technical knowledge may struggle with the system's commandline interface.

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