Forecasting of Banking Sector Securities Prices in Kenya Using Machine Learning Technique

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Authors' contributions

This work was carried out in collaboration among all authors. Author MHC devised the research, gathered and examined the data, discussed the findings, and formulated the manuscript's first document. The research was overseen by the authors AA and JM. All authors read and approved the final manuscript.

Original Research Article

Abstract

Before investing in any company, an investor should have a basic understanding of how the stock market works. With the introduction of Machine Learning (ML), more resources have been spent to this area of research and it has been proved that stock market prediction is achievable. Although studies have been conducted in this area, there has not been a study to forecast banking sector security prices in Kenya using SVM – ML. Therefore, using the Machine Learning technique, this study aimed to forecast the banking sector security prices in Kenya. The study aimed at fitting ARIMA and SVM models for forecasting banking sector security prices in Kenya. The study targeted all banks listed by the Nairobi Securities Exchange and a sample of three banks was taken – Kenya Commercial bank, Equity bank, and Co-operative bank. To determine the models' performance capability, accuracy error metrics were used to assess them. SVM had an error of 0.01482, 0.1217, 0.1114 and 0.01922 for MSE, RMSE, MAE and MAPE respectively which were lower compared to ARIMA's error results. SVM was recommended for forecasting banking sector security prices in Kenya as it proved reliable for forecasting.

Keywords: ARIMA; machine learning; stock market; SVM.

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1 Introduction

In the fields of economics, finance, business intelligence, meteorology, and telecommunications, time series forecasting is critical [1]. Since the 1950s, time series forecasting has been a hot topic of study. Since then, several types of prediction techniques have emerged. Technical and basic analysis, classical time series methods, and machine learning techniques are among them [2].

Technical analysis examines technical data such as price, volume, and price movement to estimate future pricing [3]. Fundamental analysis is used to investigate the relationship between financial data and other corporate factors such as inventory and revenue growth [4]. Traditional time series methodologies use a time series scale to predict future stock performance based on a stock's historical performance [5].

Machine Learning (ML) models are non-parametric, non-linear models that learn the stochastic relationship between past and future variables using historical data [1], [6]. They can also make better predictions by combining data from many sources, and many of them do not require data pre-processing. ML approaches have been used because of their greater performance and ease of implementation as compared to traditional statistical methods. A method of calculating the value of a company's equity or a related financial product traded on a security is called stock market prediction [7].

The ARIMA model is used to predict non-stationary time series where linearity between variables is assumed [8]. The model, like Stock Market Prices, is flexible in non-stationary and continuous data. ARIMA consists of three parts: Autoregressive (AR) functions that are reversed on a system's previous values, Moving Average (MA) functions that are purely based on a random walk with mean zero (0) and variance (σ^2), and an Integrated (I) element that separates and stabilizes the data series.

The following is the definition of an ARIMA (*p, d, q*):

$$\Delta^d Y_t = \alpha_1 \Delta^d X_{t-1} + \alpha_2 \Delta^d X_{t-2} + \cdots + \alpha_p \Delta^d X_{t-p} + \sum_{j=1}^{q} \beta_j \varepsilon_j, \tag{1}$$

where *p* represents the AR model's order, the number of times the data is differenced to ensure stationarity is represented by *d*, and *q* represents the MA model's order.

Support Vector Machine (SVM) is a self-supervised learning approach used in data mining [9]. Vapnik created the foundations of SVM, which are popular due to various features and empirical performance. SVMs were originally designed to address classification difficulties, but they have lately been extended to regression problems as well [10]. Each input data point is represented in n-dimensional space for classification, with *n* (number of input dimensions) being the number of input dimensions. Data is then classified using the hyperplane that separates the two classes. Fig. 1 shows a hyperplane that is created when categorization is completed.
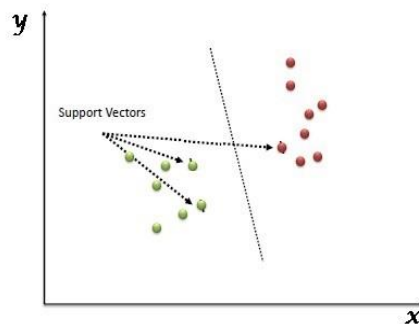

Fig. 1. Support Vector Hyperplane; Source [11]

For regression, consider a given training dataset, $D = \{(x_i, y_i) | x_i \in \mathbb{R}^d, y_i \in \mathbb{R}, i = 1,2, \cdots, n\}$, where x_i is a multidimensional input with all independent variables, the number of training samples is given by *n* and y_i is the scalar output. Support Vector Regression (SVR) is defined as follows [12]:

$$y_i = f(x_i, \omega) = \sum_{i=1}^{n} \omega . \Phi_i(x_i) + b, \tag{2}$$

where ω is the corresponding weight vector to $\Phi_i(x_i)$, ($\Phi_i(x_i)$ is mapping function for non-linear transformations), b is a fixed threshold and ω and b are to be estimated. Therefore, a linear SVR may be represented as:
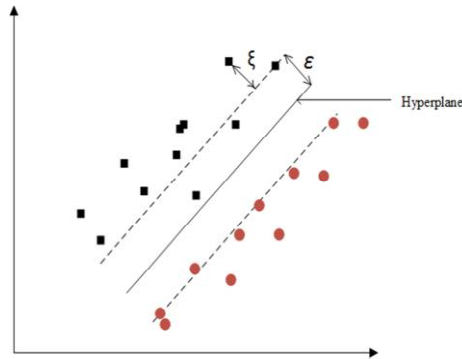

Fig. 2. Set-up of a Linear SVR; Source [13]

In the early society, when the empires needed a way to make payments for foreign goods and services, the history of banking began [14]. Coins of different sizes and metals replaced paper and this resulted to the need for safe storage. According to the World History Encyclopedia, wealthy people in ancient Rome would keep their coins in temple basements for security purposes as there were priests and temple workers who provided a sense of security [15].

In Kenya's banking sector, according to [16], changes have resulted in the proliferation of financial products, operations, and organizational structures. The financial framework's competency has improved as a result of these adjustments. The advancement of innovation has aided the transformations. The global banking sector's development has been aided by improvements and adjustments. Because of the growing importance of the banking sector in today's economies, stock forecasting has become an important topic to research.

Many studies on stock market prediction have resulted in the creation of a variety of predictive approaches, including machine learning-based algorithms, which are appropriate in today's world where a significant amount of stock market data is available. Machine learning algorithms have performed admirably in applications such as weather forecasting, fraud detection, currency exchange, disease forecasting, and pollution forecasting.

In the field of time series application, research has been done. With the advancement of technology and the development of more appropriate models, more research should be conducted. Although machine learning models such as ANN have been used to predict stock prices, no appropriate model has yet been established. As a result, the purpose of this study was to use SVM model to forecast banking sector security prices in Kenya and to advise investors on the risks of investing in these firms.

1.1 Literature review

Almasarweh and Wadi [17] highlighted the benefits of ARIMA model forecasting accuracy in their study on an ARIMA Model in forecasting banking dataset. To demonstrate ARIMA's ability to forecast banking data, data from Jordan's Amman Stock Exchange (ASE) was utilized. To make the forecast, the authors examined daily data from 1993 to 2017 and collected roughly 200 observations. On the basis of Mean Squared Error (MSE) criteria, the best ARIMA model was chosen. As a result, the ARIMA model produced substantial short-term prediction results.

Khedmati et al [5]offered time series forecasting approaches for the Bitcoin price using ARIMA as a traditional model, as well as five machine learning models: Kriging, ANN, Bayesian technique, SVM, and Random Forest (RF). Univariate and multivariate models were proposed, with univariate models including ARIMA, ANN,

Kriging, and Bayesian models, and multivariate models including ANN, SVM, RF, and Bayesian models. From December 16, 2017 to June 1, 2018, the 16 multivariate models were applied to the Bitcoin price, which included the Bitcoin price as well as the maximum, minimum, and closed prices for the same time period. When they examined the performance of the proposed models using the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) measurements, they determined that ARIMA outperformed other univariate models since it had lower RMSE and MAPE values.

Chaudhuri and Pandit [18] looked at how well time series models performed in projecting earnings for six companies between January 2010 and December 2020, a span of 11 years. The National Stock Exchange of India provided monthly average stock statistics for six companies: HCL, TCS, Infosys, Reliance, Tech Mahindra, and Wipro, for a period of 11 years. There were 132 values in each company that were graphical plotted and checked for stationarity. Both of the 6 companies' data series was revealed to be non-stationary. The series became stationary after each of them was differentiated, and graphical charting was resumed. After that, a comparison of goodness of fit statistics was used to choose the best ARIMA model for each stationary time series. The residuals were extracted after selecting the optimal ARIMA model and determined to be random with no external influences. As a consequence, the chosen model was used to anticipate the top six Indian firms' monthly average stock price in 2020. Superior ARIMA series approaches beat naive time series data in terms of mean percentage errors, AIC, and average ranks, according to their findings. Investors should base their expectations on the chosen ARIMA model, according to the findings.

Prasad Das and Padhy [19] employed two machine learning approaches to forecast future stock market prices in India: backpropagation (BP) and SVM. They used data from the National Stock Exchange of India Limited (NSE) to evaluate a machine learning model from January 1, 2007 to December 31, 2010. When the performance of these techniques was compared, it was discovered that SVM outperformed the BP technique. MATLAB and SVM Tools were used in the implementation (LS-SVM Tool Box). When the SVM method was applied, the anticipated price and real price agreed very well, according to the performance criteria set for their experiment. For all futures stock indices, the Normalized Mean Squared Error (NSME) was calculated and found to be between 0.9299 and 1.1521. The MAE requirement ranged from 55.17 to 91.2512, while the Directional Symmetry (DS) requirement ranged from 0.2379 to 0.3887.

Rajput [11]used a combined ANN, PCA, and SVM to anticipate the future trend of a stock listed on India's National Stock Exchange. For two companies, he used time series data: State Bank of India and Larsen & Toubro Limited. The State Bank of India's models were developed in 2012 and tested in 2013, while Larsen & Toubro Limited's models were developed in 2015 and tested in 2016. The PCA's goal was to convert correlated, high-dimensional data into low-dimensional, linearly uncorrelated data. The first four primary components of his study, according to the PCA, contained 98.24% information from original SBI data and 99.27% information from original Larsen & Toubro Limited data. According to the findings, The data from the State Bank of India had a 0.03 Normalized Mean Square Error (NMSE) and an a percentage error of 2.12%, while Larsen & Toubro Limited data had an NMSE of 0.09 and when applying the Nonlinear Autoregressive with External Input (NARX) prediction model with PCA data, the percentage error was 2.41 percent. Similarly, SVM assigned State Bank of India data an NMSE of 0.01 and a 1.11 percent error rate, whereas Larsen & Toubro Limited data received an NMSE of 0.04 and a 1.91 percent error rate. When compared to ANN with PCA, the computational results showed that SVM produced better results.

Vijh et al [20] proposed that an SVM model can accurately verify the Tesla Inc.'s closing share price, a tech business, and Reliance Ltd., a public corporation, in their study. Historical stock data (i.e., from November 2019 to November 2020) was used to train and evaluate SVM Kernel models for both businesses. They discovered that different data points affected the performance of each Support Vector Regression (SVR) kernel approach. Both Tesla Inc. and Reliance Ltd. chose the Radial Basis Function (RBF) SVR kernel as the best option. When compared to the original values on the same days, RBF forecasted the stock closing prices closest to them.

2 Materials and Methods

The Nairobi Security Exchange's historical financial reports on the banks' daily market performance over a five-year period, from 2016 to 2021, provided secondary data for the study. The data was split into 80% for training purposes and 20% for testing purposes. To fit an ARIMA model, this study incorporated the Box Jenkins methodology which was as follows [8].

i. Stationary check.
ii. The ADF (Augmented Dickey Fuller) was carried out. If the test's p-value was less than the (**α**) level of significance, the presence of a unit root was rejected as a null hypothesis, meaning that the series was stationary.
iii. The study used the auto_arima function in the "pmdarima" package to find the ARIMA model's parameters..
iv. Choosing the best ARIMA model with minimum value of AIC, since AIC is a measure of goodness of model fitting.
v. Performing "Residual Analysis" on the chosen model. In this case, the Ljung-Box test was used, and if the p-value was higher than the significance level (α), then the model fits the data well.
vi. Forecasting was done based on the chosen ARIMA model.

The kernel approach was used to fit an SVM model, and it is used to classify non-linear relationships between class and sample feature vectors. As a result, SVM is an effective technique for detecting non-linear relationships. Mathematically, a kernel function is defined as:

$$K(x_i, y_i) = \varphi(x_i). \varphi(y_i). \tag{3}$$

The dataset was split to 80% for training and 20% for testing. Then SVM type 2 was specified, with the following error function:

$$\frac{1}{2}\omega^T\omega - C\left[v\varepsilon + \frac{1}{N}\sum_{i=1}^{N}\zeta_i + \zeta_{i.}\right], \tag{4}$$

which minimizes the entity to;

$$\begin{aligned}
[\omega^T\phi(x_1) + b] - y_i &\leq \varepsilon + \zeta_i, \\
y_i - [\omega^T\phi(x_1) + b_i] &\leq \varepsilon + \zeta_{.i}, \\
\zeta_i, \zeta_{.i} &\geq 0, i = 1, \cdots, N, \varepsilon \geq 0.
\end{aligned} \tag{5}$$

The RBF Kernel was used to map input space in SVM classification; it is dependent on the distance between input and some of a data set's fixed points. Mathematically, it is defined as;

$$K(x_i, y_i) = exp\left(-\frac{\|x_i - y_i\|^2}{2v^2}\right), \tag{6}$$

where v is the width of the RBF. Therefore, the optimal regression function was;

$$\begin{aligned}
f(x) &= \sum_{i=1}^{N}\alpha_i y_i K(x, y) + b, \\
b &= y_j - \sum_{i=1}^{N}\alpha_i y_i K(x, y).
\end{aligned} \tag{7}$$

3 Results and Discussions

3.1 ARIMA model

To ensure that the data was good for modelling, a stationarity check was conducted for both banks. Results indicated that the data was not stationary as looking from the p-value which was a greater value than the standard value 0.05. Therefore, the data needed to be made stationary by differencing. Differencing was done once and the result was a stationary set of data. The resulting dataset was therefore suitable for modelling for ARIMA.

3.1.1 ARIMA Model for Equity Bank

Instead of looking at the ACF and PACF graphs, the auto_arima function was used to determine the best ARIMA model's p, d, and q parameters. After determining the most optimal parameters for an ARIMA model, the auto_arima function returned a fitted ARIMA model. After data processing, the best model that was generated was ARIMA (0,1,1) which implied $p = 0$, $d = 1$, $q = 1$. This was chosen since the model had the

minimum AIC. However, there was no sign of seasonality in the dataset and therefore no need of examining the seasonality aspect of the data.

Table 1. Equity Bank ARIMA Model Results

	Coefficient	Standard error	z	P-value	Confidence interval (0.025)	Confidence interval (0.975)
MA(1)	0.2865	0.017	16.927	0.000	0.253	0.320
sigma2	0.0003	7.12e-06	43.335	0.000	0.000	0.000

The resulting model for Equity Bank share prices was therefore an MA of order 1 and the resulting equation is given by;

$$Y_t = \mu + \beta_1 \varepsilon_{t-1} + \varepsilon_t, \tag{8}$$

where $\mu = 40.221263$, $\beta_1 = 0.2865$.
Therefore;

$$Y_t = 40.221263 + 0.2865\varepsilon_{t-1} + \varepsilon_t. \tag{9}$$

From the above results, the model's coefficient had a standard error of 0.017 which was significant compared to an error of 0.05 for normality tests. This therefore implied that the model was significant for the Equity Bank shares. A forecasting for the Equity Bank shares was then performed with a 95% confidence interval which was on the testing dataset and yielded the results below.
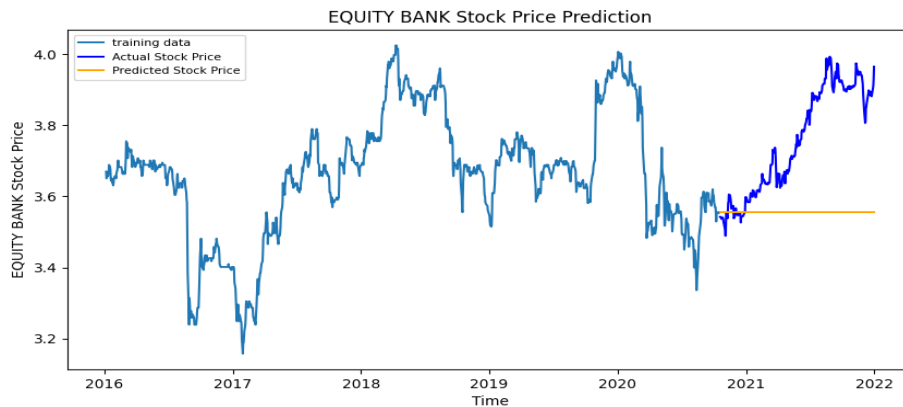

Fig. 3. Equity Bank ARIMA Models Forecast

Accuracy metrics for the dataset were performed to ascertain the predictive performance of the model and these were the results.

MSE: 0.06259   MAE: 0.2044   RMSE: 0.2501   MAPE: 0.0529.

From the above results, there is a clear indication that the model had a good predictive performance as it had an approximate 95% predictive performance under the Mean Absolute Percentage Error (MAPE) criterion.

3.1.2 ARIMA Model for KCB Bank

Similar to Equity bank, determining the appropriate model for the dataset was done by the auto_arima function in python and yielded an ARIMA model of order (0,1,1) implying that it was a Moving Average model of order 1.

Table 2. KCB Bank ARIMA Model Results

	Coefficient	Standard error	z	P-value	Confidence interval (0.025)	Confidence interval (0.975)
MA(1)	0.2858	0.014	20.621	0.000	0.259	0.313
sigma2	0.0003	5.26e-06	50.149	0.000	0.000	0.000

From the above results, the fitted model for the KCB Bank dataset was given as;

$$Y_t = 40.100165 + 0.2858\,\varepsilon_{t-1} + \varepsilon_t. \tag{10}$$

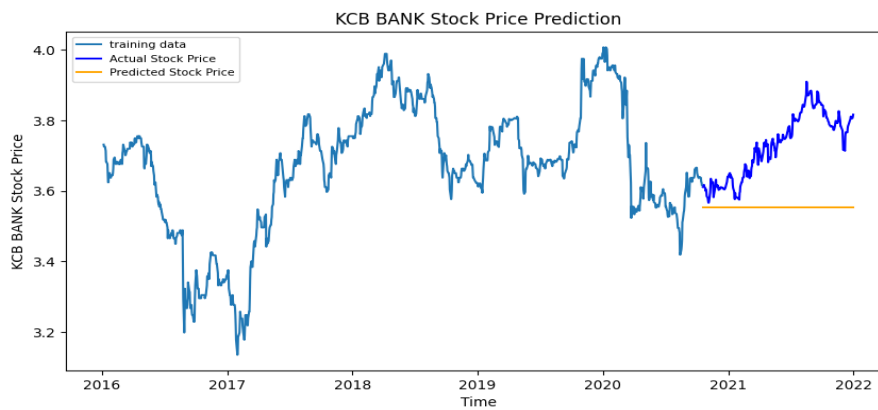Forecasting was then done for the dataset and these were the results.

Fig. 4. KCB Bank ARIMA Model Forecast

The accuracy metrics yielded these results.

MSE: 0.02101   MAE: 0.11901   RMSE: 0.1449   MAPE: 0.0314.

From the above results, there is a clear indication that the model had a good predictive performance as it had an approximate 97% predictive performance under the Mean Absolute Percentage Error (MAPE) criterion.

3.1.3 ARIMA Model for CO-OP Bank

For Co-op Bank, the best model yielded was of order (3,1,0). This implied that the best fitted model was an Autoregressive model of order 3. The table below indicates the results for the model.

Table 3. CO-OP Bank ARIMA Model Results

	Coefficient	Standard error	z	P- Value	CI (0.025)	CI (0.975)
AR (1)	0.2251	0.015	15.249	0.000	0.196	0.254
AR (2)	0.0511	0.020	2.544	0.011	0.012	0.090
AR (3)	-0.1121	0.021	-5.329	0.000	-0.153	-0.071
sigma2	0.0003	4.2e-06	61.804	0.000	0.000	0.000

The model can be expressed mathematically as;

$$Y_t = \mu + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \alpha_3 X_{t-3} + \varepsilon_t, \tag{11}$$

where $= 14.402315$, $\alpha_1 = 0.2251$, $\alpha_2 = 0.0511$, and $\alpha_3 = -0.1121$.

Substituting, the equation becomes;

$$Y_t = 14.402315 + 0.2251X_{t-1} + 0.0511X_{t-2} - 0.1121X_{t-3} + \varepsilon_t. \tag{12}$$

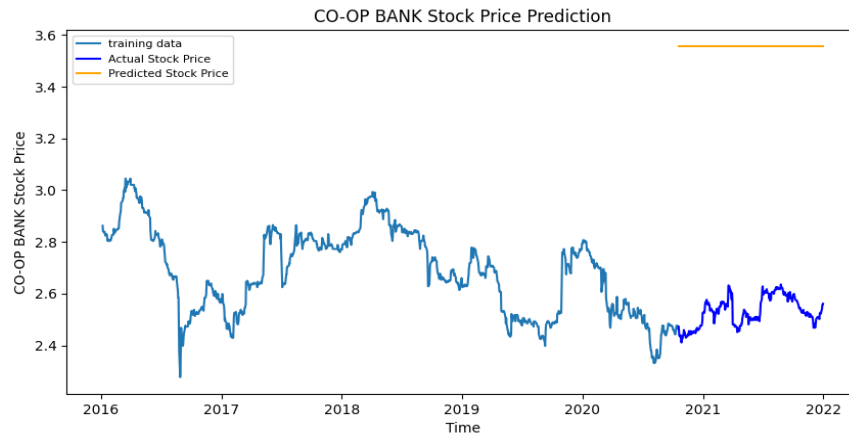Forecasting was then performed for the model and yielded the results below.

Fig. 5. CO-OP Bank ARIMA Model Results

Error metrics yielded the results below.

MSE: 0.0075   MAE: 0.0721   RMSE: 0.0866   MAPE: 0.0281.

From the above results, there is a clear indication that the model had a good predictive performance as it had an approximate 98% predictive performance under the Mean Absolute Percentage Error (MAPE) criterion.

3.2 SVM model

SVM was also evaluated using the provided datasets, the accuracy was determined, and the results were shown at the end. This ability to determine values based on forecasting data was provided by the best-estimator object function. As a result, the optimal values were determined using that function. The RBF kernel outperformed the other three SVM kernels when they were put to the test. To train and test the model, the study used these values for gamma, epsilon and count; 0.005, 0.01 and 100 respectively.

3.2.1 SVM Model for Equity Bank

A value of 0.5454 for the R^2 coefficient of determination was observed for Equity Bank. This is a clear indication that there was 54.54% variability explained by the model. The training and testing parameters were indicated below.

Table 4. Equity Bank SVM Model Results

Training		Testing	
Parameter	**Value**	**Parameter**	**Value**
Number of Observations	1209	Number of Observations	303
MSE	0.03084	MSE	0.03049
RMSE	0.1756	RMSE	0.1746
MAE	0.1855	MAE	0.1845
MAPE	0.0332	MAPE	0.0322

From the above results, there is a clear indication that the model had a good predictive performance as it had an approximate 97% predictive performance under the Mean Absolute Percentage Error (MAPE) criterion.

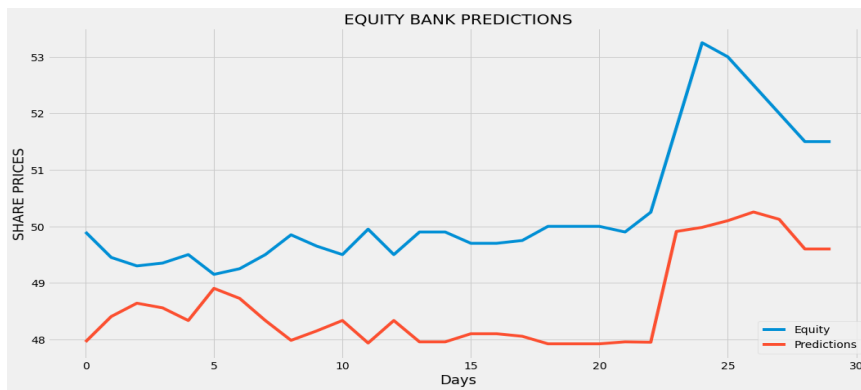Forecasting was undertaken and yielded these results:

Fig. 6. Equity Bank SVM Model Forecast

From the results above, there is a clear indication of no much variation between the actual values and the predictions.

3.2.2 SVM Model for KCB Bank

The R^2 coefficient of determination for KCB was 0.6110. In comparison to Equity bank shares, the bank's shares had a decent performance. As a result of the realization that the bank's shares had a good R^2 value, future prices were obtained. Training and testing parameters were indicated below.

Table 5. KCB Bank SVM Model Results

Training		Testing	
Parameter	Value	Parameter	Value
Number of Observations	1209	Number of Observations	303
MSE	0.00974	MSE	0.00955
RMSE	0.0987	RMSE	0.0977
MAE	0.0955	MAE	0.0945
MAPE	0.0146	MAPE	0.0136

From the above results, there is a clear indication that the model had a good predictive performance as it had an approximate 99% predictive performance under the Mean Absolute Percentage Error (MAPE) criterion. Forecasting was undertaken and yielded these results.
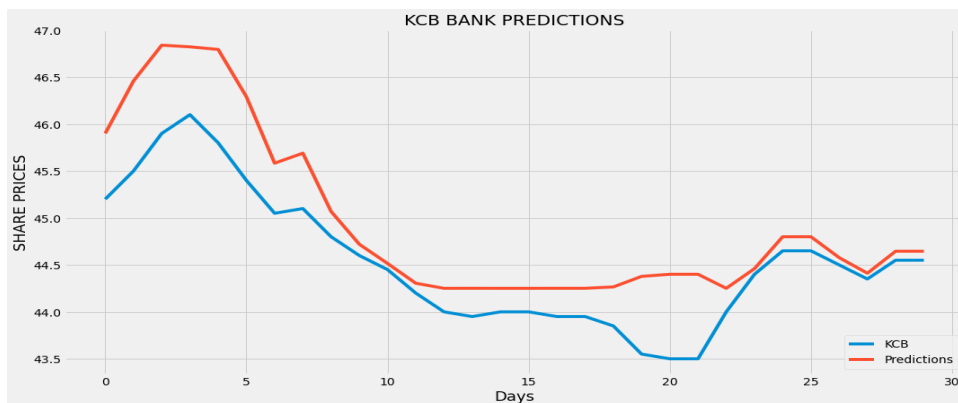

Fig.7. KCB Bank SVM Model Results

A small variation between the actual and the predictions was realized.

3.2.3 SVM Model for CO-OP Bank

The R^2 coefficient of determination for Co-op Bank was 0.6901. This was a higher value than the other banks. The implication of the above results was that the model could be used for prediction since the performance of the model using the R^2 coefficient of determination was pleasant as the values were positive and more than 0.5. The table below indicates the accuracy metrics that were established.

Table 6. Cooperative Bank SVM Model Results

Training		Testing	
Parameter	**Value**	**Parameter**	**Value**
Number of Observations	1209	Number of Observations	303
MSE	0.003869	MSE	0.00375
RMSE	0.0622	RMSE	0.0612
MAE	0.0532	MAE	0.0522
MAPE	0.00986	MAPE	0.00976

From the above results, there is a clear indication that the model had a good predictive performance as it had an approximate 99% predictive performance under the Mean Absolute Percentage Error (MAPE) criterion. The bank's forecasting was then completed, yielding these results.
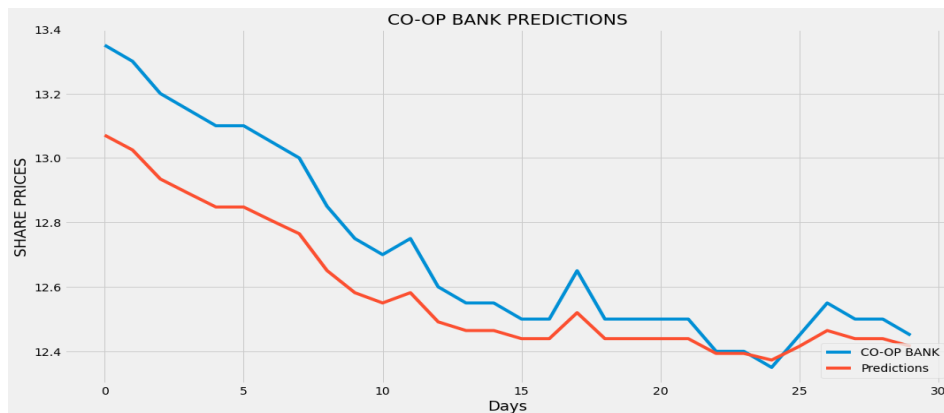

Fig. 8. Cooperative Bank SVM Model Forecast

The trend of the predictions and the actual results was evident as the predictions followed the same trend as the actual values. There was no doubt therefore on the performance of the model as it yielded better results in prediction.

4 Conclusion and Recommendation

This study found that SVM performed better than ARIMA model for forecasting banking sector security prices in Kenya. Furthermore, the models' performance was excellent because to the large amount of data collected during the training phase. Under all the accuracy metrics that the two models were subjected to, SVM proved to be better than ARIMA for forecasting purposes. These results imply that SVM can be used for prediction purposes in Kenya in the banking sector.

Moreover, for individual banks, it was evident that Cooperative Bank performed better than other banks using both models as it had the minimum error under all accuracy metrics. Therefore, those investing in the banking sector can be recommended to use SVM model to predict the future prices on whether they tend to fall or rise.

Because the study was limited to banking sector and also three banks, overcoming those obstacles would go a long way toward enhancing the precision and trustworthiness of the study's results. As a result, the first component of future work could be a mixture of past data and everyday political and financial news analysis

using Natural Language Processing (NLP) models. Furthermore, the dataset should be expanded to include a variety of datasets from different marketplaces in order to see if SVM is more accurate than ARIMA in general and to compare it to other machine learning approaches.

Disclaimer

The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

Competing Interests

Authors have declared that no competing interests exist.

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