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Research Article

Comparing Artificial Neural Network and Random Forest Models for Predicting Stock Prices at the Nairobi Securities Exchange

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Abstract

Accurate stock price prediction is challenging due to the dynamic, non-linear, and noisy nature of financial markets. Traditional methods, such as technical and fundamental analysis, are often subjective and limited. However, machine learning techniques offer significant potential for improved forecasting. This study compared the performance of Artificial Neural Network (ANN) and Random Forest (RF) models in predicting the next-day closing stock prices for five companies listed on the Nairobi Securities Exchange (NSE-20 Index): British American Tobacco Kenya Ltd (BAT), East African Breweries Ltd (EABL), Kenya Commercial Bank (KCB), Equity Group Holdings (EQTY), and Safaricom (SCOM). The study utilized a longitudinal financial dataset of 6,176 daily trading observations, spanning five years from January 2, 2020, to January 2, 2025. The implementation of the predictive models was based on three historical lagging features (Lag_{t-1}, Lag_{t-2}, and Lag_{t-3}) and a 5-day rolling moving average ($MA5$) which were created to capture localized momentum. Furthermore, a strict chronological data split involving 80% observations (n =4,941) for training partition and 20% observations (n =1,235) for testing partition was enforced to minimize data leakage and enhance model evaluation. The test partition was then used to evaluate model performance using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Bias Error (MBE), and the coefficient of determination (R2). The findings depicted high out-of-sample goodness-of-fit metrics, with R^2 values consistently exceeding 0.9300 for both ANN and RF models across all five equities. The ANN model tracking KCB Group achieved the highest R^2 of 0.9881. For BAT, the ANN achieved a lower RMSE of 4.48 (MAPE = 0.61%); however, the RF model deviated by 5.93 (MAPE = 1.01%). Moreover, the ANN model achieved a significantly lower error rate for SCOM (RMSE = 0.31) outperforming the RF model (RMSE = 0.38). The RF model depicted a highly persistent, negative bias across all equities except EABL, peaking at MBE of 0.32 for BAT Kenya. However, the ANN model depicted a mixed directional bias error, generating a positive bias of 0.19 for BAT (MBE = 0.19), while minimal negative bias errors across the remaining four companies. The persistent out-of-sample predictive achievements decisively reject the strict application of the semi-strong form of the Efficient Market Hypothesis (EMH) on the NSE, instead validating the use of the Adaptive Market Hypothesis (AMH). This implies persistent price predictability at the NSE, therefore, necessitating the need for stronger marketing strategies, improvement in investor sentiment, and enhancement of disclosure frameworks.

Keywords

Stock Price Prediction, Artificial Neural Network, Random Forest, Nairobi Securities Exchange, Time Series Forecasting, Machine Learning, Efficient Market Hypothesis

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1. Introduction

The stock market is vital for a country's economic growth, driving capital formation and investment. This process is facilitated by the financial industry, which includes banks, insurance companies, other financial institutions, and real estate organizations [18]. Through virtual trading platforms, financial market agents enable the transaction of currencies, derivatives, and stocks. Banking activities, in particular, significantly influence the economy by supporting the trading of stocks for publicly listed companies, both on and off exchanges [42].

Characterized by its dynamic, unpredictable, and non-linear nature, the stock market presents a challenge for accurate price prediction [25]. Various factors, such as political conditions, global economic trends, and company financial reports and performance, influence stock prices [1]. Consequently, analyzing past trends to forecast future stock values can be highly beneficial for maximizing profits and minimizing losses [2]. Both business experts and academics concur that precise stock price forecasting enhances profitability. Furthermore, multinational companies frequently depend on the stock market as a primary funding source [18].

While traditional approaches previously applied to predict stock prices relied on technical and fundamental analysis, the use of these approaches were limited as they were subjective in nature and often prone to errors [35]. Also, previous studies employed stand-alone deep learning techniques to predict stock prices. However, current studies have integrated deep learning neural networks with various machine learning approaches to perform predictions [5, 11, 14, 16, 19, 32]. Therefore, machine learning techniques have demonstrated a significant improvement in efficiencies, ranging from 60% to 80%, compared to previous methodological approaches [14, 43].

Most studies indicate that Kenyan stockbrokers primarily rely on technical and fundamental analysis to predict future stock price movements [35], however, these methods typically show only the direction of future trends, not precise trade price figures. Few studies have explored the application of artificial intelligence tools to assist Kenyan stockbrokers in advising clients on suitable stocks to buy or sell [17]. Therefore, there is a clear need for a prediction tool that can provide not only the direction of price movement but also the most likely future stock price value.

Moreover, the inter-market performance of these models can be variable, as highlighted by [16]. His study of Swedish, U.S., and Brazilian stocks revealed that while LSTM performed exceptionally well for Swedish stocks, its performance was poor for Brazilian and U.S. stocks. This variability underscores the importance of a focused and tailored approach to address the unique challenges of each domestic market.

ANN are particularly well-suited for stock price prediction due to their self-learning capabilities, which enable them to identify hidden features and complex input-output associations within vast datasets [16]. The choice of ANN in this study is justified since it excels at simulating and analyzing complex patterns in unstructured data, outperforming most conventional approaches. This model handle complexity in stock market by using multi-layered perceptrons (MLPs) and non-linear activation functions such as ReLU or Sigmoid [9]. This structure functions enable ANN to extrapolate trends by mapping deep, interconnected dependencies between market technical indicators and historical trends. Moreover, deep learning models involve the use of large datasets, hence ANNs can achieve exceptional convergence on historical data by optimizing smaller configurations [21]. For instance, research conducted by [27] show that ANN perform better with low error margins of MAPE under 3% even when using relative small windows of 5-year daily data.

However, the backpropagation gradient descent of the neural network can fall into local overfitting traps as it reacts so aggressively to temporary daily noise. Hence, the averaging of independent decision trees by the RF model functioned as a resilient structural shield. By using this approach of averaging terminal leaf node metrics, the ensemble model inherently smooths out high-frequency fluctuations and effectively filters out trading noise [3]. This provides a superior operational safety for this specific market regime. This signifies that a dual-model optimization algorithm is important for identifying the specific market regimes where RF's ensemble tree structures provide superior operational safety, because there is no single algorithm which universally dominates under all volatility conditions.

This paper therefore compares the performance of Artificial Neural Networks (ANNs) and Random Forest (RF) in predicting closing stock prices for firms listed at the Nairobi Stock Exchange. The methodological approach to the implementation of the two machine learning in stock price forecasting aligns with the findings of [26] who noted that traditional models like Random Forest offer interpretability through mechanisms like Gini Importance (Mean Decrease in Impurity) and Permutation Feature Importance as they often struggle with non-linear financial dynamics. In an NSE context, these mechanisms allow investors and stockbrokers to determine which indicators such as trading volumes, the NSE Share Index and historical moving averages, exert the highest predictive control over stock prices. However, ANN models especially those with dual hidden layers, are designed to address the challenge of non-linear modelling [26].

Furthermore, other modelling approaches such as Support Vector Machine (SVM), Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM) and XGBoost were not used in the study. Specifically, ARIMA model was not used since it is limited by linearity and stationarity assumptions. According to [33], ARIMA model struggles

to absorb multidimensional structural covariates such as trading volumes without complex extensions. SVR is highly sensitive to hyperparameter tuning and the selection of kernel functions, hence scales poorly in computational efficiency when tracking volatile multi-asset portfolios over time [23]. LSTM on the other hand requires large historical data sequencing data in order to avoid overfitting and degradation of gradient, hence making baseline tabular comparison more complex [30]. XGBoost minimizes errors sequentially making it highly sensitive to hyperparameter tuning and outlier noise in volatile stock markets. This makes XGBoost a different category company to parallel-bagging approach of RF which reduces the correlation among decision trees and helps to control variance. Therefore, future research should implement neural networks based on LSTM, Gated Recurrent Units (GRUs), or using attention-based Transformer models. These neural networks have specialized memory gates which allow for retention or discard of data over long periods. This makes them structurally fit for modelling long-term predictions within consideration of macro changes on the stock exchange.

The following are specific research objectives for the study:

To develop ML-based algorithms for predicting the closing stock prices of firms listed on the NSE, using ANN and RF models.

To evaluate the effectiveness of ANN and RF models in predicting the next day's closing stock price, based on their MAPE, RMSE, and MBE values, and the goodness-of-fit using the R-squared value.

2. Literature Review

2.1. Theoretical Review

2.1.1. Efficient Market Hypothesis (EMH)

According to EMH theory developed by [13] the existing securities prices are reflected on the information relating to value of the firm. This theory states that securities are given at their fair values [13]. Hence, investors cannot adjust prices or purchase undervalued securities. The weak-form of EMH theory suggests that all historical public information is reflected on the securities prices. While the semi-strong form of market efficiency states that securities prices reflect all available historical information, adjusted for the release of emerging information, the strong-form of efficiency states that they reflect both private and public information [13].

In frontier markets like the NSE, the weak form of market efficiency is usually challenged due to low level of friction, low liquidity, and the asynchronous information flow [13]. These structural anomalies are capitalize by machine learning algorithms since they act as flexible function approximators that model persistent, non-linear dependencies between historical vectors. Therefore, the EMH is the foundation theoretical assumption guiding this study. This theory test whether the algorithmic predictability can systematically exploit localized market anomalies, or whether it is an unhedged exposure to high volatility parameters.

2.1.2. Fundamental Analysis

Fundamental analysis involves evaluation of macroeconomic and microeconomic factors influencing the actual value of an investment [46]. This theory suggest that fundamental analysts enhance market efficiency by identifying news events and keeping tracks on important performance measures and ratios. For frontier equity markets, indicators such as Price-to-Earnings (P/E) ratio, dividend yield, inflation-related indicators and central bank interest rates offer a long-term comparison of equity values. Traditional time-series methods fail to integrate financial ratios with the daily pricing data, while machine learning frameworks are able to absorb the multiple time-scales at once. In this study, fundamental and macroeconomic indicators are added into the model feature pipeline and tests whether the inclusion of the financial fundamental indicators into the trading signals increases the stability of the out-of-sample forecasts.

2.1.3. Technical Analysis

The main fundamental assumption of technical analysis is that market prices do not move in a completely random manner; rather, they exhibit clear trends as a result of different combinations of buyer and seller behavior [12]. Technical analysis hopes that future price movements can be predicted based on historical market information, with the premise that price changes reflect all the available information and that price action tends to repeat itself over time. Rather than focusing on firm's value, this approach relies on the psychological mood of the market, market momentum and the distribution of volumes, using mathematical indicators such as the Relative Strength Index (RSI) or the Moving Average Convergence Divergence (MACD). In highly volatile trading markets, technical analysis track local momentum and retail herd behavior [38]. This study converts these classical technical variables into multi-dimensional tabular feature spaces. This enables the ANN and Random Forest models to assess their predictive control on short-term stock price fluctuations.

2.1.4. Chart Pattern Hypotheses of Securities Markets

The understanding of chart patterns is important as it represents visual and subjective modelling unaided by computers [6]. The use of statistical and neural network models can perform this task more systematically and consistently, guided by quantitative methods. The Dow hypothesis of chart patterns explain the mechanism of changes in the markets [44]. According to Dow theory, the markets are highly efficient, and that the bear and bull markets move in distinct phases. Moreover, the importance of averages is clearly underscored, and tracking of inter-index [6]. Hence, investors should be keen on

volume data in order to understand trend analysis. Elliot wave hypothesis of chart patterns also offers technical analysts a guide to visualizing the price patterns for predicting future trends [44]. Hence, traders observe that markets seem to be moving in repeating waves, and its practitioners supported the ability of wave analysis to pinpoint turning points in the market. Advanced machine learning techniques are capable of analyzing these patterns by evaluating the length of the sequences, price extremes and historical volatility bands and converts the subjective geometry of chart into a stream of objective numbers to assess their validity on the trading boards of NSE.

2.2. Empirical Review

2.2.1. Traditional Statistical Models

The traditional models and predictions of stock prices were highly dependent on parametric statistical models. Both of these paradigms relied on Autoregressive Integrated Moving Average (ARIMA) models [12] and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) variants [7]. These foundational models are based on linearity and stationarity structural assumptions which suggest that the source of the variation in financial asset prices is mainly associated with historical values and the structural error.

Majority of the studies done in Kenya and global frontier markets used univariate time-series as a starting point for analysis, however, these models depicted significant structural limitations when examined closely in the empirical context. For instance, [45] assess the performance of the hybridization of ARIMA and machine learning architectures in capturing stock market time series. A key finding from their research is that the residual error terms of ARIMA models have a significant non-linear pattern in the residuals that they do not capture when used alone, thus not capturing the volatile structural dynamics. However, one major drawback of their wide hybridization approach is that it does not localize for the highly illiquid frontier markets such as Nairobi Securities Exchange (NSE). The introduction of the linear filtering (ARIMA) stage makes the overall error variance smaller, but the linear filtering stage is very sensitive to the lack of trading days and structural outliers found in most emerging African markets.

Traditional architectures have been applied to large historical datasets, using standard ARIMA modeling to draw out trends in historical asset data and project future trends over long time horizons [8]. Their framework is transparent and offers a mathematical foundation for trend vectors that are smooth and continuous; however, the main problem is the assumption of stationarity of the structure over a long forecasting horizon. Financial time series are non-stationary and prone to change of regime especially in the case of frontier markets. This study restricted the model's ability to respond to unexpected changes in investor sentiment and volume dynamics by using only a historical autoregressive loop [8]. This limitation means that its out-of-sample projection errors increase quickly with time.

Therefore, traditional linear models are effective for many situations but are limited in their applicability when dealing with sudden changes in structure or political environment or extremely volatile macro-economic changes. Financial markets are complex systems with dynamic processes, where different variables interact with each other; the model with linear properties cannot capture multi-dimensional covariates, such as changes in trading volumes or parallel movements of foreign exchange rates. Thus, the use of rigid parametric models tends to underestimate the risk when trading in volatile markets. This structural failure has led to a new paradigm in the field of modern financial econometrics with the application of neural networks and algorithmic architectures that manage complex and non-linear dynamics without imposing strict prior assumptions about the distribution of the data.

2.2.2. Machine-Learning Models

Machine-learning and neural networks frameworks have greatly improved financial forecasting by mitigating linearity assumptions. Extensively used neural networks architectures by researchers include Artificial Neural Networks (ANN), and ensemble tree-based approaches like Random Forest (RF). These models are based on the assumption that matching of complex historical patterns can yield predictive insights into a range of financial factors across multiple dimensions.

Machine learning techniques have been used for stock price prediction over a period of 10 years [47]. Their findings highlighted the transition from a single shallow classifier to an ensemble of complex classifiers. According to [47], the algorithmic models consistently capture localized linear patterns. However, the study was limited from a methodological perspective as it pays much attention on high capitalisation global exchanges. Hence, [47] research clearly indicates a research gap in literature on how these machine learning techniques perform in thin and less liquid frontier markets such as the Nairobi Securities Exchange (NSE) where a small data can mislead traditional hyperparameter optimization.

Another study presents an updated review of the shallow machine learning and deep learning setups, and compares the relative performance gains realized by traversing the architectural complexity framework [49]. Their findings suggest that deep networks structurally capture more complex abstractions, but introduce extreme optimization risks, including gradient explosion and longer convergence loops. In the review, a key constraint pointed out is the "interpretability tax", which is a compromise involved in achieving slight improvement in accuracy when adopting ultra-deep architectures, that institutional risk managers in emerging financial systems are unable to afford.

Moreover, [24] conducted a comparative study between machine learning techniques and kernel-based models, and test ANNs in comparison to Support Vector Machines (SVM) in the field of stock forecasting. From their empirical results,

SVMs perform better on lower dimensional data with less dispersion, while ANNs outperform SVMs when chaotic, high-dimensional technical indices are added to the dataset. However, [24] rely on a very strict distinction between the train and test sets, which is not reflective of forward trading in practice. They use a validation layout which does not take into account the sequential temporal data leakage. This means that apparent superiority of the network over SVM as obtained may have been overstated due to over-parameterization. Hence, the current study addresses this limitation by imposing strict lag regularizations in the network.

Another study was conducted by [4] using deep learning and sophisticated machine learning models to predict macroeconomic trends and asset price movements. Their empirical findings suggest that explicit fusion of macroeconomic indicators with raw lines of historical assets builds a very stable predictive surface. However, a significant methodological limitation of [4] design is its intensive computational algorithm. The use of deep configurations which are resource-intensive limits their practical application on a day-to-day basis for fund managers who need to deploy their infrastructure in the frontier market, where lightweight tabular architectures are required to be easily retrained.

Due to the interpretability limitations of the neural networks, researchers have increasingly employed the use of ensemble learning techniques such as the Random Forest algorithm. Random Forest is a method that was introduced by [10] as a parallel bagging system where a variety of uncorrelated decision trees are constructed from random subsets of features and data rows. According to [54], the ensemble architectures typically outperform single classifiers as they reduce variance while keeping the bias low. Random Forest model uses stepwise decision boundaries that are easy to understand and interpret to creates recursive partitions of the feature space, capturing extreme non-linear relationships, multi-modal distributions and sudden threshold shifts.

Furthermore, [37] evaluated model resilience across extreme historical disruptions by comparing the performance of Random Forest with Autoregressive Deep Neural Networks (AR-DNN) before and during COVID-19. Their empirical findings show a fundamental transition. AR-DNN model achieved superior performance on large, stable pre-pandemic datasets but AR-RF model outperformed connectionist models when dealing with high volatility and low observations conditions of the pandemic period. However, the main limitation of [37] research is its narrow focus on the Karachi Stock Exchange (KSE-100) which has very different sector weights compared with those of the African frontier exchanges. Nevertheless, the key result of their research has a strong theoretical basis for this study and shows that parallel bagging ensembles preserve the good noise-filtering properties of the financial market when it experiences a structural regime change.

2.2.3. Empirical Evidence from African and Frontier Markets

Machine learning application in emerging and frontier markets is particularly challenging in African markets because of low liquidity, low trading volumes, high transaction friction and the susceptibility to external macroeconomic shocks. These inherent features may lead to an asset-pricing environment that differs markedly from that of the capitalized exchanges in Western and Asian countries, so there is a critical need for validation of the asset-pricing in the local context. For instance, in frontier markets, [31] used a combination of an optimized Sine Cosine Algorithm based LSTM network (SCA-LSTM) with the traditional statistical ARIMA-GARCH model. However, their approach was unable to handle the challenge of conditional heteroscedasticity and long-term temporal dependencies. Hence, a highly intensive hyperparameter tuning and large amount of data are required to allow for convergence of a joint SCA-LSTM and ARIMA-GARCH pipeline. This means that this framework is most likely to overfit the data when applied in smaller exchanges such as NSE, where the historical data structures are compact and tabular, thus necessitating for a direct comparison and more robust algorithms like ANNs and RFs models.

Another study by [41] predicted stock index future prices using a Multi-GARCH-LSTM framework. Their model captures complex temporal dependencies and models multi-regime conditional heteroscedasticity, however, it introduces extreme computational weight. This deep sequential layout is prone to gradient degradation and localized overfitting in data-constrained frontier markets such as NSE, making simpler, regularized connections necessary.

Empirical evidences from Pan-African markets highlight the usefulness of machine learning in dealing with the systemic volatility that are common on African exchanges. For instance, [34] review machine learning approaches specifically developed to forecast the onset of an imminent crisis in the stock market in Africa. Their findings show that tree-based ensemble models and classification models are very sensitive towards pre-crisis indicators, and have shown the ability to track structural vulnerabilities early. Likewise, [53] evaluate predictive machine learning techniques for the returns of stocks in several emerging African economies. The findings of [53] study revealed that non-linear ML methods reduce prediction error at the different regional exchanges, but the performance of the ML methods differs in each exchange depending on the liquidity characteristics. A study by [20] concentrate on improving the prediction of stock prices by providing a novel hybrid ensemble architecture. The thorough comparative study shows that the combination of various algorithmic models produces better prediction accuracy than using single models alone, especially in frontier settings with data that is highly variable.

Another study conducted by [38] examine the use of machine learning in stock return prediction by analyzing daily

technical, market and macroeconomic indicators of the Nigerian emerging market. Their findings show that the technical indicators (RSI and MACD) have the highest feature influence, while the ensemble models (XGBoost) are consistently superior to the single baseline models across all the out-of-sample evaluations. A new approach to financial market forecasting was introduced by [51] which adopted to high dimensional time-series panel data in heterogeneous environments, a perspective that adds to the traditional literature of financial market forecasting from the West Africa region. The results of [51] study support a strong argument for superiority of Artificial Neural Networks over the Random Forest models and K-Nearest Neighbors (KNN) models, indicating that the layered deep-learning configuration of an ANN is superior for modeling complex continuous structural dependency in a large amount of spatial data.

The study by [40] provides a comparative analysis and ranking of hybrid machine learning algorithms with classical GARCH techniques to model stock market volatility in Southern and East Africa Regional Contexts: Moving to the Southern African Development Community (SADC). The structural rankings highlight the importance of combining machine learning and conditional heteroskedasticity models for better risk tracking in highly volatile markets, creating a clear conceptual connection between financial econometrics and artificial intelligence [40].

Additionally, [29] fused GARCH framework with XGBoost model to track asset volatility in Johannesburg Stock Exchange. Their findings indicate that the hybrid model was able to handle conditional variance and structural asymmetries. However, this hybrid model relies on a sequential boosting which makes it prone to hyperparameter overfitting and outlier noise. This implies that for smaller emerging markets such as the NSE, this sensitivity can increase models' predictive errors during period of sudden liquidity contractions. Therefore, parallel bagging methods like RF model can become structurally more stable.

Another study conducted by [39] modelled structural market variations in the Moroccan financial market using a combination of non-linear time-series and deep learning approaches. Their findings suggest that the models achieved high predictive precision, however prone to an extreme intepretability tax. Therefore, the model masked operational variables within unmapped deep neural nodes making it unsuccessful in providing granular feature rankings which is an important aspect for institutional risk mitigation in highly illiquid African markets.

Empirical modelling in the East African context and the Nairobi Securities Exchange (NSE) has been historically confined to isolated baseline testing or a specific type of stock of the most liquid market leaders such as Safaricom PLC or Equity Group Holdings. According to a study by [28], using ARIMA and GARCH frameworks to model time-series trends and volatility clusters, however, their models were limited by the structural linearity assumptions. On the other hand, [27] designed a hybrid model that feed ARIMA outputs as input features into an Artificial Neural Network (ANN). The findings of [27] study reveal that neural networks configurations significantly lower RMSE than standalone statistical equations. However, the use of time-series approaches by [28] and [27] are largely univariate and ignore general firm-specific anomalies across trading regions. A study by [36] filled this gap by conducting a study which provided comprehensive machine learning evidence for cross-sectional stock return prediction within the small, illiquid NSE equity market. The findings by [36] clearly depicts that non-linear machine learning models outperformed traditional asset-pricing benchmarks. However, out-of-sample evaluations of these models depended directly on minimizing localized liquidity issues and high-dimensional data. Therefore, the review of these studies [27, 28, 36] reveal a clear historical transition from statistical models to multi-dimensional machine learning algorithms in frontier markets. This reinforces the adoption of robust, regularized configurations like ANN and RF models as implemented in this study which can handle the compact, volatile datasets in Kenyan stock markets.

2.2.4. Research Gaps

Despite the significant expansion of machine learning applications in global financial forecasting, a clear methodological and contextual gap persists within emerging frontier markets, particularly the Nairobi Securities Exchange (NSE). A systematic synthesis of recent literature reveals that recent global and regional trends have preferred deep neural architectures, hyper-parameterized hybrid networks, or multimodal transformer integrations such as the SCA-LSTM frameworks as evaluated by [31] or high-dimensional panel models performed by [51]. While these models perform well in highly liquid, dense trading environments, they systematically overfit, suffer from gradient degradation, or require prohibitive computational frameworks when applied to the compact, tabular daily trading datasets characteristic of frontier African markets.

However, most of the local Kenyan studies rely on traditional linear baseline models, which isolated time-series modifications like ARIMA-GARCH volatility clusters [28], or single-equity predictions optimized for a single highly liquid stock market leader such as Safaricom Plc [27]. Despite the emergence of studies utilizing cross-sectional machine learning models to predict the highly volatile equity market of the Kenyan NSE [36], there still remains a critical research gap in literature that systematically evaluates shallow neural networks architectures against parallel tree-based ensemble models across a standardized, multi-sector, long-term time series architecture. Hence, institutional fund managers, local stockbrokers, and capital market policymakers are left without a transparent model to isolate which technical or market indicators exert the highest predictive control during sudden liquidity contractions or structural regime shifts. Furthermore, emerging macroeconomic, technical, and market indicators

are rarely modeled simultaneously within a paradigm that balances raw mathematical precision with actionable feature-importance explainability. This leaves local institutional investors, fund managers, and regulatory bodies without an interpretable framework to guide asset allocation or structural risk mitigation.

2.2.5. Specific Contribution of This Study

The study addresses the identified theoretical and practical gaps by providing unique contributions to the extant body of financial econometrics models and predictive machine learning. This study moved beyond isolated single-equity testing to implementation of a comparative performance evaluation between an optimized ANN and a bagged RF model by utilizing a longitudinal cross-sector panel dataset from the NSE. Moreover, the study structurally configured and regularized a shallow Multi-Layer Perceptron (MLP) alongside a parallel bootstrap-aggregated ensemble RF model, demonstrating how high predictive accuracy can be achieved without encountering the severe overfitting traps that degrade deep sequential neural models such as LSTMs when limited by sparse, compact frontier market data. This provides a transparent, verifiable data-driven framework for local stockbrokers, quantitative portfolio managers, and capital market policymakers.

2.2.6. Comparison with Existing Approaches

Table 1. *Comparison with Existing Approaches.*

Studies	Methodologies Adopted	Target Dataset and Market Context	Evaluation Metrics	Reported Findings
[22]	Hybrid ARIMA-ANN, ARIMA-SVM and ARIMA-RF	Stock Index Returns	RMSE, MAE, Directional Accuracy	The ARIMA-Random Forest hybrid achieved top performance by isolating residual non-linear dynamics.
[45]	Hybridization of ARIMA and machine learning architectures	Stock market time-series returns	Variance minimization	Confirmed that standalone ARIMA leaves non-linear signatures in residuals. However, these models are highly sensitive to frontier outlier spikes.
[8]	Standard ARIMA modeling	Historical stock data and projections	Continuous projection bounds	Provided a clean baseline for smooth trends. However, out-of-sample accuracy degraded rapidly under non-stationary regimes.
[29]	Fusion GARCH-XGBoost framework	Johannesburg Stock Exchange	AIC, BIC, HQIC (Hannan–Quinn Information Criterion), and LL (Log-Likelihood)	HandleD conditional variance and structural asymmetries. However, its reliance on a sequential boosting routine leaves it highly susceptible to outlier noise and hyperparameter overfitting.
[41]	Multi-GARCH-LSTM framework	Stock prices future returns	$\square^2$, MSE, RMSE, MAE, and MAPE.	Captured complex temporal dependencies and modelled multi-regime conditional heteroscedasticity. However, it introduces extreme computational weight.
[39]	ARIMA, bilinear models and LSTM models	Moroccan market (MASI)	MAE, RMSE, and Trend Forecast Accuracy	The models captured complex structural trajectories. However, it suffered from an intense interpretability tax that limited functional feature rankings.
[47]	Decadal Meta-Survey of Machine Learning	Global highly capitalized equity exchanges	Survey classification mapping	Documented the broad transition to ensembles, but revealed a literature gap regarding low-liquidity frontier markets.

Studies	Methodologies Adopted	Target Dataset and Market Context	Evaluation Metrics	Reported Findings
[49]	Shallow machine learning and deep learning Review	Global predictive financial contexts	Algorithmic tax review	The findings revealed severe accuracy-interpretability trade-off. This is observed where complex architectures mask operational transparency.
[24]	Comparative performance of ANN vs. SVM	Global Equity Configurations	Standard Classification Errors	The findings show that ANNs outperform SVMs on high-dimensional technical inputs. However, the model is limited by an evaluation split that ignored temporal leakage.
[4]	Deep learning and advanced machine learning models	Apple (AAPL), Amazon (AMZN), Google (GOOG), and Microsoft (MSFT)	Precision Scale	The findings show that fusing macroeconomic factors with asset indicators led to resilient prediction surfaces. However, these models were limited by heavy computational algorithms.
[54]	Machine Learning Architectures	Global markets	Direct performance tracking	The findings depicted that ensemble models consistently outperform individual shallow classifiers. This is because these models balance bias and variance boundaries.
[37]	Autoregressive Deep Neural Networks (AR-DNN) vs. AR-RF	Karachi Stock Exchange (KSE-100 daily closing)	MAE, RMSE, MAPE and R^2	The findings showed that AR-DNN performed well on large pre-pandemic data, however, AR-RF consistently outperformed under high volatility with low-number of observation.
[34]	Machine Learning Aproaches	Pan-African stock market datasets.	Classification accuracy index	The findings revealed that tree-based ensembles pre-crisis indicators, tracking localized market stress effectively.
[53]	Predictive machine learning techniques	Emerging African markets	Comparative prediction errors	The findings showed that non-linear machine learning reduced metrics across regional exchanges. However, the performance of the ML methods differs in each exchange depending on the liquidity limits.
[20]	Advanced Hybrid Ensemble Architectures	Stock Price Time-Series returns	Comparative validation index	The findings depicted that the use of stacking and bagging multiple algorithmic models led to better prediction accuracy than using single models alone.
[38]	ANN, SVM, Random Forest, & XGBoost	Nigerian Stock Exchange	Out-of-sample cross-validation	The findings indicated that show that the technical indicators (RSI and MACD) have the highest feature influence; the ensemble models (XGBoost) achieved high predictive accuracy when compared to single baseline models.
[51]	RF, KNN and ANN	Different countries and stock markets	RMSE, MAD	ANN achieved high precision accuracy over the RF and K-Nearest Neighbors (KNN) models.

Studies	Methodologies Adopted	Target Dataset and Market Context	Evaluation Metrics	Reported Findings
[40]	Hybrid ML Models and GARCH Frameworks	Southern and East Africa Regional Contexts	Volatility ranking index	The findings show that ranked hybrid machine learning models outperform standalone financial econometrics for volatile market risk.
[31]	Hybrid SCA-LSTM Network and ARIMA-GARCH	Volatile stock price configurations	Optimization convergence rate	The findings that these models handle conditional heterosckedasticity. However, the complex framework is highly prone to systematically overfitting, suffer from gradient degradation, or require prohibitive computational on compact tabular sets.
[28]	ARIMA and GARCH Time-Series Modeling	Emerging market Equity Volatility	Volatility coefficients, AIC	This study mapped conditional heteroscedasticity trends. However, the study is limited by linear parametric limits under abrupt regime shocks.
[27]	Hybridized ARIMA and ANN	Kenyan Technical Trading Series (Closing Prices)	RMSE	The hybrid ANN achieved higher forecasting accuracy, confirming that neural networks effectively reduce residual linear errors.
[36]	Cross-Sectional Machine Learning Regressions	NSE Longitudinal Data	Out-of-sample precision, R^2	The findings suggested that model stability degrades heavily if extreme illiquidity features are unscaled.

3. Methodology

3.1. Study Design and Population

The study employed a retrospective longitudinal design with quantitative methods. The target population comprised all stocks listed on the Nairobi Securities Exchange (NSE). From the 64 publicly traded firms on the NSE, a non-probability purposive sampling technique was used to select firms based on the following criteria:

1) The stock had to be a component of the NSE-20 Index, as determined by market value.
2) The stock needed to have more than five years of available historical data, and the company must not have been introduced, removed, or suspended from trading during the study period.
3) The stock must not have undergone any share splits or bonus share issues during the five-year study period.

Based on these criteria, five qualifying stocks were selected: Safaricom Plc (SCOM), Equity Group Holdings Plc (EQTY), British American Tobacco Kenya Ltd (BAT), East African Breweries Ltd (EABL), and Kenya Commercial Bank (KCB). These five stocks represent six sectors within the 20-share index.

3.2. Data Collection

The study utilized secondary daily stock price data from the NSE, obtained via a paid subscription, for the five-year period spanning January 2, 2020, to January 2, 2025, which covers the post-COVID-19 pandemic era. The dataset, structured in a long format, contained 6,176 observations and included five input variables: open price, highest price, lowest price, close price, and trading volume.

For each stock, the daily price data was chronologically divided into an 80% training set (4,941 observations) and a 20% testing set (1,235 observations). Specifically, the first 80% of the chronological rows for each equity were allocated to the training partition, with the remaining 20% forming the out-of-sample testing partition.

3.3. Data Preparation and Feature Engineering

Data preparation involved several steps: data cleaning (removing outliers and errors), identifying and imputing missing values, modifying data types, and normalizing data. Missing values were imputed using linear interpolation, and extreme outliers were removed to prevent distortion of model performance.

Feature engineering transformed price and volume data into panel data for predicting closing stock prices. Lagged variables and rolling averages were engineered to capture temporal dependencies. Specifically, three consecutive historical lagging variables and a 5-day rolling moving average (MA5)

were created to capture localized momentum. Min-Max normalization scaled the Artificial Neural Network (ANN) input matrices linearly between 0 and 1. The numerical range (minimum and maximum limits) for normalization was derived from the historical training partition and then applied to the test partition to preserve out-of-sample validity and prevent temporal data leakage. In contrast, the tree-based ensemble framework was trained on the native financial scale, leveraging the inherent scale-invariance properties of the Random Forest regressor.

3.4. Artificial Neural Network (ANN) Model

ANN employs intelligent data mining techniques to identify fundamental trends within data and generalize from them [15]. An ANN model generates an output function when a linear combination of its inputs surpasses a predefined threshold. As a non-linear modeling technique, ANNs can process numerous input (independent) variables to evaluate one or more output (dependent) variables [9]. It is applicable in linear classification, where the desired outcome is binary (e.g., on/off, yes/no) [48]. ANNs are also utilized in regression analysis to determine real-valued target functions, such as predicting stock market prices in a financial system [55].

A neural network consists of multiple interconnected processing units called neurons. Each neuron performs two main functions: collecting inputs and producing an output. ANN structure consists of three layers: an input layer that receives collected data, an output layer that produces computed information, and one or more hidden layers that bridge the input and output layers [15]. Each input is multiplied by connection weights, and the resulting products are summed with biases before being passed through an activation function to generate an output, as depicted in Figure 1. Furthermore, neurons transmit a weighted summation of the input data based on a transfer function. This architecture allows neurons in each layer to connect to those in the preceding and subsequent layers, while connections within the same layer are prohibited.

As shown in Figure 1, the input layer has $x_1, x_2, \ldots\ldots x_m$ input variables. Each input x_i is multiplied by a connection weight w_{ij} which is between the neuron i in the input layer and the neuron j in the hidden layer. The resulting product is then added with the bias b_j forming the net input I_j as shown in equation 1.

$$I_j = \sum_{i=1}^{n} x_i w_{ij} + b_j \quad (1)$$

The net input I_j is then passed through a nonlinear sigmoid activation function to the hidden layer as shown in equation 2. The resulting output is y_j as shown in equation 3.

$$f(I) = {(1 - e^{-2I})}/{(1 + e^{-2I})} \quad (2)$$

$$y_j = f(I_j) \quad (3)$$

The resulting output y_j from the hidden layer then sends out the signal to all k neuron in the output layer o_k. The computation of the input to the k neuron of the output layer is o'_k which is expressed in the following equation.

$$o'_k = \sum_{j=1}^{h} y_j w'_{jk} + b'_k \quad (4)$$

where: w'_{jk} is the weight of the connection between the j neuron in the hidden layer to the k neuron of the output layer and b'_k is the bias.

The output layer signals are then computed by the sigmoid activation function as follows:

$$o_k = f(o'_k) \quad (5)$$

The calculation of error training between the target output and the measured data is shown in the following equation:

$$e_k = \frac{1}{2}\sum_{k=1}^{n}(t_k - o_k) \quad (6)$$

This procedure is applicable to all pairs in the training set and the training cycle known as an epoch. This is repeated until the error reduces to the limit value (Hasni et al., 2012; Celik et al., 2015).

The error gradient for output layer is shown below;

$$\delta_k = (t_k - o_k) f'(o'_k) \quad (7)$$

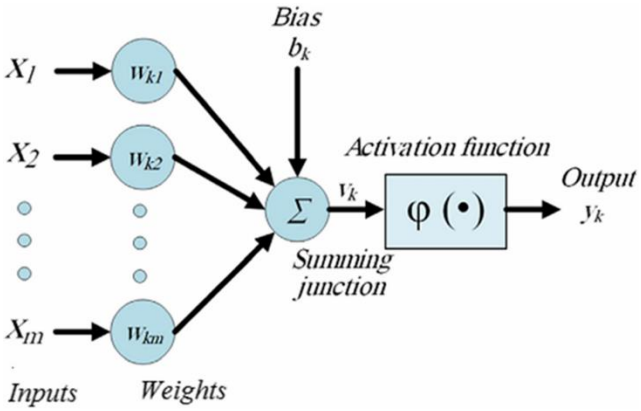


Figure 1. *ANN Architecture (Source [15]).*

There two major training algorithms including the basic backpropagation (Bp) and Bp with momentum and learning rate, however, they differ in the updates of weights. Bp algorithm with momentum and learning rate update the weights between the different layers. The error is then propagated backward from the output layer to the input layer as shown in equation 8.

$$w'_{jk}(t+1) = w'_{jk}(t) + \eta\delta_k y_j + \alpha\left(w'_{jk}(t) - w'_{jk}(t-1)\right) \quad (8)$$

where; η is the learning rate and α is the momentum coefficient.

Basic Bp algorithm on the other hand update the weight between neuron k from the output layer and neuron j from the hidden layer as follows;

$$w'_{jk}(t+1) = w'_{jk}(t) + \eta\delta_k y_j \quad (9)$$

The coefficients η and α represent the speed and stability of the network. These coefficients are used at the beginning of learning process. However, if a small learning rate η is selected, it may result to slow rate of convergence. But if a large η is selected it may indicate oscillation. The momentum coefficient uses the solution of making the network converge fast without oscillation. This is used for accelerating the convergence of the algorithm. It has the effect of changing the previous weight on the current movement direction.

The $\Delta w'_{jk}$ and $\Delta b'_k$ are then calculated to update w'_{jk} and b'_k as indicated in equation 10 and 11 respectively.

$$\Delta w'_{jk} = \eta\delta_k y_j \quad (10)$$

$$\Delta b'_k = \eta\delta_k \quad (11)$$

The error gradient for the hidden layer is then calculated as follows;

$$\delta_j = \sum_{k=1}^{n} \delta_k w'_{jk} f'(o'_k) \quad (12)$$

The weights and the biases, Δw_{ij} and Δb_j, are then computed to update Δw_{ij} and Δb_j respectively as shown in the following equations.

$$\Delta w_{ij} = \eta\delta_j x_i \quad (13)$$

$$\Delta b_j = \eta\delta_j \quad (14)$$

These weights and biases are then updated as follows;

$$w'_{jk}(t+1) = w'_{jk}(t) + \Delta w'_{jk} + \alpha\left(w'_{jk}(t) - w'_{jk}(t-1)\right) \quad (15)$$

$$b'_k(t+1) = b'_k(t) + \Delta b'_{jk} + \alpha\left(b'_k(t) - b'_k(t-1)\right) \quad (16)$$

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij} + \alpha\left(w_{ij}(t) - w_{ij}(t-1)\right) \quad (17)$$

$$b_j(t+1) = b_j(t) + \Delta b_j + \alpha\left(b_j(t) - b_j(t-1)\right) \quad (18)$$

3.5. Training Phase

The training phase involves two parts, the propagation phase and the weight update phase [15]. The input data is normalized in the propagation phase for feeding the network into the input nodes based on the following formula:

$$v' = \frac{v - minA}{maxA - minA}(new_{maxA} - new_{minA}) + new_{minA} \quad (19)$$

where: v' is the normalized input, v is the actual input, $minA$, $maxA$ are the boundary values of the old data range and new_{maxA} and new_{minA} are boundary values ranging between -1 and 1.

The normalized input data are fed into the input layer. The weights are then multiplied by each input and enter the hidden layer's neurons passing output to the output layer's next neuron. This layer then computes and presents the final output which is then compared with the real output. An error signal 'e' is then calculated as follows:

$$e = \frac{actual\ \ output - ANN\ \ output}{actual\ \ output} \quad (20)$$

Therefore, the error 'e' generated from the Propagation Phase is then used to update the weight as shown in the following formula:

$$Update\ \ Weigth = weight(old) + learning\ \ rate * output\ \ error * output(neurons\ \ i) * output(neurons\ \ i+1) * \left(1 - Output(neurons\ \ i+1)\right) \quad (21)$$

The output then enters into the second unit of the neuron containing the nonlinear activation function. Sigmoid function was used in the study based on the following formula:

$$f(x) = \frac{1}{1+e^{-input}} \quad (22)$$

After training, the neural network is ready for prediction. The weights are set into the network then the trained network was given the input dataset of the day. The trained network then predicted the price using the given input dataset.

3.6. ANN Implementation

The paper employed a feedforward multi-layer perceptron (MLP) neural network. This network consisted of an input layer with 5 neurons, a hidden layer with 11 neurons, and a single-neuron output layer. The model was designed to predict the sixth daily stock price in a series, utilizing the five preceding daily stock prices (open, high, low, close, and volume) as input. Therefore, the baseline model was formulated as follows:

1) Number of inputs=5
2) Number of hidden layers=1 with 11 neurons (i.e 2N+1; where N is the number of inputs)
3) Number of outputs=1
4) Bias per layer=1

In a simple regression analysis, the input layer units introduce normalized or filtered values of each input variable into the network. These values are then transferred to all units of the hidden layer, where they are multiplied by a unique

"weight" factor for each connection. The magnitude of this weight factor reflects the importance of that specific connection (Figure 2). For this study, the backpropagation algorithm was employed to train the network. Additionally, a sigmoid transfer function was utilized to achieve optimal results, given the non-linear nature of the phenomenon.

Finally, the optimal learning algorithm, activation function, and network architecture (specifically, the number of neurons in hidden layers) were determined through trial and error, consistent with [15] research. For ANN modeling, the dataset was divided into a training set (80% of the data) and a validation set (20% of the dataset). Specifically, the first 80% of chronological rows (n=4,941) for each equity were assigned to the training partition, while the final 20% of chronological observations (n=1,235) were used as an out-of-sample testing partition. The training set was used to fit ANN model weights based on various network configurations and training cycles. The validation set was then used to evaluate the performance of the optimized model against an unknown dataset.

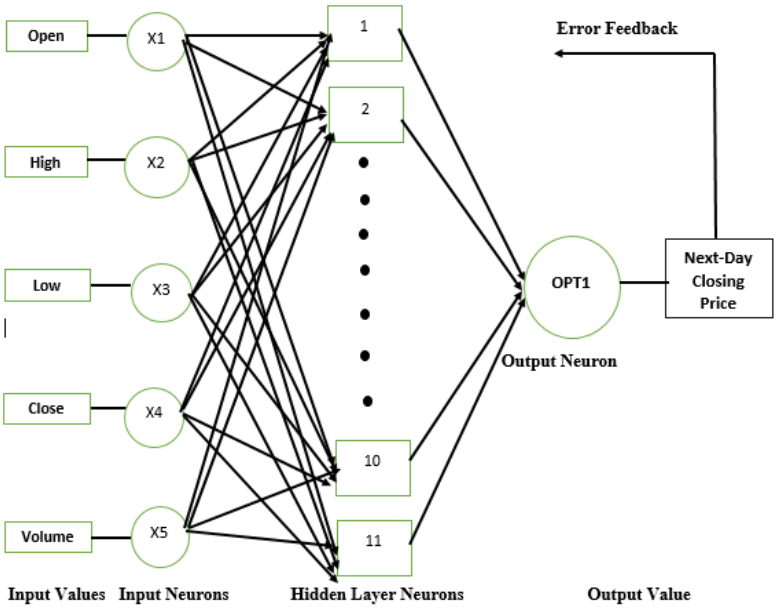


Figure 2. *Architecture of the Neural Network used in this study (Source: Author 2026).*

3.7. Random Forest (RF) Model

RF is an ensemble machine learning technique capable of performing both regression and classification tasks [50]. The model improves prediction accuracy by aggregating the predictions of multiple trees trained on bootstrapped samples of the data. For regression tasks, predictions are aggregated using the mean of outputs. The RF model reduces forecasting error by treating stock market analysis as a regression problem and uses trained variables to predict the next-day closing price of the stock for a particular company [50]. Since the stock market is usually large with high noise then trees can grow in a completely different manner than the expected growth [37]. The study models a time-dependent, continuous target variable (next-day close) which involved a regression task and not a classification problem. Therefore, RF model provide greater precision when compared to other machine learning models. This is because RF is able to handle large data with numerous variables. Furthermore, it can balance datasets when a class is more infrequent compared to other classes in the data [50].

The model constructs multiple decision trees using bootstrap samples of the training data. At each node, a random subset of features is considered for splitting, introducing diversity among trees. For regression, the ensemble prediction is:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} \hat{f}^{(b)}(x) \tag{23}$$

where B is the number of trees, $\hat{f}^{(b)}(x)$ is the prediction from tree b, based on input features x.

For a node containing samples S and a candidate split (f,θ) on feature $f \in F$ with threshold θ, then the tree splitting criterion is as follows:

Node impurity (mean squared error):

$$l(S) = \frac{1}{|S|}\sum_{i\in S}\left(y_i - \hat{y_S}\right)^2,\ \hat{y_S} = \frac{1}{|S|}\sum_{i\in S} y_i \tag{24}$$

Split selection (feature j, threshold τ) with the following left/right partitions:

$$S_L = \{i \in S : x_{ij} \leq \tau\},\ S_R = \{i \in S : x_{ij} > \tau\} \quad (25)$$

$$\Delta(j,\tau) = l(S) - \left(\frac{|S_L|}{|S|} l(S_L) + \frac{|S_R|}{|S|} l(S_R)\right) \quad (26)$$

$$\text{Choose } (\hat{j},\hat{\tau}) = argmax_{j,\tau}\Delta(j,\tau)$$

Hence, stop conditions include max depth, min samples per leaf, or zero improvement.

Of that training sample, one-third of it is set aside as test data, known as the out-of-bag (oob) sample. For each training sample *j,* define its OOB set of trees as follows:

$$TOOB\ \ (j) = \{i \in \{1, \ldots . N\}\} \quad (27)$$

Then, OOB prediction for observation *i*:

$$\hat{y_i}^{OOB} = \frac{1}{|B_i|}\sum_{b \in B_i} \hat{f}^{(b)}(x_i), \text{ Where } B_i = \{b : i \notin D^{(b)}\} \quad (28)$$

OOB error estimate is as follows:

$$MSE_{OOB} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y_i}^{OOB}\right)^2 \quad (29)$$

The oob sample was then used for cross-validation, finalizing the prediction. Walk-forward validation (rolling training window of size W) is expressed as follows:

$$\hat{y}_{t+1} = \frac{1}{B}\sum_{b=1}^{B} \hat{f}^{(b)}(x_t; D_{t-W+1:t}) \quad (30)$$

The model was configured with 500 decision trees to reduce variance and mitigate overfitting.

3.8. Performance Evaluation Metrics

The effectiveness of the two models was assessed using the following metrics on the testing data. The equations for RMSE, MAPE, MBE and Coefficient of determination (R^2) are as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(O_i - F_i)^2}{n}} \quad (31)$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{(O_i - F_i)}{O_i} * 100 \quad (32)$$

$$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}(O_i - F_i) \quad (33)$$

$$R^2 = 1 - \frac{\sum_{t=1}^{T}(O_i - F_i)^2}{O_i - \hat{F}} \quad (34)$$

where O_i is the original closing price, F_i is the predicted closing price, $\bar{O}$ is the mean of original values, and n is the total window size.

3.9. Software for Analysis

All analyses were conducted in R Studio (R Version 4.4.1) using the following packages: caret, randomForest, neuralnet, ggplot2, and tidyverse.

4. Results

4.1. Descriptive Statistics

The sample consisted of a total of 6,176 continuous daily trading observations for five corporate equities across the five-year window. Table 2 presents the descriptive statistics.

Table 2. *Descriptive Statistics of Stock Prices Across the Selected Companies.*

Company	Open		Close		High	Low	Total Volume
	M	SD	M	SD	Max	Min	
BAT	416.00	50.00	415.00	49.4	530	300	30,552,612
EABL	158.00	21.00	158.00	21.0	225	100	352,602,384
EQTY	42.9	5.78	42.8	5.83	58.2	28	1,977,617,605
KCB	36.7	7.75	36.6	7.76	55.5	14.5	1,564,119,308
SCOM	26.6	9.52	26.5	9.56	48	11.5	9,698,986,212

Note: All prices are reported in KES (Kenyan Shillings). M = Mean; SD = Standard Deviation.

BAT depicted the highest average closing price (*M*=415, *SD*=49.4). SCOM on the other hand, depicted the lowest av-

erage closing stock price of *M*=26.5 and *SD* of 9.56. Regarding market liquidity, SCOM represented heavy concentration with the largest total sum of trading volume of 9,698,986,212 shares traded over the sampled five-year window, suggesting heavy institutional participation. However, BAT, depicted lowest trading volume, showing conservative retail tracking patterns.

4.2. Model Development

Feature engineering created four major predictive features for each equity: three consecutive historical lagging variables (Lag_{t-1}, Lag_{t-2}, and Lag_{t-3}) and a 5-day rolling moving average (MA5). The data was chronologically split into training (n = 4,941) and testing (n = 1,235) partitions correspondingly. The ANN model utilized a feed-forward architecture with two hidden layers (5 and 3 neurons respectively). The RF regressor was configured with 500 decision trees to reduce variance and mitigate overfitting.

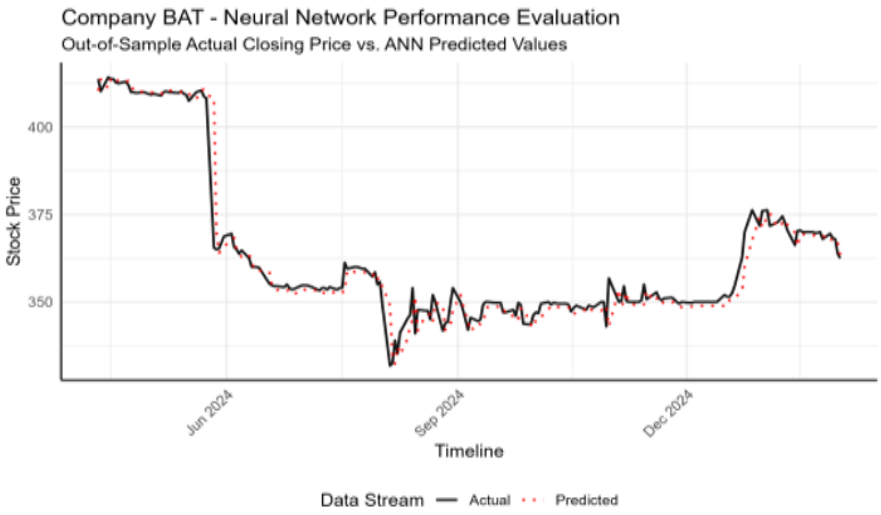
4.3. Out-of-Sample Prediction Results

Figures 3-6 present the out-of-sample predictions for each company. The neural network framework consistently demonstrated a clear performance advantage in visually tracking the behavior across all five stocks. For high-nominal value stocks like BAT and EABL, the ANN adapted to steep nominal margins with high precision, generating fluid curves that accurately mapped volatile observations. For EQTY and KCB, the ANN effectively adjusted to financial expansions, closely fitting the actual path through backpropagation weights that captured underlying momentum transitions. For SCOM, the ANN completely smoothed out artificial blocky steps, tracking volatile turns with notable accuracy and filtering out high-frequency retail micro-noise.

4.4. Evaluation of Model Fit and Out-of-Sample Predictions

An evaluation of the predictive capabilities of the trained computational frameworks under real-world, out-of-sample conditions was performed through chronological testing. Price overlay maps were generated across a 20% holdout window (n = 1,235 observations), spanning from early 2024 to early 2025. Figure 3 contrasts the original closing price of BAT stock with the predicted closing prices derived from the multi-layered ANN and the optimized random forest (RF) ensemble models.

BAT and EABL are high-nominal value stocks. The neural network framework demonstrated a clear performance advantage in tracking behavior across both stocks. For BAT, which trades at a significantly higher nominal threshold (KES 325 to KES 425), the asset experienced a massive, rapid downward structural shift around June 2024. As shown in Figure 9, the Random Forest projection effectively tracked the overall structural direction but exhibited a slight lag during sharp price changes in June 2024. It over-predicted the target closing price during the collapse period, then stabilized into a rigid, step-like pattern that slightly smoothed out subsequent micro-volatility risks. In contrast, the ANN did not exhibit this structural limitation. The observed red dotted neural curve adjusted to BAT's steep nominal margins with high precision, adapting to the severe downward step-break with negligible tracking delay. It generated a fluid, continuous curve that accurately mapped the volatile floor observations between September and December 2024.



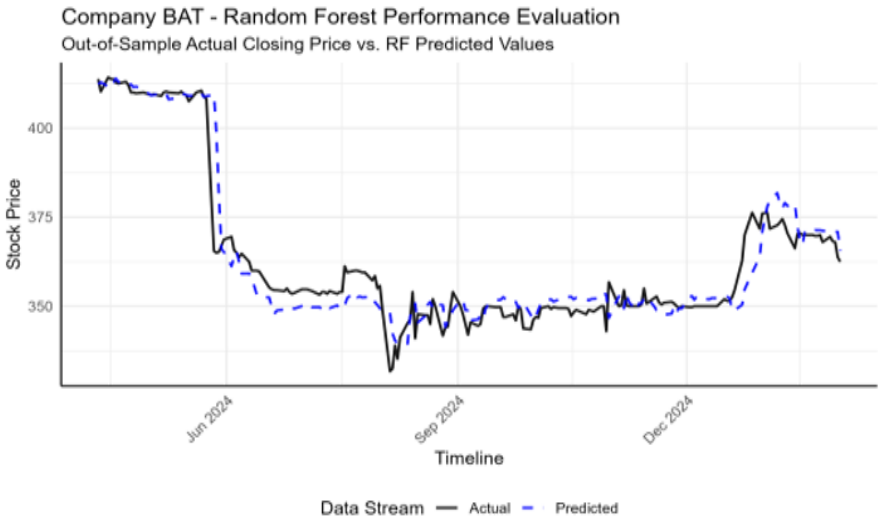


Figure 3. *Out-of-Sample Predictions for BAT.*

Figure 4 compares the actual closing price of EABL stock with the predicted closing prices generated by ANN and RF models. EABL, which typically trades in the 100-200 price range, experienced a significant upward momentum spike around October 2024.

The RF model effectively smoothed out sudden trading peaks influenced by consumer-driven volatility but struggled during unexpected market expansions. Specifically, it under-predicted the peak, visually clipping the highest spikes. This limitation arises because tree ensembles, by nature, cannot extrapolate beyond the maximum values present in their historical training data.

In contrast, the Neural Network for EABL demonstrated greater flexibility in adapting to these non-linear momentum adjustments. Its multi-layered weight configurations allowed it to accurately track the actual underlying trend lines during periods of rapid price expansion.

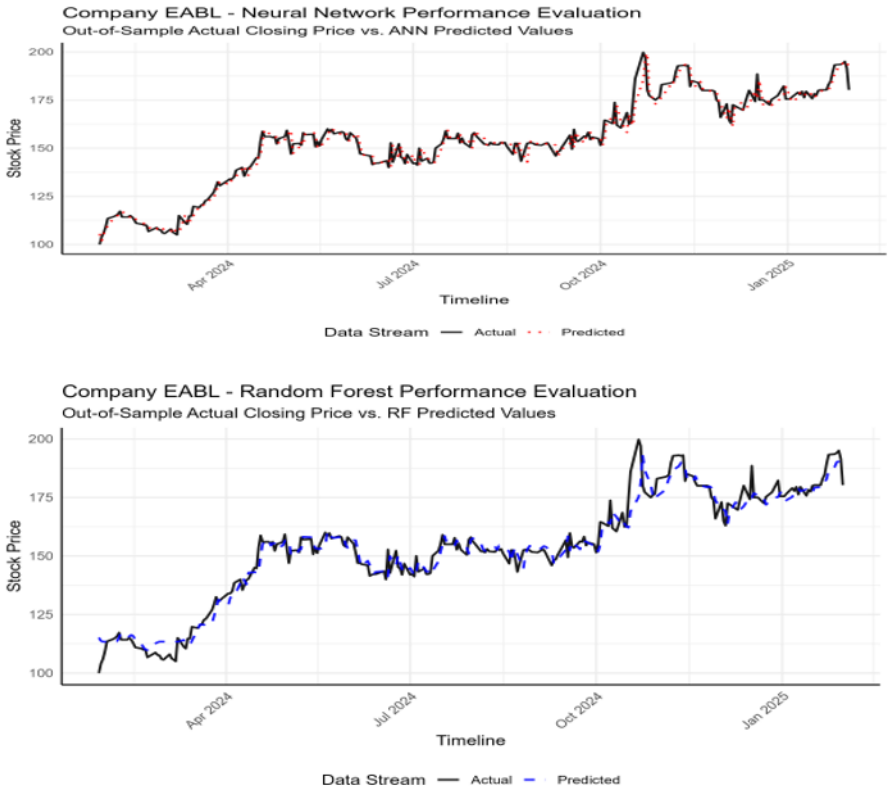


Figure 4. *Out-of-Sample Predictions for EABL.*

Figure 5 shows that EQTY, trading in the price range of 35 to 50, experienced large volumes of institutional and foreign capital trades. The RF model provided a highly stable predictive baseline compared to the ANN. The true price path depicted sharp, consecutive peaks and troughs. As observed in the figure, the curve was visibly blocky and systematically shifted to the right, confirming a localized phase lag during quick trend reversals. The averaging of 500 independent trees by the RF model functioned as a filter against temporary daily market noise. In contrast, the plotted neural network for EQTY adjusted much more effectively to the financial expansion. The red dotted line of the ANN model fit the actual path closely, indicating that the backpropagation weights effectively captured the asset's underlying momentum transitions.

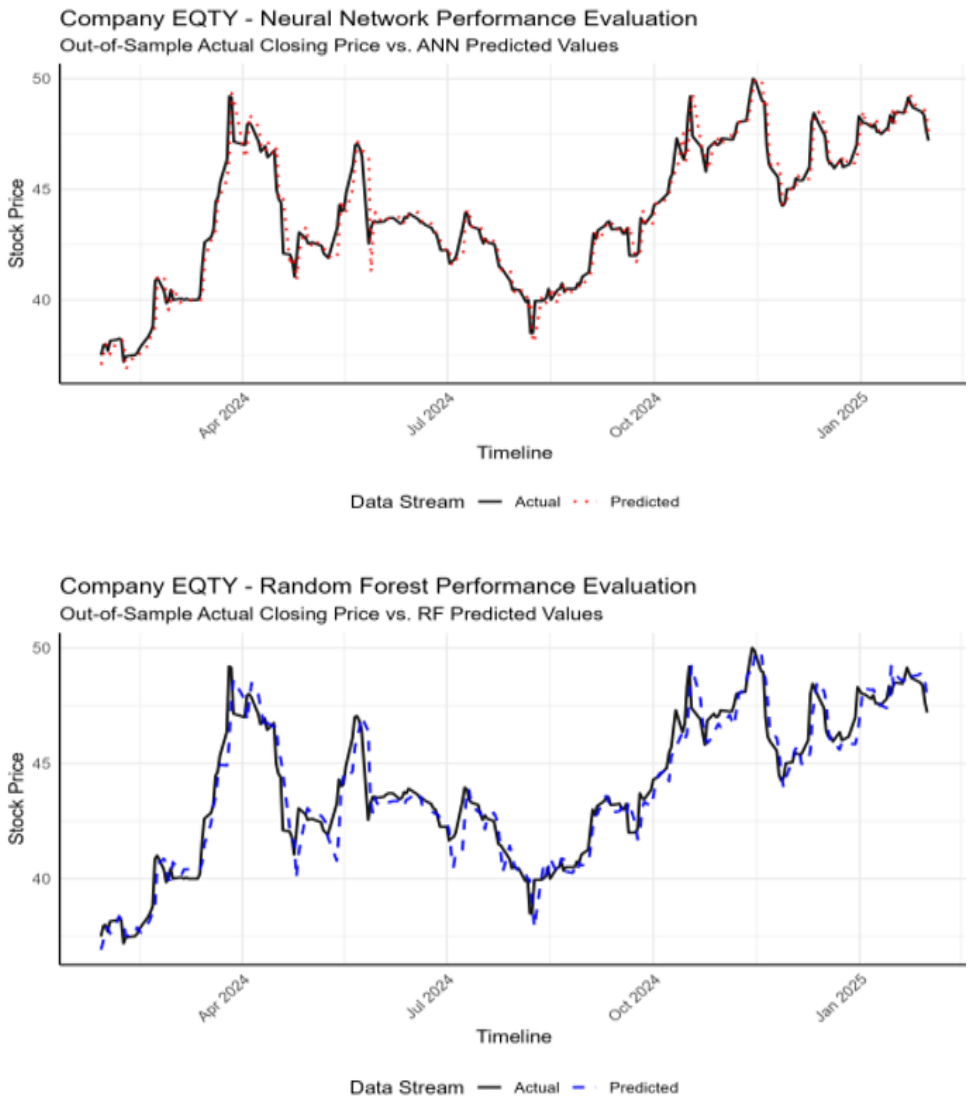


Figure 5. *Out-of-Sample Predictions for EQTY.*

Figure 6 visually demonstrates the actual KCB stock price against the predicted closing price using ANN and RF models. Both models exhibited a steady, long-term upward trend with low daily variance. Under these stable conditions, both frameworks achieved tight, precise visual overlays. The Random Forest model for KCB (trading in the price range of 20 to 45) was systematically below the solid black line during sudden market expansion, suggesting a negative Mean Bias Error. The RF curve smoothly captured the overall upward trend but also exhibited a minor horizontal phase lag during a brief upward break in April 2024. In contrast, the neural network for KCB adjusted to the tracking gap by generating a smooth, highly precise projection that remained tightly aligned with the actual asset price across the entire 12-month test evaluation window. By tuning internal connections through hidden layers, the neural model minimized absolute deviations and closely traced the upper bounds of the true asset paths during periods of heavy institutional market volume.

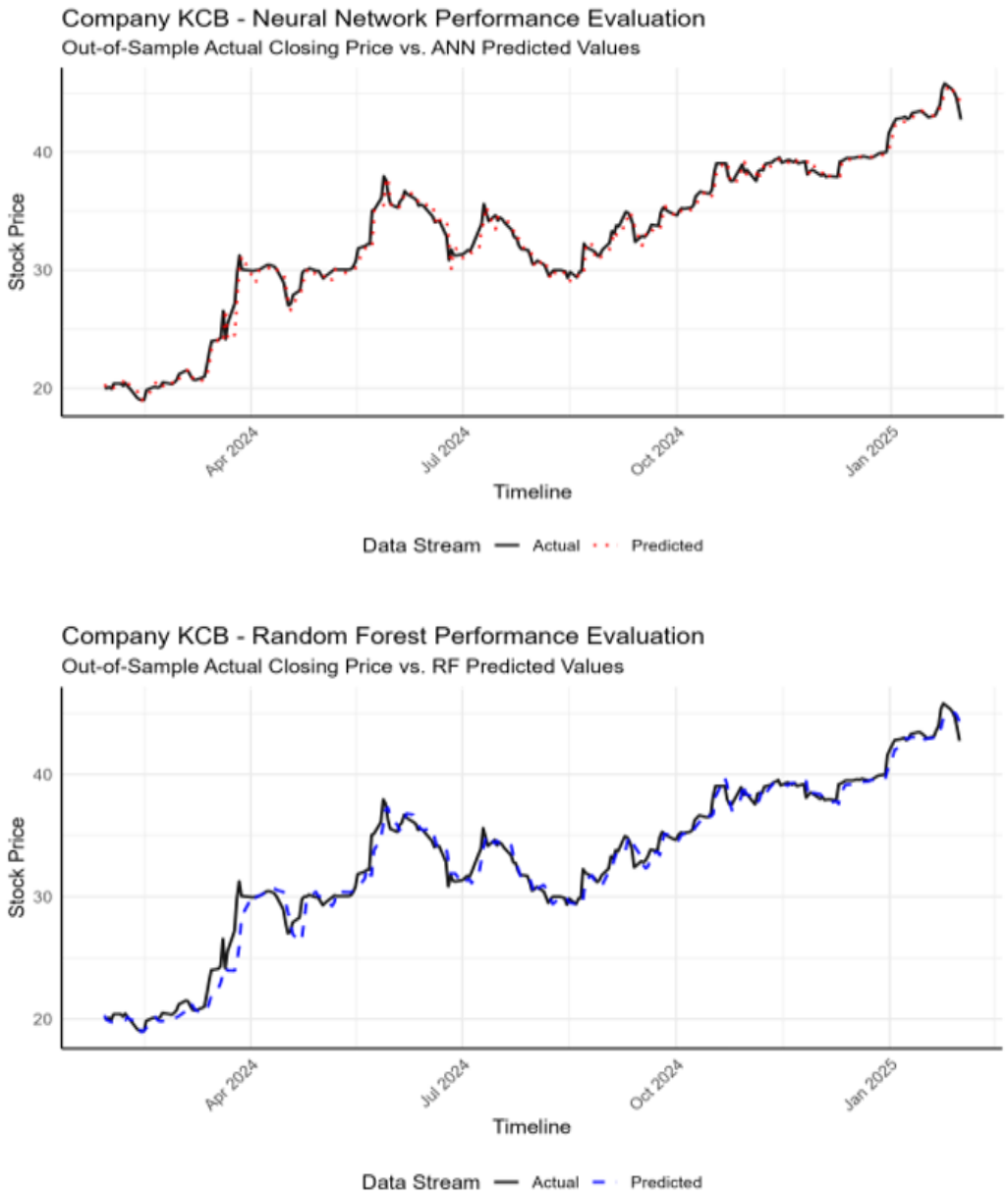


Figure 6. *Out-of-Sample Predictions for KCB.*

Figure 7 shows the actual price against predicted next day closing stock price for SCOM based on tracking of ANN and RF models. As observed, the RF model depicted a distinct, blocky stepping pattern which is attributed to the tree-based structures operating near structural price floors as a result of binary conditional splits partitioning. During the observed major upward surge in 2024, the RF model lagged behind and clipped the subsequent corrections. However, the ANN tracking for Safaricom does not depict any artificial, blocky steps, instead, it depicted volatile turns with precise accuracy that matches the extreme pricing peaks of April and July 2024. Therefore, the observed smoothness of the neural network suggests that the backpropagation hidden nodes are highly effective at filtering retail micro-noise mainly associated with lower-priced stocks. This allows it to isolate the clean underlying market trend line.

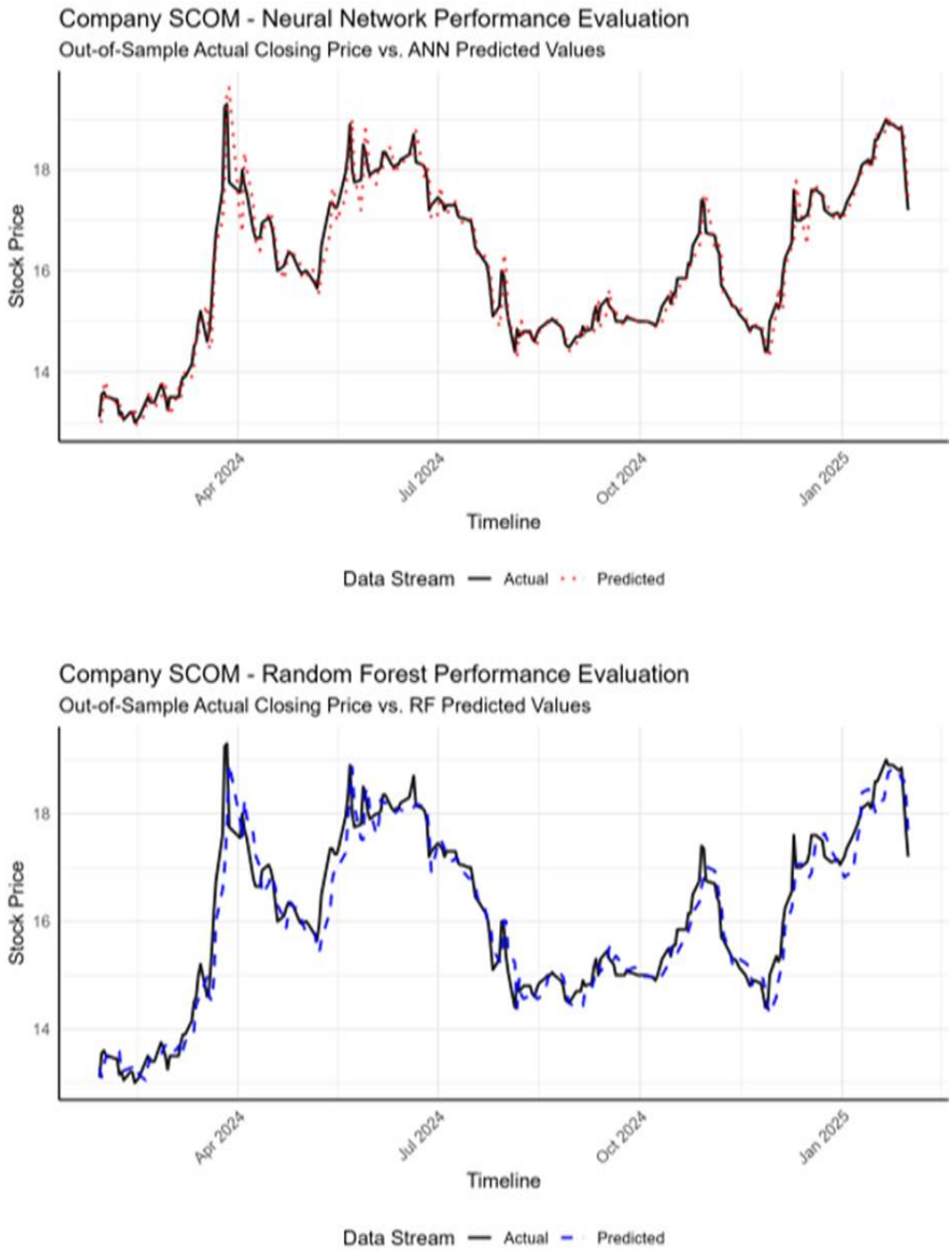


Figure 7. *Out-of-Sample Predictions for SCOM.*

4.5. Model Performance Metrics

Table 4 illustrates the comparative performance measures across all five equities. The ANN consistently demonstrated superior out-of-sample forecasting accuracy for all five equities. For BAT, the ANN achieved an RMSE of 4.48, significantly outperforming the RF model's RMSE of 5.93. The ANN model also consistently outperformed the random forest model for SCOM, yielding a significantly lower error rate (RMSE=0.31) relative to the random forest model (RMSE=0.38). Furthermore, the ANN achieved the highest overall precision for BAT, with a Mean Absolute Percentage Error (MAPE) of 0.61%. The random forest model achieved the highest percentage error when tracking EABL (MAPE=2.33%). While the RF model for SCOM exhibited the lowest variance explanation (R^2=0.9391), the ANN model for KCB showed the highest (R^2=0.9881).

Regarding Mean Bias Error (MBE), the RF model consistently displayed a persistent negative bias across all equities except EABL, with its peak underestimation rate of -0.32 observed for BAT. In contrast, the ANN model exhibited a mixed directional bias: it generated a positive bias for BAT (MBE = 0.19) but shifted to negative biases for the remaining four companies.

Table 4. Predictive Performance Metrics of ANN and RF Frameworks Across Testing Partitions.

Company	Artificial Neural Network				Random Forest			
	RMSE	*MAPE*	*MBE*	R^2	*RMSE*	*MAPE*	*MBE*	R^2
BAT	4.48	0.61%	0.19	.9704	5.93	1.01%	-0.32	.9481
EABL	4.44	1.99%	-0.11	.9623	4.79	2.33%	0.00	.9562
EQTY	0.69	1.03%	-0.05	.9599	0.82	1.28%	-0.14	.9444
KCB	0.69	1.48%	-0.12	.9881	0.95	2.04%	-0.24	.9776
SCOM	0.31	1.37%	-0.01	.9598	0.38	1.65%	-0.08	.9391

5. Discussion

5.1. Development of Machine Learning Algorithms for Predicting Stock Closing Prices

The first research objective focused on designing and implementing robust machine learning algorithms to transform unstructured time-series indicators into predictive inputs. This transformation necessitated strict synchronization to prevent data misalignment during the conversion of raw long-format data into wide time-series blocks. Feature engineering involved creating historical lagging features (Lag_{t-1}, Lag_{t-2}, and Lag_{t-3}) and a 5-day rolling moving average ($MA5$) to capture localized momentum. A strict chronological 8:2 data split was enforced to prevent data leakage and ensure true out-of-sample model evaluation. The training phase included major historical disruptions during the first quarter of 2020, while the testing partition was evaluated from January 2, 2024, to January 2, 2025. However, the study avoided traditional randomized k-fold cross-validation methods in time-series financial forecasting since they are prone to induce data leakages by unintentionally using future data points for predicting past prices.

The Random Forest (RF) regressor was configured with 500 decision trees to reduce variance and mitigate overfitting. On the other hand, the Artificial Neural Network (ANN) employed a feed-forward design that featured two hidden layers consisting of five and three neurons, respectively (hidden = c (5, 3)). However, a key operational difference between the two algorithms is observed with data scaling requirements. While, the RF regressor demonstrated complete immunity to scale variance due to its binary conditional splits, ANN transformed input features using Min-Max scaling, bounded between 0 and 1, to ensure stable backpropagation gradient descent. Additionally, scaling parameters were derived solely from the training partition and subsequently applied to the test evaluation partition. This structured approach prevented data leakage from the test set, establishing a stable and mathematically secured modeling of both algorithms.

These findings align with contemporary research. While traditional models like Random Forest offer interpretability, they often struggle with non-linear financial dynamics, a gap that ANN architectures with dual hidden layers address [26]. A research conducted by [53] observed sector-specific performance heterogeneity in emerging markets, where ANNs performed in volatile sectors while RF served as a dependable benchmark. This mirrors our finding that ANN performed better for the other four equities including BAT, EQTY, KCB and SCOM. Similarly, [20] utilized Min-Max scaling for ANN inputs and evaluated models using RMSE, MAPE, and MBE. Their findings suggested that RF persistently outperformed ANN except in more consistent datasets. This supports the validity of this study's preprocessing and evaluation protocols. The most notable finding was observed where RF had a structural advantage for EABL, which aligns with previous studies by [20, 34, 38, 54] where ensemble models consistently outperform individual shallow classifiers by balancing bias and variance boundaries. According to [20], the use of stacking and bagging multiple algorithmic models led to better prediction accuracy than using other hybrid models.

5.2. Evaluation of Algorithmic Forecasting Effectiveness and Goodness-of-Fit

The second objective involved evaluating out-of-sample predictive accuracy and structural goodness-of-fit. The goodness-of-fit evaluation revealed high variance across the entire portfolio. The lowest variance was achieved by the RF model for SCOM, while the highest was observed for the ANN tracking KCB Group. These strong goodness-of-fit metrics suggest that short-term price movements are not entirely random.

These empirical results reject the "cold" random walk model. Theoretically, these findings significantly challenge traditional economic theory, particularly [13] semi-strong form of the Efficient Market Hypothesis (EMH). According to EMH theory, emerging equity assets function as static systems

where all public data is instantly incorporated into current values, causing stock returns to follow a stochastic random walk process. If this assumption held true for firms listed on the NSE, all out-of-sample R^2 values would approach zero. However, our empirical findings show all out-of-sample R^2 values approaching one, thereby rejecting the random walk hypothesis. Contemporary studies have empirically validated the Adaptive Market Hypothesis across multiple global indices. This demonstrates that market efficiency is time-varying and historical data frequently contains significant variations, thereby challenging the static assumptions of the semi-strong EMH [52].

An examination of the absolute error magnitudes (RMSE and MAPE) depicted that the Neural Network consistently outperformed the Random Forest model across all five equities. This aligns with previous studies by [24, 27, 37, 51] where ANNs model outperformed other machine learning models. Specifically, the findings by [37] showed that AR-DNN performed well on large pre-pandemic data, however, AR-RF consistently outperformed under high volatility with low-number of observation. While visual inspections show that the neural network outperformed RF model during periods of sudden market expansion, statistical metrics clearly depict absolute performance gap when analyzing high-priced assets. Comparative study by [24] on large-cap indices have similarly reported that neural network architectures tend to yield significantly lower RMSE and MAPE values than Random Forest in out-of-sample financial evaluations. This can be attributed to the ability of the neural network to model continuous non-linear relationships. For BAT Kenya, which trades at a high nominal price, ANN achieved an RMSE of 4.48 (MAPE = 0.61%), while RF deviated by 5.93 (MAPE = 1.01%). For SCOM, ANN yielded a significantly lower error rate (RMSE = 0.31) compared to RF's 0.38. This performance gap highlights the neural network's superior capacity to eliminate "retail micro-noise." The binary conditional splits of Random Forest group small adjustments into rigid, blocky steps. The internal hidden nodes of the Neural Network however, smooth out the small adjustments, thus filtering out high-frequency noise.

The evaluation of Mean Bias Error (MBE) revealed that the RF model exhibited a highly persistent negative bias across all equities except EABL (MBE=0.00), with a peak underestimation rate of -0.32 for BAT. This indicates that tree-averaging ensembles tend to be overly regularized when faced with continuous, institution-led market conditions. However, since the final prediction is an average of 500 independent trees, the model drags its forecasts toward the historical mean, lagging behind active movements. The ANN model, however, displayed a mixed directional bias, generating a positive bias for BAT (MBE = 0.19) but shifting to minimal negative biases across the remaining four companies (EABL, EQTY, KCB and SCOM). This confirms that continuous activation layers adapt more effectively to directional market trends without introducing severe systematic errors. Hence, the non-linear processing structures within the neural networks successfully minimize prediction errors and capture change in prices more effectively when compared to the standard RF ensemble model.

6. Conclusion

This study compared the performance of Artificial Neural Network (ANN) and Random Forest (RF) models in predicting next-day closing stock prices for five firms listed on the Nairobi Securities Exchange (NSE). Raw, long-format data was transformed into wide, time-series blocks, requiring strict synchronization. To eliminate data leakage, a mandatory and strict chronological 8:2 data split was enforced. The empirical findings suggest that short-term price movements on the NSE do not follow a perfectly random walk process. This discourages the robust application of the semi-strong form of the EMH. Because the variance explanation metrics consistently exceeded.9300 across all five assets, with the highest R^2 of.9881 for KCB Group, this study then concludes that short-term asset prices on the NSE do not depict absolute stochastic movement. However, it reveals that historical technical indicators preserve valuable data patterns that possess predictive capacity regarding the next-day closing stock prices. This persistent predictability with high R^2 values close to 1 is consistent with possible market inefficiency but does not conclusively demonstrate it. To definitively prove a violation of the weak-form EMH, statistical predictability must translate directly into risk-adjusted economic value. Because this study focuses strictly on structural model comparison, several critical operational and financial variables were omitted including transaction costs, economic profitability, statistical and economic significance, and out-of-sample stability.

The findings revealed that ANN frameworks provide superior precision in mapping non-linear structural breaks and volatile expansions. The Random Forest models on the other hand offer a highly predictive and efficient framework for stable trends. The application of continuous activation functions through hidden layers in ANNs effectively maps non-linear structural breaks and filters out high-frequency retail micro-noise, which can introduce blocky artifacts into the discrete binary splits of the RF regressor. However, evaluation of Mean Bias Error (MBE) revealed that the RF model suffers from a systematic negative bias (MBE<0) due to its conservative leaf-averaging design, leading it to clip peaks and underpredict asset paths during sustained market rallies.

Therefore, the study used feed-forward neural networks which modeled non-linear relationships by utilizing inputs as isolated features and not as a continuous flow of data. Future research should implement neural networks based on LSTM, Gated Recurrent Units (GRUs), or using attention-based Transformer models. These neural networks have specialized memory gates which allow for retention or discard of data

over long periods. This makes them structurally fit for modelling long-term predictions within consideration of macro changes on the stock exchange.

Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
RF	Random Forest
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Square Error
MBE	Mean Bias Error
MAE	Mean Absolute Error
R2	Coefficient of Determination
ML	Machine Learning
DL	Deep Learning
MACD	Moving Average Convergence/Divergence
RWT	Random Walk Theory
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
SVM	Support Vector Machine
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
LSTM	Long Short Term Memory
GRU	Gated Recurrent Unit
NSE	Nairobi Securities Exchange
MLP	Multi-layer Perceptron
EMH	Efficient Market Hypothesis
BSE	Bombay Stock Exchange
PCA	Principal Component Analysis
SVR	Support Vector Regression
HMM	Hidden Markov Model
GA	Genetic Algorithms
BAT, Kenya	British American Tobacco Kenya Ltd
EABL	East African Breweries Ltd
KCB	Kenya Commercial Bank
EQTY	Equity
SCOM	Safaricom

Author Contributions

Jackline Chepngetich: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization and Writing of the original draft.

Julius Koech: Supervision, Funding acquisitions, Review and editing.

Argwings Otieno: Supervision, Funding acquisitions.

Eliud Koech: Project administration and resources

Conflicts of Interest

The authors declare no conflicts of interest.

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