Machine Learning-Based Forecasting of Financial Time Series Using Ensemble Techniques and Technical Indicators

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Abstract- ***Financial markets present a highly dynamic and nonlinear environment, making accurate time series forecasting both challenging and critical. On the other hand, investors are highly concerned about the future stock price trend. There are still challenges in the stock price prediction model, including the extensive number of methods, the selection of feature index variables, and the substantial time-effectiveness of prediction. This study aims to propose a machine learning-driven approach for stock return prediction and trading signal generation using an ensemble of XGBoost and Logistic Regression models. First, we denoise the raw data with statistical-based strategies. Second, we engineered a comprehensive feature set incorporating lagged returns, technical indicators including RSI, SMA, MACD, and volatility. Strategies were evaluated using walk-forward validation to ensure realistic simulation of evolving market behavior. Next, trade signals were filtered with RSI thresholds and capped with a stop-loss mechanism. Finally, performance was measured using risk-adjusted metrics including Sharpe, Sortino, Calmar ratios, and maximum drawdown. The results show that the ensemble strategy outperformed single-based models and traditional moving average crossover methods in both cumulative return and risk stability.***

Indexed Terms- ***Dynamic pricing, Data-driven architecture, Machine learning, XGBoost, logistic regression***

I. INTRODUCTION

Accurately forecasting asset prices within financial markets remains a persistent challenge due to the multifaceted interactions among a wide array of microeconomic and macroeconomic variables. Influences such as political developments, financial news dissemination, and corporate earnings reports significantly affect price dynamics. The complexity of this task is further intensified by the inherent non-linearity and non-stationarity of financial time series. Consequently, market analysis has become a critical approach for systematically evaluating these contributing factors, with the objective of anticipating future market movements and facilitating data-driven investment decisions.

The financial market capitalisation of US domestic listed companies exceeds 30 trillion dollars in 2019, which is more than 1.5 times the Gross Domestic Product (GDP) of the United States [3]. Whereas, it is crucial to anticipate the price movement of equities in this vast yet volatile market. According to the efficient market hypothesis (EMH), the stock's prices in an efficient market should reflect all available information, including historical prices, news, events, and so forth, [4]. In reality, the responses of various equities to distinct events are non-synchronized and non-intuitive. In a time series forecasting framework, it is therefore difficult to model this complex phenomenon, which is referred to as the lead-lag effect [5].

The financial industry has been conducting research on price prediction models since the turn of the 20th century [6] and has since refined these technologies, investing millions of dollars in the process. The prediction of stock price movements is based on historical time-series price data in traditional quantitative methodologies [7]. The objective of these models is to extract significant technical indicators and/or latent features in order to reduce randomness and record consistent patterns [8].

Recently, the prediction model's capability has been enhanced by the utilisation of unstructured news,

which has been facilitated by the advancement of natural language processing and social media technologies [9]. However, these technologies are unable to account for internal relations among equities, which restricts their potential for the forecasting model.

The modern financial landscape is segmented into several key markets, including equities, foreign exchange, commodities, and digital assets. Within the stock market, a broad range of financial instruments—such as equities, bonds, and derivatives—supports both short-term liquidity and long-term capital formation. The foreign exchange (Forex) market, recognized as the largest and most liquid financial market globally, facilitates continuous currency trading on a 24-hour basis throughout the business week. In contrast, commodities markets involve the trading of tangible goods, including agricultural products (e.g., grain, tea, wheat, salt), energy resources (e.g., oil, gas, coal), and industrial and precious metals. Additionally, cryptocurrency markets have emerged to enable the exchange of digital currencies. These assets, underpinned by cryptographic protocols and blockchain infrastructure, offer features such as decentralization, transparency, and resistance to tampering.

Time series prediction, a significant branch of dynamic data analysis, has garnered significant attention in numerous research disciplines [15]. In this discipline, a variety of forecasting methods, including local and global models, multivariate and univariate models, have been developed [16]. The future trajectory of a time series is only determined by examining its past values in univariate forecasting methods, whereas multivariate methods typically simulate the dependency structure between the time series. Global methods are suitable for predicting the demand of a large number of similar time series, as they collectively evaluate model parameters based on all the time series. In contrast, local methods evaluate parameters individually for each time series.

Conversely, financial time series are intrinsically noisy and non-stationary. The noise factor signifies the absence of thorough information regarding historical financial market behavior, which obstructs the precise depiction of the correlation between future and past prices [17]. Data excluded from the forecasting model is deemed noise, but the non-stationary characteristic signifies that the distribution of financial time series changes over time. Thus, predicting financial time series is regarded as one of the foremost issues in time series forecasting.

The principal research questions of this project are delineated as follows:

- RQ1: What are the key challenges unique to financial time series forecasting in real-world financial industry applications?
- RQ2: What financial markets and assets are frequently employed, and what are the unique characteristics of the datasets used in the current state of the art?
- RQ3: Which machine learning approach is mostly adapted to predict the financial market?
- RQ4: What metrics for evaluation are used most often to assess a model's revenue and effectiveness?

The remainder of this study is proportioned into five sections: The literature review of this study is presented into Section 2. Section 3 presents the methodology related to the financial forecasting methods. Experimental phase is analyzed in Section 4. Finally, future insights with conclusions are delivered in Section 5.

II. LITERATURE REVIEW

AI has been extensively implemented in the fields of computer vision, image processing, audio-visual recognition, and classification and prediction [18]. Deep learning (DL) was initially developed in the field of computer science; however, its applications have since expanded to encompass a wide range of disciplines, including medicine, neuroscience, physics, astronomy, and operations management [19-20]. The research community has been captivated by the resounding success of DL as a data processing technique. The utilisation of DL in financial and investment markets has become increasingly common in recent years, as a result of the excess of Fintech [21]. Three primary areas can be identified as the application domains of financial market investment:

The statistical method is a traditional modeling technique widely utilized in the financial market for technical analysis [22]. Statistical models can identify patterns by analyzing past data to forecast FTS. Classical statistical models have been developed, especially for linear and stationary processes [23]. The fundamental processes are modeled to forecast future trends, predicated on the notion that linear processes produce time series. The principal statistical methods include linear regression (LR), logistic regression, and additional techniques such as ARIMA [24].

Consequently, ML algorithms have rapidly acquired the attention of numerous researchers, who have

conducted state-of-the-art research in a variety of domains. As a result, numerous academic findings have been achieved over the past two decades. For example, Artificial neural networks (ANNs), SVMs, decision trees, and deep learning models, are the fundamental ML techniques that are generally employed in the relevant literature [24-25]. ANNs and SVMs have exhibited their comparative advantages and capabilities in financial modelling and forecasting.

Limited research has been conducted to mitigate the effects of cluttered data and enhance the robustness of Support Vector Regression (SVR). For example, Chuang et al. [26] presented an adaptive support vector regression network. To address the problem of overfitting and enhance model performance, traditional robust statistical concepts have been integrated into Support Vector Regression (SVR) frameworks. In this context, Suykens et al. [27] proposed a weighted variant of the Least Squares Support Vector Machine (LS-SVM), specifically designed to reduce the influence of outliers. Their methodology involves initially training an LS-SVM on the entire dataset to determine support values. Subsequently, a small subset of data points—corresponding to support values with the lowest magnitudes—is removed, and the model is retrained on the remaining data. This iterative pruning and retraining process continues until the kernel expansion is sufficiently compact, thereby improving generalization while preserving predictive accuracy.

Mallqui and Fernandes [28] employed machine learning techniques, specifically Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs), to forecast Bitcoin's daily closing, high, and low prices. To facilitate optimization and performance assessment, the predicted values were transformed into trend-based forecasts, enabling a more interpretable and actionable evaluation framework.

Their machine-learning algorithms effectively produced trend, interval-value, and single-point forecasts. However, in order to establish a reference for generalised decision-making, it is necessary to conduct single-point forecasts on a number of instances. This matter raises concerns regarding the time required and the accuracy of performance forecasts.

Cao and Tay [29] found that SVMs are superior to a combined model in the prediction of stock prices. Sands et al. [30] demonstrated the benefits of the SVM when implemented in conjunction with particle swarm optimization (PSO) for stock value prediction. It has been demonstrated that hybrid methods are more effective than singular models and are a promising area of research [31].

Xu et al. [32] have developed a MLSSVR method for input-output mapping in multidimensional space. Favorable outcomes were achieved through the evaluation of the training algorithm with a variety of datasets. Nevertheless, the optimization of LSSVR in multi-output cases, particularly in time series forecasting, has received minimal attention, despite the fact that a broad range of pertinent technical issues include numerous variables and are most effectively resolved through multivariate input-output mappings. Recent research has proposed the development of prediction models that are based on deep learning to predict the fundamental trends of stock prices [33]. For example, Fischer and Krauss [34] employed LSTM networks, a type of recurrent neural network (RNN), to forecast out-of-sample directional variations in the prices of the constituent stocks of the S&P 500. They realized that the LSTM surpassed memory-free classification methods. A hybrid metaheuristic deep neural network was employed by Elhoseny et al. [35] to forecast a company's financial distress.

Hao and Gao [36] proposed a hybrid model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for stock market trend prediction. Similarly, Mehtab and Sen [37] conducted a comparative analysis of multiple deep learning architectures, evaluating the performance of four CNN-based and five LSTM-based models in forecasting financial time series. While these models demonstrated promising results in predicting stock indices and market trends, they were predominantly designed for single-output prediction. However, in practical investment scenarios, stakeholders often require more comprehensive insights—such as multiple financial indicators or decision-support metrics—to make timely and informed buy or sell decisions.

Table 1 Key Contributions and Method used in the Existing Research

Reference	Methodology/Model	Key Contributions/Limitations
[22–23]	ARIMA, Linear Regression (LR)	Effective for linear/stationary FTS prediction. Require manual econometric tests for sequence-dependent data; lack automatic identification.
[24-25]	Machine Learning (ML) algorithms	Handle non-linear relationships in FTS; superior robustness in financial modeling. Overfitting risks (e.g., SVR).
[26]	Adaptive Support Vector Regression (SVR)	Reduced overfitting via robust statistics. Requires iterative refinement for learning performance.
[27]	Weighted Least Squares SVM (LS-SVM)	Mitigated outlier impact via support value filtering. Computationally intensive due to repeated retraining.
[28]	SVM, ANN for Bitcoin price forecasts	Generated trend, interval, and single-point forecasts. Time-consuming and accuracy concerns for generalized decision-making.
[29]	SVM vs. Combined Models	Demonstrated SVM superiority in stock price prediction. Focused on single-output prediction.
[30]	SVM + Particle Swarm Optimization (PSO)	Hybrid approach improved stock value prediction accuracy. Limited exploration of multivariate outputs.
[32]	Multi-Layer SVR (MLSSVR)	Effective for multidimensional input-output mapping. Understudied in multi-output time series forecasting.
[34]	LSTM Networks	Outperformed memory-free models in S&P 500 stock trend prediction. Single-output focus.
[35]	Hybrid Metaheuristic Deep Neural Network	Enhanced financial distress prediction. Complexity in real-time applications.
[36]	Hybrid CNN-LSTM	Improved stock trend forecasting via combined architectures. Limited to single-output predictions.
[37]	CNN/LSTM-Based Models	Evaluated model efficacy in FTS prediction. Narrow focus on index/trend prediction, not actionable multi-output data.

III. METHODOLOGY

3.1 Data Acquisition and Preprocessing

This study utilizes historical stock price data of HDFC Bank, covering the period from January 3, 2017, to April 15, 2021. The dataset was obtained and processed using the R programming language. The preprocessing pipeline comprised several key steps to ensure data quality and consistency for predictive modeling.

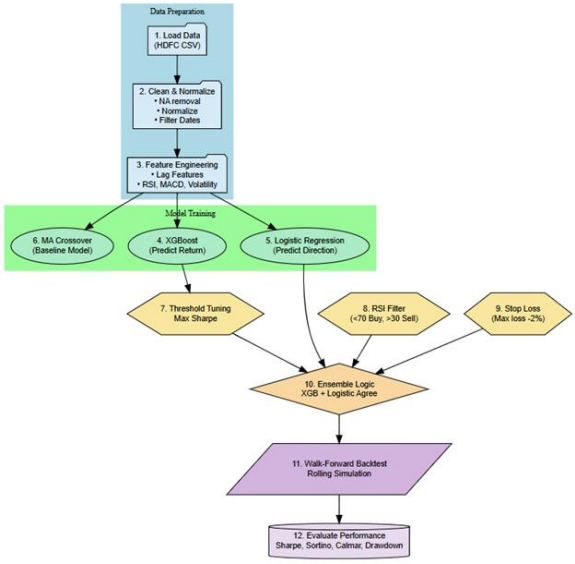

Fig 1. The overall flow of the proposed system

3.1.1 Data Cleaning and Transformation

Following data preparation and preprocessing are applied for better configuration of the data.

- Non-essential columns such as Symbol and Series were eliminated as they did not contribute to the predictive models.
- The Date column was converted into an appropriate date format and sorted in chronological order.
- The data was restricted to the defined study period to maintain consistency in analysis.
- To standardize numeric attributes for machine learning and deep learning models, all numerical columns were scaled between 0 and 1 using min-max normalization.
- Missing values introduced due to lagging and rolling computations were omitted to maintain data integrity.

3.2. Feature Engineering

To enhance predictive capabilities, several technical indicators were incorporated into the dataset. These engineered features capture price trends, momentum, and volatility, which are crucial for financial forecasting.

3.2.1 Lag Features

One-day lag of the closing price: We introduced to model temporal dependencies in stock price movements. In addition, we also Captures short-term price trends for 10-day and 50-day simple moving average which represents long-term price trends, smoothing fluctuations.

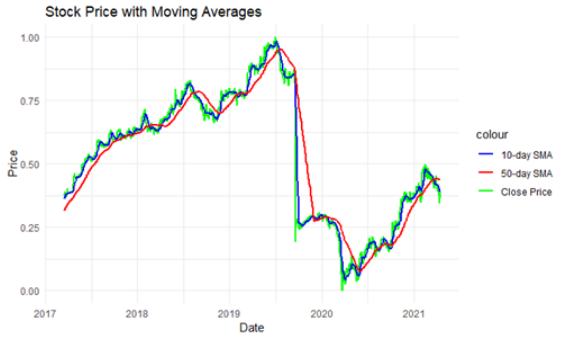

Fig 2. Stock Price with Moving Average Comparison

The 10-day SMA closely followed short-term price fluctuations, whereas the 50-day SMA captured long-term price movements.

These indicators were instrumental in identifying trend reversals and smoothing out price volatility

3.2.2 Volatility Indicator

With rolling 10-day standard deviation of the closing price, the research captures stock market volatility, measuring price fluctuations over a short-term period.

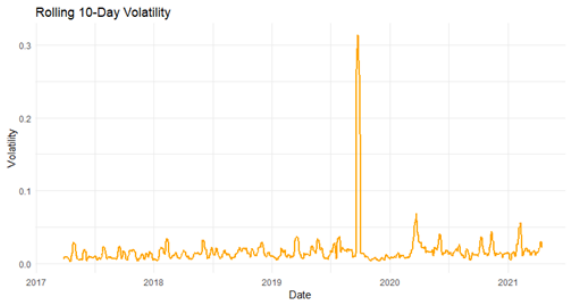

Fig. 3 Rolling 10-day Volatility

3.2.3 Momentum Indicators

The momentum indicators computed over a 14-day period to detect overbought (RSI > 70) and oversold (RSI < 30) conditions. On the other hand, moving average convergence divergence (MACD) was derived using 12-day and 26-day

A Signal Line (9-day EMA of MACD) was incorporated to indicate trend changes.

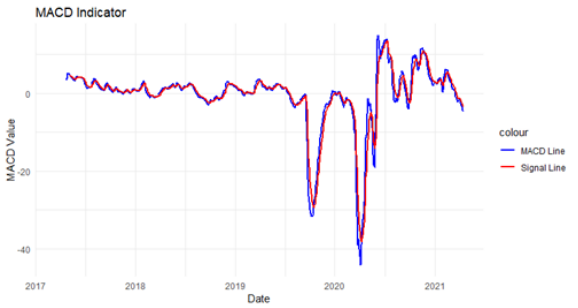

Fig. 4 Trends in MACD indicators

The MACD Line crossing above the Signal Line was indicative of bullish momentum.

Conversely, a downward cross of the MACD Line below the Signal Line signified bearish trends.

IV. EXPLORATORY DATA ANALYSIS (EDA)

This section shows that the series of visualizations were generated to understand stock price trends and validate the engineered features.

4.1 Stock Price Trends Over Time

A time series plot of the closing price revealed long-term growth from 2017 to 2019, followed by a steep decline in early 2020, coinciding with market instability attributed to the COVID-19 pandemic. A partial recovery trend was observed in 2021.

Fig. 5 Stock Price Over Time

4.2 Candlestick Chart for Price Movements

The candlestick representation depicted bullish (upward) and bearish (downward) price movements, highlighting key market shifts. A notable sharp decline in early 2020 aligned with broader market corrections.

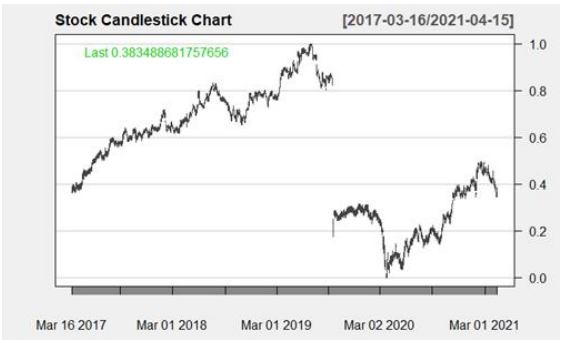

Fig. 6 Stock Canlesstick Chart (bullish and bearish market)

4.3 Trading Volume Over Time

A significant spike in trading volume in early 2020 was observed, aligning with major price movements. High trading volume typically indicates strong investor interest and potential market trend shifts.

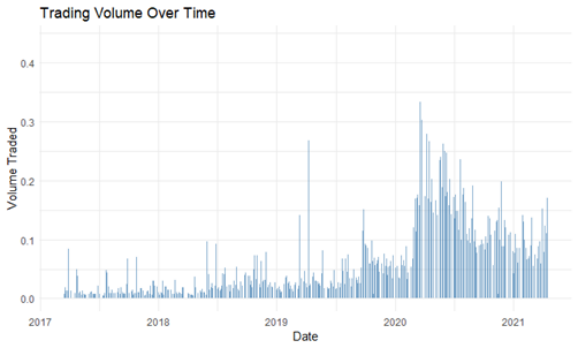

Fig. 7 Trading Volume over time

4.4 Relative Strength Index (RSI) for Momentum Analysis

The RSI fluctuated between 30 and 70, with several instances where it crossed above 70, indicating overbought conditions, often preceding price corrections. Similarly, RSI dips below 30 suggested oversold conditions, identifying potential buying opportunities.

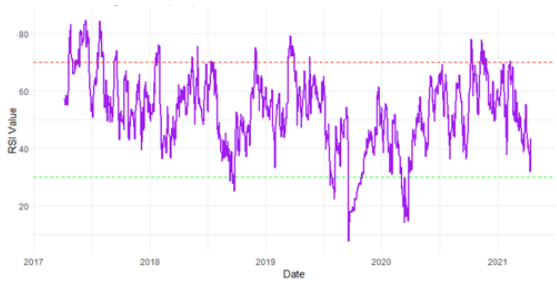

Fig. 8 RSI over Time

4.5 Autocorrelation of Stock Prices

The high autocorrelation values across multiple lags indicated that historical price data strongly influenced future prices, justifying the use of time-series forecasting models.

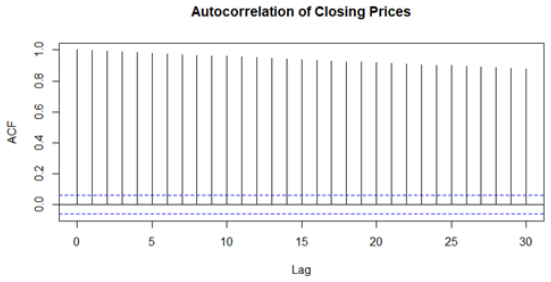

Fig. 9 Autocorrelation of Closing Prices

V. EXPERIMENTAL RESULTS AND ANALYSIS

This section involves the overall analysis conducted on the dataset. In this context, the proposed system evlauted multiple machine learning models on financial time series data such as the HDFC bank data. Additionally, we implemented walk-forward validation to simulate realistic trading conditions. The dataset was split into training and testing blocks in rolling windows. Each model was retrained for every walk-forward iteration to avoid look-ahead bias.
Furthermore, we tested model performance based on predictive accuracy, return generation, and risk-adjusted metrics, with a focus on XGBoost and ensemble approaches.

5.1 Model Analysis

The model setup comprises the following strategies:

5.1.1 XGBoost Model

The XGBoost model is an optimization algorithm that leverages gradient lifting decision trees to efficiently construct better trees and execute them in parallel [38]. In addition, XGBoost is fundamentally determined by the value of optimising the objective function. To express the XGBoost model, the model corresponding to XGBoost incorporates multiple CART trees.

$$\hat{y} = \sum_{r=1}^{R} \quad f_r(x_i), f_r \in F, (1)$$

where R is the total number of trees, F represents the CART trees, and f_r is the individual CART tree.

$$Obj^{(r)} = \sum_{i=1}^{n} \quad l\left(\left(y_i, y\hat{}^{(r-1)}\right) + f_r(x_i)\right) + \Omega(f_r) + C \quad (2)$$

also, $y\hat{}^{(r-1)}$ presents the retaining the model prediction of the previous $r - I$ round, and f_r depicts the new function, and C is a constant term.

In the analysis, we utlize lagged closing prices, technical indicators (RSI, SMA, MACD, Volatility), and min-max normalization to predict future returns. Additionally, signals were generated based on threshold crossing and filtered using RSI (long entry allowed only when RSI < 70; short when RSI > 30). A stop-loss mechanism capped per-trade losses at 2%.

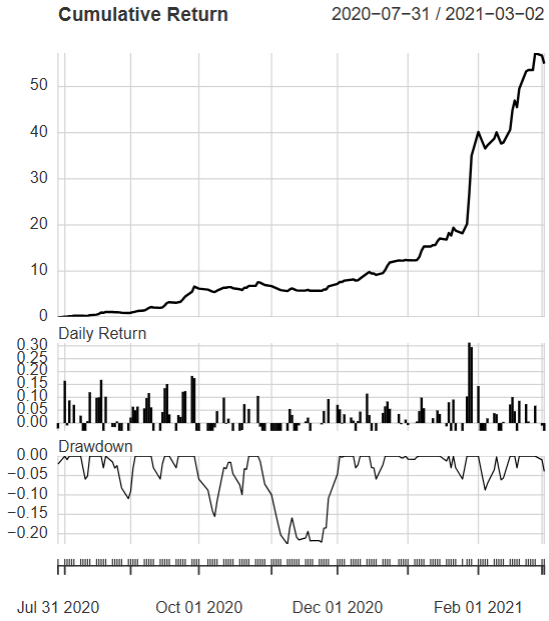

Fig 10: Performance Summary of XGBoost Strategy with Stop-Loss and RSI Filter

Figure 10 shows the performance of the XGBoost-based strategy enhanced with RSI filtering and a fixed 2% stop-loss. The cumulative return curve indicates robust growth with relatively stable gains over time. The daily return panel confirms the strategy's consistency, while the drawdown curve illustrates effective risk control.

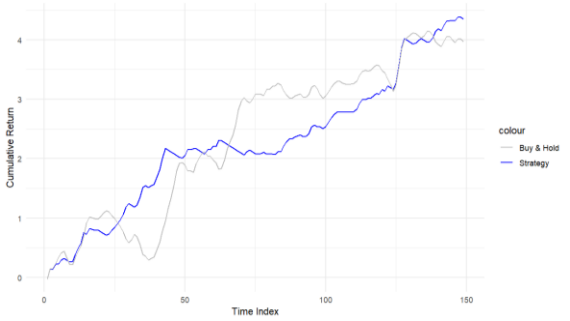

Fig 11 Comparison of Cumulative Returns between the XGBoost Strategy and Buy & Hold.

Figure 11 reveals the cumulative return of the proposed strategy compared to a Buy & Hold benchmark. While both strategies show overall growth. But the model-based strategy exhibits smoother performance with fewer sharp drawdowns. As a result. this shows the integration of signal filtering and stop-loss mechanisms provided effective downside protection.

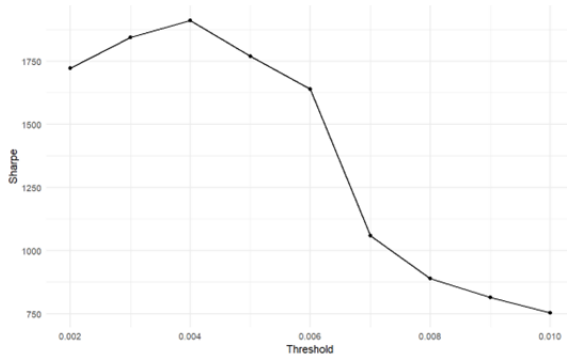

Fig 12 Sharpe Ratio vs Prediction Threshold

To calibrate the sensitivity of trade entry signals, we evaluated the performance of the XGBoost model across a range of return prediction thresholds (0.002 to 0.01) (see fig. 12).

5.1.2 Logistic Regression and Ensemble-based Strategy

Logistic regression is generally used for the classification of dependent variables in binomial or multinomial [39]. When predicting the price of stocks, the trend for the upcoming month can be classified as either '1' or '0'. '1' signifies that the average price of the following month is either higher or equal to that of the current month, while '0' is indicative of a downward trend.

In this research, we enhance the predictive robustness of the trading system using a logistic regression model. The model was incorporated alongside the XGBoost regressor. The logistic model was trained as a binary classifier, predicting whether the future return would exceed a threshold of 0.5%. A value of 1 was assigned to profitable outcomes and 0 otherwise. Therefore, this model served not as a standalone trading system, but as a filtering mechanism in an ensemble architecture.

The ensemble strategy activated trades only when both the XGBoost model predicted a strong return (above a tuned threshold) and the logistic model assigned a high probability (>0.5) to the same directional move. This dual-confirmation system significantly reduced false positives and improved the precision of trade signals.

Figure 12 shows the comparison of commulative returns over XGBoost and Ensemble approach.

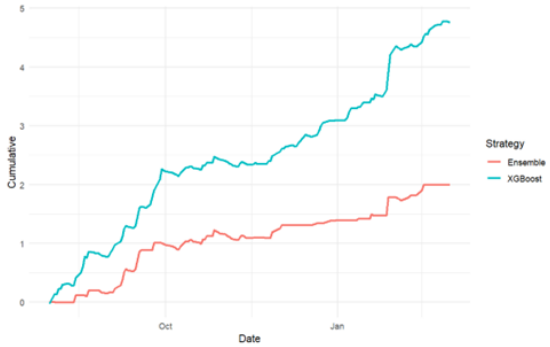

Fig 12 Comparison of Cumulative Returns for XGBoost vs. Ensemble Strategy

The resulting Ensemble_Signal was then used to generate returns with built-in risk controls, including an RSI filter and a 2% stop-loss cap. When compared to single models, the ensemble strategy achieved smoother equity growth, reduced drawdowns, and improved risk-adjusted metrics such as Sharpe and Sortino ratios (see fig 13).

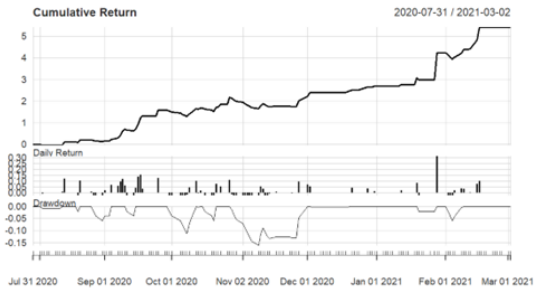

Fig 13 Ensemble Strategy Performance

Table 1 shows the algorithmic strategy that we adopted in ensembling learning approach.

Table 1 The Algorithmic framework of ensemble trading strategy

Step	Action	Details
1	Train XGBoost Model	- Input features: lagged prices, RSI, SMA, MACD, Volatility - Target: future_return (continuous) - Objective: Regression (reg:squarederror)
2	Train Logistic Regression Model	- Input features: same as XGBoost - Target: binary class 1 if future_return > 0.005, else 0 - Objective: Classification (probability of profitable trade)
3	Generate Predictions on Test Set	- Predicted_Return ← XGBoost output - logit_pred ← Logistic output (probability)
4	Threshold Filtering	- Identify optimal threshold best_t (e.g., 0.004) via Sharpe optimization - Filter trades where: → Predicted_Return > best_t AND logit_pred > 0.5 → Long → Predicted_Return < -best_t AND logit_pred < 0.5 → Short
5	Apply Risk Controls	- Longs only if RSI < 70, Shorts only if RSI > 30 - Stop-loss at ±2% - Transaction cost: 0.1%
6	Generate Returns	- Calculate Ensemble_Return based on above rules: → If Signal = 1: future_return - 0.001, capped at -0.02 if loss → If Signal = -1: -future_return - 0.001, capped at -0.02 if loss
7	Evaluate Strategy	- Compute Sharpe, Sortino, Calmar, Max Drawdown - Compare against Buy & Hold, XGBoost alone

The XGBoost model used min-max normalized lag features and technical indicators (RSI, SMA, MACD, Volatility), while the Logistic model was trained using binary classification. A moving average crossover strategy was also implemented as a technical benchmark. Finally, we evaluated an ensemble approach that only activated signals when both XGBoost and Logistic models agreed.

Risk mitigation techniques such as RSI filtering and a 2% stop-loss were applied to prevent catastrophic drawdowns.

Threshold optimization was performed to maximize the Sharpe ratio, with 0.004 identified as the optimal cutoff.

5.2 Trade-Level Risk Analysis

While cumulative returns and Sharpe ratios shows high-level strategy performance. This section will provide trade-by-trade analysis insights into behavioral patterns of profitability, drawdown risk, and recovery consistency.

To further evaluate the performance characteristics of the ensemble strategy, we analyzed individual trade outcomes over the backtesting period. Figure 14 shows the cumulative profit and loss (PnL) per trade, along with the classification of each trade as a win or loss.

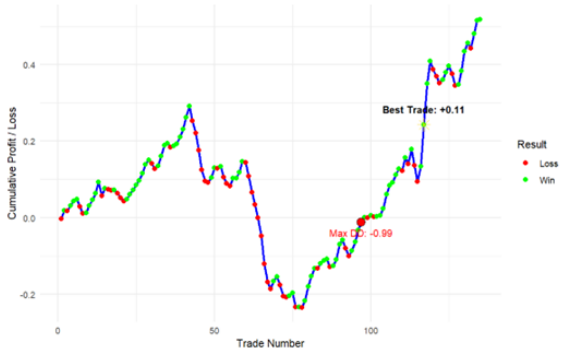

Fig 14 Trade-by-Trade Cumulative Profit and Loss (PnL) with Maximum Drawdown and Best Trade Annotated. Each dot represents an individual trade outcome — green for wins and red for losses. A strong uptrend in PnL reflects a consistent and risk-aware trading process.

Figure 15 shows the distribution of profit and loss per trade.

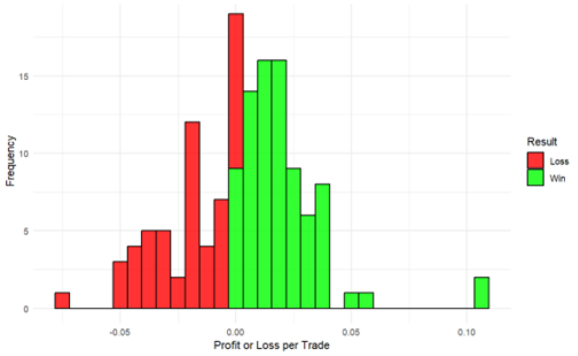

Fig 15 Distribution of Profit and Loss per Trade

The histogram shows that the majority of trades clustered around small to moderate gains, with relatively fewer large losses — indicative of effective risk control and trade management.

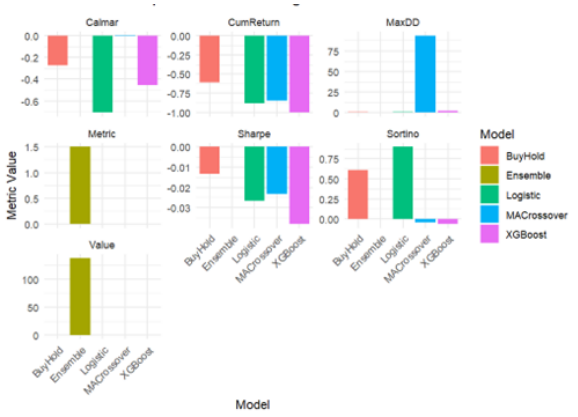

Fig 16 Risk Metric Comparison Across Strategies

Figure 16 shows the comprehensive visual comparison of multiple trading strategies across key risk-adjusted performance metrics.

On the other hand, the Ensemble strategy shows the best risk-return trade-off — not the highest profit, but the most stable and consistent performance with controlled risk. In addition, the this strategy effectively balances gains (like XGBoost) with risk control (like Logistic/BuyHold), making it the most well-rounded strategy based on the result.

CONCLUSION

Stock index prediction is important for making informed investment decisions. This research involves the efficacy of incorporating ML models with conventional trading logic to enhance financial time series prediction. In addition, this research involves the ensemble strategy that combines XGBoost and Logistic Regression to reveal stable and consistent signals. The results have shown ensemble learning models have outperformed baseline models on key metrics such as sharpe ratio and maximum drawdown.

This research also introduced features including, threshold tuning, RSI filters, and walk-forward backtesting. The findings of this research revealed that ensemble-based stratiegies boosts the need for hybrid strategies in volatile markets and underscores the importance of combining predictive modeling with practical risk management.

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