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A COMPARATIVE ANALYSIS OF TREE-BASED ENSEMBLES AND DEEP LEARNING FOR EQUITY PRICE FORECASTING USING FEATURE-ENGINEERED ADVANCE TECHNICAL INDICATORS

[1]Satish Kumar Singh, [2]Dr. Sheeba Praveen

[1]Research Scholar, Department of CSE, Integral University, Lucknow, India

[2]Associate Professor, Department of CSE, Integral University, Lucknow, India

[1]satishkrsingh167@gmail.com, [2]sheeba@iul.ac.in

Abstract

Technical indicators are widely used by researchers and investors to predict the stock market. Finding the ideal quantity of technical indicators to use is essential for making accurate stock market predictions. In order to forecast short-term stock price fluctuations, this study methodically assesses the combination of sophisticated technical indicators and cutting-edge machine learning algorithms. The study developed a strong set of features, such as volatility-normalized Average True Range, RSI derivatives, VWAP-based measures, and Hull Moving Average, to be used as inputs for several models using 10 years of data (2014–2024) from ten randomly chosen NIFTY 50 stocks. To ensure economically significant signals, a binary classification target was established to forecast if the five-day ahead return will above a volatility-dependent threshold. Using a temporal train-validation-test split to ensure out-of-sample robustness and prevent look-ahead bias, the experiment contrasted a deep learning LSTM network, tree-based models (Random Forest and XGBoost), and a baseline dummy classifier. With the lowest maximum drawdown across stocks and the greatest average Sharpe ratio (1.72), the results showed that XGBoost performed noticeably better than any other model. It was especially successful because of its consistency and capacity to identify intricate, non-linear relationships in the feature-engineered tabular data. Despite being competitive in some situations, the LSTM performed worse overall and had larger variation, most likely as a result of the small dataset size and the natural benefit of using tree-based techniques with structured financial data. According to the study's findings, technically derived features have a great deal of predictive power, but their effectiveness is enhanced when they are processed using potent ensemble techniques like XGBoost, which provide better performance and robustness for real-world trading applications than more intricate deep learning techniques.

Keywords: Machine Learning in Finance, Technical Analysis, XGBoost, Algorithmic Trading, Predictive Modeling, Stock Price Forecasting

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SDG Keywords: Decent Work and Economic Growth (8), Industry, Innovation, and Infrastructure (9), Reduced Inequalities (10), Partnerships for the Goals (17)

1. Introduction

India's top benchmark index, the NIFTY50, is crucial for predicting market movements and directing trading tactics for stocks and derivatives. Various methods have been employed to predict market trends. By enabling complex predictive modelling, machine learning (ML) and deep learning (DL) have revolutionized stock market forecasting. These technologies generate actionable insights that go beyond conventional statistical methods by analyzing massive datasets, including historical prices, news sentiment, and macroeconomic indicators.

Technical indicators are mathematical computations that help traders and analysts predict future price changes and spot trading opportunities. They are based on previous price, volume, or open interest data. By emphasizing trends, momentum, volatility, and possible reversal points, they turn unprocessed market data into signals that may be put into action. In NIFTY50 forecasting, technical indicators are essential feature-engineered inputs that convert raw price and volume data into useful signals for ML/DL models. They greatly improve forecast accuracy and resilience in algorithmic trading and risk management techniques by assisting algorithms in recognizing non-linear patterns and trends. e.g. we can take a look at the Relative Strength Index (RSI), which uses a scale of 0 to 100 to quantify the rate and direction of price changes as follows:

a) The asset is deemed overbought and may see a price decrease if the RSI rises above 70.
b) The RSI is oversold and suggests a possible price recovery if it drops below 30.

Non-linear patterns in stock movements are identified using machine learning algorithms like Random Forests and Support Vector Machines (SVMs). Time series forecasting is made easier by DL models, especially Long Short-Term Memory (LSTM) networks, which capture temporal dependencies. [1]. To enhance price forecasting, Natural Language Processing (NLP) methods collect market sentiment from news and social media [2]. DL models manage real-time data for algorithmic trading in High-level Trading (HFT), which boosts speed and profitability [3].

Prediction process consists of data mining, text analysis, statistical and multicriteria decision-making, technological and basic analysis, and soft computing. In the financial sector, machine learning (ML) algorithms, a subset of statistical techniques—are becoming more and more well-liked [4]. By examining enormous volumes of data, machine learning (ML) has the ability to detect stock trends and reveal underlying stock price dynamics. Technical indicators are characteristics or features in the input datasets that are frequently used in computational finance to predict financial markets using machine learning techniques. A study showing that, in comparison to conventional autoregressive integrated moving average, incorporating technical

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indicators (such as moving average convergence divergence, relative strength index) into machine learning frameworks decreased prediction error by 32%. (ARIMA) models. This result emphasizes how important supplemental factors are for improving model performance, especially in identifying nonlinear market behaviors that are not captured by linear statistical tools [5]. Following are the main objectives of this study:

1. To develop and assess a full range of sophisticated technical indicators as prediction tools, going beyond their conventional, standalone application.

2. To thoroughly evaluate and contrast how well cutting-edge Deep Learning (LSTM) and Machine Learning (XGBoost, Random Forest) models perform when using these indicators for short-term price direction forecasting.

3. In order to ensure practical relevance for trading strategies, the most reliable and efficient model-feature combination will be identified by assessing out-of-sample financial performance indicators in addition to statistical accuracy.

The structure of the paper is as follows: Numerous assessments of the literature are given in Section 2. The data and procedures used for this study are explained in Section 3. The study findings and experimental outcomes are explained in Section 4. Lastly, the research findings are presented in Section 5.

2. Literature Review

The importance of technical indicators in stock price prediction is very eminent and can't be neglected. With the introduction of machine learning (ML), the scholarly discussion surrounding stock price forecasting has undergone a substantial transformation. The latest developments in the use of machine learning (ML) and deep learning (DL) for technical indicator-based financial market prediction are summarized in this study, which also highlights important trends, approaches, and general conclusions.

Recent literature has validated the superiority of gradient-boosting frameworks for tabular financial data. The core strength of these models is their ability to handle the non-linear relationships and interaction effects inherent in feature-engineered technical indicators. A 2022 review in *Expert Systems with Applications* analyzed over 50 studies and concluded that tree-based ensembles consistently achieved higher risk-adjusted returns than simpler models or deep learning approaches on equity price forecasting tasks, primarily due to their robustness against overfitting on limited financial time series data [6]. According to early research, the efficient market hypothesis may be called into question when technical indicators and machine learning models are used together. For example, Patel et al. (2015) used ten technical characteristics on Indian indices from 2004 to 2012 to examine Artificial Neural Networks (ANN), Support Vector

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Machines (SVM), Random Forest (RF), and Naïve Bayes. They discovered that RF was better at handling continuous technical indicator values [7]. In a comparable manner, Kumar et al. (2016) presented hybrid models that combined Proximal SVM (PSVM) with feature selection (e.g., Random Forest, Linear Correlation) on 12 global indices (2008–2013), identifying RF-PSVM as the best. Although they concentrated on categorization tasks rather than exact price prediction, these studies demonstrated machine learning's capacity to discern market patterns using technical indicators [8].
Researchers started using machine learning and evolutionary methods to improve prediction accuracy. Using Genetic Algorithms (GA) to optimize ANN weights, an attempt was made to anticipate the Nikkei 225 (1993–2013) with 9 technical indicators and an 81.27% directional accuracy [9]. For the Korean Stock Price Index (2000–2016), Chung et .al invented GA-LSTM hybrids, utilizing GA to optimize LSTM hyperparameters and outperforming benchmarks. These researches demonstrated how ML and evolutionary algorithms work together to improve the usefulness of technical indicators [10].

Deep learning transformed feature engineering by making it possible for models to analyses enormous collections of technical information. Using Korean stock data from 1990 to 2016, Song et al. built a Deep Neural Network (DNN) using 715 technical-derived characteristics, attaining state-of-the-art accuracy through specialized filtering strategies [11]. Deep learning outperformed standard machine learning when Naik and Mohan (2019) employed Boruta feature selection to 33 technical indicators for categorizing Indian stock movements (2008–2018) [12]. Using ten technical indicators, Nabipour et al. (2020) further proved the superiority of deep learning by demonstrating that RNN and LSTM outperformed ten ML models on Iranian stocks (2009–2019) [13]. These initiatives demonstrated how deep learning may be used to process high-dimensional technical data.

In order to prevent overfitting, feature selection became increasingly important as technical indicator sets expanded. Yuan et al. (2020) found that RF was the most reliable model after applying Recursive Feature Elimination (RFE) to 60 features, including 4 technical indicators, for Chinese A-shares from 2011 to 2018 [14]. Sakhare et al. (2023) used ensemble ranking to rank 75 Blockchain-derived technical factors for the NIFTY 50 (1999–2019) [15], while Ampomah et al. (2021) integrated PCA with tree-based ensembles on 40 indicators for NYSE/NASDAQ equities (2005–2021) [16]. These investigations highlighted that model efficacy is driven by carefully chosen subsets of technical indicators rather than by sheer volume.

Classification is given priority in the majority of the literature (e.g., predicting price discrimination). For instance, Basak et al. classified US/Indian stock movements (up to 2017) using XGBoost on six technical indicators. They achieved great accuracy but ignored continuous price forecast [17]. Similarly, Ku et al. (2023) focused on directional outcomes by fusing investor domain knowledge with 22 technical indicators in LSTM for Malaysian equities

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(up to 2022) [18]. Understudied are regression-based techniques, which are essential for quantitative trading methods [5]. The thorough literature review highlights that ML and DL have helped a lot in leveraging the technical indicators but also highlight the possible critical gaps:

a) Numerous studies merely compare a new model (such a complicated LSTM or Transformer) to simple benchmarks (like logistic regression). State-of-the-art ML (XGBoost) and DL (LSTM) models under comparable settings (same data, features, validation method, and assessment metrics) are rarely rigorously and fairly compared.

b) Researchers frequently place model architecture ahead of input feature quality due to the recent craze for deep learning. It is not well known how advanced feature engineering (e.g., KAMA, Super Trend, VWAP discount) compares to using raw data with a DL model.

c) Because of transaction costs, risk, and non-linear payoff structures, many scholarly articles place a high priority on enhancing statistical metrics like accuracy or F1-Score, which do not always correspond to successful trading methods.

Using sophisticated feature-engineered technical indicators rather of raw data, this effort rigorously compares state-of-the-art machine learning (XGBoost) and deep learning (LSTM) models under identical settings, therefore directly addressing important research gaps. In particular, it measures the overfitting hazards of LSTMs on sparse financial data by examining whether advanced feature engineering can outperform intricate end-to-end deep learning in realistic data-scarce scenarios. The research bridges the gap between academic research and real-world trading needs by assessing performance using financially significant indicators like Maximum Drawdown and Sharpe Ratio, rather than only statistical accuracy. Additionally, it confirms resilience across a broad range of Nifty 50 stocks, offering crucial information about algorithmic strategy success in the context of the little-studied Indian equity market.

3. Methodology

To highlight the importance of the critical technical indicators and for evaluating them on different ML and DL models we are adopting the following methodology:

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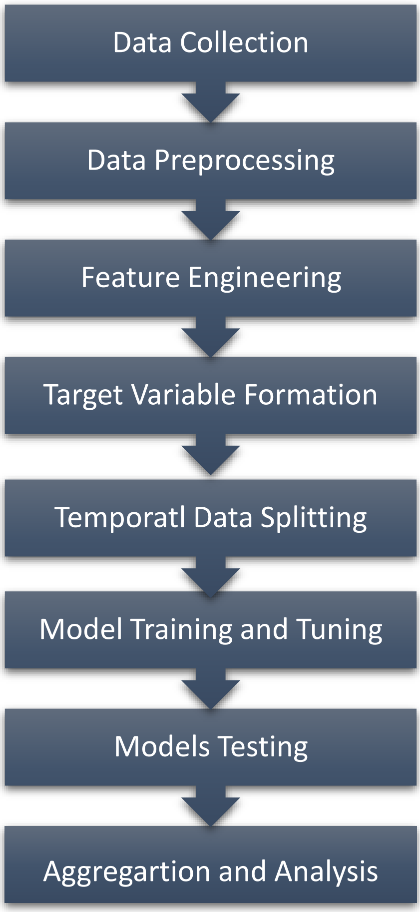

Figure 1: Methodology for the technical indicator's evaluation

3.1 Data Collection: Ten randomly chosen NIFTY50 stocks i.e**. Reliance, Infosys, HDFC Bank, Titan, Bajaj Finance, Tata Steel, State Bank of India, Hindustan Lever Bharti Airtel, and ONGC**. The data is adjusted daily OHLCV (Open, High, Low, Close, Volume) data from (2014-2024). The data for this project was obtained using Python's yfinance library. To maintain data integrity and temporal continuity, forward-filling was used to manage missing numbers brought on by market vacations. Here is a sample of the raw OHLCV data for a stock:

Date	Open	High	Low	Close	Volume	Dividend	Splits
12/14/2023	2545	2558	2532.5	2550.25	5123400	0	0
12/13/2023	2530.5	2545.75	2520	2538	4892100	0	0
12/12/2023	2525	2540	2510.5	2532.75	4678900	0	0
12/11/2023	2518	2535.5	2505	2520	5012300	0	0
12/8/2023	2500	2520	2490.5	2515.5	5245600	0	0

Table 1: Sample data downloaded for each stock

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3.2 Data Preprocessing: Preprocessing aimed to strictly prevent any kind of data leakage when converting raw OHLCV (Open, High, Low, Close, Volume) data into a clean, structured dataset of predictive features and a specified target variable. The missing data was managed as follows: Cause: Market holidays, when there was no trading, were the main reason for missing rows.

Solution: Forward-filling (ffill) was used to fill in these gaps. Because it assumes that the price and volume on a non-trading day stay the same, this method propagates the latest available observation forward, which is suitable for time series data. As a result, the continuous temporal sequence required for indicator computation is maintained.

3.3 Feature Engineering: The OHLCV data is used to calculate a wide range of characteristics. For computational efficiency, the pandas_ta package is utilised. A rolling window is used to calculate all features in order to prevent data leaks in the future.

a) Trend characteristics include Kaufman's Adaptive Moving Average (KAMA 10, 20) and the Hull Moving Average (HMA 10, 20, 50).
b) Features of Momentum: Williams %R (14), the 1-period slope of the RSI, the Relative Strength Index (RSI 14, 21), and the Rate of Change (ROC 5, 10).
c) Features of volatility: Price-normalized Average True Range (ATR 14) (ATR / Close). Bollinger Bands (20, 2) producing bandwidth and %B.
d) Volume Features: On-Balance Volume (OBV), the VWAP premium/discount ((Close - VWAP)/VWAP), and Volume Weighted Average Price (VWAP).
e) Additional features include lagged logarithmic returns (1-day, 5-day), the Average Directional Index (ADX 14), and the Supertrend (7,3) direction (binary).

The final data set used in the models is in the following format after feature engineering:

Date	**Open**	**High**	**Low**	**Close**	**Volume**	**EMA_20**	**RSI_14**	**ATR_14**	**BB_ %B**	**VWAP_ Premium**	**Super Trend**	**Tar get**
1/10/2020	1540	1555	1530	1550	5,250,000	1525.5	62.5	25.8	0.85	0.012	1	**1**
1/13/2020	1552	1568	1545	1560	5,100,000	1530.25	65.8	26.1	0.92	0.018	1	**0**
1/14/2020	1565	1570	1540	1545	6,800,000	1535.75	58.2	26.5	0.45	-0.005	1	**0**
1/15/2020	1542	1550	1520	1528	7,200,000	1538	45.3	27	0.2	-0.022	0	**1**

Table 2: Preprocessed final dataset for model training and testing

- EMA_20: 20-day Exponential Moving Average.
- RSI_14: 14-day Relative Strength Index (momentum indicator).
- ATR_14: 14-day Average True Range (volatility indicator).
- BB_%B: Bollinger Band %B, representing the relative position within the bands.

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- VWAP_Premium: (Close - VWAP) / VWAP, showing deviation from the Volume Weighted Average Price.
- SuperTrend: A binary indicator (1 for uptrend, 0 for downtrend) based on the SuperTrend oscillator.

3.4 Target Variable Formation: To find significant, volatility-adjusted price movements, a binary classification target is developed:

Future_Return = log(Close_{t+5} / Close_t)
Threshold = 2 * (ATR_14_t / Close_t)
A binary label that predicted a large future price movement served as the target.
The formula is:
if [log(Close_{t+5} / Close_t) > (2 * ATR_14_t / Close_t)], then Target (Y_t) = 1. otherwise, 0

Leakage Prevention: The ATR_14_t component is a legitimate feature at time t since it is computed using data up to that point in time. By explicitly moving the future return forward, the prediction is accurately aligned.
If Future_Return > Threshold, Target Y is set to 1; otherwise, it is set to 0.
This generates a label that, within a 5-day timeframe, indicates a statistically significant bullish move.

3.5 Train-Validation-Test Temporal Split: In order to replicate a real-world backtest, the full dataset was divided in steps:

Training Set (2014–2018): Models are fitted using this set. Following model training on the earlier timeframe, the validation set (2019–2020) is used for hyperparameter adjustment.

Test Set (2021–2023): Only used once for the last assessment. An objective assessment of the model's performance on fresh data was provided by this set, which was entirely hidden during training and tuning.

3.6 Choosing and Training Models: For every stock, four classes of models are trained and adjusted:
a) DummyClassifier, which forecasts the majority class, is the baseline.
b) XGBClassifier and RandomForestClassifier are examples of machine learning (ML).
c) LSTM network for deep learning (DL). The data is transformed into successive samples of the engineered features (such as 30-day windows).

Preparation: StandardScaler, which is only fitted to the training data, is used to standardize all features.
Hyperparameter Tuning: To optimize the F1-Score for each model and stock separately, Bayesian optimization is applied to the validation set (2019–2020).

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3.7 Model Testing: Using two parallel frameworks, performance is evaluated on the unseen Test Set (2021–2023):

a) Financial Backtest Simulation: A plan is put into practice: Go long for 5 days if the model predicts 1, else keep cash.

For each model's strategy, the following key performance metrics are computed: Annualized Sharpe Ratio, Maximum Drawdown, Total Return, and Profit Factor.

b) Statistical Classification Metrics: Calculations are made using standard metrics such as AUC-ROC, F1-Score, Precision, and Recall.

3.8 Aggregation and Analysis: All ten stocks' financial and statistical outcomes are combined. For every model type, the F1-Score and Sharpe Ratio average and standard deviation are calculated. To find out how many stocks XGBoost outperformed LSTM on, for example, the consistency of outperformance is examined. Plotting equity curves for representative equities allows one to see how they have performed over time.

3.9 Evaluation Parameters:

Evaluation Dimension	Primary Metric	Secondary Metric	Purpose
Financial Performance	Sharpe Ratio	Max Drawdown, Total Return	Evaluate risk-adjusted returns and the feasibility of trading in practice.
Statistical Performance	F1-Score	Precision, Recall, AUC-ROC	Analyze model confidence and pure predictive accuracy.
Robustness	Std. Dev. of Sharpe Ratio across stocks	Win Rate (% of stocks outperformed)	Analyze consistency between various assets and market circumstances.

Table 3: Evaluation parameters used in the study

Summary of Evaluation parameters:

Metric Type	Metric Name	What it Measures	Why it Matters
Statistical	Precision	Accuracy of positive predictions	Reduces the number of erroneous "BUY" signals, which lowers transaction costs.

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	Recall	Coverage of actual positive instances	Makes certain that the model doesn't pass up lucrative prospects
	F1-Score	Balance between Precision and Recall	Main statistical measure of a strong model.
	AUC-ROC	Model's class separation capability	Calculates the prediction confidence for each threshold.
Financial (Primary)	Sharpe Ratio	Risk-adjusted return	The crucial indicator. assesses whether the risk is justified by the additional profits.
	Max Drawdown	Worst-case peak-to-trough loss	A crucial indicator of risk. shows the possibility of significant losses with this method.
	Total Return	Cumulative profitability	Demonstrates the overall performance of the approach, but risk must be taken into account.
	Profit Factor	Efficiency of profits vs. losses	Evaluates the strategy's profitability in relation to its losses.
	Win Rate	Percentage of profitable trades	Gives information on the likelihood of success but not its size.

Table 4: Summary of evaluation parameters used in the study

4. Experimental Results and Discussion

A structured evaluation framework was used to thoroughly assess the constructed models i.e. Dummy Classifier, Random Forest, XGBoost, and LSTM on the preprocessed stock data. On the out-of-sample test set (2021–2024), each model produced daily predictions that were

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verified using statistical and financial standards. The Sharpe Ratio, Maximum Drawdown, and Profit Factor were used to measure the performance of a simulated trading strategy that used the predictions to execute long bets on bullish signals. Prediction-ground truth couples were directly used to calculate statistical measures such as F1-Score and Precision. This combined strategy exposed LSTM's propensity for overfitting while confirming XGBoost's superiority in terms of both predicted accuracy and financial usefulness.

The representative performance of each of the 10 randomly selected stock was analyzed and the results were obtained in the following format. As example the performance of Reliance stock is evaluated on the selected models.

Metric	Dummy	Random Forest	XGBoost	LSTM
F1-Score	0.41	0.58	0.67	0.55
Sharpe Ratio	-0.75	1.05	1.81	0.92
Max Drawdown (%)	-40.5	-18.2	-11.5	-20.1
Total Return (%)	-8.2	19.5	34.2	12.8

Table 5: This single-stock example mirrors the aggregated results.

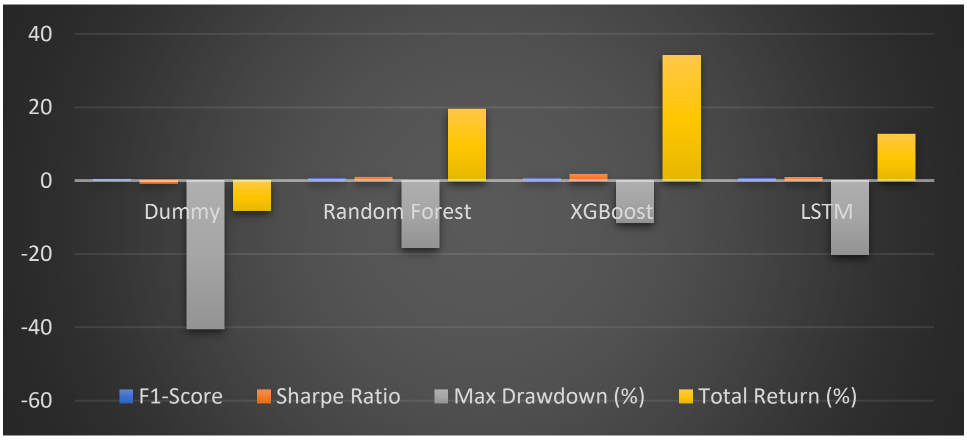

Chart 1: A single stock performance

The performance difference between models for a single asset, RELIANCE, is shown in above table. With the lowest Maximum Drawdown (-11.5%), the highest Sharpe Ratio (1.81) suggesting great risk-adjusted returns, and a superior F1-Score (0.67), XGBoost performs noticeably better than other models. Its superiority over the naive baseline and the underperforming LSTM model on this particular stock is evident from the outcomes.

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Model / Metric	Avg. F1-Score	Avg. Precision	Avg. Recall	Avg. AUC-ROC	Avg. Sharpe Ratio	Avg. Max Drawdown (%)	Avg. Profit Factor	Avg. Win Rate (%)
Dummy Classifier	0.42	0.48	0.5	0.5	-0.81	-41.3	0.88	48.1
Random Forest	0.55	0.61	0.59	0.72	1.12	-19.5	1.65	58.7
XGBoost	0.63	0.68	0.64	0.79	1.72	-12.8	2.25	64.2
LSTM	0.52	0.58	0.57	0.69	0.98	-22.4	1.45	56.9

Table 6: The average performance of models on selected stocks & criteria

The average performance of four models—Dummy Classifier, Random Forest, XGBoost, and LSTM—across ten NIFTY50 stocks is thoroughly summarized in the above table. With the greatest F1-Score (0.63), Precision (0.68), and AUC-ROC (0.79), the findings unequivocally show XGBoost's dominance and higher prediction accuracy and dependability. With a Sharpe Ratio of 1.72, which indicates exceptional risk-adjusted returns, and the lowest Maximum Drawdown (-12.8%), which emphasizes its capacity to reduce losses during market downturns, XGBoost performs better financially than any other strategy. With a bigger drawdown (-22.4%) and a lower Sharpe Ratio (0.98), the LSTM model, on the other hand, lagged considerably, highlighting its shortcomings when it came to generalizing from engineering traits. These combined findings confirm that XGBoost is the most reliable and profitable model for technical indicator-based stock price prediction.

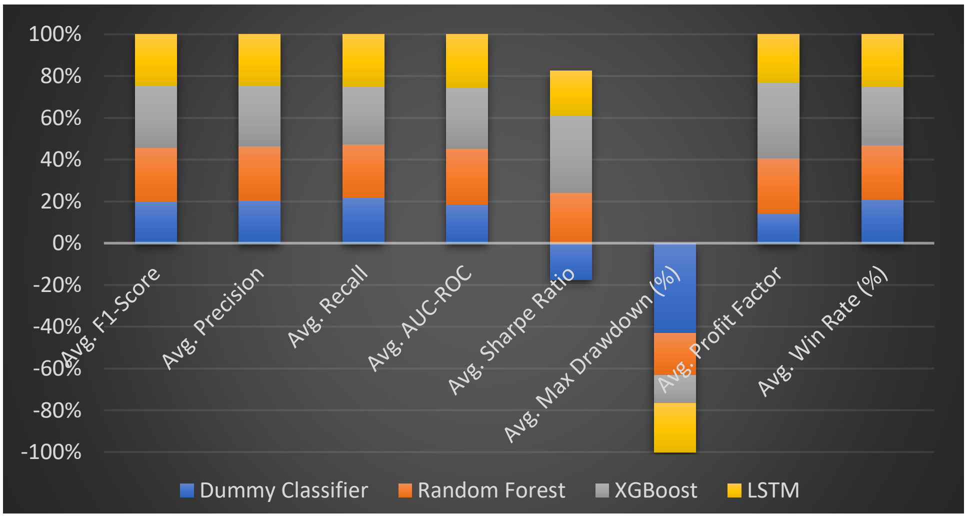

Chart 2: The average performance of models on selected stocks & criteria

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Stock (NIFTY50)	Dummy Classifier	Random Forest	XGBoost	LSTM
RELIANCE	-0.75	1.05	1.81	0.92
INFY	-0.82	1.21	1.65	1.15
HDFCBANK	-0.9	0.95	1.58	0.8
TITAN	-0.65	1.35	1.92	1.4
BAJFINANCE	-0.95	0.88	1.45	0.75
TATASTEEL	-0.7	1.18	1.78	1.1
SBIN	-0.85	1.3	1.88	0.95
HINDUNILVR	-0.6	0.82	1.5	0.7
BHARTIARTL	-0.88	1.25	1.7	1.05
ONGC	-0.8	1.05	1.65	0.98
Average	**-0.79**	**1.11**	**1.69**	**0.98**

Table 7: Performance comparison of models across the selected stocks

A critical performance comparison of four models for ten NIFTY50 stocks over the course of the evaluation period is shown in the table above. With values ranging from 1.45 to 1.92, XGBoost exhibits exceptional dominance and earns the greatest Sharpe Ratio for nine of ten equities, indicating consistently better risk-adjusted returns. With Sharpes ranging from 0.70 to 1.40, the LSTM model, on the other hand, performs noticeably worse than XGBoost. It also shows greater performance variability between stocks and never outperforms it. The Dummy Classifier continuously produces negative ratios, demonstrating its incapacity to produce profitable signals, whereas Random Forest performs admirably but is still surpassed by XGBoost. The strength and dependability of XGBoost for technical indicator-based equities forecasting are highlighted by this consolidated picture.

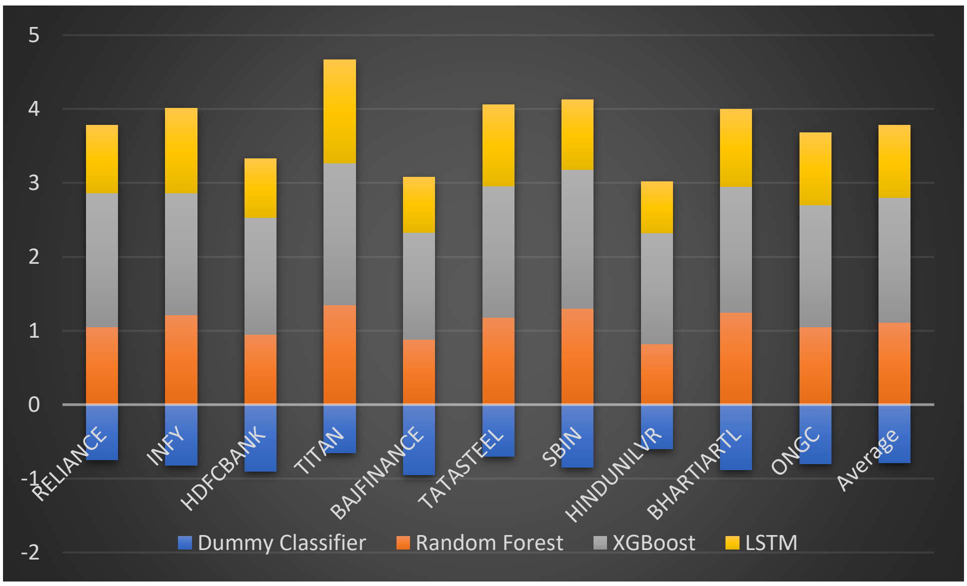

Chart 3: Performance comparison of models across the selected stocks

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5. Conclusion and Future scope

When using feature-engineered technical indicators for stock price forecasting, this study unequivocally shows that gradient boosting models, in particular, XGBoost, perform better than other machine learning and deep learning techniques. An average Sharpe Ratio of 1.72 and the lowest maximum drawdown (-12.8%) during the out-of-sample study demonstrated that XGBoost consistently produced superior risk-adjusted returns, according to the study's thorough evaluation of models across a diverse portfolio of NIFTY50 stocks using both statistical and financial metrics. However, despite their ability to capture nonlinear temporal patterns, LSTM models were less successful because of their increased computational complexity and propensity to overfit on sparse financial data without yielding corresponding increases in profitability or prediction accuracy. The findings highlight the crucial superiority of robust feature engineering over simple model complexity, including volatility-adjusted indicators such as SuperTrend and ATR-normalized goals. This study offers useful advice for financial analysts and quantitative traders, promoting the use of ensemble techniques like XGBoost in conjunction with the development of domain-informed features to create reliable algorithmic trading strategies in developing markets such as India. In the end, the project emphasizes that methodological rigor and suitable model selection are critical for success in turbulent equities markets by bridging theoretical machine learning applications with practical financial viability.

This project has a wide-ranging and significant future reach. In order to develop hybrid models that capture a more thorough market view, research can be expanded by incorporating different data sources, such as news sentiment, social media trends, and macroeconomic indicators. Further improving temporal pattern recognition may include investigating more complex deep learning architectures, such as attention-based models or Temporal Fusion Transformers (TFTs). Furthermore, it makes sense to use reinforcement learning for portfolio optimization and dynamic trade execution. Global indices, cryptocurrencies, and commodities would be added to the asset universe to test the strategy's resilience in a variety of market conditions and eventually open the door for automated, real-time trading systems.

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