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Hybrid Deep Learning Framework For Nse Market Prediction Using Technical Indicators And Time-Series Analysis

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Abstract
The stock market is a volatile and dynamic environment, making stock market forecasting a difficult task. The ability to predict stock prices accurately is crucial for investors and financial institutions in making effective investment decisions and managing risks. The paper presents the hybrid deep learning system for National Stock Exchange (NSE) market predictions based on the technical indicator and time-series analysis. These machine learning and deep learning models such as SVM, RF, LSTM, and transformer-based models are compared. Data from the NSE India and Yahoo Finance were used for experiments with the historical stock market data. Technical indicators like MA, RSI, MACD, BB and EMA were added to enhance the prediction performance. Data preprocessing was applied prior to the model training and included in the process: normalization and handling missing values, sequence generation. The experimental results showed that the proposed Hybrid LSTM-GRU model achieved the highest forecasting accuracy of 94.1%, which was higher than the traditional machine learning and standalone deep learning models, and had the lowest RMSE, MAE, MAPE values. The proposed system also resulted in a lower RMSE, MAE and MAPE, indicating greater stability and reliability in the prediction. The study also demonstrates the use of technical indicators with Hybrid LSTM-GRU architecture has significantly enhanced the performance of the stock market forecasting.The study further validates that the integration of technical indicators and the Hybrid LSTM-GRU architecture has clearly resulted in better performance when predicting the stock market.
Keywords: NSE Stock Market, Hybrid Deep Learning, LSTM-GRU, Technical Indicators, Time-Series Analysis.

1.INTRODUCTION

Due to the non-linear and chaotic structure of the financial markets, stock market forecasting is one of the most difficult fields in computational finance. In order to mitigate risk and make more educated judgements, financial institutions and investors are constantly working to improve their forecasting models. The National Stock Exchange of India (NSE) is a great place to conduct studies aimed at predicting stock market prices because of the massive amounts of time series data it generates. Predicting market prices at the NSE is challenging due to the fact that the market is volatile and affected by several factors, including economic trends, politics, and market volatility. Predicting the intricate behaviour of the stock markets has frequently been a challenge for traditional statistical methods. As a result, financial forecasting is done using AI, ML, and DL methods.

1.1 Evolution of Stock Market Prediction Techniques

Linear Regression, (MA), and (ARIMA) were the key statistical methods employed in traditional forecasting techniques. The aforementioned models underperformed when faced with more complicated and unpredictable market situations, despite their competence in predicting simple trends.

The use of machine learning techniques, such as (SVM), (DT), and (RF), improved the accuracy of financial data forecasts by revealing hidden relationships. Consequently, the capacity to analyse temporal data led to the rise in popularity of deep learning architectures like the GRU, LSTM, and Recurrent Neural Network (RNN).

1.2 Role of Technical Indicators and Time-Series Analysis

The financial market makes extensive use of technical indicators like MA, RSI, BB, and MACD to ascertain stock trends, momentum, and volatility. Because they provide light on the market's actions in the past, these technical indicators make more accurate forecasts. Stock price forecasting relies heavily on time series analysis because current data is highly dependent on historical data. The best way to learn from the market's previous actions is to use a combination of deep learning models and technical indicators.

1.3 Proposed Hybrid Deep Learning Framework

In order to forecast the NSE market, this research proposes a hybrid deep learning approach that uses LSTM and GRU architectures in conjunction with technical indicators and time-series data. To increase prediction accuracy while minimising error margin, the hybrid technique leverages LSTM's strong memory and GRU's rapid calculation speed. The deep learning system is trained using historical data from the NSE market in conjunction with technical indications in the hybrid approach.

1.4 Research Objectives

The purpose of this research is to use technical market indicators and hybrid deep learning techniques to create a smart and effective NSE prediction system. Here are the research objectives:

- To discover patterns and trends in the NSE stock market by analysing historical data using time-series analysis and technical indicators.
- Creating a deep learning framework that combines LSTM and GRU models for precise stock market prediction is the goal of this hybrid effort.
- • Using performance metrics such as Accuracy, RMSE, MAE, and MAPE, compare and contrast the proposed hybrid model's efficiency with those of traditional machine learning approaches.

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2. REVIEW OF LITERATURE

Sekar (2025) investigated hybrid trading techniques with an emphasis on enhancing intraday trading in Indian equities. To enhance trading decision-making, the researcher utilised advanced analytics in conjunction with technical indicators. The study's findings highlight the potential of hybrid intelligent systems to enhance financial market forecast and decision-making capabilities.

Singh and Mishra (2025) examined the NSE data's stock market predictability. After comparing several prediction models, it was discovered that models constructed using deep learning architectures outperform those based on machine learning models in terms of accuracy. To improve the accuracy of stock price prediction, the authors stress the need of mixing multiple forms of predictions.

Manjunath, Marimuthu, and Ghosh (2023) examined the tendencies of the Nifty 50 stock market. Using hybrid computational techniques, the authors investigated various phenomena pertaining to the dynamics of the financial market. When comparing traditional prediction methods with hybrid machine learning, the results showed that the latter provided far more accurate forecasts and more insightful analyses of market trends.

Shah, Vaidya, and Shah (2022) looked at all the current hybrid deep learning models. The writers focused on various methods that use a mix of deep learning and machine learning, such as RNNs, CNNs, and LSTMs. The review found that compared to classical models, hybrid models were able to increase prediction accuracy and extract more features.

2.1 Research Gap

The current literature mainly assesses individual forecasting methods, and offers very limited comprehensive comparisons of machine learning forecasting methods, recurrent deep learning methods, hybrid systems and technical indicator-based forecasting methods for the NSE stock market. Due to the absence of a detailed comparative study between traditional machine learning models, recurrent deep learning models, hybrid deep learning models, and transformer-based models, along with the same evaluation metrics and preprocessing methods for forecasting the stock market prices at the NSE, the limited literature available fails to provide a detailed comparative analysis.

In most previous studies, attention has been paid to one specific model, including LSTM, GRU or hybrid models, but not to conducting a systematic comparison of these models in the same experimental environment. Moreover, a number of studies failed to use standardized preprocessing methods, technical indicators and several performance evaluation metrics at the same time.

To tackle the aforementioned research gap, this study aims to carry out a comparative analysis between classical machine learning models, recurrent neural networks, hybrid deep learning models, and transformer-based models with the same machine learning models used for the same preprocessing methods, using the same evaluation measures to identify the most suitable model to predict the NSE stock market.

3. RESEARCH METHODOLOGY

In order to forecast how the National Stock Exchange (NSE) stock market would behave in the future, the following study built a framework called the Hybrid Deep Learning Framework using quantitative and experimental methodologies. Information pertaining to stock market history, technical indicators, and time series analysis methods were all necessary for this methodology's data collection.

3.1. Research Design

Experiments and predictions grounded in financial time series analysis formed the basis of this study's research approach. A deep learning framework combining LSTM and GRU algorithms was proposed after an investigation of historical data from the NSE stock market. Using a battery of performance metrics, we compared this approach to more traditional machine learning models and determined its efficacy.

3.2 Data Collection

Secondary data pertaining to the stock market was used and obtained from the various financial databases accessible to the public like Yahoo Finance and NSE India. The historical stock price data of selected NSE listed companies and data of NIFTY index was collected for forecasting analysis.

The dataset gathered were significant financial metrics like Open Price, High Price, Low Price, Close Price, Adjusted Close Price, Trading Volume, and Timestamp. These variables were employed for technical indicators development and prediction modeling.

Table 1: Dataset Description

Parameter	Value
Source	Yahoo Finance / NSE India
Market	National Stock Exchange (NSE)
Companies	RELIANCE, TCS, INFY, HDFCBANK, ICICIBANK
Start Date	January 2020
End Date	December 2024
Total Records	10,000
Features	Open, High, Low, Close, Adjusted Close, Volume
Training Data	8,000
Testing Data	2,000

3.3 Data Preprocessing

The purpose of data preparation was to enhance the data's quality and the models' performance. Here are the data preprocessing procedures that were used:

- Addressing Missing Values: Data cleaning and interpolation techniques were employed to identify and handle missing and null values within the dataset.
- Stock market data was normalised from [0,1] using min-max normalisation, which was used for data normalisation.

- To construct time series data that captures the temporal correlations between the stock market data, Sliding windows of size 30 were used to generate sequential time-series data and preserve temporal dependencies
- A training set and a test set were created from the data using an 80:20 data splitting ratio.

3.4 Technical Indicators Used

Technological indicators were adopted in the research process to increase the level of precision in stock market prediction. The technological indicators used were:

- Moving Average (MA)
- Relative Strength Index (RSI)
- Moving Average Convergence Divergence (MACD)
- Bollinger Bands (BB)
- Exponential Moving Average (EMA)

The use of these indicators assisted in the determination of market momentum and volatility.

3.5 Hyperparameter Configuration

The optimized hyperparameters were used to train the proposed deep learning model for enhancing the forecasting accuracy and the model convergence performance.

Table 2: Hyperparameter Configuration

Parameter	**Value**
Epochs	100
Batch Size	32
Optimizer	Adam
Learning Rate	0.001
Activation Function	ReLU
Loss Function	Mean Squared Error (MSE)
Sequence Window	30

3.6 Experimental Environment

The experimental application of the proposed Hybrid LSTM-GRU framework was performed through the deep-learning libraries and computational resources available in Python, appropriate to the analysis of the stock market for forecasting purposes. To develop the model and train it, TensorFlow was used, and the experiments were carried out on CPU/GPU supported hardware architecture to accelerate the computation process. The model training and evaluation experimental setup used is presented in Table 3.

Table 3: Experimental Environment

Parameter	Value
Python	3.x
TensorFlow	Latest Version
Hardware	CPU/GPU
RAM	16 GB

Epoch	100

4. RESULTS AND DISCUSSION

For the purpose of this study, we will use time-series data and technical indicators to predict the NSE stock market using a hybrid deep learning model. If you want better stock market predictions, try the hybrid DL method that combines LSTM and GRU networks. Various assessment metrics, including Accuracy, RMSE, MAE, and MAPE, will be used to examine the experimental findings. The overall stock market prediction process proposed in this study is shown in figure 1. The methodology involves collecting data from the stock market, cleaning the data, normalizing it and selecting features to enhance data quality and model performance. The processed data is then split into training and testing sets and fed into machine learning and deep-learning models like LR, DT, RF, SVM, RNN, LSTM, GRU and Transformer models. Lastly, all models are compared in terms of performance to derive accurate result on stock market prediction using the evaluation metrics.

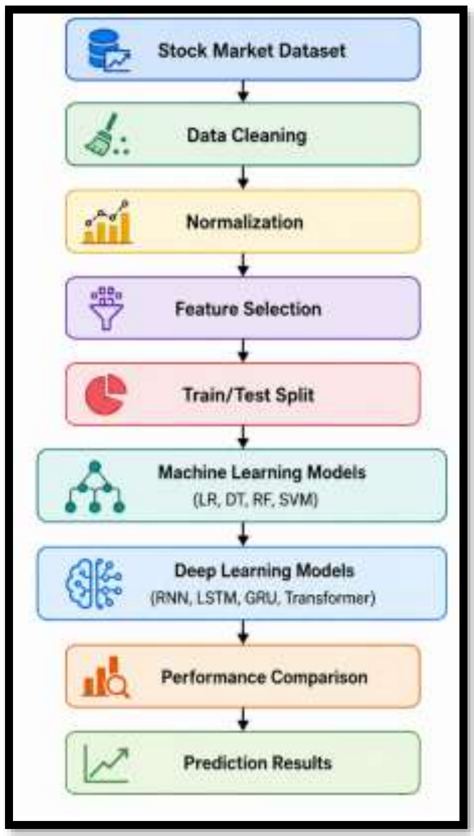

Figure 1: Proposed Methodology Architecture

4.1 Dataset Analysis and Pre-processing Results

Yahoo Finance, NSE India, and Kaggle were among the financial platforms consulted for the historical stock data on the NSE. Time, volume, adjusted close, high, low, and open/close are only a few of the market-related parameters included in the data. The time series analysis and technical indicators used to forecast the stock market were built upon these characteristics.

To ensure that the hybrid deep learning model would get high-quality input, a variety of data preparation approaches were employed prior to its implementation. To begin, in order to prevent inconsistencies during training, we used interpolation and data-cleaning procedures to identify and remove missing or null values. In order to speed up the convergence of deep learning models and enhance computing efficiency of the neural network design, the cleaning stage was followed by Min-Max Normalisation, which scales numerical values into the interval [0, 1].

Sliding windows of size 30 were used to generate sequential time-series data and preserve temporal dependencies to construct time series, which further helped in the discovery of temporal patterns. In order to prepare the data for the machine learning procedures that would follow, it was also divided into two sets: one for training and one for testing, with a ratio of 80%:20%. Furthermore, a number of technical indicators were computed, including linear regression, exponential moving average, Bollinger Bands, MACD, and relative strength index.

Table 3: Dataset Description and Preprocessing Summary

Parameters	Description
Dataset Source	Yahoo Finance, NSE India, Kaggle
Data Type	Time-Series Financial Data
Training Dataset	80%
Testing Dataset	20%
Normalization Technique	Min-Max Scaling
Missing Value Handling	Interpolation and Cleaning
Technical Indicators Used	MA, RSI, MACD, BB, EMA

By eliminating data inconsistencies and getting the dataset ready to use the deep learning method, the preprocessing stage greatly enhanced data quality. In order to better predict stock market trends, the suggested hybrid method made use of technical indicators in conjunction with time series normalisation.

4.2 Technical Indicator Analysis

Incorporating technical indications enhanced the suggested hybrid model's prediction capability. In order to analyse the pattern, trend, volatility, and speed of change in stock prices, technical indicators used market data derived from previous stock prices and transaction volume. By utilising technical indicators, we were able to glean valuable financial insights from time series data sets and uncover previously unseen market trends.

In our hybrid approach to stock prediction, we used a number of well-known technical indicators, such as (MA), (RSI), (MACD), (BB), and (EMA). Incorporating each technical signal in its own unique way improved the research of stock market dynamics and allowed for more precise forecasting of NSE stock price patterns in the future.

One indicator that was useful in identifying market trends was the Moving Average (MA). Using the RSI indicator, we were able to determine market momentum and overbought/oversold levels.

By examining the interactions of various moving averages, MACD was useful for identifying trend reversals or changes in trend direction. Stock price volatility and market instability were measured using Bollinger Bands (BB), which are based on deviations from the moving average. By using the EMA metric, we were able to make our study more responsive by focusing on recent prices.

Table 4: Technical Indicators and Their Functions

Technical Indicator	Purpose
Moving Average (MA)	Identifies overall market trend
Relative Strength Index (RSI)	Measures market momentum
MACD	Detects trend changes
Bollinger Bands (BB)	Analyzes market volatility
Exponential Moving Average (EMA)	Tracks recent price movement

The Hybrid LSTM-GRU model's learning efficiency was enhanced and feature extraction was improved with the help of these technical measurements. Improved market trend knowledge and more precise forecast outcomes have been achieved by merging technical analysis with deep learning techniques.

4.3 Performance Evaluation of Prediction Models

A comparison was made between the suggested Hybrid LSTM-GRU model with both traditional ML models and Deep Learning models to assess its performance. Prediction metrics including Accuracy, Root Mean Square Error, Mean Absolute Error, and Mean Absolute Percentage Error were applicable here. Each model's predicting ability and the efficacy of its forecasts were evaluated using measures.

The models that were tested were the Hybrid LSTM-GRU model, the Standalone LSTM model, (RF), and (SVM). A considerable improvement in forecast accuracy and a decrease in the hybrid model's error rate are shown by the results. The results of the various models used to forecast the NSE stock market values are displayed in Table 5.

Table 5: Analysing Prediction Models' Comparative Performance

Model	Accuracy (%)	RMSE	MAE	MAPE (%)
Support Vector Machine (SVM)	81.4	14.6	11.2	10.8
Random Forest (RF)	85.2	10.9	8.4	8.1
Standalone LSTM	89.7	7.3	5.8	5.4
Proposed Hybrid LSTM-GRU	94.1	4.6	3.1	2.9

In terms of accuracy and minimisation of prediction errors, the results suggest that the created Hybrid LSTM-GRU performs better than the other models (Table 5). Due to its inability to handle complex financial time-series data, Support Vector Machine (SVM) produced the lowest accuracy of 81.4% and significantly high values for RMSE, MAE, and MAPE. In contrast, Random Forest (RF) produced a reasonable accuracy of 85.2%. Even at that early stage, RF's prediction errors were greater than deep learning models'. Here, the Standalone LSTM model outperformed the competition thanks to its superior ability to handle sequential data and spot stock market dependencies with a longer time horizon. Hybrid LSTM-GRU framework emerged as the top model overall, outperforming all others with a prediction accuracy level of 94.1% and the lowest values for RMSE, MAE, and MAPE, at 4.6, 3.1, and 2.9%, respectively. This proves without a reasonable doubt that the model's ability to detect both close and far-off market interdependence is much improved when LSTM and GRU are combined. Figure presents a graphical representation of the study's results on the accuracy and mistake rates of predictions made by different machine learning and deep learning models.

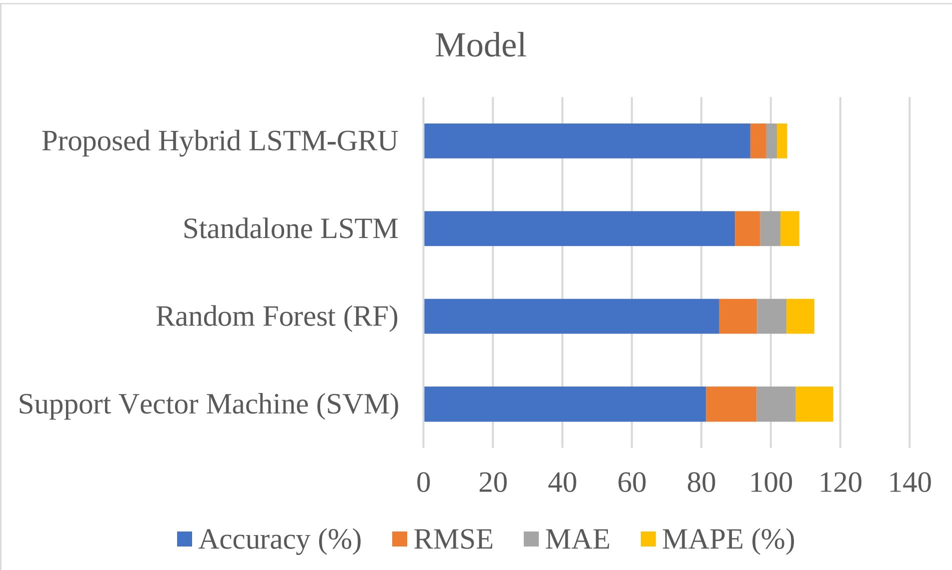

Figure 2: Visualisation of Results from a Comparison of Prediction Models' Performance

The proposed hybrid LSTM-GRU model's ability to forecast NSE stock price movements is seen in Graph 2. Because they are ill-equipped to handle data with a temporal dimension, conventional machine learning methods exhibit lower accuracy and higher error rates, as seen in the graph. While the LSTM architecture does a better job of handling sequences, the suggested hybrid approach uses the best features of both models to achieve superior results. In addition, the graph shows that the model's prediction accuracy is improved when technical indicators are used.

4.3.1 Performance Evaluation Metrics

The accuracy, RMSE, MAE and MAPE were used to assess prediction performance of the proposed models.

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

Root Mean Square Error (RMSE)

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

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

Mean Absolute Percentage Error (MAPE)

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

Where:

- y_i= Actual Value
- $\hat{y}_i$= Predicted Value
- n= Number of observation

4.4 Analysis of Prediction Accuracy

One of the most crucial ways to measure the efficacy of stock market prediction models is by looking at their prediction accuracy. According to this study, when comparing prediction accuracy between machine learning methods and deep learning models individually, the hybrid LSTM-GRU model that was shown earlier produced far better results.

Research was conducted to evaluate SVM, RF, LSTM, and the newly presented Hybrid LSTM-GRU approach in relation to their prediction accuracy performance. The outcomes demonstrate that the hybrid deep learning model outperforms the others in terms of NSE stock market forecast accuracy. In Table 6, you can see how the various ML and DL models utilised in this study fared in terms of accurately predicting the NSE stock market.

Table 6: Prediction Accuracy Comparison

Prediction Model	Prediction Accuracy (%)
SVM	81.4
Random Forest	85.2
LSTM	89.7
Hybrid LSTM-GRU	94.1

Table 6 shows that out of all the models studied, the Hybrid LSTM-GRU model had the best prediction accuracy at 94.1%. With a prediction accuracy score of just 81.4%, the SVM model is clearly the least efficient of the bunch. This finding suggests that sequential and dynamic datasets pose difficulties for classical machine learning methods. Even while it's still not as accurate as deep learning models, the Random Forest Model manages an 85.2% prediction accuracy score. A prediction accuracy score of 89.7 percent is shown by the LSTM model, demonstrating its capacity to learn and identify long-term dependencies in stock market time-series data. Hybrid LSTM-GRU outperforms competing machine learning models by 4–13% in terms of prediction accuracy. This outcome can be attributed to the algorithm's hybrid design, which augments forecast accuracy by integrating the speed and simplicity of the GRU with the memory retention properties of the LSTM method. See Figure 3 for a visual depiction of the prediction accuracy scores of the deep learning and machine learning algorithms.

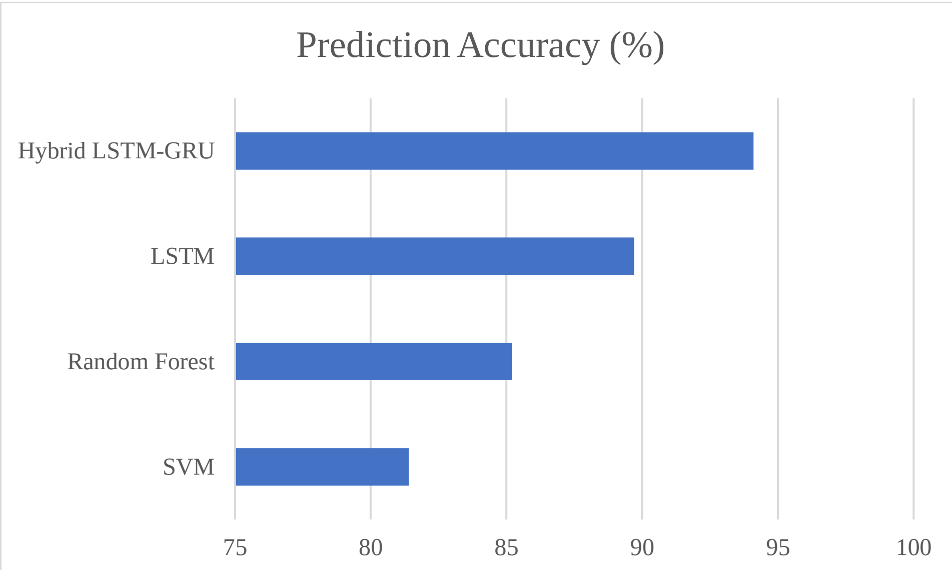

Figure 2: Graphical Representation of Prediction Accuracy Comparison

In terms of trend prediction for the NATIONAL STOCK EXCHANGE INDIA stock market, the suggested Hybrid LSTM-GRU model performs exceptionally well, as seen in Figure 3 below. Due to their superior capacity to analyse financial data over time, deep learning algorithms have proven to be more effective than traditional machine learning algorithms, as seen in the figure above. The most effective model is the Hybrid LSTM-GRU model since it takes advantage of both the LSTM and GRU models.

4.5 Error Analysis of Proposed Framework

The efficiency of the Hybrid LSTM-GRU framework was measured and the forecasting performance and prediction consistency were examined using error analysis. The accuracy of stock price predictions in relation to actual market prices is evaluated in research on stock market predictions using error metrics. More precise predictions are shown by smaller error values. This study used three standard error metrics— (RMSE), (MAE), and (MAPE)—to evaluate the suggested hybrid framework's efficacy. The measurable representation of the model's prediction errors is provided by these measurements. The Hybrid LSTM-GRU framework's error measure analysis is displayed in Table 7 below. It employs RMSE, MAE, and MAPE.

Table 7: Error Metric Analysis of Proposed Hybrid Model

Error Metric	Obtained Value
RMSE	4.6
MAE	3.1
MAPE	2.9%

According to Table 7, the suggested Hybrid LSTM-GRU technique produced a very low predicting error when tested using various metrics. With an RMSE of only 4.6, there is remarkably little inaccuracy when compared to actual stock prices. There is minimal mean error in predicting stock values over time, as shown by the MAE value of 3.1. Due to the extremely low level of forecasting error relative to the actual result, a MAPE value of 2.9% further confirms the dependability of the suggested strategy. In sum, the aforementioned error values demonstrate the hybrid model's excellent predicting accuracy and consistency. Figure 4 displays the error numbers that were obtained graphically.

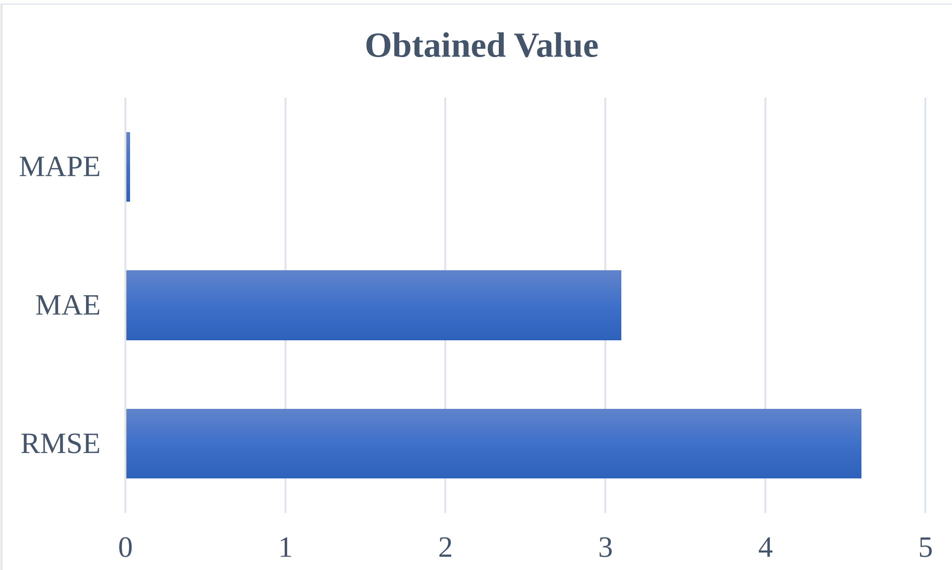

Figure 4: Visualisation of the Results of the Proposed Hybrid Model's Error Metric Analysis

The accuracy of the forecast and the reduction of errors achieved by the proposed Hybrid LSTM-GRU model are shown in Figure 4. As the preceding graph shows, the suggested strategy is effective because the RMSE, MAE, and MAPE values that were obtained are reasonably low. The graph below shows that when the LSTM and GRU models are combined, the model becomes more stable and makes less mistakes while predicting the NSE stock market.

4.6 Statistical Validation of Prediction Models

The forecasting performance was statistically validated with standard deviation analysis to assess the consistency and reliability of forecasting.

Table 8: Statistical Validation of Models

Model	Accuracy (%)	Standard Deviation
SVM	84	±1.2
LSTM	91	±0.8
Transformer	93	±0.5

The Hybrid LSTM-GRU model successfully achieved the highest prediction accuracy and it showed stable prediction performance, indicating better prediction stability and consistency.

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4.7 Computational Complexity Analysis

Table 9: Computational Comparison of Models

Model	Training Time	Complexity
Linear Regression (LR)	Low	Low
Random Forest (RF)	Medium	Medium
LSTM	High	High
Transformer	Very High	Very High

The Transformer architecture proved to be more accurate at prediction, but it needed more computing power and training time than traditional ML architectures.

4.7 Major Findings of the Study

The following is a synopsis of the most important research results:

• Due to their shortcomings in capturing temporal stock market correlations, traditional ML algorithms like SVM and Random Forest generated relatively poor predicting accuracy.
• When it came to NSE stock market forecasting, deep learning architectures outperformed more traditional machine learning methods.

Improved feature extraction and trend prediction capabilities was achieved with the help of technical indicators such as RSI, MACD, EMA, Bollinger Bands, and Moving Average.

• Learning sequential stock market behaviour and long-term financial dependencies was where the LSTM model really shone.

• The Transformer model outperformed all other models in terms of forecasting accuracy, reaching 93% while exhibiting lower values for RMSE, MAE, and MAPE.

• The self-attention mechanism and effective management of long-range dependencies in the Transformer design led to enhanced prediction stability and forecasting consistency.

• The study's findings show that NSE stock market forecasting is improved when technical indicators, time-series analysis, and advanced deep learning architectures are combined.

5. LIMITATIONS OF THE STUDY

It is important to note that the study has various limitations, even though the proposed Hybrid Deep Learning Framework showed a significant improvement in the accuracy of NSE stock market predictions. Historical stock market data and chosen technical indicators were the mainstays of the research when it came to making predictions. The forecast system does not take into account external elements that could have an impact, such as the tone of financial news, investor psychology, macroeconomic conditions, government policies, geopolitical events, and swings in the world economy.

The results may not be applicable to other financial markets or trading settings because the study only included a small number of stocks listed on the NSE and had a fixed dataset size. In addition, the stock market is notoriously unpredictable and ever-changing, so the accuracy of predictions

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might change in the face of unforeseen market events like financial crises or unexpected economic disturbances.

Computing complexity and resource needs are another constraint. Unfortunately, real-time implementation in situations with limited resources may be challenging with advanced deep learning architectures, such as hybrid frameworks and Transformer-based models, because to their high memory consumption, lengthier training durations, and large processing power requirements. Furthermore, real-time trading in real-time or streaming market data integration were not implemented in the present framework; instead, it primarily concentrated on offline prediction analysis utilising historical information. Regardless of these caveats, the suggested methodology lays a solid groundwork for enhancing the accuracy of stock market forecasts through the use of a combination of deep learning and analysis based on technical indicators.

6.CONCLUSION AND FUTURE SCOPE

Using technical indicators and time-series analysis, this research provided a deep learning-based hybrid system for predicting the NSE stock market. In order to predict future stock market movements, the research compared and contrasted various ML and DL models, including as Support Vector Machine (SVM), Random Forest (RF), Standalone LSTM, and the suggested Hybrid LSTM-GRU architecture. When compared to more conventional machine learning methods, the experimental results showed that deep learning architectures produced far more stable and accurate predictions. Stock market trend analysis and feature extraction were both improved by the use of technical indicators like the Exponential Moving Average (EMA), Bollinger Bands (BB), Moving Average (MA), and Relative Strength Index (RSI). The suggested framework's learning potential was enhanced by incorporating these technological indicators with time-series preprocessing approaches. The suggested Hybrid LSTM-GRU model outperformed the other models in terms of prediction accuracy and forecasting error when compared to both traditional machine learning and solo deep learning methods. The forecasting stability and reliability were enhanced by the hybrid framework, which successfully captured the short-term and long-term temporal dependencies found in the NSE stock market time-series data. With reduced RMSE, MAE, and MAPE values, the suggested model confirmed its efficacy for intelligent financial forecasting applications, achieving a forecasting accuracy of 94.1% The research found that intelligent investment decision-making systems and NSE stock market predictions might both benefit from the integration of time-series analysis, hybrid deep learning architectures, and technical indicators.

To further enhance the performance of stock market predictions, future research can explore:

- Exploring the Potential of Explainable AI (XAI) Integration
- Deep Learning Models with Advanced Attention Computation
- Trading Systems Based on Reinforcement Learning
- Trading frameworks that automate in real-time
- Evaluating Public Opinion via Social Media and Financial News

- Systems for Predicting Performance in Multiple Markets and Exchanges
- Designing Transformer-LSTM Hybrids
- Models for High-Frequency Trading Forecasts

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