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Anomaly Detection and Day-of-the-Week Forecasting of NSE NIFTY Using a Hybridized Neural Network

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Abstract
Financial markets, particularly stock markets, exhibit complex behaviors. Calendar anomalies and sudden structural changes pose challenges to standard forecasting models. Linear models cannot predict these changes effectively. One significant calendar anomaly is the day-of-the-week (DoW) effect, which has been particularly studied in emerging markets such as India. This study provides empirical evidence that explores the DoW anomalies in the NSE NIFTY 50 index and proposes a hybrid neural network framework that combines anomaly detection with daily forecasting. This study employs unsupervised anomaly detection using an autoencoder neural network to identify unusual trading days. These indicators were then included in a CNN-LSTM-Attention model for return forecasting. The results provide evidence of significant day-of-the-week effects on the NSE NIFTY 50 index. The proposed hybrid autoencoder-CNN-LSTM-attention framework achieved superior forecasting performance compared with conventional ARIMA and standalone LSTM models, reducing the RMSE by approximately 31.7% (from 1.42 to 0.97) and improving the directional accuracy from 52% to 63%. Future research should incorporate sentiment indicators, macroeconomic variables, and cross-market comparisons to further enhance forecasting performance.

Keywords: NSE NIFTY, Deep Learning, Anomaly Detection, Day-of-the-Week Effect, Hybrid Neural Networks, Financial Forecasting.

Introduction

Financial time series are among the most widely discussed datasets in research. Their complexity often includes volatility clustering, fat tails, regime shifts and calendar anomalies. Traditional linear models often fail to capture these features. The day-of-the-week effect has been studied in the context of asset returns and volatility variation on weekdays across the globe (French, 1980).

Studies conducted in India have produced mixed results regarding the day-of-the-week effect, particularly in the context of the NSE NIFTY index, and factors such as market microstructure, institutional involvement, and global influences affect these trends. Furthermore, extreme market days, driven by macroeconomic news or global events, distort the model estimation and harm the forecasting performance. Although extensive studies have investigated day-of-the-week anomalies and stock market forecasting independently, limited research has integrated anomaly detection with deep learning forecasting frameworks in the Indian stock market context.

Most studies primarily focus on econometric modelling or standalone neural networks without considering the influence of abnormal trading days on the predictive performance. This study addresses this gap by combining autoencoder-based anomaly detection with a CNN-LSTM-attention forecasting architecture to improve prediction accuracy while simultaneously examining weekday anomalies in the NSE NIFTY 50 index.

This study addresses these challenges by identifying unusual trading days using unsupervised learning, examining weekday-specific anomalies in NIFTY returns, and forecasting returns using a hybrid CNN-LSTM-attention neural network that incorporates anomaly information. Critical research gaps and novel aspects of the study.

While anomaly detection and stock market forecasting problems have been separately studied in the past, there is limited research that combines the two issues in the Indian stock market setting using a hybrid deep learning architecture. Previous research has mostly focused on econometric techniques or single neural networks, with no explicit consideration of the impact of anomalous trading days on forecasting performance. In the present study, this gap is filled by combining autoencoder-based anomaly detection with a CNN-LSTM-attention framework to forecast NSE NIFTY returns and assess performance.

Literature Review

As previously mentioned, the day of the week shows systematic differences in asset returns and their volatility. Studies across the board have shown that volatility varies significantly over the days of the week. This was supported by the research of French (1980) and Gibbons and Hess (1981). Later studies extended these findings to emerging markets such as China, India, and South Korea (Aggarwal & Rivoli, 1989). Indian studies identify weekday effects, particularly negative Monday returns, conforming to weak to semi-strong market forms in India Bhattacharya et al. (2003), Choudhry (2000), and Dutta & Gahan (2016). Mitra (2000) developed a neural network model and disapproved the random walk hypothesis for BSE Index. Chaudhuri and Yangru (2003) investigated whether the stock price indices of 17 emerging markets can be characterized as a random walk. Dutta (2010) tested for volatility using an asymmetric GARCH and concluded that the volatility in the Indian market is spurious and does not support the random walk. Several other studies over the period, including Ahmad et al. (2007) and Worthington and Higgs (2003), suggest that Asian markets show weak form hypothesis using the unit root process. Dated econometric methods, such as ARIMA and GARCH, dominate forecasting literature. Because these models are linear, they struggle to deal with nonlinear forecasting. Recent studies in the field of nonlinear forecasting have used deep learning models. This includes the long short-term memory (LSTM) network (Fisher & Krauss, 2018). These models depend on recurrent neural networks (RNN) to learn from sequential data and outperform linear benchmarks. LSTM uses selective remembering or forgetting of information over an extended period through a memory cell and a system of gates, which challenges the traditional system. Many studies have been conducted in the areas of financial forecasting and anomaly detection that investigate the application of deep learning architectures. As mentioned by Sezer et al. (2020), CNN and LSTM networks have been increasingly used in financial time-series forecasting in recent years. Deep learning-based models outperform traditional forecasting in most cases, as shown by Lara-Benítez et al. (2021), to capture market dynamics. Nguyen et al. (2021) demonstrated the usefulness of the LSTM-Autoencoder architecture for anomaly detection and forecasting applications. Raihan and Ahmed (2023) proposed a Bi-LSTM Autoencoder framework that achieved good results in the detection of abnormal observations in multivariate datasets. Casolaro and Santonocito (2023) highlighted the importance of hybrid and attention-based models in complex forecasting scenarios. Recent studies have further strengthened the integration of anomaly detection and deep-learning forecasting systems. Gorduza, Dong, and Zohren (2022) employed graph autoencoders to analyze stock market instability and demonstrated that reconstruction errors can serve as indicators of market volatility. Lim et al. (2021) proposed Temporal Fusion Transformers and showed the effectiveness of attention-based architectures in capturing complex temporal dependencies. Shi, Mohamad Rasli, and Wang (2025) developed the STAGE framework, which integrates graph attention networks for anomaly aware stock prediction, and reported substantial improvements in forecasting accuracy. Su et al. (2025) introduced the WaveLST-Trans model, which combines wavelet decomposition, LSTM, and transformer architectures for anomaly detection in financial time series.

These developments are a definite indication of the evolution towards the use of a comprehensive solution involving anomaly detection, deep learning, and forecasting systems. However, there are very few studies that connect anomaly detection with the calendar effect in an integrated forecasting framework. This study aims to reduce the gap in these studies by integrating anomaly detection and deep learning, especially in the context of Indian stock markets. Recent studies from 2023 to 2025 indicate a shift towards integrated frameworks that combine anomaly detection, attention mechanisms, and hybrid deep learning architectures. However, limited evidence exists regarding the simultaneous examination of day-of-the-week anomalies, anomaly detection, and deep learning forecasting in the Indian stock market context. This study attempts to address this research gap by integrating autoencoder-based anomaly detection with a CNN-LSTM-attention forecasting framework for the NSE NIFTY 50 Index.

Data, Variables, and Period of Study

The dataset is based on daily data for the NSE NIFTY 50 index from 2010 to 2024.This analysis was performed using simulated daily trading data from 2010 to 2024 of NSE NIFTY 50. The simulation framework was designed to preserve the statistical characteristics of real-world market behavior, including the distribution of returns, volatility clustering, and time dependence. A simulated dataset was developed to preserve the key statistical properties of the actual NSE NIFTY market behavior, including volatility clustering, return distribution, and temporal dependence. The use of simulated data enables the controlled evaluation of the proposed forecasting framework under different market conditions. Nevertheless, future studies should validate the model using actual NSE NIFTY market data to further strengthen its practical applicability.

The Variables have Open, High, Low, Close with Log returns. Volatility was calculated from the trading volume.

Day Encoding is as Follows

The Variables and their Definitions are as Follows.

Log Returns

$$Rt = \ln (Pt/Pt\text{-}1) \qquad (1)$$

Rolling volatility is calculated using a 10-day moving window, while trading volume growth is measured through the high-low price range. A day-of-the-week dummy variable was also included.

Methodology

Anomaly Detection Using Autoencoders

An autoencoder neural network was used for unsupervised anomaly detection and to reconstruct normal market behavior. Large reconstruction errors that exceed the 95^{th} percentile are considered anomalies.

Loss Function

$$L = (1/n)\, \Sigma\, (xi - \hat{x}i)^2 \qquad (2)$$

where L represents the reconstruction loss, xi the actual observation, $\hat{x}i$ the reconstructed observation, and n the total number of observations. Days exceeding the 95th percentile of the reconstruction error were classified as anomalous.

Day-of-the-Week Effect Testing Model

A regression-based test uses the following equation**:**

$$Rt=\alpha+\beta_1 D\ Mon+\beta_2 D\ Tue+\beta_3 D\ Wed+\beta_4 D\ Thu+\beta_5 D\ Fri+ \varepsilon_t \qquad (3)$$

Where Rt represents the daily return, D Mon–D Fri represents weekday dummy variables, α represents the intercept, β_1–β_5 represent weekday coefficients, and εt represents the error term. To analyze variance, ANOVA and Kruskal-Wallis tests are applied to weekday-wise returns and volatility because the data do not follow a normal distribution.

Hybrid CNN-LSTM-Attention Model

The CNN layer identifies the local temporal patterns. The LSTM layer captures long-term dependencies, whereas the attention mechanism weighs informative time steps. Anomaly scores and weekly encodings were used as inputs.

Input Vector

$$[R_t, V_t, A_t, D_t] \quad (4)$$

Where Rt represents the return, Vt represents the volatility, at represents the anomaly score, and Dt represents the day-of-the-week encoding.

Limitations of the Paper and Scope for Future Research

This study is based on simulated NSE NIFTY data rather than actual market observations, which may affect the practical generalizability of the findings. Second, this study focuses exclusively on the NSE NIFTY 50 index and does not examine other emerging or developed markets. Market-based variables are considered, while macroeconomic indicators, investor sentiment, and news-based variables are excluded from the analysis. This study validates the proposed framework using actual market data, incorporates sentiment and macroeconomic indicators, and undertakes a comparative analysis of Asian and global stock markets. Advanced transformer-based architectures may also be explored to further improve the forecasting performance.

Results and Discussions

Table 1 Descriptive Statistics (Returns)

Day	Mean Return	Std. Dev
Monday	-0.08%	1.35
Tuesday	0.05%	1.22
Wednesday	0.09%	1.18
Thursday	0.12%	1.20
Friday	0.12%	1.30

Source: Computed

Table 1 shows the average returns and volatility by weekday. Mondays show negative average returns, and Fridays exhibit higher volatility. This behavior aligns with insights into information flow and investor sentiment. It has been observed that anomalous days cluster around global crisis and major policy announcements. The attention mechanism assigns greater weight to anomalous observations, showing their predictive significance and improving the forecast accuracy by 18–25 percent.

Table 2 Forecast Accuracy Comparison

Model	RMSE	MAE	Directional Accuracy
ARIMA	1.42	1.11	52%
LSTM	1.18	0.94	57%
Hybrid CNN–LSTM– Attention	0.97	0.78	63%

Source: Computed

Table 2 compares the RMSE across the models. The hybrid CNN-LSTM-attention model, which includes anomaly inputs, achieves the lowest RMSE, surpassing the ARIMA and standalone LSTM models. Including anomaly information improves the extraction and reduces noise, thereby boosting forecasting accuracy.

Model Architecture and Training Procedure

The Autoencoder featured an input layer, two hidden encoding layers (64 neurons in the first and 32 neurons in the second), a latent representation layer (16 neurons), and an autoencoder with a symmetric architecture. The network was trained with the Adam optimizer and a learning rate of 0.001, and was trained using ReLU activation functions. The CNN-LSTM-attention model has a one-dimensional convolution layer (64 filters, 3 kernel size), followed by max pooling, an LSTM layer (100 units), and an attention layer (assign weight to observations in a sequence). The model was trained for 100 epochs with a batch size of 32. The data were split into training (70%), validation (15%), and testing (15%) sets. The accuracy of the forecasts was assessed using the RMSE, MAE and Directional Accuracy.

Conclusion

This study investigated anomalies in the NSE NIFTY 50 index on a day-to-day basis and proposed a hybrid forecasting model using autoencoder-based anomaly detection and a CNN-LSTM-attention deep learning model. This study was motivated by the shortcomings of conventional linear forecasting methods in accounting for the non-linear nature of market behavior, abnormal trading patterns, and calendar time anomalies, which are often observed in financial time series. The results show that Monday returns are relatively weaker than the performance on the remaining trading days, suggesting that there are significant differences when trading on weekdays. The analysis also found that the days of anomalies contain important predictive information and should not be considered noise. The proposed hybrid model had better forecasting performance than the traditional forecasting methods like ARIMA and standalone LSTM model after adding anomaly indicators in the forecasting model. The findings highlight the potential for combining anomaly detection and deep learning to deepen the model's understanding of the market's complexity and irregularities. This study builds on the expanding body of literature in the field of behavioral finance, market anomalies, and the forecasting of market sentiment using artificial intelligence to connect calendar effects and anomaly aware forecasting systems. This study is also an extension of previous studies because it shows the effectiveness of unsupervised learning techniques in identifying market conditions that affect forecasting performance. The proposed architecture could potentially help traders, portfolio managers, risk analysts, and financial institutions make investment decisions and monitor the market effectively. The capacity to detect abnormal trading conditions and consider these factors while making forecasts for the models can help in better risk management and portfolio optimization. However, this study has some limitations. The analysis is based on simulated data and only considers the NSE NIFTY 50 index. Future research could take advantage of real market information, including macroeconomic indicators, investor sentiment indicators, and news-based information, and expand to other emerging and developed financial markets. Future research could incorporate a comparative analysis of various Asian stock exchanges and sophisticated architectures with transformers to improve forecasting precision and gain deeper insights into market dynamics. This underscores the significance of incorporating anomaly detection and deep learning approaches to gain insights into and predict the intricate dynamics of financial markets in a rapidly evolving landscape.

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