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Full Length Research Article

PREDICTIVE MACHINE LEARNING METHODS FOR STOCK RETURNS AMONG EMERGING ECONOMIES IN AFRICA

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ABSTRACT.
The study examined the performance of competing models across the stock returns of three African countries, namely Nigeria, Tanzania, and Uganda, to determine whether a single predictive model dominates across emerging markets. The study utilised secondary data from the stock markets of Nigeria, Tanzania, and Uganda, sourced from the website (www.investing.com), spanning 11 years and comprising a total of 2772 observations for Nigeria, 2862 observations for Tanzania, and 2798 observations for Uganda. The descriptive statistics of the stock returns across Nigeria, Tanzania and Uganda revealed that the mean returns are lowest for Uganda and highest for Nigeria. This showed that Nigerian stock gained more during the period under review, followed by Tanzania stock returns. The standard deviation for Nigerian stock returns was highest, showing evidence of high volatility in Nigerian stock returns. The stock returns across the countries exhibited positive skewness. Among the stock returns, Tanzania and Uganda exhibited very high kurtosis. Lastly, across the countries, all the stock returns exhibited non-normality (p-values<0.05), which is mostly the case for stock returns. The findings from the training models revealed that the following: Artificial Neural Network dominated for Nigeria stock returns, no single model dominated for Tanzania stock returns, Autoregressive Integrated Moving Average with exogenous variables (ARIMAX) model dominated for Uganda stock returns. While the summary from the testing models revealed that the following: Random forest dominated for Nigeria stock returns, Support vector machine for Tanzania stock returns, and Artificial Neural Network dominated for Uganda stock returns. This study concluded that the performance of the predicting models for training and testing performed differently, as no single predicting model dominated across the African countries considered. This study recommended that data scientists, machine learning experts and policy makers in the stock market should consider competing models in different scenarios across emerging markets in Africa to enhance reliable prediction and decision making.

Keywords: Predictive model, Emerging market, stock markets, Linear Regression, Support Vector Machine, Decision Tree, Neural Network. Random Forest, ARIMAX.

INTRODUCTION

The International Monetary Fund (IMF) Fiscal Monitor reclassifies Emerging Markets and Developing Economies as Emerging Markets and Middle-Income economies due to their higher incomes (Jing 2023). Beyond income, an emerging market has other characteristics. Most of these economies show steady, robust growth and stability in terms of income, trade participation, and financial market integration, which allows them to produce goods with higher added value (Blanchard *et al*, 2021) of which Nigeria, Uganda and Tanzania are classified as emerging markets.

Emerging markets offer an interesting opportunity for investors to diversify their selections at this time of rising interest rates and high inflation in the developed world. The population of emerging markets is maturing more quickly, and a middle class with significant disposable income is beginning to emerge. Africa is one of the emerging stock markets that needs more attention (Bajja *et al*., 2024).

Predicting the stock market has been done for a long time using traditional methods by analyzing fundamental and technical aspects. With machine learning, stock market predictions are made accessible and more accurate (Mintarya *et al*., 2023). Timmerman (2021) used machine learning to predict stock price returns using such method as linear regression, LS-SVM, Regression Trees and Random Forest. Through those methods, a promising daily return and Sharpe ratios were obtained using Random Forest and Linear regression. Naeem *et al.* (2024) predicted stock market crises in Africa (Morocco, Tanzania, Ghana, Kenya, South-Africa, Rwanda and Nigeria) using machine learning classification techniques (Random Forest, XGBoost, Gradient boost, Support Vector Classification (SVC), Decision Tree, K-nearest neighbours, Logistic Regression). It was revealed that extreme gradient boosting (XGBoost) emerged as the most effective way of predicting crises. Other studies that have implemented machine learning to stock prices and returns include Idowu *et al.,* (2012); Oyewole, *et al*. (2019); Iliya *et al.* (2024); Akhtar *et al.,* (2022); Hanauer and Kalsbach (2023); Phouc *et al.,*(2024).

This study aims to explore predictive models across stock market prediction of emerging economics in Africa. To see if a single predictive model dominated across the emerging markets.

This research focused on a machine learning technique and ARIMAX. The model was constructed using the R models library provided in the package. The machine learning techniques namely Support Vector Regression, Decision Trees, Random Forest, Artificial Neural Network were employed in this study. The study used secondary data of stock market for Nigeria, Tanzania and Uganda, sourced from the website (www.investing .com), covering 11 years with total of 2772 observations for Nigeria, 2862 observations for Tanzania and 2798 observations for Uganda.

Predictive Models

Machine Learning Model Specifications Techniques

Supervised machine learning comprised of regression analysis, which involves forecasting a continuous independent target based on a collection of other predictor variables (Bishop, 2006). Regression and binary classification differ in the target range.

Linear Regression Model: In machine learning and statistics, linear regression is a basic and often used technique for predicting a continuous result variable based on one or more predictor

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factors. Finding the best-fitting linear relationship (line) that minimizes the difference between the outcome variable's actual and predicted values is the aim of linear regression. The model is given as:

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon_i$ (1)

where Y is the dependent variable, while X_1, X_2.... xX_n are the independent variables,

β_0 is the intercept, and $\beta_1$1, β_2, ... β_n are the coefficients and ε_i is the error term.

Support Vector Regression: Support Vector Regression (SVM) is a machine learning method, which was proposed by (Boser *et al*., 1992). It has been used to solve non-linear classification, regression, and predictions recently (Kandiri et al., 2022). One of the main advantages of SVR is that its computational complexity does not depend on the dimensionality of the input space. Additionally, it has excellent generalization capability, with high prediction accuracy (Awad and Khanna, 2015). SVR is a statistical machine learning method that has been applied in financial stocks, industrial and engineering processes (Ji et al., 2022). For a training set $T = \{(X_i, Y_i), i = 1, \ldots l\}$ where $X_i \in R^N, Y_i \in R$.

SVR aims at finding a regression function that can fit all training samples,

$f(x) = \boldsymbol{w}^T \phi(x) + b$ (2)

where **w** is a coefficient vector in feature space, $\phi(x)$ is a kernel function to map input x to a vector in feature space, and b is an intercept. The solution of **w** and b can be obtained by solving the optimization problems.

Random Forest Regression: Is a multiple decision tree for each training on a random forest. Random forest is an algorithm where each data point is developed into a large number of trees (in a forest) and the results are combined for a model (Toomey, 2014). Random forests for regression are formed by growing trees depending on a random vector Θ such that the tree predictor $h(\boldsymbol{x}, \Theta)$ takes on numerical values as opposed to class labels (Breiman, 2001). The output values are numerical and we assume that the training set is independently drawn from the distribution of the random vector Y The mean-squared generalization error for any numerical predictor h(**x**) is

$E_{X,Y}(Y - h(X))^2$ (3)

The random forest predictor is formed by taking the average over k of the trees $\{h(\boldsymbol{x}, \Theta_k)\}$. Its application in financial and engineering can be seen in change effort (Riesener et al., 2021) and in Machine fault diagnosis (Han *et al*., 2006).

Artificial Neural Network: Artificial Neural Network (ANN) consist of input, hidden and output layers with connected neurons (nodes) to simulate the human brain. The ANN is a good method to solve problems with nonlinear relationship without knowing the exact function. The ANN techniques that use supervise learning algorithm have proved to be more useful than statistical regression techniques considering factors like modelling case and prediction accuracy (Golnaraghi et al., 2019). There are typically three parts in neural network: an input layer, with units representing the input fields; one or more hidden layers; and an output layer, with a unit or units representing the target field(s).

Decision Tree Regression: Decision tree is a non-parametric supervised learning algorithm use for classification and regression tasks. Decision Tree for regression is similar to classification trees with the difference that it contains values or piecewise models at leave rather than class labels (Jena & Dehuri, 2020).

ARIMAX Model: The ARIMA model will be extended into ARIMA model with explanatory variable (X_t), called ARIMAX(p,d,q). Specifically, ARIMAX(p,d,q) can be represented by

$$\phi(L)(1-L)^d Y_t = \Theta(L) X_t + \theta(L)\varepsilon_t$$

Where L is the lag operator, d=difference order, p is the AR order, q is the MA order, explanatory variables (X_t) and ε_t is the error term while ϕ, Θ, θ are the coefficients of the AR, MA and the exogenous variables (Adenomon & Madu, 2022; Kongcharoen and Kruangpradit, 2013).

Performance Metrics

This study employed three major performance metrics namely, as shown in Table 1: Root Mean Square Error (RMSE), Coefficient of determination and Mean Absolute Error (MAE). Any technique with the smallest values of RMSE and MAE is adjudged the superior model among the competing models. While higher values of R-square would be used to select the appropriate model.

Table 1: Performance metrics equation and their ideal value.

S N	Parameter	Equation	Ideal Value
1	Root mean square error (RMSE)	RMSE = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$ n is the sample size	0
2	Coefficient of determination (R^2)	$R^2 = \frac{\sum_{i=1}^{n}(y_i - y_{mean})^2 - \sum_{i=1}^{n}(y_i -}{\sum_{i=1}^{n}(y_i - y_{mean})^2}$ y_i and $\hat{y}_i$ are the actual and predicted i^{th} value	1
3	Mean absolute error (MAE)	MAE= $\frac{1}{n}\sum_{i=1}^{n}\lvert(\hat{y}_i - y_i)\rvert$	0

Stock price prediction is a challenging task due to market volatility and nonlinear relationships. Machine learning models are evaluated using **RMSE which** Measures prediction error magnitude such that lower RMSE indicates better accuracy. **R-Squared (R²)** measures how well the model explains variance in stock prices and higher values (closer to 1) indicate better performance. **Mean Absolute Error (MAE) me**asures average absolute error such that lower values indicate better predictive accuracy (Brockwell *et al*., 2002; Campbell and Yogo, 2006).

RESULTS AND DISCUSSION

The section presents the results and discussion from the findings of this study. The results are presented in tables and figures below. To guarantee accurate and trustworthy predictions in machine learning, especially in regression analysis and other models tested, it is crucial to assess three key metrics performance model such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R²) (James, *et al*., 2013).

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Table 2: Descriptive statistics of Stock Returns

	Nigeria	Tanzania	Uganda
Mean	0.038498	0.000138	4.05E-05
Median	0.000000	0.000000	0.000000
Maximum	8.312278	0.328128	0.423618
Minimum	-4.908385	-0.320935	-0.403313
Std. Dev.	0.964208	0.016008	0.019432
Skewness	0.403441	0.295897	0.505328
Kurtosis	8.987175	145.0478	173.7930
Jarque-Bera	4215.441	2406219.	3400885.
Probability	0.000000	0.000000	0.000000
Sum	106.7151	0.395958	0.113342
Sum Sq. Dev.	2576.193	0.733145	1.056160
Observations	2772	2862	2798

In Table 2 the mean returns is lowest for Uganda and highest for Nigeria. This shows that Nigeria stock gained more during the period under review, followed by Tanzania stock returns. The standard deviation for Nigeria stock returns was highest showing evidence of high volatility in the Nigeria stock returns. The stock returns across the countries exhibited positive skewness. Among the stock returns, Tanzania and Uganda exhibited very high kurtosis. Lastly, across the countries, all the stock returns exhibited non-normality (p-values<0.05) which is mostly the case of stock returns (Adenomon *et al.* 2022). Also, all the stock returns exhibited stationarity as evidenced in figures 1, 2 and 3.

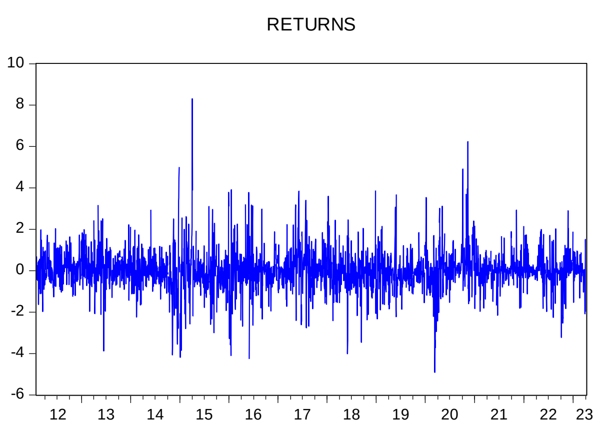

Figure 1: Nigeria Stock Returns

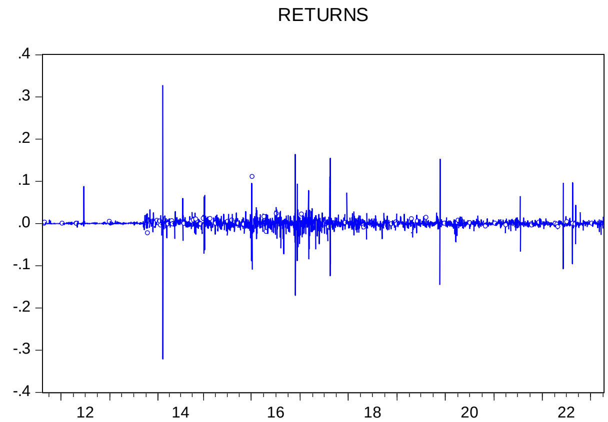

Figure 2: Tanzania stock Returns

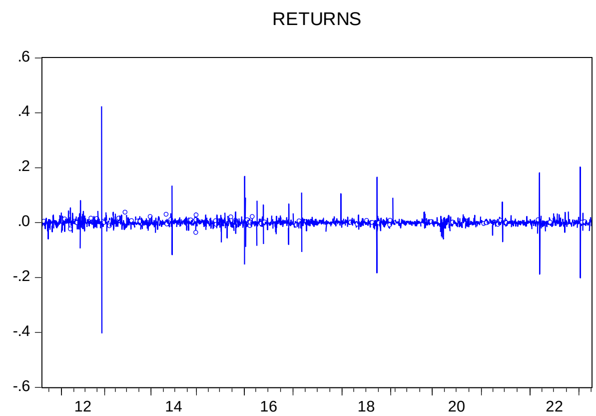

Figure 3: Uganda Stock Returns

Table 3: Training model for stock Returns of Nigeria, Tanzania and Uganda using RMSE

MODELS/COUNTRY	**Nigeria**	**Tanzania**	**Uganda**
Linear Regression	2.19584	0.03154492	**0.0122593**
Support vector machine.	1.171653	0.01594806	0.01427321
Decision Tree	0.939612	0.01595409	0.01506792
Artificial Neural Network	**0.1070**	0.47015677	0.01487647
Random forest	230.1936	0.0180770	0.01628986
ARIMAX	0.9165	**0.01471343**	0.01243139

In Table 3, for Nigeria stock returns, artificial Neural Network performed best while random forest performed worst. For Tanzania stock returns, ARIMAX performed best while artificial neural network performed worst. For Uganda stock returns, linear regression performed best while random forest performed worst (Timmerman, 2021; Mintarya et al., 2023; Naeem et al. 2024)

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Table 4: Training model for stock Returns of Nigeria, Tanzania and Uganda using R-Square

MODELS	**Nigeria**	**Tanzania**	**Uganda**
Linear Regression	0.370396	**0.7304139**	0.2563843
Support vector machine.	**0.7109384**	0.03844322	0.1946955
Decision Tree	0.09174755	0.01335425	0.009272694
Neural Network	0.1948	NA	NA
Random forest	0.5292895	0.004509841	0.01787639
ARIMAX	-	0.2185763	**0.3322182**

In Table 4, for Nigeria stock returns, Support Vector Machine performed best while decision tree performed worst. For Tanzania stock returns, Linear Regression performed best while Random forest performed worst. For Uganda stock returns, ARIMAX performed best while Decision tree performed worst (Timmerman, 2021; Mintarya et al., 2023; Naeem et al. 2024)

Table 5: Training model for stock Returns of Nigeria, Tanzania and Uganda using MAE

MODELS/ COUNTRY	**Nigeria**	**Tanzania**	**Uganda**
Linear Regression	0.6482833	0.007498591	0.007043997
Support vector machine.	0.5296749	0.00645195	0.007852688
Decision Tree	0.6352292	0.006677006	0.008189341
Artificial Neural Network	**0.0705**	**0.006371343**	0.008020255
Random forest	149.8600	0.00829754	0.009349689
ARIMAX	0.6214592	0.006447163	**0.007040015**

In Table 5, for Nigeria stock returns, Artificial Neural Network performed best while Random Forest performed worst. For Tanzania stock returns, Artificial Neural Network performed best while Random forest performed worst. For Uganda stock returns, ARIMAX performed best while Random Forest performed worst (Timmerman, 2021; Mintarya et al., 2023; Naeem et al. 2024)
The summary from the training models revealed that the following: Artificial Neural Network dominated for Nigeria stock returns, No single model dominated for Tanzania stock returns, ARIMAX model dominated for Uganda stock returns (Uzoaga et al., 2025).

Table 6: Testing model for stock Returns of Nigeria, Tanzania and Uganda using RMSE

MODELS/ COUNTRY	**Nigeria**	**Tanzania**	**Uganda**
Linear Regression	0.5944	0.01347634	0.4646277
Support vector machine.	0.4731	**0.01345809**	0.03227508
Decision Tree	0.6106	0.01347811	0.03103056
Artificial Neural Network	0.6125	0.0134769	**0.03101952**
Random forest	**0.4350**	0.01571867	0.03175071
ARIMAX	0.5976	0.01348863	0.04630508

In Table 6, for Nigeria stock returns, Random Forest performed best while Artificial Neural Network performed worst. For Tanzania stock returns, Support Vector Machine performed best while Random Forest performed worst. For Uganda stock returns, Artificial Neural Network performed best while Linear Regression performed worst (Timmerman, 2021; Mintarya et al., 2023; Naeem et al. 2024).

Table 7: Testing model for stock Returns of Nigeria, Tanzania and Uganda using R-Square

MODELS/ COUNTRY	**Nigeria**	**Tanzania**	**Uganda**
Linear Regression	0.5371	0.0039083	**0.1088142**
Support vector machine.	**0.7724**	**0.003689267**	0.0003016172
Decision Tree	0.0391	NA	NA
Artificial Neural Network	0.00002	NA	NA
Random forest	0.5328	0.0007889559	0.002199168
ARIMAX	0.7369	0.002944068	0.01086442

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In Table 7, for Nigeria stock returns, Support Vector Machine performed best while Artificial Neural Network performed worst. For Tanzania stock returns, Support Vector Machine performed best while Random forest performed worst. For Uganda stock returns, linear regression performed best while Support Vector Machine performed worst (Timmerman, 2021; Mintarya et al., 2023; Naeem et al. 2024)

Table 8: Testing model for stock Returns of Nigeria, Tanzania and Uganda using MAE

MODELS/ COUNTRY	**Nigeria**	**Tanzania**	**Uganda**
Linear Regression	0.9290	0.006230093	0.01054996
Support vector machine.	0.7328	**0.006152062**	0.01044311
Decision Tree	0.9494	0.006156666	0.01016186
Artificial Neural Network	0.9621	0.006153485	**0.01015935**
Random forest	**0.6781**	0.008006289	0.01176233
ARIMAX	0.9353	0.006179085	0.0105448

In Table 8, for Nigeria stock returns, Random Forest performed best while Artificial Neural Network performed worst. For Tanzania stock returns, Support Vector Machine performed best while Random forest performed worst. For Uganda stock returns, Artificial Neural Network performed best while Random Forest performed worst (Timmerman, 2021; Mintarya et al., 2023; Naeem et al. 2024).
The testing models revealed Random forest dominated for Nigeria stock returns, Support vector machine for Tanzania stock returns, Artificial Neural Network dominated for Uganda stock returns (Uzoaga *et al.,* 2025).
Lastly, the predicting performance of the models are presented in Figure 4 for Nigeria stock returns, Figure 5 for Tanzania stock returns and Figure 6 for Uganda stock returns.

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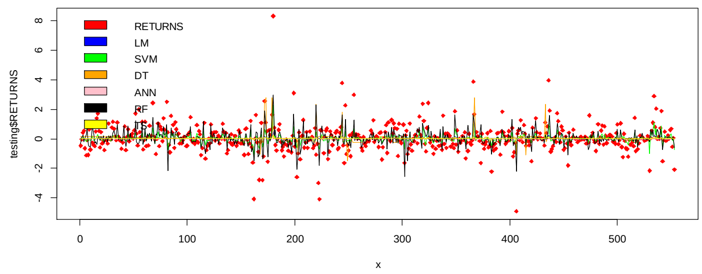

Figure 4: Testing models for Nigeria stock returns

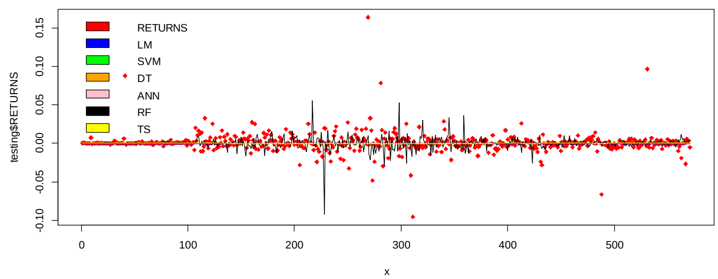

Figure 5: Testing models for Tanzania stock returns

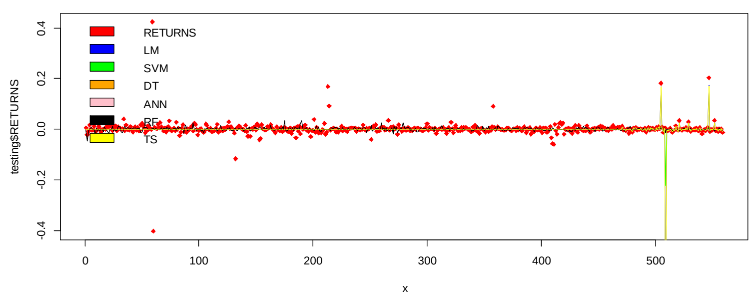

Figure 6: Testing models for Uganda stock returns

Conclusion

This study concluded that the performance of the predicting models for training and testing performed differently as no single predicting model dominated across the stock returns of the emerging economics of the African countries considered. This study recommended that data scientist, machine learning experts and policy makers in stock market should consider competing models in different scenarios across emerging markets in Africa to enhance reliable prediction and decision making.

Suggestion for Further Studies

In our further studies, we hope to explore Generalized Autoregressive Conditional Heteroscedasticity-Machine learning (GARCH-ML) and Autoregressive Integrated Moving Average – Machine Learning (ARIMA-ML) models to explore the potentials of stock returns of emerging market in Africa.

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