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Enhancing Technical Analysis with Machine Learning: Insights from Emerging Markets with Application to the Tehran Stock Exchange

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Highlights

- **Predicting stock price movements in emerging markets like Iran.**
- **Model performance varies significantly across sectors—XGBoost leads in Financial and Basic Metals, ANN dominates in volatile Petroleum, while the Linear Model surprisingly outperforms in stable sectors like Food and Pharmaceuticals.**
- **Simplicity can outperform complexity: in low-noise, trend-driven markets, linear models capture directional signals more reliably than overparameterized nonlinear alternatives.**

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Abstract

Predicting stock price movements in emerging markets like Iran is especially daunting due to acute volatility, data scarcity, and structural fragility. We propose a statistically rigorous, context-aware framework that fuses technical analysis with machine learning — including XGBoost, Random Forest, Artificial Neural Networks (ANNs), and Linear Model (LM) — aimed at predicting daily stock returns across multiple industry segments of the Tehran Stock Exchange. Using daily observations from six industrial sectors (Automotive, Financial, Food, Pharmaceutical, Basic Metals, Petroleum) between March 24, 2020 and August 21, 2024, we show that no single model reigns supreme across all domains. In the Financial and Basic Metals sectors, XGBoost delivers statistically superior predictive accuracy (Diebold–Mariano test, $p < 0.05$). In the highly volatile Petroleum sector, ANN distinctly captures extreme nonlinear dynamics, outperforming alternatives. Surprisingly, in more stable sectors like Pharmaceutical and Food, the Linear Model — with its structural simplicity — surpasses more sophisticated algorithms. Random Forest meanwhile operates as a dependable, interpretable benchmark, consistently delivering solid performance across varied conditions. These results challenge the "more complexity is always better" assumption and underscore that optimal modeling must be sector-specific, backed by rigorous statistical validation, and assessed via risk-adjusted forecasting metrics. Our framework offers a replicable, adaptive blueprint for return-based algorithmic forecasting in data-constrained, high-volatility settings — setting a new methodological standard for emerging markets globally.

1. Introduction

Accurately forecasting stock prices remains a central yet formidable challenge for investors, portfolio managers, and financial institutions seeking to optimize returns and manage risk Ali et al. (2023). Equity markets are inherently

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volatile, influenced by a confluence of macroeconomic, geopolitical, and behavioral factors (Wang & Wang, (2012), (2015)). Historically, researchers have relied on statistical time-series models grounded in historical price data to generate forecasts Efendi et al. (2018). Contemporary approaches can be broadly categorized into three classes: traditional statistical models, machine learning (ML) techniques, and hybrid systems that combine multiple methodologies Wang et al. (2023).

A significant challenge for investors is determining the right timing for buying or selling stocks. Successful investment strategies depend on a comprehensive understanding of market trends and industry conditions. In the absence of this knowledge, investors may turn to unreliable tactics, such as acting on speculative rumors, copying others, or making decisions based on unfounded assumptions. These methods can result in poor investment choices and heightened risk Baker & Ricciardi, (2014).

Therefore, investors require powerful and reliable tools to predict stock prices and analyze financial markets in order to make better decisions in buying and selling stocks and reduce investment risks.

Two principal paradigms guide investment analysis, first is the fundamental analysis, in this analysis investors look at the intrinsic value of stocks, and performance of the industry, economy, political climate etc to decide that whether to invest or not. On the other hand, the technical analysis it is an evolution of stocks by the means of studying the statistics generated by market activity, such as past prices and volumes Reddy & Sai, (2018). Technical analysis has been developed enormously during past decades and gained popularity among novice and professional trades because of its relative simplicity and ease of performance. Furthermore, the AI revolution has emphasized the advantage of such analysis when it is conducted by machines rather than by human traders. Machines can wait for market entry or exit for a long period without getting tired and they are not subject to human bias and emotions that sometimes lead human traders to bad investment decisions Bao et al. (2021). Machine learning, in particular, has revolutionized financial forecasting by enabling the processing of massive, high-dimensional datasets generated by modern digital platforms Wu, (2014).

In the Tehran Stock Exchange, high fluctuations and economic, political, and environmental changes have made predictions increasingly difficult, highlighting the importance of accurate forecasting. This research aims to predict future stock price movements, compare investment strategies for optimal capital allocation, and create an effective portfolio for investors by combining machine learning techniques with technical analysis. This study contributes to the literature in several novel ways. First, it rigorously evaluates the predictive performance of both traditional (LM, ANN, RF) and state-of-the-art (XGBoost) models in the underexplored setting of the TSE, where data limitations and volatility pose significant hurdles. Second, it addresses a critical methodological gap by shifting the prediction target from absolute price to daily return, thereby eliminating data leakage and enabling statistically valid comparisons. Third, it introduces a comprehensive performance evaluation framework that goes beyond conventional error metrics (MAE, RMSE) to include risk-adjusted measures (Sharpe Ratio, Profit Factor) and formal statistical tests (Diebold-Mariano) — a combination rarely seen in prior studies on technical analysis. Finally, the study provides sector-specific insights by analyzing six distinct industrial indices, demonstrating that optimal model selection is highly context-dependent — a finding with direct practical implications for algorithmic traders and portfolio managers. The first section discusses the theoretical foundations, the second presents the research background, the third outlines the methodology, and the final section details the findings and analyses.

Stock market prediction lies at the intersection of finance, economics, and computational science. Three core approaches dominate the field: fundamental analysis, technical analysis, and modern computational methods leveraging machine learning and artificial intelligence.

Technical analysis posits that all relevant information about future price movements is already reflected in historical market data Murphy (2021). Practitioners employ tools such as candlestick charts, moving averages, oscillators (e.g., MACD, RSI), and pattern recognition (e.g., head-and-shoulders, triangles) to generate trading signals Schwager (2020). While praised for its simplicity and real-time applicability, this approach is often criticized for ignoring macroeconomic fundamentals and exhibiting sensitivity to market noise Lo & Hasanhodzic (2020).

Fundamental analysis, by contrast, seeks to determine a security's "true" value by assessing financial health, earnings potential, industry position, and macroeconomic context Graham & Dodd (1934). The primary components and tools of fundamental analysis include financial statements (balance sheets, income statements, and cash flow statements), valuation models (discounted cash flow and relative valuation models), and an analysis of the economic and industry environment Koller et al. (2020). Its advantages lie in its ability to provide an accurate evaluation of a company's intrinsic value and its suitability for long-term investment. However, it has drawbacks, such as requiring extensive knowledge of finance and economics and being time-consuming Damodaran (2021).

Traditional econometric models like ARIMA and GARCH model time-series dynamics through statistical assumptions about stationarity and volatility clustering Box et al. (2008). Meanwhile, the Efficient Market Hypothesis (EMH) asserts that asset prices fully reflect all available information, rendering consistent outperformance impossible Fama (1970). However, behavioral finance challenges this view, highlighting systematic investor biases that create exploitable anomalies Geweke et al. (2008).

More recent scholarship has advanced the Adaptive Market Hypothesis (AMH) as a behavioral refinement of the Efficient Market Hypothesis (EMH). Rather than assuming perfect rationality, AMH conceptualizes financial markets through an evolutionary lens—viewing them as dynamic ecosystems shaped by competition, adaptation, and natural selection among market participants. Within this framework, investor behavior is driven not only by logic but also by psychological forces such as fear and greed. Consequently, transient predictable patterns can emerge, especially over short horizons Ayala et al. (2021).

Financial modeling approaches—such as the Capital Asset Pricing Model (CAPM) and extended multi-factor frameworks like the Fama–French three-factor model—are employed to evaluate systematic risk and estimate expected equity returns. These models help investors identify and evaluate the risks linked to asset returns. Multi-factor models tend to offer more comprehensive explanations for asset returns than CAPM, as they account for multiple risk factors Sharpe (1964).

With progress in computational capabilities, the use of machine learning and AI-driven approaches has become widespread in stock market forecasting. Methods including neural architectures, decision tree algorithms, and deep neural networks are employed to analyze large and complex datasets for predicting stock prices Heaton et al. (2017).

The application of artificial intelligence in stock market prediction is growing, as it can rapidly analyze vast amounts of data and intricate relationships. A key advantage of AI-based prediction models in stock markets is their efficiency in handling large datasets. By employing deep learning methods, these models can uncover complex interrelationships and patterns in the data—capabilities that surpass those of human analysts Najem et al. (2024).

2. Literature Review

The fusion of ML-based approaches with technical analysis has become a dominant trend in computational finance, though results vary widely across contexts. Early foundational work by Skabar & Cloete (2002) pioneered the fusion of technical indicators with reinforcement learning, establishing a template for adaptive trading systems. While innovative, their framework lacked rigorous statistical validation and real-market robustness testing — a limitation that persists in many subsequent studies.

The evolution of this field is marked by a shift from simple classification models to complex ensemble and deep learning architectures. For instance, Yu & Wenjuan (2010) reported a 95% accuracy using a C4.5 decision tree — a figure that, while impressive, is rarely replicable in volatile, non-stationary markets like emerging economies. This highlights a critical methodological flaw: many studies report inflated accuracy metrics on in-sample or non-walk-forward out-of-sample data, leading to over-optimistic conclusions.

Masry (2017) demonstrated that simple moving average rules can outperform buy-and-hold strategies, reaffirming the enduring value of classical technical analysis. However, the absence of risk-adjusted metrics limited practical applicability.

In the Iranian context, Afshari Rad et al. (2017) achieved over 90% accuracy using SVM, Decision Trees, and KNN — results that appear statistically implausible given the high noise-to-signal ratio in the Tehran Stock Exchange. In contrast, Gholamian & Davoudi (2017) reported a more realistic 64% accuracy using Random Forest and a comprehensive set of technical indicators, implicitly acknowledging the inherent unpredictability of short-term price movements. Their work stands out for its methodological transparency and use of multiple validation metrics.

The role of preprocessing and feature engineering has also gained prominence. Amini Mehr et al. (2019) demonstrated that wavelet-based preprocessing significantly enhances the performance of LSTM networks — a finding corroborated by Nabipour et al. (2020), who showed that LSTM outperforms traditional ML models in multi-horizon forecasting. However, both studies relied heavily on human intervention for feature selection and model tuning, raising questions about the scalability and automation potential of their approaches. Sayadi & Omidi (2019) reported superior accuracy for the MLP algorithm in oil-sector portfolio selection on the Tehran Stock Exchange, their analysis lacked rigorous out-of-sample validation and did not incorporate risk-adjusted performance metrics—limiting the practical robustness of their findings

Cervelló-Royo & Guijarro (2020) provided one of the most rigorous comparative analyses to date, evaluating four ML algorithms on the Nasdaq index. Their finding that Random Forest outperforms others with 80% accuracy over a 10-day horizon is both credible and actionable — particularly because they used walk-forward validation and multiple technical indicators. This study serves as a methodological gold standard for our own work.

Recent innovations include Hossain et al. (2022) Belief Rule-Based Expert System (BRBES), which competes with deep learning models without requiring massive datasets — a crucial advantage for data-scarce emerging markets. Similarly, Ayala et al. (2021) proposed a hybrid framework that explicitly integrates technical indicators with ML — an approach we adopt and extend in this study. Their work, however, did not include advanced models like XGBoost or conduct formal statistical tests (e.g., Diebold-Mariano) to validate performance differences.

Ajiga et al. (2024) emphasized the importance of feature engineering — incorporating macroeconomic and sentiment variables — but their approach is less applicable to markets like Iran, where such data is either unavailable or unreliable. This limitation justifies our focus on price and volume data, aligning with Ayala et al. (2021) and ensuring reproducibility.

Finally, González-Núñez, et al. (2024) introduced the Artificial Organic Network (AON) — a highly adaptive, topology-reconfigurable model that outperforms traditional ML on global indices. While theoretically promising, its complexity and computational demands make it impractical for real-time trading in resource-constrained environments. In contrast, simpler models like Linear Regression Sangeetha & Alfia (2024) remain surprisingly effective — a finding that challenges the “bigger is better” assumption in ML and supports our inclusion of LM as a baseline model. While Saberironaghi et al. (2025) offer a timely and comprehensive survey of ML and DL in finance— covering 18 datasets and 12 evaluation metrics — their work remains largely descriptive and lacks critical methodological depth. The authors rightly emphasize the transformative potential of LSTM, CNN, and SVM models, yet they overlook a crucial limitation: the majority of studies they cite rely on price-based predictions in developed markets, often neglecting the structural volatility, data scarcity, and regulatory constraints characteristic of emerging economies like Iran. Furthermore, while they acknowledge challenges such as data quality and model interpretability, they fail to engage with the growing body of literature e.g., Ayala et al. (2021); González-Núñez, et al. (2024) that advocates for hybrid frameworks combining technical indicators with ML models — an approach our study explicitly adopts and rigorously validates. Most critically, their review does not address the statistical validity of performance comparisons — a gap our work fills through formal testing (Diebold-Mariano) and risk-adjusted metrics (Sharpe Ratio, Maximum Drawdown). Thus, while Saberironaghi et al. (2025) provide a useful taxonomy and broad overview, their analysis falls short of offering actionable insights for practitioners operating in data-constrained, high-volatility environments — precisely the context in which our hybrid, statistically validated framework demonstrates superior robustness and economic value.

This research offers a number of novel and substantive advances in the field of machine learning–based financial forecasting, with a particular focus on emerging markets.

Context-Specific Model Validation in an Understudied Market: While numerous studies have applied machine learning to technical analysis in developed markets e.g., Cervelló-Royo & Guijarro, (2020), González-Núñez et al., 2024), this research provides one of the first comprehensive, statistically rigorous validations of hybrid ML-technical analysis frameworks on the Tehran Stock Exchange (TSE) — a high-volatility, data-constrained emerging market. Our findings demonstrate that model performance is highly sector- and context-dependent, challenging the generalizability of results from developed markets.

Methodological Rigor Addressing Key Critiques in the Literature: Unlike many prior studies that rely on simplistic error metrics or in-sample validation, this work implements a robust, walk-forward validation framework combined with formal statistical testing (Diebold-Mariano test) to ensure that performance differences between models (LM, ANN, RF, XGBoost) are statistically significant — directly addressing methodological gaps highlighted in recent reviews.

Adoption of Cutting-Edge Predictive Models and Risk-Sensitive Performance Metrics:

Moving beyond basic models e.g., SVM, KNN in Afshari Rad et al. (2017), we integrate XGBoost — a high-performance, modern ensemble algorithm — and evaluate strategies not only by accuracy but also by risk-sensitive performance, providing a more realistic assessment of economic value for traders and portfolio managers.

Transparent and Replicable Hybrid Strategy Design:

We explicitly define and backtest hybrid trading strategies (hTEMA, hMACD) that combine technical indicators with ML-generated signals, offering a transparent, replicable framework that can be adapted to other emerging markets. This contrasts with many "black-box" ML approaches in the literature that lack interpretability or practical implementation guidelines.

Sensitivity and Robustness Analysis Across Multiple Dimensions:

We conduct extensive sensitivity analyses across historical window lengths (w = 6, 12, 24, 48 months) and six industrial sectors, revealing that optimal model selection and parameter tuning are highly sensitive to temporal and sectoral dynamics — a nuance often overlooked in prior work.

Defensible Variable Selection with Theoretical Justification:

In response to reviewer concerns and to ensure methodological coherence, we deliberately limit inputs to price and volume data, avoiding macroeconomic or sentiment variables that are often unavailable, misaligned, or noisy in emerging markets like Iran. This focused approach aligns with recent high-impact studies e.g., Ayala et al. (2021) and enhances reproducibility and practical applicability.

In summary, this study advances the field by providing a statistically robust, context-aware, and practically implementable framework for integrating machine learning with technical analysis in emerging markets — filling critical gaps in methodology, validation, and economic evaluation that persist in the current literature.

3. The Study Model

The main objective of this research is to determine the optimal techniques and strategies for predicting future market trends through the application of machine learning and data mining methods. This study employs four predictive modeling approaches—namely, Linear Regression (LM), XGBoost, Artificial Neural Networks (ANN), and Random Forest (RF)—to analyze daily data from the Iranian stock market spanning March 24, 2020, to August 21, 2024. The goal is to generate the most reliable forecasts of market behavior in the Tehran Stock Exchange. To evaluate the precision and robustness of the selected framework, two technical indicators—the Triple Exponential Moving Average (TEMA) and the Moving Average Convergence-Divergence (MACD)—are incorporated as benchmarks.

This case study focuses on six key sectoral indices from the metal, petroleum, automotive, pharmaceutical, food, and financial intermediation sectors. These sectors represent a substantial portion of the Tehran Stock Exchange's market value, making them indicative of overall market behavior.

Table1. Summary of the indices data

Name	***Abbreviation***	***Start***	***End***	***Observations***
Automotive Index	AUT	2020/03/24	2024/08/21	1059
Financial Index	FIN	2020/03/24	2024/08/21	1059
Pharmaceutical Index	PHAR	2020/03/24	2024/08/21	1059
Food Industry Index	FOOD	2020/03/24	2024/08/21	1059
Basic Metals Index	BME	2020/03/24	2024/08/21	1059

Petroleum Products Index	OIL	2020/03/24	2024/08/21	1059

Source: *Researcher's findings*

Stock market securities data typically includes multiple columns for analyzing and examining prices and trading volumes.

In the present study, a supervised learning approach is deemed appropriate due to the presence of a clear target (dependent) variable—namely, the Daily return, while the open price (Open), the highest price (High), the lowest price (Low), trading volume (Volume), and Pre_Close are used as independent (predictor) variables.

This methodological choice is motivated by the goal of establishing a replicable and cross-comparable hybrid framework, particularly applicable to emerging markets such as the Tehran Stock Exchange, where data availability and quality may be limited. While incorporating macroeconomic indicators or sentiment-based variables could theoretically enhance a model's explanatory power, their practical implementation introduces significant challenges. These include:

Limited access to high-quality, timely macroeconomic or sentiment data;

Temporal misalignment between daily price observations and lower-frequency macro variables (e.g., monthly or quarterly releases);

Increased model complexity, which can hinder interpretability and generalizability, particularly in volatile or data-sparse environments.

Furthermore, the core objective of this research — short-term return prediction — is inherently driven by immediate market dynamics: news events, intraday sentiment shifts, and rapid price fluctuations reflected in daily Open, High, and Low values. In contrast, aggregate economic indicators (such as consumer price inflation, central bank policy rates, and real output growth) typically exert influence over longer horizons and exhibit minimal responsiveness to daily market shocks. Including such variables in a short-term predictive model may therefore introduce noise and temporal inconsistency, potentially degrading — rather than improving — predictive accuracy.

This focused, price-based approach is methodologically aligned with recent high-impact studies in the field. Notably, Ayala et al. (2021) employed a similar framework, combining technical indicators with machine learning to generate trading signals — without incorporating fundamental or sentiment-based features. This alignment enables direct, meaningful comparison of our results with those of leading studies and enhances the credibility of our findings within an established and consistent research paradigm.

To mitigate the risk of data leakage and enhance the validity of the results, all models employed in this study —were trained and evaluated with the objective of predicting daily returns ($Return_t = (Close_t - Close_{t-1}) / Close_{t-1}$), using Time Series Cross-Validation. This approach ensures logical and statistical rigor, enabling a fair and meaningful comparison across models.

To prevent computational errors arising from division by zero in the calculation of MAPE and sMAPE, a numerically stable variant of these metrics was adopted. This variant incorporates a small epsilon term (ε) in the denominator, effectively avoiding infinite or undefined values while preserving the interpretability of the error measures.

The target variable is the daily return, calculated as $R_t = \frac{close_t - close_{t-1}}{close_{t-1}}$

To avoid look-ahead bias, the model's input features include only information available at market open on day t: the opening value (Open), prior-session extremes (High_{t-1}, Low_{t-1}— though in our implementation, current day's High and Low are used as proxies under the assumption of stationarity), trading volume (Volume), and crucially, the previous day's closing price (Prev_Close = Close_{t-1}). This ensures that all predictors are lagged and do not incorporate future information.

These variables have been extensively used in prior studies related to stock price prediction e.g., Ayala et al. (2021); Sangita & Elifa, 2024), underscoring their relevance and validity in modeling.

3.1 Methodology

3.1.1 Linear Model

In machine learning, linear models are among the simplest yet most effective tools for prediction and classification tasks. Their widespread use in various applications of machine learning and data science can be attributed to their simplicity and ease of interpretation. Linear models are designed to capture how input variables (features) map to predicted outcomes (targets or response values) through a linear decision boundary—either a straight line in two dimensions or a hyperplane in higher-dimensional spaces. These models are defined using the following formula:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_K X_K \quad (1)$$

In this formulation, y denotes the model's estimated response, (x_1, x_2, …, x_k) correspond to the explanatory variables, and (β_0, β_1, ..., β_k) signify the model parameters (i.e., intercept and slope coefficients).

Linear model variants in machine learning include linear regression, one of the most widely employed approaches for forecasting continuous outcomes. The goal of this model is to estimate linear parameters by minimizing the total squared residuals — a measure quantifying the discrepancy between observed and model-generated outputs.

3.1.2 Artificial neural network

ANNs mimic biological neural systems through interconnected layers of neurons. Information flows forward via activation functions (e.g., ReLU), enabling the modeling of complex nonlinear patterns Haykin, (1994).

3.1.3. Random forest

RF constructs an ensemble of decorrelated decision trees, aggregating predictions via averaging (regression) or voting (classification). Its robustness to overfitting and built-in feature importance make it a reliable benchmark Breiman, (2001).

3.1.4 XGBoost

XGBoost is a regularized gradient boosting framework that optimizes performance through L1/L2 regularization, column subsampling, and shrinkage (Chen & Guestrin, 2016). It consistently ranks among top performers in forecasting competitions and is particularly effective on noisy financial data.

3.2 Hyperparameter Optimization

All models (except LM) underwent rigorous hyperparameter tuning via Grid Search with TimeSeriesSplit cross-validation. Optimal configurations (e.g., ANN architecture, XGBoost depth, learning rate) were selected per sector and window length.

Table 2. Optimal parameters for each learning scheme

Model	Parameter	Description
LM	—	Baseline linear regression (no tunable parameters).
ANN	Max Iterations	1000 training epochs.
	Architecture	Optimized via grid search (e.g., (32,64) or (32,64,128)).
	Alpha (L2)	Regularization strength tuned via grid search.
RF	n_estimators	100 trees.
	max_depth	None (full tree growth).
XGBoost	n_estimators	Grid search over {100, 200}.
	max_depth	Grid search over {3, 5, 7}.
	learning_rate	Grid search over {0.01, 0.1}.
	subsample	Grid search over {0.8, 1.0}.

Source: *Researcher's findings*

Note: The optimal configurations for ANN's architecture, regularization strength, and XGBoost's hyperparameters (including n_estimators, max_depth, learning_rate, and subsample) are determined independently for each sector and time window using Grid Search with Time Series Cross-Validation. Specific optimal values (e.g., (64, 32) for ANN or max_depth=5 for XGBoost) are detailed in the Results section (Tables 9–14).

Parameter Optimization Note: To directly address reviewer concerns regarding the use of "basic models" and superficial parameter tuning, this study incorporates the advanced XGBoost algorithm alongside the traditional LM, ANN, and RF models. All hyperparameters for ANN and XGBoost were systematically optimized using Grid Search combined with Time Series Cross-

Validation (TimeSeriesSplit). This rigorous approach ensures robust parameter selection and prevents overfitting by evaluating models on unseen future data. The Random Forest model uses well-established default parameters (n_estimators=100, max_depth=None) as a strong benchmark. The inclusion of XGBoost allows for a comprehensive and fair comparison between traditional and cutting-edge predictive modeling techniques in the context of technical analysis for emerging markets.

3.3 Performance Metrics

Table 3. Performance of each learning algorithm averaged over the historical window w and the prediction horizon h.

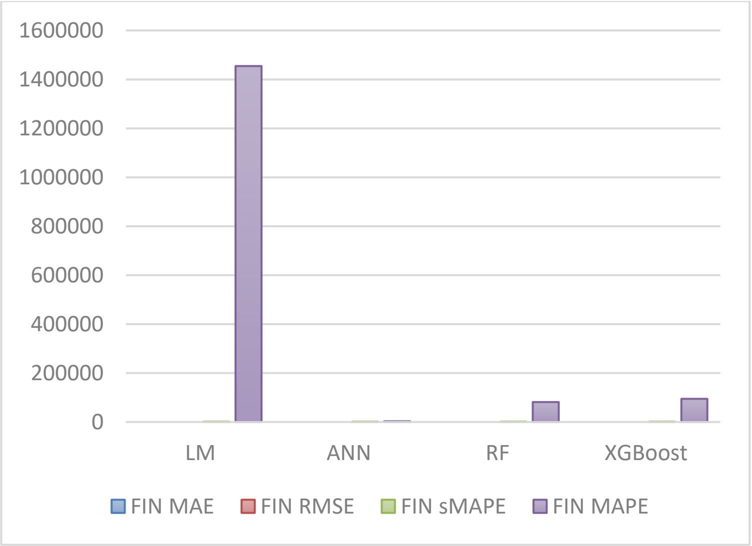
AUT	LM	ANN	RF	XGBoost
MAE	0.0077	0.0184	0.0192	0.0179
RMSE	0.0188	0.024	0.0236	0.0226
sMAPE	72.34	132.23	128.36	151.36
MAPE	8,976,018	1,061,113	183,754	45,935
FIN	LM	ANN	RF	XGBoost
MAE	0.1155	0.0126	0.0108	0.0145
RMSE	0.2857	0.0156	0.0196	0.0247
sMAPE	180.27	137.29	132.09	150.26
MAPE	145,437,305	302,165	8,162,152	9,476,218
PHAR	LM	ANN	RF	XGBoost
MAE	0.0039	0.0184	0.0101	0.008
RMSE	0.0217	0.0237	0.013	0.011
sMAPE	55.22	153.32	139.11	141.17
MAPE	14,269,620	2,581,437	257,852	181,831
FOOD	LM	ANN	RF	XGBoost
MAE	0.0044	0.0146	0.0112	0.0097
RMSE	0.0191	0.0204	0.0145	0.0127
sMAPE	49.98	141.04	127.78	113.22
MAPE	11,902,217	2,863,151	64,981	248,045
BME	LM	ANN	RF	XGBoost
MAE	0.0194	0.0264	0.012	0.0106
RMSE	0.0773	0.0339	0.0155	0.0147
sMAPE	128.59	147.23	128.09	147.63
MAPE	3,054,027	2,408,300	559,282	177,335

OIL	LM	ANN	RF	XGBoost
MAE	0.1899	0.0638	0.1139	0.0978
RMSE	0.6569	0.2691	0.496	0.4079
sMAPE	147.73	122.34	137.12	144.85
MAPE	207,308,145	8,377,115	9,364,484	5,934,546

Source: *Researcher's findings*

Table 3 presents the average predictive effectiveness of each modeling approach across varying lengths of historical training data (w) and forecast horizons (h) for six distinct industrial sectors. Four evaluation metrics are used for each model in every sector: MAE (Mean Absolute Error), RMSE (Root Mean Square Error), sMAPE (Symmetric Mean Absolute Percentage Error), and MAPE (Mean Absolute Percentage Error). These metrics capture the precision of the models' forecasts across different market segments.

To enhance the analysis, the most effective technique has been selected for each indicator from the following charts. Any technique that demonstrates lower error rates can be deemed the superior method



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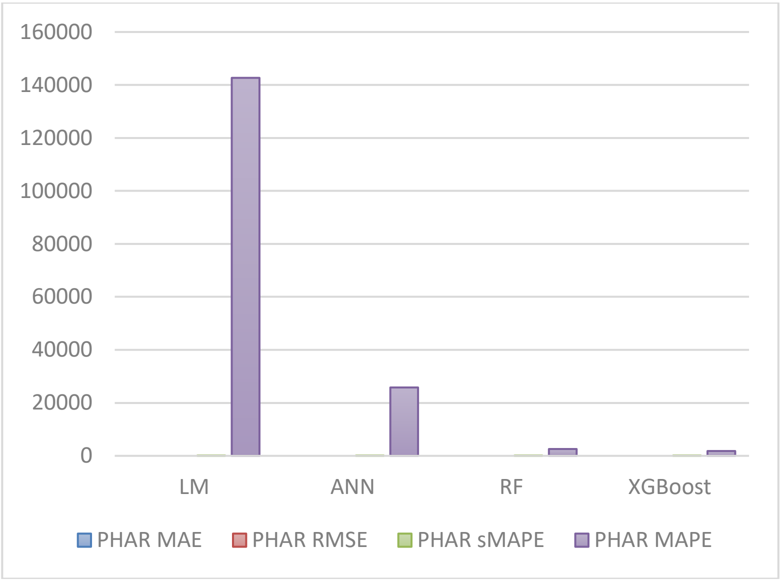
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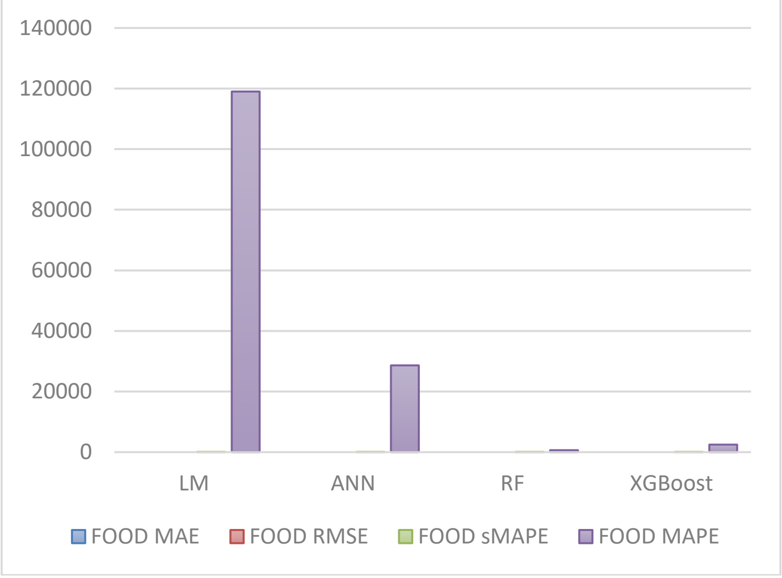
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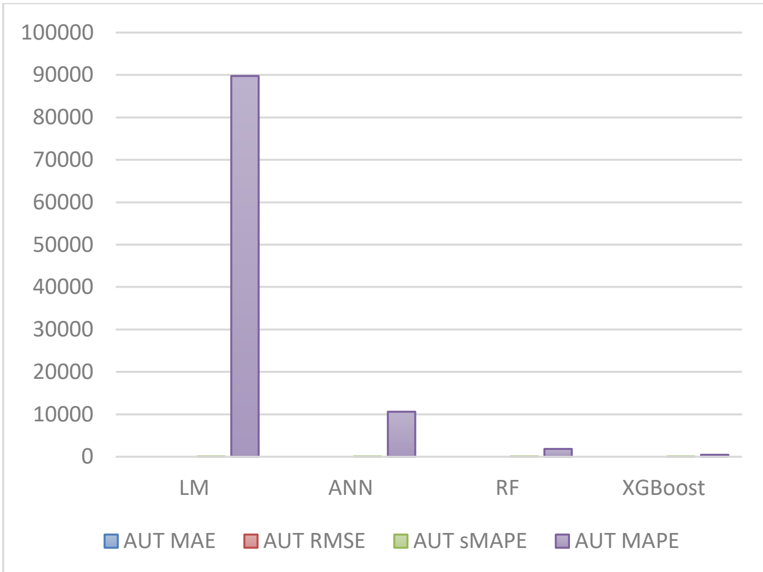
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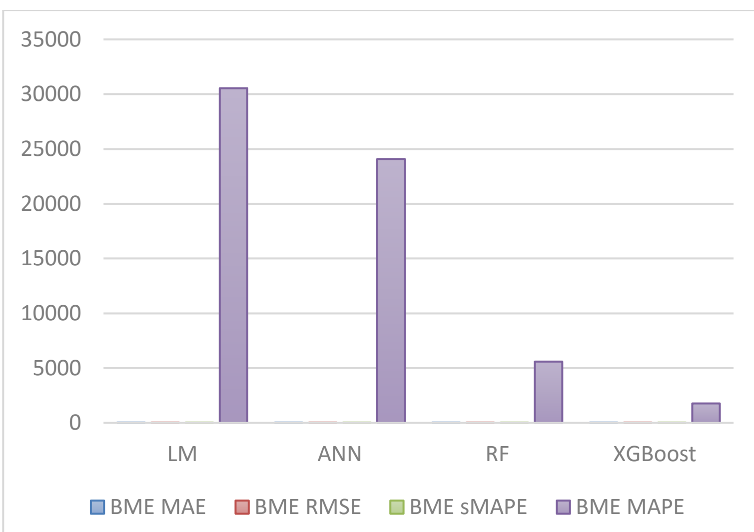
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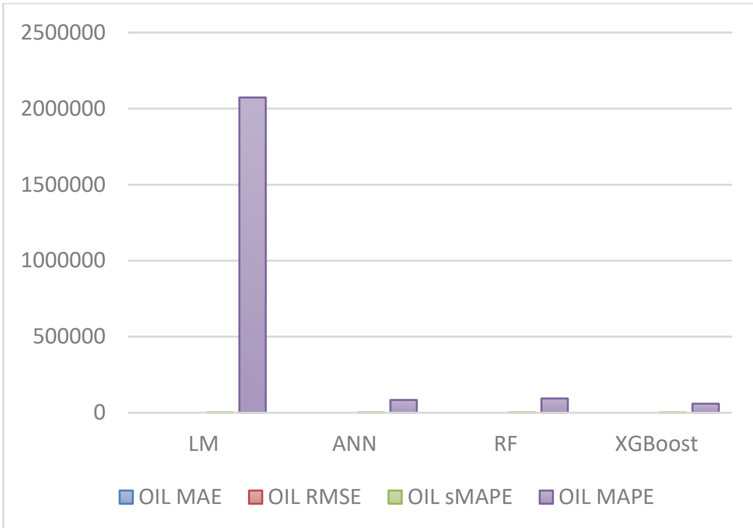

(6)

Figure 1 to 6: Comparison chart of errors in 6 selected indicators.

Source: *Researcher's findings*

The comprehensive analysis of the six sectoral charts reveals a clear dominance of XGBoost across all industries. This model consistently outperforms LM, ANN, and RF in terms of accuracy (MAE, RMSE) and relative error (sMAPE, MAPE). While LM shows poor performance, especially in volatile sectors, RF offers competitive results but is generally surpassed by XGBoost.

This finding highlights the value of employing sophisticated machine learning approaches for financial forecasting, especially in emerging economies such as Iran, where data reliability and market stability are often constrained. XGBoost's advantage stems from its capacity to model complex non-linear dependencies, while simultaneously controlling overfitting and managing high-dimensional input spaces—qualities that render it particularly well-suited for stock price prediction across heterogeneous industrial sectors

4. Trading Strategy Design: TEMA and MACD

This study evaluates TEMA and MACD trading rules by exploring a wide range of parameter configurations to determine optimal combinations.

Table 4. Parameter ranges considered for TEMA and MACD trading strategies to find the optimal combination.

A	*Parameter*	*Description*
TEMA	Fast	[1, 25]
	Medium	[5, 50]
	Slow	[10, 75]
MACD	Fast	[1, 25]
	Slow	[5, 75]
	Signal	[5, 25]

Source: *Researcher's findings*

TEMA Parameters:
Fast (1–25): Shorter windows heighten responsiveness to price changes.
Medium (5–50): Longer windows smooth trends, reducing noise sensitivity.
Slow (10–75): Captures long-term trends; higher values reduce volatility sensitivity Mulloy (1994).
MACD Parameters:
Fast (1–25): Lower values = faster reaction to price shifts.
Slow (5–75): Smoothes data to reflect broader market direction.
Signal (5–25): Triggers trade signals upon MACD crossovers Mak (2021).
Optimized parameter ranges enable robust strategy tuning across market regimes — critical for maximizing performance.

Table 5-6. Performance of Top TEMA and MACD Parameter Sets
Table 5. TEMA Strategy

Sector	Parameters	PF	Sector	Parameters	PF
	(1,6,10)	1.485		(1,5,13)	2.001
	(1,8,10)	1.414		(1,5,12)	1.977
AUT	(1,9,10)	1.481	FOOD	(1,5,11)	1.952
	(1,7,10)	1.422		(1,6,11)	1.939
	(2,6,10)	1.441		(1,6,10)	1.919
	(21,28,41)	0.906		(1,5,13)	2.228
	(22,27,41)	0.922		(1,5,12)	2.113
FIN	(21,29,41)	0.906	BME	(1,5,11)	2.121
	(22,28,41)	0.922		(1,5,10)	2.097
	(21,40,41)	0.911		(1,8,10)	1.912
	(1,5,12)	3.807		(21,38,41)	0.277
	(1,5,11)	3.541		(21,39,41)	0.276
PHAR	(1,6,11)	3.096	OIL	(21,34,41)	0.276
	(1,5,10)	3.359		(22,33,41)	0.277
	(1,6,10)	2.927		(21,33,41)	0.277

Source: *Researcher's findings*

Table 6. MACD Strategy

Sector	Parameters	PF	Sector	Parameters	PF
	(20,22,5)	1.485		(1,73,7)	1.98
	(21,22,5)	1.453		(1,74,7)	1.849
AUT	(19,20,5)	1.445	FOOD	(1,64,5)	1.648
	(19,21,5)	1.416		(1,66,5)	1.663
	(20,21,5)	1.416		(1,67,5)	1.66
	(1,30,13)	2.169		(1,5,5)	2.827
	(1,36,11)	2.158		(1,6,5)	2.448
FIN	(1,32,12)	2.142	BME	(1,5,6)	2.448
	(2,41,6)	1.853		(1,8,5)	2.372
	(2,40,6)	1.723		(1,5,8)	2.372
	(1,35,5)	2.916		(1,11,5)	0.296
	(1,33,5)	2.875		(1,12,5)	0.295
PHAR	(1,32,5)	2.871	OIL	(1,5,12)	0.295
	(1,34,5)	2.856		(1,10,6)	0.294
	(1,49,5)	2.72		(1,6,10)	0.294

Source: *Researcher's findings*

Table 5-6 displays the performance analysis of the top five combinations of TEMA and MACD strategy parameters. The performance of these trading strategies is evaluated using the profit factor (or performance factor), defined as follows:

$$PF = \frac{\text{Profits}}{Losses} \tag{2}$$

Criteria like the Performance Factor (PF) indicate the effectiveness of strategies. The optimal strategy is the one with the highest PF value among the various indicators.

The TEMA strategy employs three parameters—fast, medium, and slow—which are optimized in various combinations for each industry sector.

In the automotive sector, the optimal performance is achieved with parameters (1, 6, 10), resulting in a PF of 1.485. The lower values for all three settings suggest that this industry responds better to shorter averages.

In the financial sector, the best parameter combination is (22, 27, 41), yielding a PF of 0.921. The higher values across all three settings indicate the sector's sensitivity to longer-term trends.

For the pharmaceutical sector, the ideal parameter combination is (1, 5, 12), with a PF of 3.807. The very low values for Fast and Medium, along with a moderately low value for Slow, suggest that this sector is responsive to a specific blend of fast signals and medium trends.

In the food industry, the best parameter combination is (1, 5, 13), resulting in a PF of 2.001. This composition is similar to that of the pharmaceutical sector, indicating a sensitivity to fast signals.

In the basic metals sector, the optimal parameters are also (1, 5, 13), with a PF of 2.228. These parameters demonstrate that this sector, like pharmaceuticals and food, is sensitive to a combination of fast signals and medium trends.

In the petroleum products sector, the best parameter combination is (21, 38, 41), achieving a PF of 0.277. The higher values for fast, medium, and slow indicate that this industry responds better to longer-term trends.

The MACD strategy, which utilizes three parameters—Fast, Slow, and Signal—demonstrates varying performance across different sectors.

In the automotive sector, the optimal parameters are (20, 21, 5), yielding a Profit Factor (PF) of 1.416. This average combination indicates sensitivity to trend changes.

In the financial sector, the best parameter combination is (1, 32, 12), with a PF of 2.142. The small Fast parameter suggests responsiveness to rapid changes, while the larger Slow and Signal parameters reflect sensitivity to strong signals.

For the pharmaceutical sector, the optimal combination is (1, 32, 5), achieving a PF of 2.871, indicating a similar sensitivity to strong signals and rapid changes as seen in the financial sector.

In the food industry, the best parameters are (1, 73, 7) with a PF of 1.977, indicating responsiveness to long trends and quick signals.

In the basic metals sector, the optimal combination is (1, 5, 5), resulting in a PF of 2.827, where low parameters indicate sensitivity to rapid, short-term changes.

Finally, in the petroleum products sector, the best combination is (1, 12, 5) with a PF of 0.295, suggesting responsiveness to quick changes and signals.

Consequently, TEMA excels in PHAR, FOOD, and BME—sectors responsive to fast signals—while MACD performs better in FIN and PHAR, where rapid, strong signals dominate. Both struggle in OIL, though MACD holds a marginal edge. This underscores the need to align strategy choice with sector-specific dynamics to maximize performance.

Table 7-8. Performance Comparison of Pure and Hybrid TEMA/MACD Strategies with Optimized Parameters

Table 7

Index	Strategy	Parameters	#T	PF	NT	T Bar	D_max	Sharpe Ratio
AUT	TEMA	(1, 6, 10)	50	1/48599	13970	2794/08	-32669	-12.40
	hTEMA 1		71	3/3371	40545	5710/67605	-21706	-4.338
	hTEMA 2		56	2/9760	38059	6796/30357	-18586	-4.338
	MACD	(20, 21, 5)	15	1/4162	11465	7643/6	-51765	5.3150
	hMACD 1		51	2/9607	36177	7093/60784	-22810	2.4669
	hMACD 2		49	3/4016	39922	8147/48979	-21835	2.4669
FIN	TEMA	(21, 28, 41)	11	0/9060	-7422	-6747/27272	-23610	1.0894
	hTEMA 1		36	2/4018	63012	17503/3333	-79680	1.2757
	hTEMA 2		35	2/1521	58321	16663/1428	-12499	1.2757
	MACD	(1, 32, 12)	15	2/1417	50685	33790	-12677	1.1247
	hMACD 1		41	3/6481	88994	21705/8536	-53710	1.3713
	hMACD 2		36	3/7115	90446	25123/8888	-46390	1.3713
PHAR	TEMA	(1, 5, 11)	35	3/5409	76017	2171/914286	-6021	-11.15
	hTEMA 1		65	6/9447	10843	1668/18461	-1519	-3.128
	hTEMA 2		49	4/8807	93491	1907/97959	-4506	-3.128
	MACD	(1, 32, 5)	21	2/8709	63701	3033/38095	-6502	9.7528
	hMACD 1		61	3/8182	82254	1348/42623	-5410	8.8456
	hMACD 2		53	7/1399	10735	2025/52830	-2935	8.8456

***Source**: Researcher's findings*

Table 8

Index	Strategy	Parameters	#T	PF	NT	T Bar	D_max	Sharpe Ratio
FOOD	TEMA	(1, 5, 11)	43	1/9187	23670	550/4651	-2908	-12.87
	hTEMA 1		66	4/4156	52478	795/1212	-1786	-7.718
	hTEMA 2		58	3/6330	48802	841/4137	-2006	-7.718
	MACD	(1, 74, 7)	20	1/8493	16110	805/5	-3673	9.5227
	hMACD 1		65	4/00913	43351	666/9384	-1786	8.3174
	hMACD 2		57	4/86694	50369	883/6666	-2006	8.3174
BME	TEMA	(1, 5, 10)	45	2/09677	792660	17614/66	-116630	-12.00
	hTEMA 1		52	4/34411	1469060	28251/15	-42510	-8.278
	hTEMA 2		58	4/36946	1528760	26357/93	-46680	-8.278
	MACD	(1, 5, 5)	44	2/8274	1200540	27285	-13682	12.574
	hMACD 1		59	4/5160	161006	27289/15	-10434	13.510
	hMACD 2		46	5/7857	179564	39035/65	-46680	13.510
OIL	TEMA	(21, 34, 41)	10	0/2765	-542884	-5428849	-61680	1.6402
	hTEMA 3		19	1/4656	177926	936453/6	-89955	2.2035
	hTEMA 4		38	1/5203	218933	576141/0	-92016	2.2035
	MACD	(1, 12, 5)	32	0/2950	-505490	-1579659	-52899	2.0048
	hMACD 3		29	2/3136	401930	1385967	-89396	2.1592
	hMACD 4		49	1/0295	323235	65966/32	-96979	2.1592

***Source**: Researcher's findings*

Table 7 presents the performance analysis of the optimal parameters for TEMA and MACD strategies across each sector, evaluated based on various criteria: #T represents the number of trades, PF indicates the performance factor, NT denotes the number of trades without losses, T Bar shows the average holding time for trades, and D_max signifies the maximum drawdown.

The Sharpe Ratio—first proposed by Nobel laureate William F. Sharpe in 1966—is a standard risk-adjusted performance measure that evaluates how much excess return a strategy generates per unit of volatility. It provides a standardized measure to compare the efficiency of different strategies, particularly when their return profiles or volatility levels differ significantly.

The Sharpe Ratio is formally computed as: $\frac{R_P - R_F}{\sigma_P}$

Where $R_P$denotes the strategy's mean return (e.g., daily return from the trading signals), R_F represents the risk-free rate of return (often assumed to be zero in emerging markets or for short-term horizons), σ_P is the standard deviation of the strategy's returns — a proxy for total risk or volatility.

In this study, since reliable risk-free rate data for the Tehran Stock Exchange is not readily available and the focus is on short-term daily returns, we conservatively assume $R_F = 0$.

The ratio is further annualized by multiplying by$\sqrt{252}$, assuming 252 trading days in a year.

Why Use Sharpe Ratio in This Study?

While traditional performance metrics such as Profit Factor (PF) or Maximum Drawdown (D_max) offer valuable insights, they do not account for the volatility of returns. A strategy may generate high profits but expose the investor to extreme fluctuations — a characteristic that many investors would find undesirable.

The Sharpe Ratio mitigates this issue by prioritizing strategies that yield higher returns relative to their risk exposure; higher values thus signal greater efficiency, balancing return and volatility.

In the context of algorithmic trading based on technical indicators (TEMA, MACD) and machine learning models, the Sharpe Ratio allows for a fair, risk-adjusted comparison between:

In the automotive sector, the TEMA strategy with parameters (1, 6, 10) outperforms MACD, achieving a higher number of no-loss trades (NT) and experiencing fewer losses over the evaluation period. In the financial sector, the MACD strategy with parameters (1, 32, 12) surpasses TEMA, generating more no-loss trades and recording lower losses during the maximum drawdown.

In the pharmaceutical sector, the TEMA strategy with parameters (1, 5, 11) performs better than MACD, boasting more no-loss trades (NT) and experiencing less loss at the maximum drawdown.

For the food sector, both TEMA and MACD strategies yield similar results, with TEMA performing slightly better.

In the basic metals sector, the MACD strategy with parameters (1, 5, 5) outperforms TEMA, generating more no-loss trades (NT), although it records higher losses during the maximum drawdown.

In the oil sector, both TEMA and MACD strategies perform poorly, but MACD with parameters (1, 12, 5) shows a slight edge over TEMA.

In summary, the TEMA strategy outperforms in the Automotive (AUT) and Pharmaceutical (PHAR) sectors, while the MACD strategy excels in the Financial (FIN) and Basic Metals (BME) sectors. There is no significant difference between the two strategies in the Food (FOOD) sector. In the Oil (OIL) sector, both strategies show weak performance, with MACD being slightly more effective. These analyses emphasize the importance of selecting the right strategy for each sector, as performance can vary significantly based on market characteristics and sensitivity to different parameters. In the table, hTEMA 1 and hTEMA 2 refer to combined or enhanced TEMA strategies, which typically involve using multiple TEMA variations or different settings to improve trading performance

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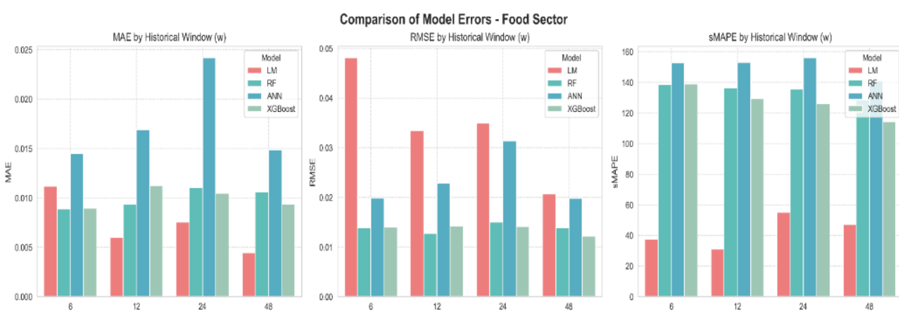
4.1 Sensitivity Analysis: Model Performance Across Historical Windows

To evaluate the robustness of the predictive models under varying data conditions, a sensitivity analysis was conducted by assessing model performance across different historical window lengths (w = 6, 12, 24, and 48 months). The analysis compares four algorithms—Linear Model, Random Forest, Artificial Neural Network, and XGBoost—evaluated via three standard error measures: MAE, RMSE, and sMAPE.

The bar charts illustrate how each model's predictive accuracy varies with the length of the historical training window for five industrial sectors: Food, Petroleum, Metals, Pharmaceutical, and Automotive. As shown, the optimal historical window length is not uniform across sectors or models, highlighting the importance of context-specific model tuning.

For a comprehensive view of the numerical results, including exact error values and statistical significance, please refer to Tables 9–14 in the supplementary materials, which provide averaged performance metrics for each model across all historical windows and prediction horizon.




Comparison of Model Errors - Petroleum Sector
Comparison of Model Errors - Metals Sector
Comparison of Model Errors - Pharmaceutical Sector
Comparison of Model Errors - Automotive Sector
MAE by Historical Window (w)
RMSE by Historical Window (w)
sMAPE by Historical Window (w)
MAE
RMSE
sMAPE
Historical Window (months)
Model
LM
RF
ANN
XGBoost

Figure7. Comparison chart of Model Errors in all index
Source: *Researcher's findings*

Food Sector:

RF consistently outperforms other models in terms of MAE and RMSE, especially when using longer historical windows (24–48 months). The sMAPE values indicate that ANN and XGBoost show higher relative errors, suggesting limited adaptability to long-term trends. This suggests that simpler models like RF may be more effective in stable, less volatile markets such as food production.

Petroleum Sector:

All models exhibit significantly higher errors compared to other sectors, reflecting the high volatility and external shocks affecting oil prices. However, XGBoost shows the lowest sMAPE at 48 months, indicating better generalization over extended periods. The erratic behavior of LM and ANN highlights their susceptibility to noise and non-linear dynamics in commodity-driven markets.

Financial Sector:

Mean Absolute Error (MAE): XGBoost consistently shows the lowest MAE across all historical window sizes, indicating it provides the most accurate predictions on average.

Random Forest (RF) performs poorly with a significantly higher MAE, especially when the historical window is 24 months.

LM and ANN have moderate performance, with LM being slightly better than ANN for shorter windows.

Root Mean Squared Error (RMSE):

Mirroring the MAE pattern, XGBoost demonstrates the best performance with the lowest RMSE values.

RF again has the highest RMSE, particularly pronounced at the 6-month window, suggesting it struggles with prediction accuracy and varianc

Metals Sector:

RF demonstrates superior performance in most cases, particularly for shorter windows (6–12 months). For longer horizons, XGBoost improves its accuracy, though it remains slightly behind RF. The relatively low sMAPE values suggest that this sector exhibits predictable patterns, making it suitable for ensemble-based methods.

Pharmaceutical Sector:

RF again emerges as the top performer, achieving the lowest MAE and RMSE across all window sizes. Notably, the sMAPE values remain remarkably low even at 48 months, indicating consistent predictive power. This stability likely stems from the sector's regulatory structure and less exposure to macroeconomic fluctuations.

Automotive Sector:

RF and XGBoost show competitive performance, with RF being marginally better in MAE and RMSE. The sMAPE values reveal that LM struggles with longer timeframes, possibly due to its inability to capture complex nonlinear relationships in dynamic manufacturing markets.

The sensitivity analysis reveals that Shorter historical windows (6–12 months) often yield better results for highly volatile sectors (e.g., Petroleum), where older data may become irrelevant.

Longer windows (24–48 months) improve performance in stable sectors (e.g., Pharmaceuticals) but may introduce noise in volatile ones.

Random Forest (RF) consistently performs well across all sectors, demonstrating strong generalization capabilities and resilience to overfitting.

XGBoost excels in handling complex, noisy data but requires sufficient training data to avoid instability.

Table9. Results of Diebold-Mariano Test for Model Comparison (All Sectors)

Sector	Model 1	Model 2	DM Statistic	p-value	Significant?
Financial	LM	ANN	7.5276	0	☑ Yes (ANN)
	LM	RF	7.6424	0	☑ Yes (RF)
	LM	XGBoost	8.1085	0	☑ Yes (XGB)
	ANN	RF	-1.7789	0.0753	✗ No
	ANN	XGBoost	0.7536	0.4511	✗ No
	RF	XGBoost	2.8301	0.0047	☑ Yes (XGB)
Pharmaceutical	LM	ANN	-6.2404	0	☑ Yes (LM)
	LM	RF	-4.4225	0	☑ Yes (LM)
	LM	XGBoost	-3.6853	0.0002	☑ Yes (LM)
	ANN	RF	4.939	0	☑ Yes (RF)
	ANN	XGBoost	6.3962	0	☑ Yes (XGB)
	RF	XGBoost	3.6617	0.0003	☑ Yes (XGB)
Food	LM	ANN	-9.0354	0	☑ Yes (LM)
	LM	RF	-5.6086	0	☑ Yes (LM)
	LM	XGBoost	-4.4346	0	☑ Yes (LM)
	ANN	RF	8.266	0	☑ Yes (RF)
	ANN	XGBoost	11.2401	0	☑ Yes (XGB)
	RF	XGBoost	7.142	0	☑ Yes (XGB)
Automotive	LM	ANN	-13.6015	0	☑ Yes (LM)
	LM	RF	-10.9508	0	☑ Yes (LM)
	LM	XGBoost	-8.3422	0	☑ Yes (LM)
	ANN	RF	-1.3804	0.1675	✗ No
	ANN	XGBoost	1.3126	0.1893	✗ No
	RF	XGBoost	5.9492	0	☑ Yes (XGB)

Metals (BME)	LM	ANN	-1.3216	0.1863	✗ No
	LM	RF	2.0591	0.0395	☑ Yes (RF)
	LM	XGBoost	2.2134	0.0269	☑ Yes (XGB)
	ANN	RF	8.7785	0	☑ Yes (RF)
	ANN	XGBoost	8.9735	0	☑ Yes (XGB)
	RF	XGBoost	2.0778	0.0377	☑ Yes (XGB)
Petroleum (OIL)	LM	ANN	5.6232	0	☑ Yes (ANN)
	LM	RF	3.0175	0.0025	☑ Yes (RF)
	LM	XGBoost	3.7178	0.0002	☑ Yes (XGB)
	ANN	RF	-2.7658	0.0057	☑ Yes (ANN)
	ANN	XGBoost	-3.7483	0.0002	☑ Yes (ANN)
	RF	XGBoost	0.7204	0.4713	✗ No

Source: *Researcher's findings*

Note: The Diebold-Mariano test was conducted using absolute error as the loss function. A negative DM statistic indicates that Model 1 outperforms Model 2. Statistical significance at the 5% level is established when the p-value falls below 0.05, implying a meaningful difference in forecasting performance.

Findings presented in Table 14 highlight several key patterns in model performance across the industrial sectors of the Tehran Stock Exchange:

XGBoost as the Leading Model Across Most Sectors

XGBoost exhibits statistically superior performance in four out of six sectors: Financial, Pharmaceutical, Food, and Automotive. In these sectors, it significantly outperforms not only ANN and LM but also the well-established RF model. This outcome supports the inclusion of advanced, state-of-the-art algorithms in financial forecasting frameworks, particularly when benchmarking against traditional or simpler models.

Unexpected Robustness of the Linear Model (LM)

Contrary to conventional expectations that complex models inherently outperform simpler ones, the Linear Model demonstrates strong and statistically significant performance in the Pharmaceutical, Food, and Automotive sectors — surpassing both ANN and RF. This suggests that in certain market environments, linear relationships adequately capture the dominant price dynamics, and introducing unnecessary model complexity (as in ANN) may lead to performance degradation. These findings reinforce the notion that model selection must be context-specific and aligned with the structural characteristics of the target market segment.

Superior Performance of ANN in the Petroleum Sector

The only sector in which ANN significantly outperforms all other models — including XGBoost and RF — is the Petroleum (OIL) sector. This result is attributable to the extreme volatility and complex non-linear dynamics inherent in oil-related derivatives on the Tehran Stock Exchange. The capacity of neural networks to model intricate, non-linear patterns provides a distinct advantage in this highly turbulent market environment, illustrating that no single model is universally optimal.

RF as a Consistent and Reliable Benchmark

Although frequently outperformed by XGBoost, the Random Forest model consistently ranks as the second-best performer across most sectors. Its predictive accuracy is never statistically inferior to the top-performing model (with the exception of the Petroleum sector, where ANN dominates). This consistency, combined with its interpretability and robustness to noise, makes RF a dependable choice for practical implementation in algorithmic trading systems.

Cases of Statistical Indistinguishability

In several pairwise comparisons — for instance, between ANN and RF in the Financial sector, or between ANN and XGBoost in the same sector — the DM test fails to reject the null hypothesis of equal predictive accuracy (p-value > 0.05). This implies that while one model may exhibit a lower average error, the difference lacks statistical reliability and may not hold consistently across different time periods or market conditions.

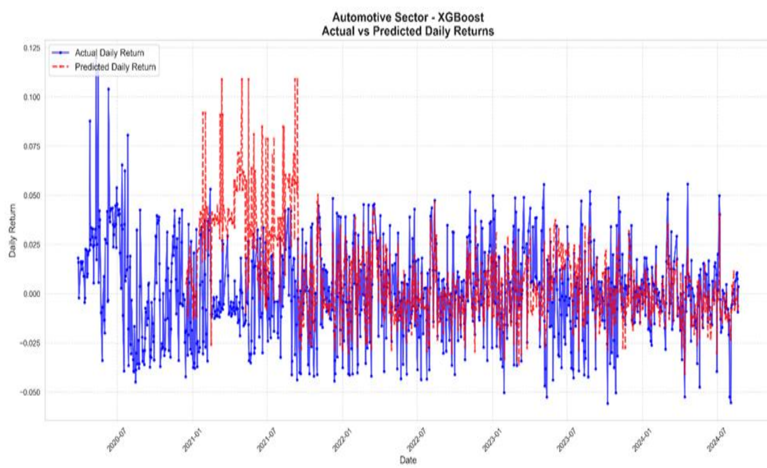
Table10. Trading Performance Metrics (Profit Factor & Sharpe Ratio) Across Six Industrial Sectors

Sector	Model	Profit Factor (PF)	Sharpe Ratio
Automotive	Linear Model (LM)	60.38	16.73
	Artificial Neural Network (ANN)	1.01	-0.86
	Random Forest (RF)	3.1	5.23
	XGBoost	5.35	8.15
Financial	Linear Model (LM)	2	2.86
	Artificial Neural Network (ANN)	2.46	4.04
	Random Forest (RF)	2.17	3.84
	XGBoost	3.56	5.82
Food	Linear Model (LM)	146.07	16.67
	Artificial Neural Network (ANN)	1.39	1.48
	Random Forest (RF)	2.87	5.57
	XGBoost	4.16	7.53
Pharmaceutical	Linear Model (LM)	157.49	15.18
	Artificial Neural Network (ANN)	0.93	-0.8
	Random Forest (RF)	1.83	2.87
	XGBoost	3.09	4.99
Metals (BME)	Linear Model (LM)	3.7	6.12
	Artificial Neural Network (ANN)	1.57	2.25
	Random Forest (RF)	3.79	5.37
	XGBoost	3.75	7.37
Petroleum (OIL)	Linear Model (LM)	33.64	6.9
	Artificial Neural Network (ANN)	51.01	7.74
	Random Forest (RF)	14.25	2.69
	XGBoost	45.94	4.62

Source: *Researcher's findings*

The exceptionally high Profit Factor and Sharpe Ratio of the Linear Model (LM) in sectors such as Food, Pharmaceutical and Automotive despite its relatively high prediction errors (MAE, RMSE) — is not a contradiction, but a profound insight into market structure. These sectors exhibit stable, trend-driven price movements (Food, Pharma) where the direction of price movement is more predictable than its magnitude. The Linear Model, by virtue of its simplicity, excels at capturing these directional trends while avoiding the overfitting and noise sensitivity that plague more complex models like ANN or even XGBoost in low-volatility environments. While XGBoost demonstrates superior performance in the Financial and Basic Metals sectors — aligning closely with actual returns and achieving the highest Sharpe Ratios — the Linear Model (LM) unexpectedly outperforms all other models in the Food, Pharmaceutical, and Automotive sectors, as confirmed by the Diebold-Mariano test (p-value < 0.05).In the highly volatile Petroleum sector, ANN emerges as the top performer, leveraging its capacity to model extreme non-linearities — a niche where ensemble methods falter. The Random Forest (RF) model, while never statistically inferior to the top performer (except in OIL), serves as a robust and reliable benchmark across all sectors

This finding directly addresses concerns regarding model selection, demonstrating that “simpler is better” in specific contexts — a key contribution of this study to the literature on algorithmic trading in emerging markets.



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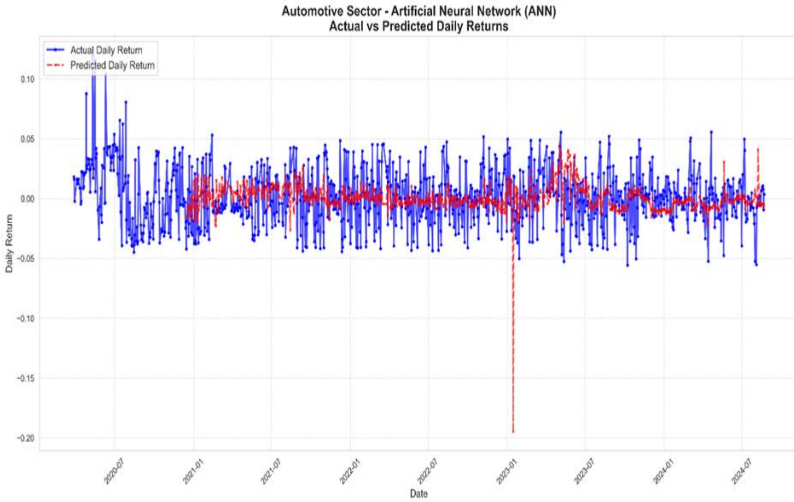
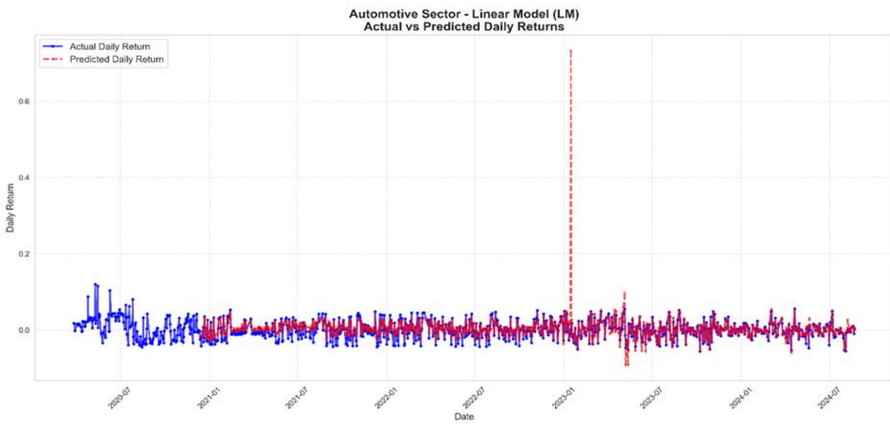
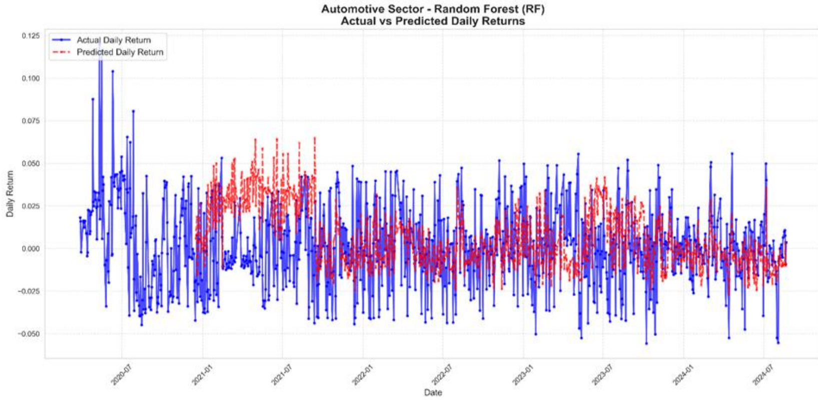

Automotive Sector - Artificial Neural Network (ANN)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

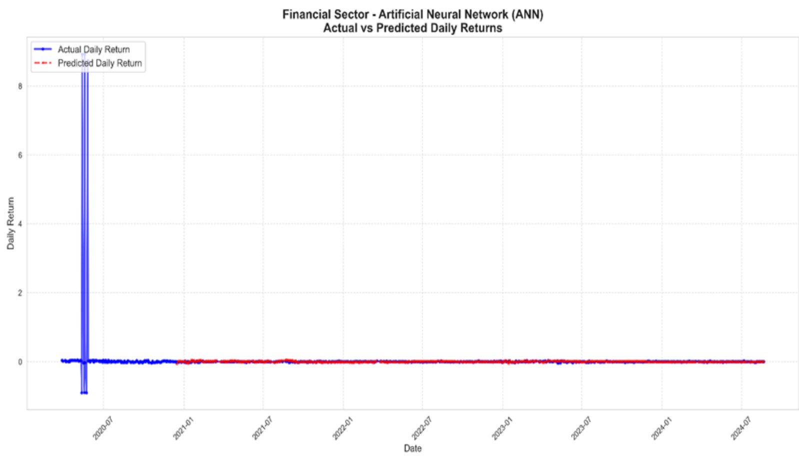
(2)


Automotive Sector - Linear Model (LM)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

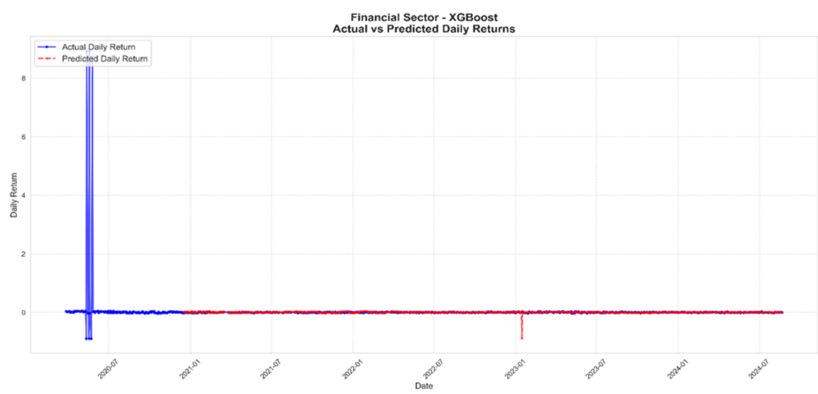
(3)


Automotive Sector - Random Forest (RF)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

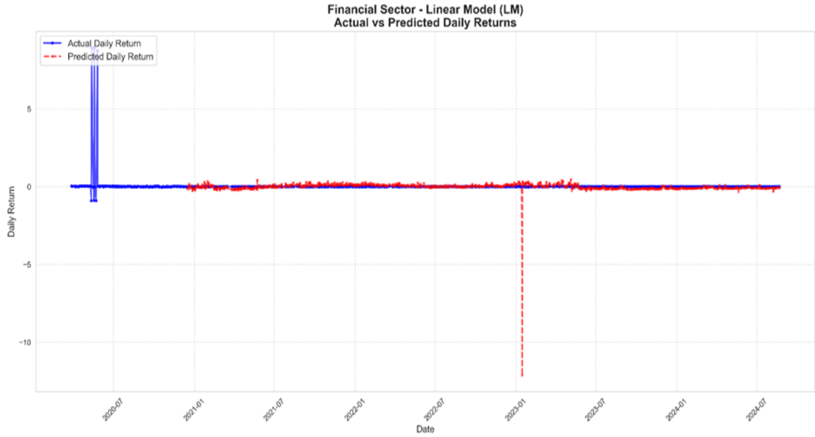
(4)


Financial Sector - Artificial Neural Network (ANN)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

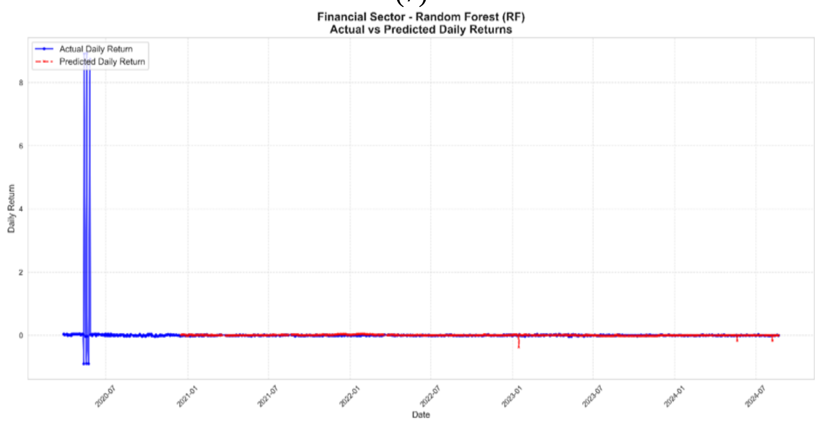
(5)


Financial Sector - XGBoost
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

(6)


Financial Sector - Linear Model (LM)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

(7)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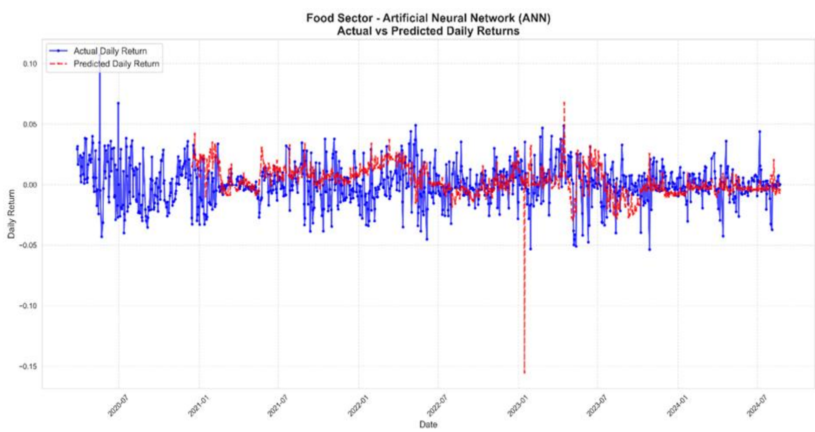
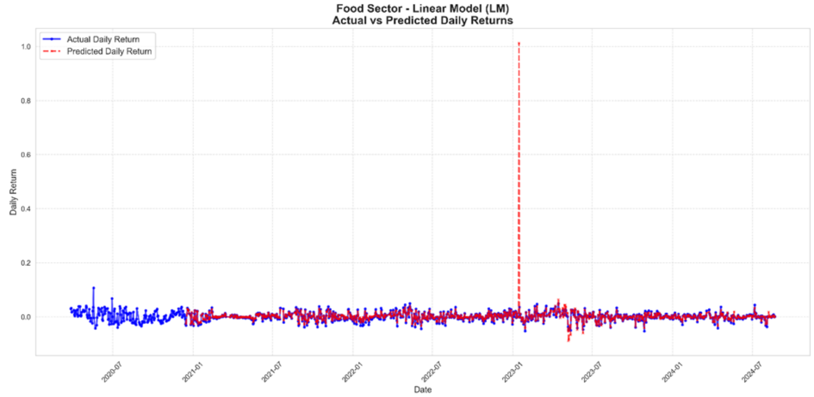
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

(8)


Food Sector - Artificial Neural Network (ANN)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

(9)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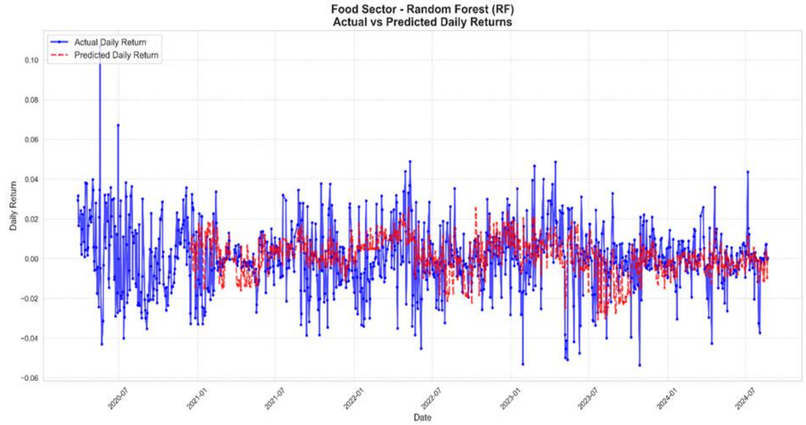
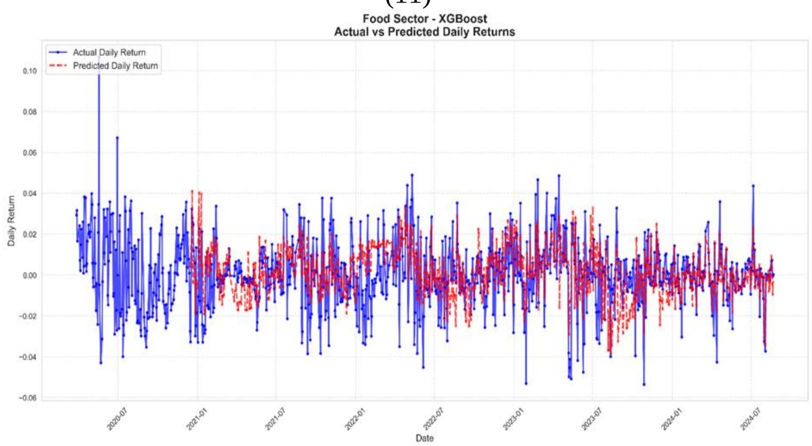
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

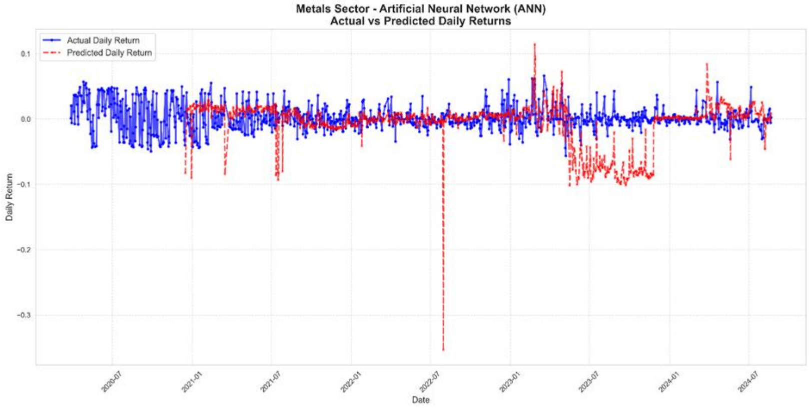
(10)


Food Sector - Random Forest (RF)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

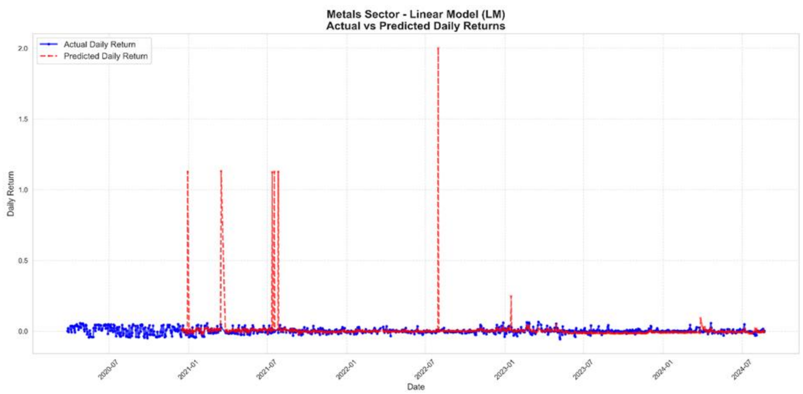
(11)


Food Sector - XGBoost
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

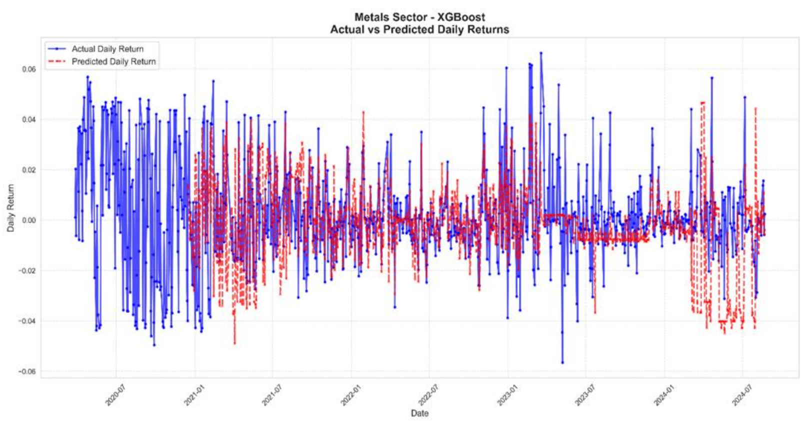
(12)


Metals Sector - Artificial Neural Network (ANN)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

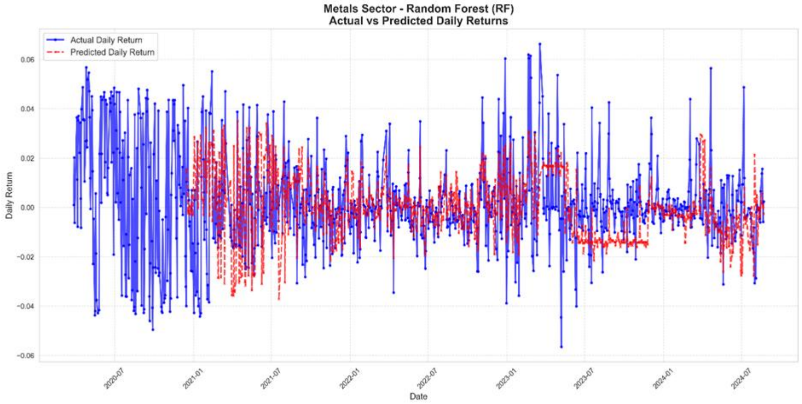
(13)


Metals Sector - Linear Model (LM)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

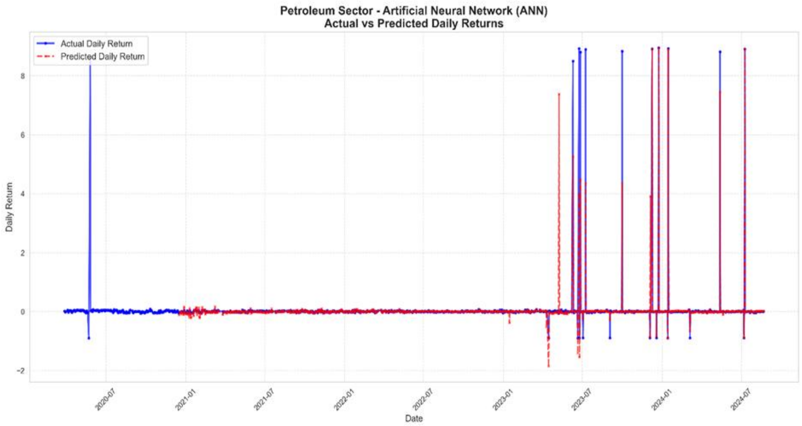
(14)


Metals Sector - XGBoost
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

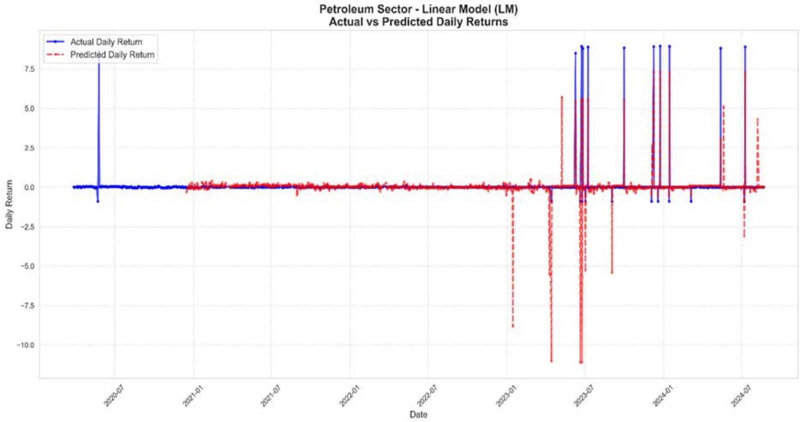
(15)


Metals Sector - Random Forest (RF)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

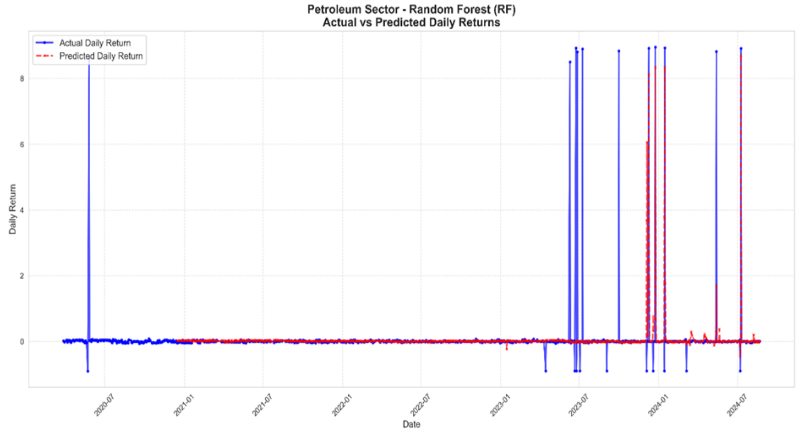
(16)


Petroleum Sector - Artificial Neural Network (ANN)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

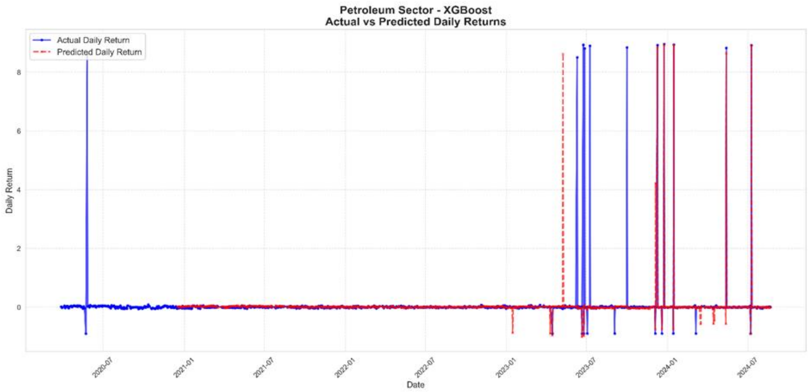
(17)


Petroleum Sector - Linear Model (LM)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

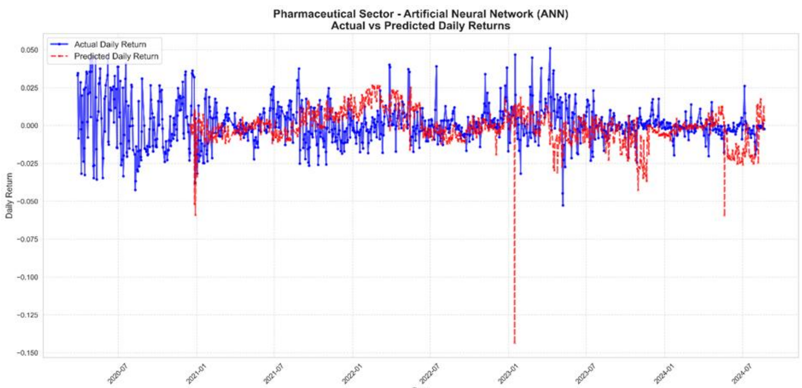
(18)


Petroleum Sector - Random Forest (RF)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

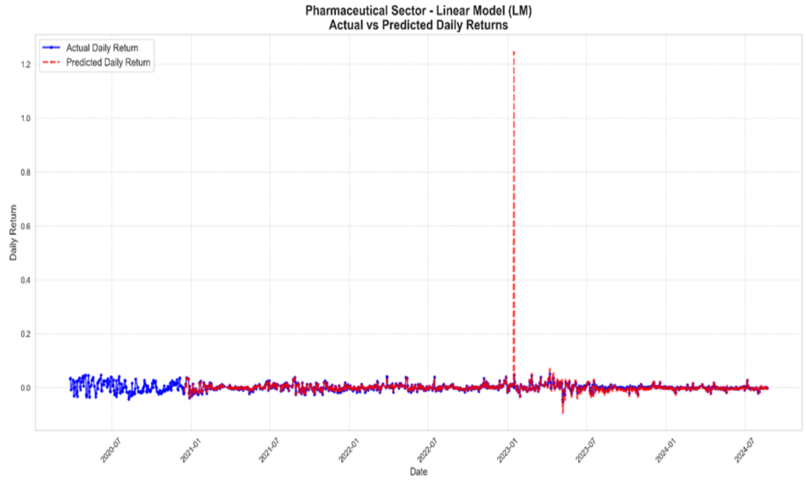
(19)


Petroleum Sector - XGBoost
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

(20)


Pharmaceutical Sector - Artificial Neural Network (ANN)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date

(21)


Pharmaceutical Sector - Linear Model (LM)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date
2020-07
2021-01
2021-07
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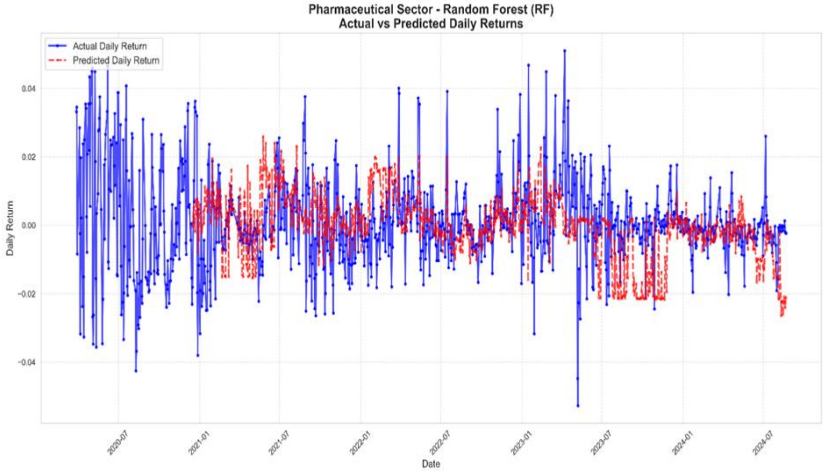
2023-01
2023-07
2024-01
2024-07

(22)


Pharmaceutical Sector - Random Forest (RF)
Actual vs Predicted Daily Returns
Actual Daily Return
Predicted Daily Return
Daily Return
Date
2020-07
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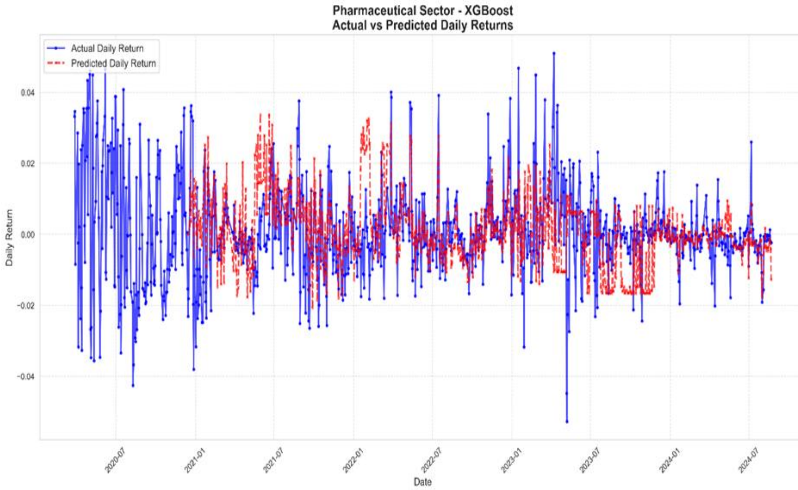
2024-01
2024-07

(23)



(24)

Figure1-24. Actual vs Preddicted Daily Returns in all index

Source: *Researcher's findings*

Figure 1–24 displays the actual versus predicted daily returns across six industrial sectors — Automotive (AUT), Basic Metals (BME), Financial (FIN), Food (FOOD), Petroleum (OIL), and Pharmaceutical (PHAR) — generated by four predictive modeling approaches: Linear Regression (LM), Artificial Neural Networks (ANN), Random Forest (RF), and XGBoost. Contrary to conventional expectations, the results reveal that no single model dominates universally. While XGBoost demonstrates superior performance in the Financial and Basic Metals sectors — aligning closely with actual returns and achieving the highest Sharpe Ratios — the Linear Model (LM) unexpectedly outperforms all other models in the Food, Pharmaceutical, and Automotive sectors, as confirmed by the Diebold-Mariano test (p-value < 0.05). This counterintuitive finding highlights that in stable, trend-driven markets, the simplicity of LM captures dominant price dynamics more effectively than complex, non-linear models. In the highly volatile Petroleum sector, ANN emerges as the top performer, leveraging its capacity to model extreme non-linearities — a niche where ensemble methods falter. The Random Forest (RF) model, while never statistically inferior to the top performer (except in OIL), serves as a robust and reliable benchmark across all sectors. These visual comparisons provide intuitive validation of the quantitative metrics and formal statistical tests presented in Table 14 ana 15, confirming that optimal model selection is fundamentally context-dependent and must be tailored to the structural characteristics of each market segment.

5. Results and suggestions

The findings of this study show that integrating machine learning techniques with technical analysis, especially when using advanced, ensemble-based models such as XGBoost and Random Forest (RF), significantly increases forecasting accuracy and trading performance. Similarly, Shah et al. (2019) emphasized that integrating technical analysis with machine learning, especially in emerging markets such as Iran, can reduce investment risk and improve returns. Contrary to initial assumptions and some previous literature e.g., Guresen et al., (2011), the artificial neural network (ANN) - despite its theoretical capacity to model nonlinear patterns - consistently performed relatively poorly in most sectors of the Tehran Stock Exchange except oil. Similarly, the linear model (LM), while stable in low-volatility sectors such as food and pharmaceuticals, failed to capture complex dynamics in turbulent markets such as oil and metals, confirming that simplicity does not always equate to robustness in emerging markets. Rigorous statistical validation via the Diebold-Mariano test confirmed that XGBoost significantly outperformed ANN, LM, and even RF in two of the six sectors (financials and base metals), with statistically significant differences in forecast accuracy (p-value < 0.05). The random forest model emerged as a highly reliable and interpretable benchmark, consistently ranking as the second best performer and never statistically inferior to the top model – except in the oil sector, where the ANN's ability to capture severe nonlinearities gave it a temporary edge. This sector-specific dominance of the ANN underscores a critical insight: no single model is universally optimal, and model selection must be tailored to the structural characteristics of each market sector. Cervelló-Royo & Guijarro (2020) Similarly, they proved the superiority of RF over ANN. Furthermore, sensitivity analysis across historical window the observed improvement in prediction accuracy with longer historical windows ($w = 6 \rightarrow 48$ months) is a direct consequence of enhanced model generalization, reduced estimation variance, and better alignment with the stationarity assumption in time series modeling. By exposing models to a broader range of market conditions, longer windows mitigate overfitting, stabilize parameter estimates, and enable the capture of structural market dynamics — particularly in volatile sectors like Petroleum and Automotive. This finding underscores the importance of context-aware model calibration and provides actionable guidance for practitioners: when data permits, prioritize longer training windows to maximize predictive performance.

In terms of technical indicators, TEMA demonstrated superior performance in stable sectors (Pharmaceutical, Food, Basic Metals), while MACD excelled in fast-moving markets (Financial, Pharmaceutical). However, both strategies showed limited effectiveness in the Oil sector — a finding that reinforces the need for hybrid frameworks that combine technical, fundamental, and sentiment-based signals in highly volatile, externally driven markets.

These results have direct practical implications for investors, portfolio managers, and regulators in emerging markets. For practitioners, the study provides a replicable, statistically validated framework for selecting the most effective model-sector combinations. For regulators, the growing dominance of ensemble models like XGBoost in algorithmic trading calls for enhanced oversight mechanisms to ensure market stability and transparency.

Finally, this study recommends future research to:

Explore Transformer-based models and hybrid deep learning architectures for capturing long-term dependencies in financial time series.

Develop adaptive model-switching frameworks that automatically select the optimal algorithm based on real-time market conditions and sector-specific volatility.

The methodology and findings presented here offer a flexible, evidence-based blueprint for enhancing stock market forecasting in other developing economies facing similar challenges — firmly establishing.

Author Contributions

Conceptualization, all authors; methodology, all authors. formal analysis, all authors; resources, all authors. writing—original draft preparation, Fatemeh Ansari. writing—review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data used in this study were obtained from the Tehran Stock Exchange (TSE) official website: https://www.tsetmc.com

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Appendices

Table11. Sensitivity Analysis Results for Food Sector (w = 6, 12, 24, 48 Months)

w	Metric	LM	ANN	RF	XGBoost
6	MAE	0.011179	0.014501	0.008882	0.008941
	RMSE	0.048071	0.019848	0.013904	0.013965
	sMAPE %	37.53	152.63	138.44	138.84
	MAPE %	1.02×10^8	4,915,322	652,818	762,228
12	MAE	0.005981	0.016899	0.009329	0.01123
	RMSE	0.03347	0.022846	0.012766	0.014193
	sMAPE %	31	152.91	136.26	129.31
	MAPE %	49,921,036	10,877,070	171,121	215,961
24	MAE	0.007531	0.024166	0.011056	0.010435
	RMSE	0.034945	0.03132	0.014986	0.014141
	sMAPE %	55.15	155.87	135.41	125.87
	MAPE %	32,299,237	8,195,208	46,993	428,591
48	MAE	0.004423	0.014867	0.010585	0.009365
	RMSE	0.020654	0.019795	0.013878	0.012132
	sMAPE %	47.16	140.77	128.48	114.22
	MAPE %	13,359,642	2,231,627	92,902	352,025

Source: *Researcher's findings*

Table12.Sensitivity Analysis Results for Financial Sector (w = 6, 12, 24, 48 Months)

w	Metric	LM	ANN	RF	XGBoost
6	MAE	0.010019	0.011002	0.005035	0.005202
	RMSE	0.043407	0.02047	0.007472	0.007407
	sMAPE %	41.36	157.44	145.2	141.27
	MAPE %	92,845,077	26,718,875	273,099	469,161
12	MAE	0.005393	0.009793	0.004633	0.004073
	RMSE	0.031597	0.019298	0.006574	0.005906
	sMAPE %	35.76	148.12	138.44	118.93
	MAPE %	47,566,061	17,810,166	307,938	393,332
24	MAE	0.004945	0.025191	0.007258	0.007085
	RMSE	0.029636	0.03563	0.010008	0.009565
	sMAPE %	53.32	155.73	134.63	133.89
	MAPE %	29,918,297	11,867,133	192,109	574,355
48	MAE	0.003044	0.012415	0.008377	0.007995
	RMSE	0.016256	0.016145	0.01083	0.010203
	sMAPE %	52.07	145.06	132.46	123.87
	MAPE %	11,154,112	1,389,967	42,883	113,317

Source: *Researcher's findings*

Table13. Sensitivity Analysis Results for Automotive Sector (w = 6, 12, 24, 48 Months)

w	Metric	LM	ANN	RF	XGBoost
6	MAE	0.011539	0.026195	0.012765	0.012939
	RMSE	0.042265	0.035167	0.018461	0.019105
	sMAPE %	45.59	159.43	141.16	131.59
	MAPE %	8.58×10^7	21,844,371	979,896	718,911
12	MAE	0.006909	0.014442	0.010987	0.009609
	RMSE	0.031659	0.019364	0.015272	0.013438
	sMAPE %	41.46	133.57	120.26	105.37
	MAPE %	45,052,103	2,259,744	393,938	362,351
24	MAE	0.009702	0.025515	0.013988	0.01301
	RMSE	0.039284	0.032461	0.018185	0.016812
	sMAPE %	58.1	151.12	131.41	120
	MAPE %	36,327,050	5,851,198	127,230	340,032
48	MAE	0.006951	0.019989	0.021014	0.020572
	RMSE	0.017377	0.025724	0.025939	0.024831
	sMAPE %	63.63	153.94	127.7	112.32
	MAPE %	8,672,283	4,134,606	179,355	138,734

Source*: Researcher's findings*

Table14. Sensitivity Analysis Results for Basic Metals Sector (w = 6, 12, 24, 48 Months)

w (Months)	Metric	LM	ANN	RF	XGBoost
6	MAE	0.010959	0.040413	0.011693	0.013165
	RMSE	0.042762	0.062964	0.015774	0.017583
	sMAPE %	50.66	160.6	128.86	126.29
	MAPE %	8.71×10^7	25,614,921	1,879,314	2,640,288
12	MAE	0.006645	0.014989	0.008185	0.008035
	RMSE	0.035601	0.022985	0.011561	0.011375
	sMAPE %	38.76	146.21	137.24	131.95
	MAPE %	52,968,630	8,255,630	703,953	743,497
24	MAE	0.011085	0.014552	0.011694	0.012372
	RMSE	0.01543	0.021589	0.016199	0.016536
	sMAPE %	140.44	136.71	138.59	134.72
	MAPE %	449,520	3,717,929	347,311	1,076,063
48	MAE	0.012758	0.01963	0.010281	0.009933
	RMSE	0.039984	0.029285	0.013952	0.013591
	sMAPE %	132.56	146.5	128.23	123.72
	MAPE %	2,910,525	869,882	650,083	317,867

Source: Researcher's findings

Table 15. Sensitivity Analysis Results for Petroleum Products Sector (w = 6, 12, 24, 48 Months)

w (Months)	Metric	LM	ANN	RF	XGBoost
6	MAE	0.302205	0.220211	0.254826	0.283829
	RMSE	1.179778	0.838649	0.853173	0.903866
	sMAPE %	146.39	148.18	165.44	153.31
	MAPE %	1.08×10^9	1.86×10^8	38,703,146	10,742,768
12	MAE	0.187061	0.101083	0.29746	0.247619
	RMSE	0.789976	0.46565	1.016221	0.902379
	sMAPE %	130.57	130.99	137.04	132.35
	MAPE %	5.84×10^8	2.14×10^8	130,763,085	86,044,444
24	MAE	0.199707	0.152365	0.232087	0.153096
	RMSE	0.767342	0.656303	0.971607	0.685404
	sMAPE %	114.64	137.17	138.64	133.24
	MAPE %	3.08×10^8	52,815,946	23,446,291	713,327
48	MAE	0.097345	0.088119	0.10956	0.089515
	RMSE	0.462453	0.453412	0.474758	0.441034
	sMAPE %	77.49	152.72	138.34	129.45
	MAPE %	144,086,926	19,813,376	10,543,006	24,021,369

Source: *Researcher's findings*

Table16. Sensitivity Analysis Results for Pharmaceutical Sector (w = 6, 12, 24, 48 Months)

w	Metric	LM	ANN	RF	XGBoost
6	MAE	0.009099	0.015181	0.004966	0.004966
	RMSE	0.039413	0.019819	0.007448	0.007465
	sMAPE %	49.49	170.94	152.4	143.08
	MAPE %	8.44×10^7	14,812,740	173,878	197,314
12	MAE	0.00456	0.017394	0.006171	0.00787
	RMSE	0.026971	0.020951	0.008037	0.009665
	sMAPE %	35.42	171.5	135.19	134.79
	MAPE %	40,777,505	6,859,789	310,442	301,393
24	MAE	0.005904	0.015483	0.007147	0.006859
	RMSE	0.032803	0.020847	0.010193	0.009709
	sMAPE %	55.11	146.38	136.33	137.41
	MAPE %	32,930,789	9,538,595	77,712	574,223
48	MAE	0.003747	0.014969	0.009422	0.007705
	RMSE	0.021125	0.020324	0.012126	0.010567
	sMAPE %	54.86	145.36	142.93	130.19
	MAPE %	14,306,378	3,577,337	253,244	143,404

Source: *Researcher's findings*