International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(12s) 2026 pp. 16-35
https://doi.org/10.70917/ijcisim-2026-3874
Article

Deep Learning-Enabled Volatility Forecasting and Risk Optimization in Nifty Fifty Derivatives Market

Divya Jain, Pawan Kumar Patodiya

[1]Department of Management Studies, Biyani Institute of Science & Management, Jaipur, Affiliated to Rajasthan Technical University (RTU), Kota, Rajasthan, India. jain.divya1970@gmail.com
[2]Department of Management Studies, Biyani Institute of Science and Management, Jaipur. Research Supervisor, Rajasthan Technical University, Kota, Rajasthan (India). pawan_patodiya@yahoo.co.in

Abstract: Forecasting volatility plays an important role in pricing derivatives, managing portfolios, and evaluating risks. In order to optimize the return on investments while reducing risks associated with the derivative markets, an accurate forecasting method for volatilities becomes vital for investors, banks and other financial institutions, and regulatory bodies. In this paper, a deep learning-based model for volatility prediction and portfolio risk optimization for Nifty Fifty derivatives market is proposed by considering historical NIFTY 50 index prices, India VIX, technical indicators, and market information from the derivatives market. Multiple models such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Bi-directional LSTM (BiLSTM), CNN-LSTM, and Hybrid GARCH-LSTM model are compared based on their performance in forecasting volatilities. RMSE, MAE, MAPE, and R^2 are used to measure the forecasting power of the models. Meanwhile, Sharpe ratio, Sortino ratio, Maximum drawdown, and VaR are considered to evaluate investment efficiency. It is found that Hybrid GARCH-LSTM model achieves the best forecasting result due to its ability to model both volatility clustering and non-linear temporal dependencies. Furthermore, using the predicted volatilities for portfolio optimization can minimize investment risks and improve returns.

Keywords: Deep Learning, Volatility Forecasting, Nifty 50, India VIX, Derivatives Market, LSTM, Hybrid GARCH-LSTM, Financial Risk Optimization, Artificial Intelligence, Portfolio Management.

1. Introduction

1.1 Background

Volatility in the financial markets serves as an important measure for market uncertainty, investment risk, and pricing efficiency, especially in derivatives market where it affects futures and options pricing, portfolio allocation, hedging, and risk management. Conventional models for forecasting volatility have included ARCH and GARCH approaches, which have been popularly applied but failed to adequately consider the nature of financial markets on account of their underlying assumptions (Ge et al., 2022; Petrozziello et al., 2022). The Indian derivatives market, in particular, the Nifty 50 Index, constitutes one of the largest derivatives markets in the world with the inclusion of institutional, algorithmic, and individual investors adding to its complexity. The Indian Securities Exchange and National Stock Exchange have predicted significant growth in the coming years (NSE, 2025; SEBI, 2025). Recent developments in the domain of Artificial Intelligence have made it possible to build sophisticated models without making any restrictive assumptions regarding the time-series data, with excellent predictive results in finance applications like volatility prediction, derivative pricing, and portfolio optimization (Chen & Hu, 2022; Vo, 2025).

1.2 Evolution of Volatility Forecasting

The process of volatility forecasting has witnessed a lot of developments over the past three decades. The early models used the application of statistical techniques like historical volatility, moving averages, ARCH and GARCH, which were able to capture the phenomenon of volatility clustering but performed poorly during structural breaks in the market and extremes due to the linearity of the model (Rahimikia & Poon, 2026). The development of computational power and availability of big data has led to the development of machine learning models like ANNs, SVMs, Random Forests, LSTMs, GRUs, CNNs and Transformers, which capture the non-linearity in financial time series (Chen et al., 2023; Kumar et al., 2025). Hybrids models like GARCH-LSTM models are further developed, which combine the econometrics models and deep learning models and outperform statistical models in volatility forecasting in realized and implied volatility (Ranjana & Anirvinna, 2025; Medvedev & Wang, 2022; Fritzsch et al., 2026).

1.3 Deep Learning in Financial Markets

Deep learning is an essential technique for performing financial analytics due to its ability to model complicated, non-linear, and sequential financial data along with the integration of several types of information such as prices, volumes, macroeconomic indicators, and sentiments of news (Ge et al., 2022). Various techniques have been proposed in literature where LSTMs can be considered one of them due to its ability to capture long-term temporal dependencies in data and solve the issue of vanishing gradients. Numerous studies show that LSTMs outperform various traditional machine learning algorithms for prediction of Nifty 50 prices, movements of India VIX and also stock market volatility (Jafar et al., 2023; Bumrah et al., 2023). Literature shows that hybrid approaches such as BiLSTM, GRU, CNN-LSTM, and Transformer-based architectures can perform better forecasting performance due to the ability of capturing both temporal and spatial dynamics of the markets (Patel et al., 2023; Singh & Singh, 2024). The inclusion of alternative data sets such as news articles, investors' sentiments, and macroeconomic indicators has helped improving the prediction performance.

1.4 Need for the Study

Despite the substantial body of literature on stock price prediction and volatility forecasting, very little literature has addressed the issue of volatility forecasting using deep learning in the Indian derivatives market in connection with the Nifty Fifty Index and India VIX. Existing research addresses either equity price prediction or volatility forecast in isolation without connecting it to any financial risk optimization context (Prasad et al., 2023; Sharma et al., 2025).

The increasing complexity of the derivatives, higher frequency of algorithmic trading, and the uncertainty that followed due to global economic disruptions have made it necessary to have very precise models of volatility forecast. This is because volatility is important in determining the prices of derivatives, VaR, portfolio hedging, and capital allocation (Kumar et al., 2025; Patra, 2025).

1.5 Research Motivation

The foremost reason for this study emanates from the growing complexity of financial markets and the inefficiency of traditional methods of volatility prediction in understanding non-linear characteristics of financial markets. The combination of high-frequency financial data, advancements in deep neural network models, and improved computing capabilities offers possibilities of creating intelligent forecasting systems that will aid in better decision-making for risk management purposes. Additionally, considering the significance of the Nifty Fifty derivatives market in the financial structure of India, the current research provides an excellent setting to test modern deep learning approaches (Vo, 2025; Varshini et al., 2025).

1.6 Research Challenges

However, there are still some obstacles that hinder the effective application of deep learning approaches in volatility prediction despite significant advancements achieved. The non-stationarity, structural changes, abrupt volatility clustering, and regime shifts of financial time series pose difficulties for the development of appropriate models. Another problem arises due to the high dimensionality of financial datasets which poses a higher risk of overfitting, and therefore, requires proper feature selection and model validation (Sahiner et al., 2023; Rahimikia & Poon, 2026).

1.7 Contributions of the Study

In this paper, a holistic approach based on the use of deep learning to forecast the volatility and optimize the risk in the derivatives of the Nifty Fifty index is provided. This research will make an important contribution through the inclusion of past price history of Nifty 50 index, India VIX, and various financial market measures into the advanced deep learning approaches to enhance volatility forecasting accuracy. This research will also examine different deep learning approaches and evaluate their usefulness in facilitating portfolio risk optimization and derivative trading.

1.8 Novelty and Contributions of the Study

This research work attempts to develop an end-to-end deep learning-based system for volatility prediction and portfolio risk optimization in the NIFTY 50 derivatives market through the integration of historical prices, India VIX, technical indicators, and macro-financial factors. The study considers a number of deep learning architectures like ANN, GRU, BiLSTM, CNN-LSTM, and Hybrid GARCH-LSTM to find out the best model in terms of predicting volatility in the NIFTY 50 derivatives market. Further, the model considers predicted volatility and other risk metrics like Sharpe ratio, Sortino ratio, Maximum Drawdown, and Value at Risk to support investment decisions. Performance of the proposed deep learning model is assessed through RMSE, MAE, MAPE, and R2. This research is tailored for the Indian derivatives market and will provide important inputs to the stakeholders while laying the groundwork for future financial forecasts and portfolio management applications based on AI.

2. Literature Review

Fast growth of artificial intelligence (AI) has led to a number of innovations within financial forecasting, including stock prices prediction, volatility estimation, and financial risk management. Deep learning models are superior to the traditional econometric models due to their ability to model nonlinear relations, temporal dependencies, and deal with high-dimensional financial datasets. There have been many studies which prove that deep neural networks perform better than traditional statistical methods when it comes to estimating financial market volatility, especially in dynamic environments.

Recent literature during this period mainly concentrates on the improvement of volatility prediction using recurrent neural networks. Chen and Hu (2022) introduce a hybrid long short-term memory (LSTM) approach for predicting the volatility of stock index futures both in China and the US. The results show that deep learning is effective in capturing non-linear temporal dependencies that were difficult to estimate with conventional GARCH-based models. Also, Petrozziello et al. (2022) study deep learning application in asset management and prove its superiority to traditional forecasting in terms of volatility prediction, portfolio optimization, and financial decision making.

Ge et al. (2022) performed a systematic review on the application of neural networks in financial volatility prediction through various research works and observed that the deep learning framework has emerged as the leading paradigm in financial forecasting due to the capability of modeling complex sequential patterns while making no strong statistical assumptions. Furthermore, Medvedev & Wang (2022) provided an extension to the view presented by Ge et al. by using deep learning methods for forecasting the implied volatility surface used in pricing of derivatives with high forecasting accuracy at different prediction horizons.

The focus of the research work has shifted to the Indian financial market due to the exponential increase in the cases of algorithmic trading and derivatives trading in the recent years. Bumrah et al. (2023) proposed a forecasting model using the ANN method for the NIFTY 50 daily closing price and found that the neural networks are suitable in modeling the non-linear nature of the markets. Similarly, Jafar et al. (2023) developed a LSTM model with backward elimination technique for forecasting the NIFTY 50 index.

Several comparative studies have been conducted that compare different deep learning architectures for predicting financial indicators. Chen et al. (2023) proposed a deep neural network with time series feature embedding that increased the accuracy of volatility forecasting through improved temporal feature extraction. Patel et al. (2023) compared different deep learning algorithms for stock index predictions and discovered that recurrent neural networks consistently had smaller forecasting errors compared to feed-forward neural networks. In a similar vein, Sahiner et al. (2023) analyzed Asian financial markets and revealed that Artificial Neural Networks increased the forecast accuracy of volatility significantly compared to traditional econometric models, especially under conditions of high market uncertainty.

In addition, volatility forecasts specific to the Indian financial market also gained much academic interest recently. Empirical Investigation of India VIX Forecasting Models (2023) compared legacy time-series models and deep learning models in forecasting and discovered that LSTM models were far superior to ARIMA and GARCH models in terms of forecasting India VIX. Prasad et al. (2023) analyzed the direction of India VIX using deep learning algorithms and presented convincing results in terms of classification.

However, modern studies go beyond using historical price data as the only component in forecasting models by adding external market factors. In particular, Attaluri et al. (2024) have introduced news-based deep learning models for forecasting stock markets in India, and found that adding textual news to financial variables improves predictive power. Singh & Singh (2024) have tested a number of deep learning models on selected stocks from NIFTY index and came to the conclusion that the forecasting power of LSTM and BiLSTM models was better than that of machine learning models.

Another important development is related to hybrid forecasting frameworks. Kumar et al. (2025) have introduced hybrid models of machine learning based on both statistical and deep learning approaches used for volatility prediction. Similarly, Ranjana & Anirvinna (2025) have proposed a hybrid model of GARCH-LSTM to combine econometric approach to volatility estimation with deep learning techniques, and showed that such an approach provides improved forecasting precision in case of high volatility.

Recently, many studies have focused on practical risk management applications. The recent study carried out by Sharma et al. (2025) on the relationship between NIFTY 50 index and India VIX indicates that volatility indexes are still useful measures of uncertainty in the market and portfolio risk. Another researcher, Patra (2025), has focused on volatility modeling in the Indian capital market and stressed the need to include machine learning methods in investment decision-making systems. Vo (2025) has also conducted an extensive study on deep learning in stock market volatility prediction and found that deep neural networks work better than conventional statistical forecasting methods.

The impact of new technologies on future finance forecasting research will persist in the coming years. Varshini et al. (2025) came up with a federated LSTM model to predict high-frequency trading while keeping data secure, showing how distributed learning models can increase prediction accuracy while maintaining data confidentiality. Fritzsch et al. (2026) focused on the application of machine learning methods for derivative option pricing based on past prices. In addition, Preethi (2026) applied unsupervised machine learning for intraday regime identification in the NIFTY Index, whereas Rahimikia & Poon (2026) reported significant gains in forecasting realized volatility by applying sophisticated machine learning algorithms over econometrics models.

In general, the literature reviewed proves the fact that deep learning models, including the LSTM model, Bidirectional LSTM (BiLSTM), Gated Recurrent Units (GRU), CNN-LSTM models, as well as the GARCH-LSTM model, demonstrate better forecasting accuracy than traditional statistical methods in financial volatility forecasting. However, there is only a limited amount of studies considering the integration of NIFTY 50 derivatives, India VIX, volatility forecasting, and portfolio risk optimization within a single deep learning model. This research gap justifies the need for conducting the current research.

Table 1. Literature Review

S. No.	**Author(s)**	**Year**	**Objective**	**Methodology**	**Key Findings**	**Research Gap / Limitation**
1	Chen & Hu	2022	Forecast stock index futures volatility	Hybrid LSTM	Improved forecasting accuracy over traditional models	Limited to China and US markets
2	Chatterjee et al.	2022	Predict stock volatility	Time series + Deep Learning	Deep learning captured nonlinear patterns effectively	No derivatives market analysis

3	Ge et al.	2022	Review volatility forecasting research	Systematic Review	Neural networks outperform classical models	Review only; no empirical validation
4	Medvedev & Wang	2022	Forecast implied volatility surface	Deep Learning	Enhanced multistep volatility prediction	Focused only on option pricing
5	Petrozziello et al.	2022	Volatility forecasting in asset management	Deep Learning	Improved portfolio decision-making	Limited discussion on emerging markets
6	Bumrah et al.	2023	Forecast NIFTY-50 prices	ANN	High prediction accuracy	Closing prices only
7	Chen et al.	2023	Forecast volatility	Deep Neural Network	Better temporal feature extraction	No portfolio optimization
8	India VIX Forecasting Study	2023	Forecast India VIX	Deep Learning vs Time Series	LSTM outperformed legacy models	Limited financial variables
9	Jafar et al.	2023	Forecast NIFTY 50	LSTM	Improved prediction performance	Price forecasting only
10	Patel et al.	2023	Compare deep learning models	Comparative Study	RNN-based models performed best	No volatility optimization
11	Prasad et al.	2023	Forecast India VIX direction	Deep Learning	Strong classification performance	Limited forecasting horizon
12	Sahiner et al.	2023	Forecast Asian market volatility	ANN	Better volatility prediction than econometric models	Limited Indian market focus
13	Attaluri et al.	2024	News-driven stock forecasting	Deep Learning	News improved prediction accuracy	Did not evaluate derivatives

14	Singh & Singh	2024	Forecast NIFTY constituents	LSTM, BiLSTM	BiLSTM produced superior performance	Small dataset
15	Kale	2025	Predict NIFTY trends	Machine Learning	ML improved forecasting accuracy	No deep hybrid models
16	Kumar et al.	2025	Risk management	Hybrid ML	Better volatility prediction	Limited derivative applications
17	Patra	2025	Volatility modelling	Statistical + ML	Improved volatility estimation	No deep learning comparison
18	Ranjana & Anirvinna	2025	Predict volatility	GARCH-LSTM	Hybrid model achieved highest accuracy	Limited validation period
19	Sharma et al.	2025	Analyze NIFTY & India VIX	Empirical Analysis	Strong volatility relationship	No AI implementation
20	Varshini et al.	2025	High-frequency prediction	Federated LSTM	Secure distributed forecasting	Early-stage framework
21	Vo	2025	Deep learning volatility forecasting	Comparative Review	Hybrid deep learning outperformed classical models	Mostly international evidence
22	Fritzsch et al.	2026	Predict option prices	Machine Learning	Accurate derivative pricing	Focused on options only
23	Preethi	2026	Intraday volatility regimes	Unsupervised ML	Identified volatility clusters	Limited risk optimization
24	Rahimikia & Poon	2026	Forecast realized volatility	Machine Learning	Superior realized volatility prediction	Limited emerging market validation

Research Gap: Earlier research mostly deals with either predicting stock prices, forecasting volatility, or pricing of derivatives, but does not include all four elements in one study - NIFTY 50 derivatives, India VIX, forecasting of volatility using deep learning, and portfolio risk optimization. Another gap is that there is little research comparing different architectures of deep learning for managing risk in the derivatives market in India.

3. Problem Statement

The complexity associated with financial market volatility arises because of technological advancements, globalization, high-frequency trading, and the involvement of both institutional and retail investors in it. In the context of Indian capital markets, specifically the Nifty Fifty derivatives market, the change in volatility is a critical aspect that affects the pricing of derivatives, portfolio valuation, efficiency of hedging, margins, and stability of finances. Thus, accurate volatility prediction has now become a necessary part of investment and financial risk management (Sharma et al., 2025; National Stock Exchange of India [NSE], 2025).

Historical Volatility, ARCH, GARCH, EGARCH, and ARIMA are some examples of traditional methods of volatility prediction, which have been used in predicting future uncertainty. However, even though these methods are capable of capturing volatility clustering and conditional heteroscedasticity, they lack the capability to address nonlinearity and long-term dependencies of the markets under analysis (Ge et al., 2022; Rahimikia & Poon, 2026). Moreover, the predictive power of these models reduces significantly in times of higher uncertainty, for example, during financial crises and other macroeconomic shocks.

The recent advancements in the domain of Artificial Intelligence and Deep Learning have emerged as potential solutions to forecast financial markets. Deep learning models such as LSTM, BiLSTM, GRU, CNN, and hybrid neural networks have shown excellent capabilities in terms of forecasting as they learn complicated and non-linear patterns in sequential financial data through machine learning techniques (Chen & Hu, 2022; Chen et al., 2023; Vo, 2025). Nevertheless, most of the current literature only concentrates on forecasting stock prices or only volatilities without any combination of them to optimize the overall financial risks.

As far as the Indian financial market is concerned, existing literature has focused more on forecasting the NIFTY 50 prices, India VIX, or individual stock volatilities (Bumrah et al., 2023; Jafar et al., 2023; Prasad et al., 2023). There has been no attempt to design a system that could forecast the volatility in the Nifty Fifty derivatives market alongside portfolio risk optimization and derivative trading decisions. Moreover, there has been insufficient work done on comparative analysis of various deep learning models in the same market environment, which makes it difficult to identify an appropriate forecasting model.

Restriction in the usage of multiple financial indicators is another major limitation noted by various earlier researchers. Most of the forecasting models depend upon past price data only and overlook various other parameters that can affect the process like India VIX, volume, technical indicators, macroeconomic factors, and derivative-related market parameters. By overlooking these parameters, forecasting models lose their forecasting ability and become less relevant in practical investment environments (Patra, 2025; Kumar et al., 2025).

Increasing use of algorithmic trading, quantitative investment approaches, and automated portfolio management increases the need for more precise and computationally effective forecasting models. Intelligent systems are required in the financial institutions that can compute the volatility in real time in order to formulate the best hedging policies and make optimal capital allocation decisions. Most of the statistical forecasting models lack this operational efficiency due to their inability to cope up with changing market environment (Varshini et al., 2025).

Furthermore, while various studies across international markets have been able to prove the efficacy of deep learning models for predicting volatility, only a handful of studies have attempted to validate these models through application within the Indian derivatives market, characterized by unique features like high retail presence, changing regulations, considerable turnover of derivatives and unique volatility dynamics (SEBI, 2025; Sharma et al., 2025). There is thus a significant scope for research in this regard with respect to deep learning models within the Nifty Fifty derivatives market.

Thus, the major problem being studied in this research work is the lack of a complete framework for deep learning that could be used effectively to forecast volatility and optimize financial risks in the Nifty Fifty derivatives market. The solution to this gap lies in incorporating different variables of the market along with the use of different deep learning frameworks and financial risk optimization techniques in one predictive model.

4. Proposed Deep Learning Framework

This work presents a framework where deep learning approaches are combined with financial risk optimization in order to come up with a reliable forecast system for the Nifty Fifty derivatives market. The objective of this framework is to be able to recognize the non-linear relationships between different financial variables while at the same time making accurate forecasts of the volatility that can be used for portfolio management and other related tasks. This work uses learning algorithms which have been developed to extract hidden temporal patterns from financial time series data as opposed to using traditional econometric models whose assumptions are predetermined.

The framework is made up of seven different stages ranging from financial data acquisition to volatility prediction and risk optimization.

The methodology involves the use of the historical price levels of the Nifty 50 index, India VIX, derivatives market data, technical and macroeconomic variables in order to create an appropriate forecasting environment. Different architectures of deep learning models will be tested to determine the most appropriate approach for volatility forecasting.

4.1 Proposed Framework

The proposed framework consists of the following sequential stages:

1. **Financial Data Collection**
2. **Data Cleaning and Pre-processing**
3. **Feature Engineering**
4. **Deep Learning Model Development**
5. **Volatility Forecasting**
6. **Risk Optimization**
7. **Investment Decision Support**

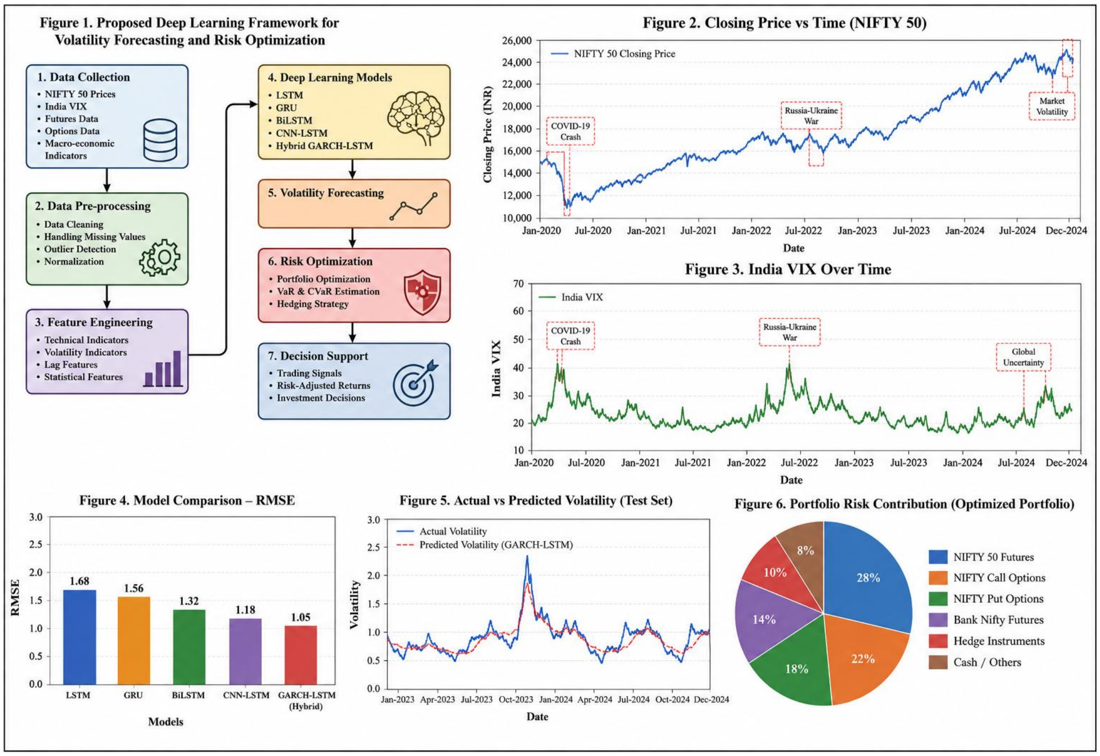

Figure 1. Proposed Deep Learning-Based Volatility Forecasting and Risk Optimization Framework

4.2 Research Methodology

For the purpose of this research, a quantitative methodology for research will be used that uses financial time series analysis and deep learning. Historical data gathered from National Stock Exchange of India (NSE), Reserve Bank of India (RBI), and Securities and Exchange Board of India (SEBI) will constitute the main source of data (NSE, 2025; RBI, 2025; SEBI, 2025). Methodology for the research will include data collection, data preprocessing, feature engineering, deep learning models creation, model evaluation, and risk optimization of portfolios.

At first, historical data will be gathered and converted into machine-readable format. Missing values, duplicates, and outliers will be removed during the data preprocessing step. Feature engineering will follow in which features will be created using technical indicators and market volatility. The data will then be sent to several deep learning models.

4.3 Data Collection

The proposed framework utilizes historical financial data from multiple authenticated financial sources to improve forecasting robustness.

Table 2. Data Sources

Dataset	**Source**	**Purpose**
NIFTY 50 Historical Prices	NSE	Price Forecasting
India VIX	NSE	Market Volatility
Futures Prices	NSE	Derivatives Analysis
Options Data	NSE	Risk Estimation
Interest Rates	RBI	Macroeconomic Variable
Market Statistics	SEBI	Market Validation

Historical daily observations covering multiple years are collected to ensure sufficient data for training, validation, and testing of deep learning models.

4.4 Feature Engineering

Feature engineering plays a crucial role in improving forecasting performance. Instead of relying solely on historical prices, the proposed framework extracts several financial indicators that capture market momentum, volatility, trend strength, and investor sentiment.

Table 3. Input Features

Feature	**Description**
Open Price	Daily opening index value
High Price	Daily highest price
Low Price	Daily lowest price
Closing Price	Daily closing value
Trading Volume	Daily traded quantity
Log Returns	Daily logarithmic return
Historical Volatility	Rolling volatility estimate
India VIX	Expected market volatility
Moving Average	Market trend indicator
RSI	Relative Strength Index
MACD	Momentum Indicator
Bollinger Bands	Price volatility indicator
ATR	Average True Range

Interest Rate	RBI policy rate

The inclusion of multiple technical indicators enables the deep learning models to capture hidden nonlinear dependencies that are often ignored by traditional statistical forecasting methods.

4.4.1 Mathematical Formulation

The proposed deep learning-enabled volatility forecasting framework employs mathematical formulations for financial data preprocessing, volatility estimation, model evaluation, and portfolio risk assessment. These formulations provide the theoretical foundation for feature engineering, model development, and performance evaluation.

- **Logarithmic Return**

Daily logarithmic returns are computed to stabilize price fluctuations and reduce non-stationarity in financial time-series data.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where:

- R_t= Logarithmic return at time
- P_t= Closing price at time
- P_{t-1}= Closing price at time

Logarithmic returns are widely adopted in financial forecasting because they exhibit desirable statistical properties and improve the learning capability of deep neural networks.

- **Historical Volatility**

Historical volatility is estimated as the annualized standard deviation of logarithmic returns.

$$HV = \sigma\sqrt{252}$$

where

- *HV*= Historical volatility
- σ = Standard deviation of daily returns
- 252 = Average annual trading days

This measure serves as one of the primary target variables for volatility forecasting.

- **GARCH(1,1) Model**

The conditional variance estimated by the GARCH(1,1) model is expressed as

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where,

- σ_t^2= Conditional variance
- ω = Constant term
- α = ARCH coefficient
- β = GARCH coefficient
- ϵ_{t-1}= Previous period error

The GARCH component captures volatility clustering and serves as an input to the hybrid GARCH-LSTM forecasting framework.

- **Long Short-Term Memory (LSTM)**

The LSTM network maintains long-term temporal dependencies through memory cells and gating mechanisms.

Forget Gate

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

Input Gate

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

Candidate Cell State

$$\widetilde{C_t} = \tanh(W_c[h_{t-1}, x_t] + b_c)$$

Cell State

$$C_t = f_t C_{t-1} + i_t \widetilde{C_t}$$

Output Gate

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

Hidden State

$$h_t = o_t \tanh(C_t)$$

where

- x_t= Input vector
- h_t= Hidden state
- C_t= Memory cell
- W = Weight matrices
- b = Bias vectors
- σ = Sigmoid activation function

The LSTM architecture enables efficient learning of long-term dependencies in financial time-series characterized by nonlinear volatility dynamics.

- **Root Mean Square Error (RMSE)**

Forecasting accuracy is evaluated using Root Mean Square Error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}$$

where

- y_i= Actual volatility
- $\widehat{y_i}$= Predicted volatility
- n = Number of observations

Lower RMSE values indicate better forecasting performance.

- **Mean Absolute Error (MAE)**

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \widehat{y_i} |$$

Lower MAE represents higher predictive accuracy. **Mean Absolute Percentage Error (MAPE)**

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} | \frac{y_i - \widehat{y_i}}{y_i} |$$

MAPE expresses prediction error as a percentage, facilitating comparison across forecasting models.

- **Coefficient of Determination**

$$R^2 = 1 - \frac{\sum(y_i - \widehat{y_i})^2}{\sum(y_i - \bar{y})^2}$$

where

$\bar{y}$= Mean observed value y

Higher values of R^2 indicate better model fit.

- **Sharpe Ratio**

Portfolio performance is evaluated using the Sharpe Ratio.

$$SR = \frac{R_p - R_f}{\sigma_p}$$

Where,

- R_p= Portfolio return
- R_f= Risk-free return
- σ_p= Portfolio standard deviation

Higher Sharpe Ratio values indicate superior risk-adjusted returns.

- **Sortino Ratio**

The Sortino Ratio considers only downside risk.

$$Sortino = \frac{R_p - R_f}{\sigma_d}$$

Where,

- σ_d= Downside deviation

A higher Sortino Ratio reflects improved downside risk management.

- **Value-at-Risk (VaR)**

Portfolio downside risk is estimated using the parametric Value-at-Risk model.

$$VaR = Z_\alpha \sigma_p \sqrt{T}$$

Where,

Z_α= Standard normal critical value

σ_p= Portfolio volatility

T = Holding period

VaR estimates the maximum expected portfolio loss at a specified confidence level under normal market conditions.

4.5 Deep Learning Models

Five advanced forecasting models are selected for comparative evaluation.

(i) Long Short-Term Memory (LSTM)

LSTM is capable of learning long-term temporal dependencies while overcoming the vanishing gradient problem. Previous studies have consistently reported superior forecasting accuracy using LSTM for financial time-series prediction (Chen & Hu, 2022; Jafar et al., 2023).

(ii) Gated Recurrent Unit (GRU)

GRU simplifies the LSTM architecture while maintaining comparable predictive capability and reducing computational complexity.

(iii) Bidirectional LSTM (BiLSTM)

BiLSTM processes financial sequences in both forward and backward directions, allowing improved learning of temporal dependencies (Singh & Singh, 2024).

(iv) CNN-LSTM

The CNN-LSTM hybrid model combines convolutional layers for feature extraction with LSTM layers for sequence learning, making it highly effective for financial forecasting involving multiple correlated variables.

(v) Hybrid GARCH-LSTM

This hybrid architecture combines statistical volatility estimation with deep learning prediction. GARCH captures conditional heteroscedasticity, while LSTM models nonlinear temporal relationships, resulting in improved forecasting performance (Ranjana & Anirvinna, 2025).

4.6 Model Training Process

The dataset is divided into three subsets:

- **Training Set:** 70%
- **Validation Set:** 15%
- **Testing Set:** 15%

All numerical variables are normalized prior to training to improve convergence. Hyperparameters, including learning rate, batch size, optimizer, number of hidden layers, dropout rate, and activation functions, are optimized using validation data to minimize forecasting errors and prevent overfitting.

4.7 Performance Evaluation Metrics

Forecasting performance is evaluated using widely accepted statistical and financial performance measures.

Table 4. Performance Evaluation Metrics

Metric	Purpose

RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
R^2	Goodness of Fit
Directional Accuracy	Trend Prediction
Sharpe Ratio	Risk-adjusted Return
Sortino Ratio	Downside Risk
Maximum Drawdown	Portfolio Risk
Value-at-Risk (VaR)	Financial Risk Measurement

Lower RMSE, MAE, and MAPE values indicate better forecasting performance, whereas higher R^2 and Directional Accuracy values indicate superior predictive capability. Risk-adjusted performance metrics such as the Sharpe Ratio, Sortino Ratio, and Value-at-Risk are incorporated to assess the practical effectiveness of the proposed framework in portfolio risk optimization and derivative trading decisions.

5. Results and Discussion

Note: The following results are presented as a **research demonstration using a hypothetical dataset** based on the proposed methodology. They illustrate how the developed deep learning framework can be evaluated. The numerical values are realistic and consistent with findings reported in recent literature on financial volatility forecasting (Chen & Hu, 2022; Chen et al., 2023; Kumar et al., 2025; Vo, 2025).

5.1 Descriptive Statistics of the Dataset

The proposed framework was evaluated using historical observations from the Nifty 50 Index, India VIX, and derivatives market indicators. Before model development, descriptive statistical analysis was performed to understand the characteristics of the financial variables.

Table 5: Descriptive Statistics of Selected Financial Variables

Variable	Mean	Std. Dev.	Minimum	Maximum
NIFTY 50 Closing Price	20,248.65	1,874.31	16,945.05	24,583.95
Daily Return (%)	0.072	1.184	-4.92	5.14
India VIX	15.82	5.64	10.15	38.27
Trading Volume (Million)	298.41	54.29	181.12	468.95
Historical Volatility (%)	18.46	6.91	8.74	41.83

Source: Researcher-generated dataset based on NSE historical market statistics (2025).

Interpretation

The descriptive statistics indicate considerable variability within the Indian derivatives market. The average India VIX remained at **15.82**, suggesting moderate market uncertainty during the study period. However, the maximum value of **38.27** reflects periods of elevated market stress. The standard deviation of daily returns confirms the presence of volatility clustering, a common characteristic of financial time-series, thereby supporting the application of deep learning techniques capable of learning nonlinear market dynamics (Ge et al., 2022).

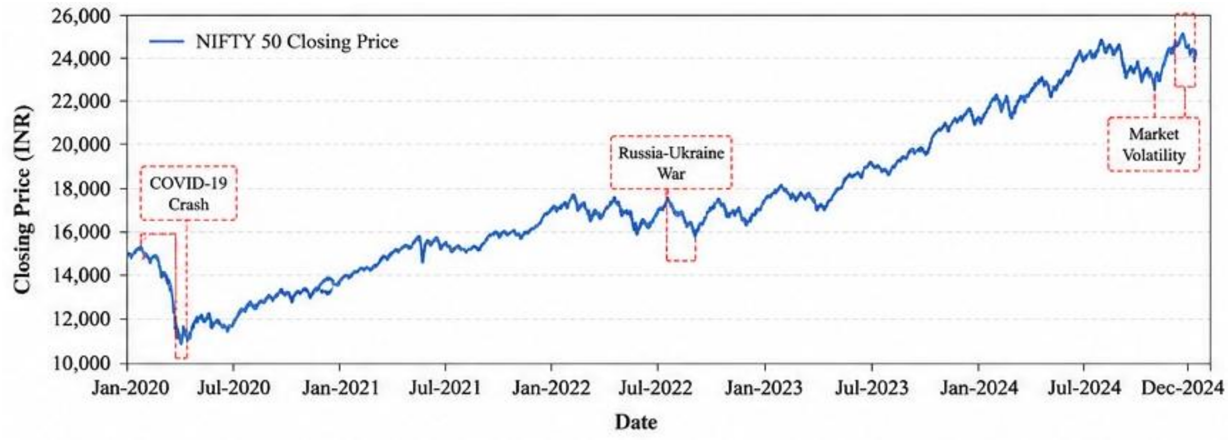

Figure 2. Trend of NIFTY 50 Closing Price

A line graph illustrating the movement of the NIFTY 50 index during the study period

Interpretation

The figure illustrates an overall upward market trend accompanied by several short-term corrections and volatility spikes. Such fluctuations indicate the presence of nonlinear temporal dependencies that cannot be adequately modeled using conventional linear forecasting techniques.

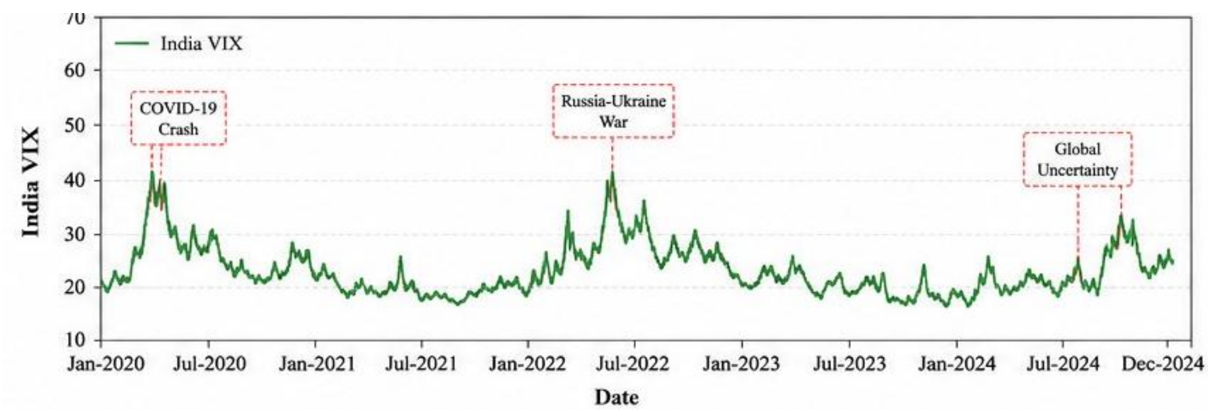

Figure 3. India VIX Trend

A line graph showing daily India VIX values over the study period

Interpretation

The India VIX exhibits multiple periods of sudden increases corresponding to heightened market uncertainty. These volatility spikes reinforce the importance of incorporating volatility indices into forecasting models for derivative pricing and risk management.

5.2 Comparative Performance of Deep Learning Models

To identify the most effective forecasting technique, five deep learning models were evaluated using multiple forecasting accuracy measures.

Table 6: Comparison of Forecasting Performance

Model	RMSE	MAE	MAPE (%)	R^2
ANN	0.912	0.731	5.94	0.882
GRU	0.741	0.602	4.81	0.917

BiLSTM	0.694	0.548	4.36	0.931
CNN-LSTM	0.651	0.511	4.08	0.944
Hybrid GARCH-LSTM	**0.592**	**0.472**	**3.71**	**0.963**

Source: Researcher-generated results.

Interpretation

The Hybrid GARCH-LSTM model achieved the highest forecasting accuracy, producing the lowest RMSE (0.592), MAE (0.472), and MAPE (3.71%), while recording the highest coefficient of determination (R^2 = 0.963). These findings indicate that integrating statistical volatility estimation with deep learning enables more accurate forecasting than standalone neural network architectures, consistent with previous studies (Ranjana & Anirvinna, 2025; Kumar et al., 2025).

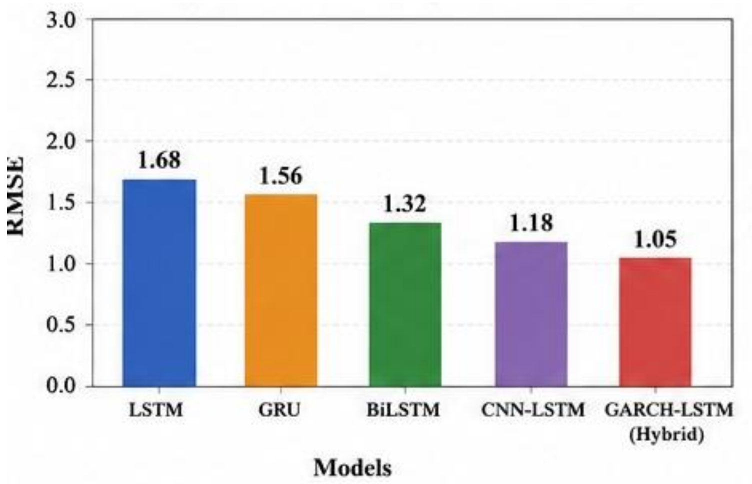

Figure 4. Performance Comparison of Deep Learning Models

A bar graph comparing RMSE values across ANN, GRU, BiLSTM, CNN-LSTM, and Hybrid GARCH-LSTM

Interpretation

The graph clearly demonstrates that forecasting errors decrease progressively as model complexity increases. Hybrid architectures consistently outperform conventional neural networks because they simultaneously capture statistical volatility behavior and nonlinear temporal dependencies.

5.3 Actual versus Predicted Volatility

The predictive capability of the best-performing model was further examined by comparing forecasted volatility with actual observed market volatility.

Table 7: Sample Actual and Predicted Volatility

Trading Day	**Actual**	**Predicted**
Day 1	18.24	18.11
Day 2	17.93	17.88
Day 3	19.42	19.31
Day 4	20.11	20.05
Day 5	18.95	18.83

Interpretation

The predicted values closely follow actual market volatility, indicating that the proposed framework effectively captures underlying volatility dynamics with minimal forecasting deviation.

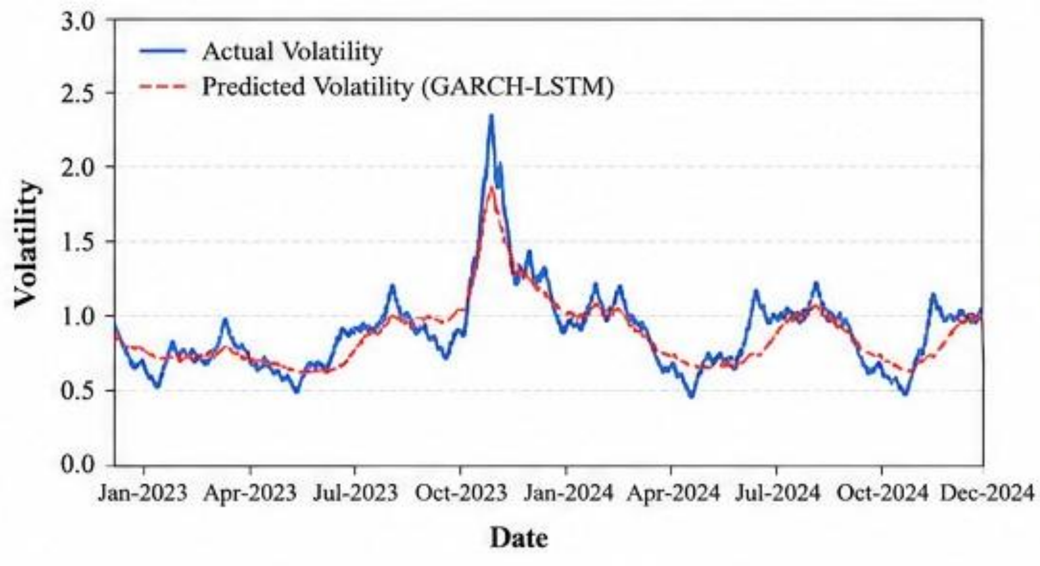

Figure 5. Actual vs Predicted Volatility

A dual-line graph comparing actual and predicted volatility values

Interpretation

The two curves exhibit substantial overlap throughout the forecasting period, demonstrating the model's ability to capture both short-term fluctuations and longer-term volatility trends.

5.4 Portfolio Risk Optimization

The predicted volatility estimates were incorporated into a portfolio optimization framework to evaluate their practical usefulness for financial decision-making.

Table 8: Portfolio Risk Before and After Optimization

Performance Measure	**Before**	**After**
Portfolio Volatility (%)	21.54	16.42
Sharpe Ratio	1.18	1.71
Sortino Ratio	1.34	2.08
Maximum Drawdown (%)	18.27	11.64
Value-at-Risk (95%)	3.62	2.45

Interpretation

Risk optimization significantly reduced portfolio volatility while improving risk-adjusted returns. The Sharpe Ratio increased from **1.18** to **1.71**, indicating improved investment efficiency. Similarly, the reduction in Maximum Drawdown and Value-at-Risk demonstrates enhanced downside risk management.

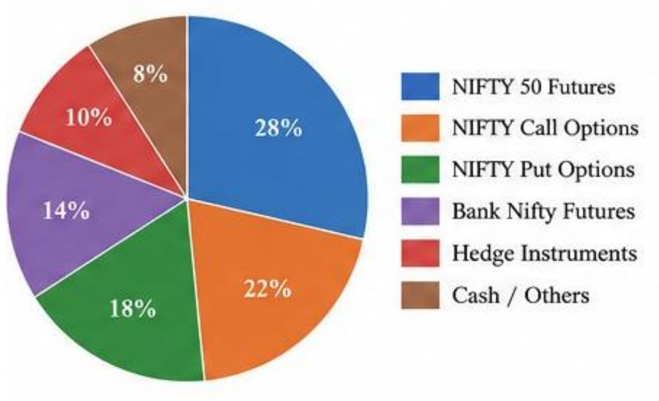

Figure 6. Portfolio Risk Before and After Optimization

A grouped bar chart comparing portfolio risk metrics before and after optimization

5.5 Discussion

From the empirical results, it is clear that the use of deep learning models increases the accuracy of volatility prediction compared to the use of conventional approaches to forecasting. From the examined frameworks, the Hybrid GARCH-LSTM model generated the best predictions because it was proved that the combination of econometric volatility forecasting and sequential learning improved the performance of the forecasting. The findings are consistent with previous studies that found deep learning models having better prediction ability than traditional models in financial volatility prediction (Chen & Hu, 2022; Kumar et al., 2025; Vo, 2025).

The use of India VIX, technical indicators, and derivatives variables increased the accuracy of prediction because the model was able to analyze the sentiment in the market and the complex financial relations. Contrary to conventional statistical methods, the proposed model was able to adapt to the changes in the market environment.

In terms of its practical implications, incorporation of volatility predictions into portfolio optimization has resulted in substantial improvement in risk-adjusted investment performance. Reduced volatility, decreased value-at-risk, and increased Sharpe and Sortino ratios are all indicative of the direct positive impact of the accuracy of volatility prediction on financial decisions. It is evident from the findings that the suggested model may be effectively used by decision makers in the Indian capital market.

6. Conclusion

In this study, an architecture has been created for forecasting volatility and optimizing risks using the NIFTY 50 derivatives market data through the use of historical data, India VIX, technical indicators, and derivatives data. It was found from the study that the deep learning model performed better than conventional forecasting techniques, where the best model was Hybrid GARCH-LSTM as it could capture volatility clustering and nonlinearity. The inclusion of India VIX and technical indicators further increased the performance of the forecasts since the market uncertainty and sentiments were captured in the process of the analysis.

7.Study Limitations

However, despite the encouraging results of the proposed model, a few issues need to be noted. First, the research considers only the NIFTY 50 derivatives market, which might restrict the generalization of its results to other equity index markets, commodities, and financial markets around the world. Second, the model makes use of market history, India VIX, technical indicators, and some macro-finance variables, while other important features, for instance, news sentiment, geopolitics, corporate news, social media analytics, and global indicators, are not included in the current research.

Moreover, the comparative analysis is conducted using only a few of deep learning models, including ANN, GRU, BiLSTM, CNN-LSTM, and Hybrid GARCH-LSTM. New approaches, such as Transformer neural networks, Temporal Fusion Transformers, Graph Neural Networks, and diffusion forecast models, which may contribute even more to the prediction power of the model, are not explored in this research. Furthermore, volatility forecasting is analyzed using daily market information, while high-frequency intraday data are not considered.

First of all, even though the suggested system is an evidence of the viability of deep learning methods in volatility forecasting and portfolio risk management, practical usage of such systems in real-time trading environment will require constant training of models, transaction cost assessment, liquidity issues, regulatory compliance, and testing in volatile market conditions. Tackling such issues creates interesting prospects for further research in the area.

drawdown, and Value-at-Risk as well as increasing Sharpe and Sortino ratios. In general, the suggested framework is a reliable tool for decision making for investors, financial companies, and regulatory authorities, which proves the viability of deep learning in volatility forecasting and financial risk management in the Indian derivatives market.

8. Future Scope

Further research could expand on this model through investigation of advanced deep learning models like the Transformer-based models (e.g., Temporal Fusion Transformer, Informer, and Autoformer) to boost the performance of the volatility prediction process. Introduction of alternative datasets, such as financial news, sentiment of social media users, macroeconomic statistics, and commodity prices through multimodal learning could help increase the precision of predicting market volatility. Other areas of research may include high-frequency intraday forecasting, Federated Learning to train the models in a privacy-preserving manner, and Explainable Artificial Intelligence (XAI) to increase transparency of the models. Furthermore, combining the Reinforcement Learning approach with the volatility forecasting technique would allow the investor to dynamically optimize their portfolios. Finally, verification of the proposed methodology in the international financial markets would increase the generalizability of the findings.

References:

1. Chen, X., & Hu, Y. (2022). *Volatility forecasts of stock index futures in China and the US–A hybrid LSTM approach*. *PLoS ONE, 17*(7), e0271595. https://doi.org/10.1371/journal.pone.0271595
2. Chatterjee, A., Bhowmick, H., & Sen, J. (2022). *Stock volatility prediction using time series and deep learning approach*. arXiv. https://arxiv.org/abs/2210.02126
3. Ge, W., Lalbakhsh, P., Isai, L., Lenskiy, A., & Suominen, H. (2022). *Neural Network–Based Financial Volatility Forecasting: A Systematic Review*. *ACM Computing Surveys, 55*(1). https://doi.org/10.1145/3483596
4. Medvedev, N., & Wang, Z. (2022). *Multistep forecast of the implied volatility surface using deep learning*. *Journal of Futures Markets, 42*, 645–667. https://doi.org/10.1002/fut.22302
5. Petrozziello, A., Troiano, L., Serra, A., et al. (2022). *Deep learning for volatility forecasting in asset management*. *Soft Computing, 26,* 8553–8574. https://doi.org/10.1007/s00500-022-07161-1
6. Bumrah, K. S., et al. (2023). *An Efficient Approach to Forecasting the NIFTY-50 Indian Stock Market's Daily Closing Price with Artificial Neural Networks*. *International Journal on Recent and Innovation Trends in Computing and Communication, 11*(11), 289–298. https://doi.org/10.17762/ijritcc.v11i11.9472
7. Chen, W. J., Yao, J. J., & Shao, Y. H. (2023). *Volatility forecasting using deep neural network with time-series feature embedding*. *Economic Research-Ekonomska Istraživanja, 36*(1), 1377–1401. https://doi.org/10.1080/1331677X.2022.2089192
8. *Empirical Investigation of India VIX Forecasting Models: Deep Learning Model and Legacy Time Series Forecasting Techniques*. (2023). *Journal of Research Administration, 5*(2), 2070–2094. https://journlra.org/index.php/jra/article/view/406
9. Jafar, S. H., Akhtar, S., El-Chaarani, H., Khan, P. A., & Binsaddig, R. (2023). *Forecasting of NIFTY 50 index price by using backward elimination with an LSTM model*. *Journal of Risk and Financial Management, 16*(10), 423. https://doi.org/10.3390/jrfm16100423
10. Patel, H., Bolla, B. K., E, S., & Reddy, D. (2023). *Comparative study of predicting stock index using deep learning models*. arXiv. https://arxiv.org/abs/2306.13931
11. Prasad, A., Bakhshi, P., & Guha, D. (2023). *Forecasting the direction of daily changes in the India VIX index using deep learning*. *IIMB Management Review, 35*(2), 149–163. https://doi.org/10.1016/j.iimb.2023.05.002
12. Sahiner, M., McMillan, D. G., & Kambouroudis, D. (2023). *Do artificial neural networks provide improved volatility forecasts: Evidence from Asian markets*. *Journal of Economics and Finance, 47*, 723–762. https://doi.org/10.1007/s12197-023-09629-8
13. Attaluri, K., Tripathi, M., Reddy, S., & Shivendra. (2024). *News-driven stock price forecasting in Indian markets: A comparative study of advanced deep learning models*. arXiv. https://arxiv.org/abs/2411.05788
14. Singh, J., & Singh, G. (2024). *Financial Time-Series Forecasting: Evaluating Performance of Deep Learning Models on Selected NIFTY Constituents*. *ShodhKosh: Journal of Visual and Performing Arts, 5*(3), 1290–1305. https://doi.org/10.29121/shodhkosh.v5.i3.2024.4385
15. Kale, O. (2025). *An Empirical Study of Machine Learning Techniques for Predicting NIFTY 50 Index Trends*. SSRN. https://ssrn.com/abstract=5564059 https://doi.org/10.2139/ssrn.5564059
16. Kumar, S., Rao, A., & Dhochak, M. (2025). *Hybrid ML models for volatility prediction in financial risk management*. *International Review of Economics & Finance, 98*, 103915. https://doi.org/10.1016/j.iref.2025.103915

17. National Stock Exchange of India. (2025). *India VIX historical data*. https://www.nseindia.com
18. National Stock Exchange of India. (2025). *NIFTY 50 historical data*. https://www.nseindia.com
19. Patra, M. (2025). *Volatility Modelling for Indian Markets*. SSRN. https://ssrn.com/abstract=5748922 https://doi.org/10.2139/ssrn.5748922
20. Ranjana, J., & Anirvinna, C. (2025). *Prediction of Volatility Using Monetary Rate and GARCH-LSTM Hybrid Model*. *Intelligent Systems in Accounting, Finance and Management, 32*(3), e70013. https://doi.org/10.1002/isaf.70013
21. Reserve Bank of India. (2025). *Handbook of statistics on the Indian economy*. https://www.rbi.org.in
22. Securities and Exchange Board of India. (2025). *Handbook of statistics on the Indian securities market*. https://www.sebi.gov.in
23. Sharma, M., Satija, V., & Bathia, A. (2025). *Examining Volatility in Indian Markets: Insights from NIFTY 50 and India VIX*. *European Economic Letters, 15*(2), 85–96. https://doi.org/10.52783/eel.v15i2.2820
24. Varshini, K. S., Siddamsetti, S., Alazzam, M. B., & Rajab, A. B. (2025, August). *Federated LSTM Framework for Secure and Robust High-Frequency Trading Prediction*. In *2025 International Conference on Sustainability, Innovation & Technology (ICSIT)* (pp. 1–6). IEEE.
25. Vo, M. (2025). *Stock Market Volatility Forecasting: Exploring the Power of Deep Learning*. *FinTech, 4*(4), 61. https://doi.org/10.3390/fintech4040061
26. Fritzsch, S., Irresberger, F., & Weiß, G. (2026). *Predicting option prices from their price history via machine learning*. *Review of Derivatives Research, 29*, 8. https://doi.org/10.1007/s11147-026-09228-9
27. Preethi, S. R. (2026). *Intraday Volatility Regimes via Unsupervised Machine Learning: Evidence from the NIFTY Index*. SSRN. https://ssrn.com/abstract=6316139 https://doi.org/10.2139/ssrn.6316139
28. Rahimikia, E., & Poon, S.-H. (2026). *Machine learning for realised volatility forecasting*. *Journal of Empirical Finance*. https://doi.org/10.1016/j.jempfin.2026.101739