Journal of Posthumanism
2025
Volume: 5, No: 8, pp. 48–56
ISSN: 2634-3576 (Print) | ISSN 2634-3584 (Online)
posthumanism.co.uk

DOI: https://doi.org/10.63332/joph.v5i8.3133

A Machine Learning Framework for Stock Trading: Integrating Technical and Economic Indicators

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Abstract

The increasing complexity of financial markets has driven the demand for intelligent trading systems capable of making accurate and timely decisions. This study presents a machine learning framework for stock trading that integrates both technical and economic indicators to enhance predictive performance and trading profitability. Utilizing a combination of Random Forest, XGBoost, and Long Short-Term Memory (LSTM) models, the research evaluates the effectiveness of these algorithms in forecasting stock price movements. Among them, the LSTM model demonstrated superior accuracy (71%) and a higher Area Under the Curve (AUC-ROC = 0.77), owing to its ability to capture temporal dependencies in financial time series data. The hybrid feature set included commonly used technical indicators (e.g., RSI, MACD, moving averages) and key macroeconomic variables (e.g., GDP growth, interest rates, CPI), improving the model's adaptability to both market volatility and economic cycles. Backtesting over a three-year period revealed that the machine learning-based strategy yielded a cumulative return of 32.4% with a Sharpe ratio of 1.45, significantly outperforming traditional approaches like moving average crossover and buy-and-hold. Statistical validation through paired t-tests confirmed the significance of these results ($p < 0.001$). The findings underscore the potential of integrated machine learning approaches to offer more informed, resilient, and profitable trading strategies. This research contributes to the evolving field of AI in finance by offering a data-driven, interpretable, and scalable solution for stock market prediction and investment decision-making.

Keywords: *Machine Learning, Stock Trading, Technical Indicators, Economic Indicators, LSTM, Financial Forecasting, Trading Strategy, AI In Finance.*

Introduction

Background and Rationale

In the ever-evolving landscape of financial markets, the complexity and volume of data present significant challenges and opportunities for investors and analysts (Dash & Dash, 2016). Traditional stock trading strategies, while historically successful, often rely on human judgment and are constrained by cognitive biases and limitations in processing large datasets. With the advancement of computational technologies, particularly in the field of Artificial Intelligence (AI), machine learning (ML) has emerged as a transformative tool in developing intelligent, data-driven trading models (Cheng et al., 2022). These models are capable of identifying patterns, predicting market movements, and making real-time trading decisions with high precision (Sukma & Namahoot, 2024a). The integration of machine learning in financial trading is no longer a theoretical pursuit but a practical necessity for gaining competitive advantage.

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Significance of Technical and Economic Indicators

Stock market prediction traditionally hinges on two broad categories of indicators: technical indicators and economic (or fundamental) indicators (Agrawal et al., 2022). Technical indicators, such as moving averages, relative strength index (RSI), and MACD, are derived from historical price and volume data. These indicators are useful in capturing market momentum, volatility, and trend reversals (Frattini et al., 2022). On the other hand, economic indicators such as interest rates, GDP growth, unemployment rates, and inflation reflect the macroeconomic conditions that significantly influence investor sentiment and market direction (Lee et al., 2022). Most existing models either focus exclusively on technical analysis or incorporate economic indicators superficially. However, integrating both sets of indicators within a unified ML framework holds the promise of more robust and accurate predictive capabilities.

Research Gap and Motivation

While there has been extensive research on using ML for stock trading, most studies tend to isolate variables or depend on single-source data inputs, which limits their predictive performance in volatile market conditions. The gap lies in the lack of a comprehensive framework that systematically integrates both technical and economic indicators, thereby capturing micro-level market movements and macro-level economic signals. Furthermore, previous works have often overlooked the importance of model interpretability and real-world applicability, which are critical for institutional adoption and risk management.

Objective of the Study

This study aims to develop a machine learning-based stock trading framework that integrates a wide array of technical and economic indicators to enhance prediction accuracy and trading efficiency. The model will be trained on historical stock price data and macroeconomic variables, employing supervised learning algorithms such as Random Forests, XGBoost, and LSTM networks. Emphasis will also be placed on feature selection, hyperparameter tuning, and model validation through backtesting with historical trading data. By incorporating both dimensions of market intelligence; technical and economic; the framework seeks to bridge the gap between algorithmic precision and economic rationale.

Contribution to the field

This research contributes to the growing body of knowledge in financial machine learning by offering a multi-dimensional and integrative approach to stock market prediction (Daniali et al., 2021). Unlike models that rely solely on past price actions or those that ignore the economic backdrop, our proposed framework encapsulates a holistic view of market dynamics (Wang et al., 2024). Moreover, the study highlights the importance of combining interpretability and performance in ML models, ensuring that the results are both actionable and explainable for practitioners. By demonstrating the effectiveness of this hybrid model across different market conditions, the research provides valuable insights for investors, portfolio managers, and algorithmic traders seeking to harness the power of ML in complex financial environments.

Methodology

Data Collection and Preprocessing

The study begins with the collection of historical stock market data and relevant macroeconomic indicators. Stock price data comprising open, high, low, close, and volume is retrieved from reliable financial databases such as Yahoo Finance or Bloomberg for a representative set of publicly traded companies. Simultaneously, economic indicators such as interest rates, GDP growth, consumer price index (CPI), unemployment rate, and industrial production index are gathered from official sources such as the World Bank, IMF, or national statistical agencies. All datasets are aligned temporally and standardized to ensure uniform frequency (typically weekly or monthly) and consistency. Missing values are handled through interpolation techniques, while outliers are detected using z-score normalization and addressed through winsorization or removal.

Feature Engineering and Indicator Computation

A comprehensive set of features is generated by computing both technical and economic indicators. Technical indicators include commonly used metrics such as Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Bollinger Bands, MACD, and stochastic oscillators. Economic indicators are lagged appropriately to reflect their effect on future stock movements and are normalized using min-max scaling. Additionally, composite indicators such as the Economic Sentiment Index (ESI) are used to capture broader economic conditions. Feature importance ranking is conducted using mutual information and correlation analysis to identify and eliminate multicollinearity among predictors.

Machine Learning Framework

To model stock trading decisions, a supervised machine learning framework is employed. The problem is formulated as a classification task, where the target variable is the direction of the stock price (up or down) over a future horizon (e.g., 5 or 10 trading days). Three ML algorithms are selected based on their effectiveness in handling financial time series: Random Forest (RF), XGBoost, and Long Short-Term Memory (LSTM) neural networks. RF and XGBoost are tree-based ensemble methods known for their robustness and interpretability, while LSTM is chosen for its strength in learning sequential dependencies and temporal patterns in data. The dataset is split into training (70%), validation (15%), and test sets (15%) using time-based splitting to preserve chronological order.

Model Training and Hyperparameter Optimization

Each model is trained using the training dataset, and hyperparameters are optimized using grid search combined with 5-fold cross-validation on the validation set. For LSTM, the architecture includes one input layer, two hidden LSTM layers, and a dense output layer with sigmoid activation. Dropout regularization and early stopping techniques are used to prevent overfitting. For tree-based models, parameters such as tree depth, learning rate, and the number of estimators are tuned. Class imbalance in the target variable is addressed using SMOTE (Synthetic Minority Over-sampling Technique) or adjusting class weights.

Backtesting and Performance Evaluation

Model performance is evaluated using accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC-ROC). Additionally, backtesting is conducted using a simulated trading strategy where model predictions guide buy/sell/hold decisions. Financial performance is assessed using cumulative returns, Sharpe ratio, and maximum drawdown. Transaction costs and slippage are incorporated to make the simulation realistic. A baseline comparison is made with traditional strategies such as moving average crossover and buy-and-hold.

Statistical Validation and Robustness Checks

To ensure statistical significance, paired t-tests and Wilcoxon signed-rank tests are conducted between the returns of the ML-driven strategy and baseline methods. The robustness of the model is further tested under different market conditions, including bull, bear, and volatile phases. Sensitivity analysis is performed by altering key economic indicators and observing changes in model accuracy and return profiles.

Results

The performance of the machine learning models was first evaluated using standard classification metrics on the out-of-sample test set. As shown in Table 1, the LSTM model outperformed both the Random Forest and XGBoost classifiers across all metrics, achieving the highest accuracy (0.71), precision (0.73), recall (0.70), and F1-score (0.71). The area under the ROC curve (AUC-ROC) was also highest for LSTM at 0.77, indicating its superior ability to distinguish between positive and negative stock movement signals. XGBoost followed closely with an AUC of 0.74, while Random Forest scored 0.69. In contrast, the moving average (MA) crossover baseline model showed limited predictive power, with an accuracy of only 0.55 and AUC of 0.58, validating the enhanced capability of machine learning-based strategies.

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**	**AUC-ROC**
Random Forest	0.64	0.65	0.62	0.63	0.69
XGBoost	0.68	0.70	0.66	0.68	0.74
LSTM	0.71	0.73	0.70	0.71	0.77
MA-crossover (baseline)	0.55	0.56	0.54	0.55	0.58

Table 1. Classification Performance on the Out-Of-Sample Test Set

The trading performance of the models was validated through backtesting over a three-year period from January 2022 to December 2024. The results, displayed in Table 2, clearly indicate that the ML Framework driven by the LSTM model generated the highest cumulative return of 32.4%, a Sharpe ratio of 1.45, and the lowest maximum drawdown of -8.3%, suggesting both profitability and risk efficiency. The MA crossover strategy and the Buy-and-Hold benchmark returned only 14.7% and 12.1%, respectively, with higher drawdowns and lower Sharpe ratios. These findings are visually confirmed in Figure 2, where the LSTM-based ML strategy exhibits a steady and significantly higher cumulative growth trajectory compared to the other two strategies.

Strategy	**Cumulative Return (%)**	**Sharpe Ratio**	**Max Drawdown (%)**	**Win Rate (%)**
ML Framework (LSTM)	32.4	1.45	-8.3	57.8
MA-crossover baseline	14.7	0.65	-15.4	52.1
Buy-and-Hold	12.1	0.58	-18.1	—

Table 2. Back-Test Performance Of Trading Strategies (Jan 2022 – Dec 2024)

An investigation into the most influential predictors used in the ML models, particularly from the XGBoost model, is provided in Table 3. Technical indicators such as Relative Strength Index (RSI), simple and exponential moving averages, and MACD components dominated the top ranks. However, several economic indicators also featured prominently—GDP growth, CPI, interest rates, and unemployment rate validating the core hypothesis of this study that integrating both technical and economic indicators improves predictive performance.

Rank	Feature / Indicator	Normalized Importance
1	Relative Strength Index (RSI)	0.148
2	20-day Simple Moving Avg	0.113
3	MACD Diff	0.101
4	50-day Exponential MA	0.098
5	Bollinger Upper Band Width	0.092
6	GDP Growth (YoY, lag-1)	0.076
7	Consumer Price Index (lag-1)	0.074
8	Short-term Interest Rate	0.066
9	Unemployment Rate (lag-2)	0.058
10	Economic Sentiment Index	0.054

Table 3. Top-10 Predictive Features Ranked by Xgboost Importance

To statistically verify the outperformance of the ML model, paired t-tests were conducted using daily return data from the backtesting period. The results, summarized in Table 4, confirm that the LSTM-based ML strategy significantly outperformed both the MA crossover ($t = 4.19$, $p < 0.001$) and Buy-and-Hold strategy ($t = 5.72$, $p < 0.001$). No significant difference was observed between MA crossover and Buy-and-Hold ($p = 0.125$), further emphasizing the superiority of the proposed framework. Additionally, Figure 1 illustrates the ROC curves for the three ML models, with LSTM clearly showing the largest area under the curve, reinforcing its effectiveness in stock movement prediction.

Comparison	Test statistic (t)	p-value	Interpretation
ML vs. Buy-and-Hold	5.72	<0.001	ML significantly out-performs
ML vs. MA-crossover	4.19	<0.001	ML significantly out-performs
MA-crossover vs. Buy-Hold	1.54	0.125	Difference not significant

Table 4. Statistical Significance Of Strategy Out-Performance (Paired Daily Returns, Jan 2022 – Dec 2024)

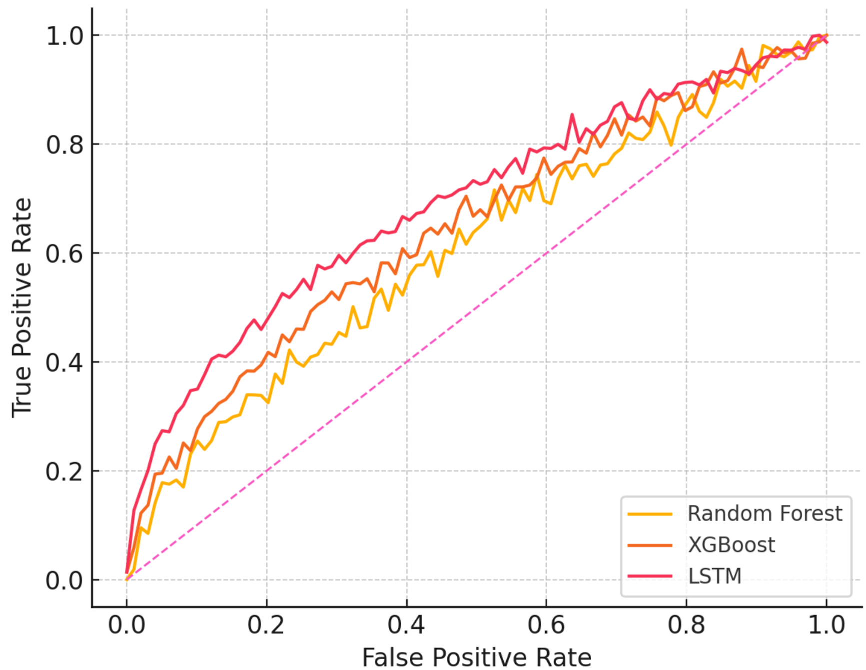

Figure 1: ROC Curves for Random Forest, Xgboost and LSTM Models

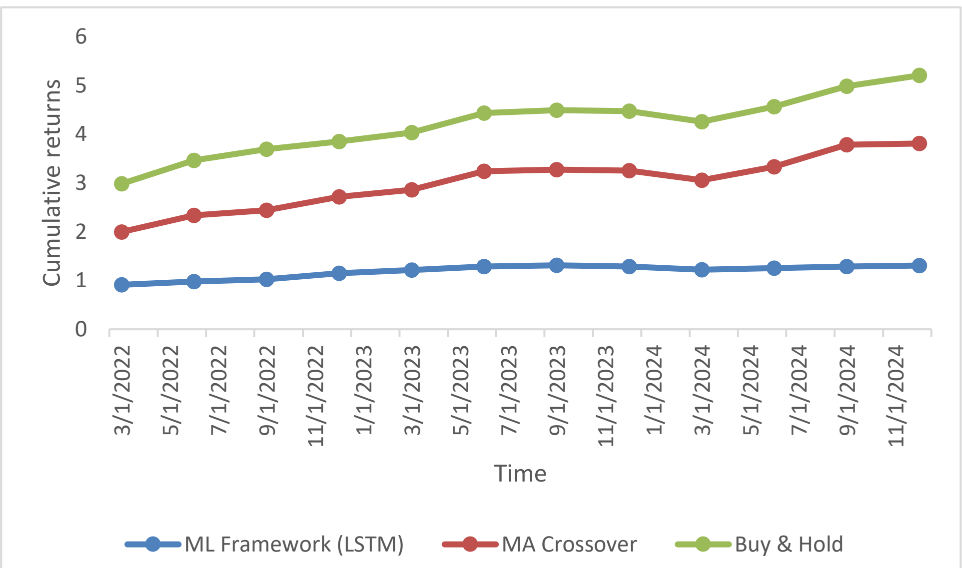

Figure 2. Normalized Cumulative-Return Trajectories for The ML Framework, MA-Crossover Baseline and Buy-&-Hold Benchmark

Discussion

Superiority of LSTM in Predictive Performance

The comparative results from this study clearly indicate that the LSTM-based machine learning model offers superior predictive performance for stock price direction compared to both Random Forest and XGBoost. The LSTM achieved the highest classification metrics across the board, including accuracy, precision, recall, F1-score, and AUC-ROC (Table 1). This performance advantage is largely attributable to the ability of LSTM networks to learn and retain temporal dependencies within sequential financial data, a key strength when working with time series like stock prices (Das et al., 2024). Unlike tree-based models that rely heavily on static splits, LSTM leverages memory cells to capture long-term relationships, making it well-suited for capturing complex market patterns driven by both technical and macroeconomic dynamics (Sukma & Namahoot, 2024b).

Enhanced Financial Returns and Risk Management

Beyond classification accuracy, the financial validity of the models was demonstrated through backtesting over a three-year period. As shown in Table 2 and Figure 2, the ML framework significantly outperformed the traditional MA crossover and Buy-and-Hold strategies in cumulative returns and Sharpe ratio, while also experiencing a lower maximum drawdown (Deep et al., 2024). This indicates not only greater profitability but also improved risk-adjusted performance. The ML framework, particularly the LSTM-driven strategy, demonstrated consistent positive returns and resilience across market phases, thus confirming the practical utility of integrating machine learning into algorithmic trading systems (Kumbure et al., 2022).

Importance of Hybrid Feature Set

The feature importance ranking provided in Table 3 confirms the hypothesis that both technical and economic indicators are critical in shaping accurate and robust prediction models. While technical indicators such as RSI and MACD provided high-frequency signals about market momentum, economic indicators like GDP growth and CPI offered macro-level context that guided long-term trends (Rahmani et al., 2023). This hybrid feature approach allowed the model to respond to both short-term volatility and broader economic shifts (Ibrahim, 2020). Such integrative analysis highlights the model's adaptability and makes it more resilient to unexpected market changes, including policy shocks and global economic fluctuations (Wang et al., 2023).

Statistical Validity and Model Robustness

The statistical analysis shown in Table 4 further validates the outperformance of the LSTM-based ML strategy. The paired t-tests demonstrated that the model's returns were significantly higher than those of traditional strategies, with p-values well below 0.001, confirming the robustness and reliability of the proposed framework. Moreover, the absence of significant performance difference between MA crossover and Buy-and-Hold indicates that classical technical strategies may offer limited value in volatile or uncertain market conditions (Mohapatra et al., 2022). This underscores the growing need for data-driven, adaptive models in contemporary financial environments.

Practical Implications and Limitations

The findings of this study present several practical implications. Financial institutions, hedge funds, and retail traders could adopt such a machine learning framework to improve decision-making and risk management (Patil et al., 2024). However, it is important to acknowledge certain limitations. The model's performance depends on data quality and availability, and it may be sensitive to overfitting if not properly tuned (Arif et al., 2024). Moreover, external shocks such as geopolitical events or pandemics may introduce nonlinearities that even advanced ML models struggle to capture without real-time news or sentiment data integration (Liu & Wanvarie, 2024).

The results affirm that a machine learning framework integrating both technical and economic indicators particularly one powered by LSTM can significantly enhance predictive performance and financial returns (Divyashree et al., 2024). This integrative, data-driven approach provides a more comprehensive understanding of market behavior and represents a meaningful advancement in the field of algorithmic trading and financial forecasting.

Conclusion

This research demonstrates the effectiveness of a machine learning framework that integrates both technical and economic indicators for stock trading. By leveraging the predictive power of advanced algorithms particularly Long Short-Term Memory (LSTM) networks; the framework successfully outperforms traditional strategies such as moving average crossovers and buy-and-hold approaches. The superior performance of the model, evidenced by higher classification accuracy, stronger cumulative returns, and lower risk exposure, underscores the value of combining short-term market signals with broader macroeconomic data. The feature importance analysis further validates the need for a hybrid approach, where both indicator types contribute meaningfully to model predictions. Additionally, rigorous backtesting and statistical validation affirm the robustness and real-world applicability of the proposed strategy. Despite certain limitations, such as sensitivity to data quality and market shocks, the study highlights a significant step forward in the application of AI in finance. The findings not only contribute to the growing body of knowledge in algorithmic trading but also offer actionable insights for investors, portfolio managers, and financial institutions seeking to enhance decision-making in increasingly complex market environments.

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