



Performance Evaluation of Self-Organizing Feature Maps and Support Vector Machines in Predicting Stock Prices: A Comparative Study

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Abstract: Stock market forecasting plays a critical role in guiding investors and policymakers in dynamic financial environments. Despite advancements in predictive modeling, the comparative evaluation of machine learning techniques, such as Self-Organizing Feature Maps (SOFM) and Support Vector Machines (SVM), within the Nigerian Exchange Group (NGX) context has been limited. This study addresses this gap by investigating the performance of SOFM and SVM in predicting stock prices for five NGX-listed companies: United Bank for Africa (UBA), First Bank of Nigeria Holdings (FBNH), Guaranty Trust Bank (GTB), Nestlé (NESTLE), and Dangote Cement (DANGCEM), spanning financial, consumer goods, and industrial sectors. The dataset consisted of approximately 2,665 daily stock price observations (about 533 per company), covering the period 2011–2019. Following data cleaning and quality checks, preprocessing included Min-Max normalization and transformation into time-series matrices to ensure robustness and consistency. The dataset was divided into training (2011–2016, about 70%) and testing (2017–2019, about 30%) periods. SOFM was utilized for clustering and pattern recognition, while SVM incorporated technical indicators such as moving averages and price fluctuations. Implementation was conducted in MATLAB R2018a with a custom graphical user interface (GUI) for result visualization. Results revealed that SVM consistently outperformed SOFM across all datasets. For the UBA dataset, SVM achieved superior metrics, including an accuracy of 90.63%, specificity of 88.89%, and F1-score of 92.82%, with a computation time of 33.10 seconds. In comparison, SOFM demonstrated slightly lower performance with an accuracy of 88.13%, specificity of 85.19%, and an F1-score of 90.91%, and a computation time of 47.02 seconds. These findings establish SVM as a reliable and efficient model for stock price prediction on the NGX. Future research could explore hybrid models and broader datasets to enhance predictive accuracy and applicability in real-time investment strategies and risk management.

Keywords: Stock Price Prediction, Self-Organizing Feature Maps, Support Vector Machines, Machine Learning, Nigerian Exchange Group

1. INTRODUCTION

The stock market serves as a key indicator of a nation's economic health, reflecting the collective judgment of investors regarding companies' financial prospects. However, its inherent volatility introduces significant challenges for accurate prediction [1]. Factors such as macroeconomic conditions, geopolitical events, and investor sentiment drive stock prices, adding layers of complexity to forecasting efforts [2, 3]. Traditional methods, including time series analysis and regression models, often fall short in addressing these complexities, necessitating the adoption of advanced machine learning approaches [4, 5]. Machine learning techniques, including Self-Organizing Feature Maps (SOFM) and Support Vector Machines (SVM), have gained traction for their ability to model intricate relationships within financial data. SOFM, developed by Kohonen in the 1980s, is particularly adept at clustering and dimensionality reduction, offering insights into hidden patterns without labeled training data [6, 7]. It has been effectively applied to financial time series analysis, uncovering clusters and trends in historical stock data [8, 9].

SVM, introduced by Vapnik in the 1990s, excels at handling high-dimensional, non-linear data through its use of kernel functions, making it a preferred choice for financial forecasting [10, 11]. Studies have demonstrated its superiority over traditional models in stock price prediction, particularly in volatile markets [12]. Recent advancements in machine learning have integrated external factors such as news sentiment and social media trends to enhance predictive accuracy. These

innovations have proven particularly effective in addressing the challenges posed by emerging markets like the Nigerian Exchange Group (NGX), where local economic and political influences add unique dynamics [13].

To evaluate and compare the performance of SOFM and SVM, this research investigates their application in predicting stock prices on the Nigerian Exchange Group (NGX). SOFM leverages its clustering and dimensionality reduction capabilities to identify hidden patterns in financial data, while SVM applies its strength in handling high-dimensional, non-linear data for precise forecasting. Utilizing these advanced algorithms, the study aims to enhance stock price prediction accuracy and provide actionable insights for investment decisions in emerging markets, addressing the unique challenges posed by the NGX [6, 11].

2. LITERATURE REVIEW

The domain of stock price prediction has undergone substantial research, using many machine learning models and approaches to enhance accuracy and dependability. Self-organising Feature Maps (SOFM) and Support Vector Machine (SVM) are esteemed for their efficacy in managing intricate and non-linear financial data [14, 15]. These approaches have been utilised on various datasets to evaluate their effectiveness in modelling intricate financial patterns. Heo and Yang [16] assessed the efficacy of Support Vector Machines (SVM) in predicting stock prices based on company financial information. The study emphasised the efficacy of SVM in forecasting stock price movements based on fundamental financial metrics, although saw a deterioration in its accuracy over time owing to market fluctuations. These findings corroborate the efficient market concept, highlighting the decreasing significance of static financial statements when market conditions change. Liu et al. [17] introduced a stock price prediction model utilising an enhanced Radial Basis Function (RBF) Support Vector Machine (SVM) algorithm to tackle the volatility issues in China's stock market. The research highlighted the model's capacity to improve predictive accuracy while preserving computing economy. Experimental findings indicated the model's proficiency in properly approximating short-term stock price patterns, providing a dependable basis for precise forecasting and facilitating technological developments in the stock market. Ji [18] performed a comparative examination of three machine learning models—Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF)—for the prediction of stock prices. The analysis of historical stock and gold price data revealed that the Random Forest (RF) model was the most successful, surpassing both Artificial Neural Networks (ANN) and Support Vector Machines (SVM) in accuracy. The research determined that RF provides substantial benefits for investors and firms seeking to enhance forecasting precision and get a competitive advantage in the stock market. Osama et al. [19] assessed the predicted efficacy of four machine learning models—Long Short-Term Memory (LSTM), Random Forest, Support Vector Regression (SVR), and Linear Regression—on Oracle stock prices utilizing a dataset that encompasses nearly four decades. The analysis identified SVR as the most precise model, attaining the lowest error rates across assessment measures, with LSTM closely following. Linear Regression exhibited intermediate effectiveness, however Random Forest had the least efficacy, suggesting its inadequacy for the particular dataset. The results underscore the significance of choosing suitable machine learning models for stock price prediction according to data attributes. Huang and Tsai [20] examined a hybrid model that integrates Self-organizing Feature Map (SOFM) and Support Vector Regression (SVR) alongside a filter-based feature selection for stock market prediction. The study revealed SOFM's proficiency in properly clustering training samples, while the filter-based feature selection recognized crucial input features to improve prediction accuracy. Support Vector Regression (SVR) was employed for forecasting, demonstrating enhanced predictive accuracy and decreased training duration relative to conventional SVR. The use of Taiwan Index Futures (FITX) underscored the efficacy of hybrid methodologies in tackling intricate financial time series issues. Syukur and Marjuni [21] introduced an innovative approach for stock price prediction utilizing Singular Spectrum Analysis (SSA) in conjunction with the Hadamard Transform to enhance time series embedding. The research tackled the issue of choosing a suitable window length by utilizing the Hadamard spectrum for direct assessment. The experimental findings demonstrated that the suggested method surpassed conventional SSA techniques in minimizing errors, highlighting its efficacy in enhancing time series decomposition for financial forecasting.

While both SOFM and SVM offer significant advantages, they are not without limitations. SOFM lacks direct prediction capabilities, and SVM can be computationally intensive with large datasets. Combining these models or integrating them with deep learning techniques could enhance their effectiveness. Future research should explore the use of hybrid models in emerging markets and investigate their performance with real-time market data. Existing literature affirms the importance of machine learning in stock market forecasting, yet comparative analyses of SOFM and SVM remain limited in emerging markets like Nigeria. Prior studies emphasize predictive accuracy and efficiency, underscoring the need to evaluate these models within NGX to guide investment and policymaking.

3. METHODOLOGY

This research compares the analysis of a Self-Organizing Feature Map (SOFM) and Support Vector Machine (SVM) for stock price prediction on the Nigerian Exchange Group (NGX), using five listed companies as case studies. The process included acquiring an 8-year dataset (2011-2019) from NGX publications, followed by data preprocessing (cleaning and normalization), sampling into training and testing datasets, and training both SOFM and SVM models. The models were then tested, and their stock price prediction performance was evaluated. Figure 1 depict the Scheme of the Technique of the study.

3.1 Data Acquisition

The dataset for this research was acquired from the Nigerian Stock Exchange (NGX) for five companies: First Bank of Nigeria Holdings Plc, Guaranty Trust Company, NESTLE, United Bank for Africa, and Dangote Cement, covering 8 years of data from 2011 to 2019. In total, the dataset comprised approximately 2,665 daily trading records (averaging about 533 observations per company), providing sufficient volume and quality for robust analysis. The data included key stock metrics such as High, Low, Open, Close, Previous Close, and Volume. The Open, Close, and Previous Close columns represented daily trade prices, while the High and Low columns indicated the highest and lowest stock prices for the day. The Total Trade Quantity reflected the number of shares traded, and the Turnover column represented the company's daily financial turnover. Six derived variables were created for predicting the stock closing price: Differences between Stock High and Low price (DSHL), Differences between Stock Close and Open price (DSCO), Stock price's seven-day moving average (SPMA-7), fourteen-day moving average (SPMA-14), twenty-one-day moving average (SPMA-21), and Stock price's standard deviation for the past seven days (SPSD-7). These variables were calculated using the five fundamental data points (Open, High, Low, Close, Volume), with moving averages calculated by summing stock prices over a specified period and dividing by the number of periods.

The dataset from the Nigerian Stock Exchange (NGX) is uniquely characterized by high volatility, market inefficiencies, and liquidity variations, reflecting the dynamics of an emerging economy. Influenced by policy shifts, speculative investor behaviour, and dual exposure to global oil shocks and domestic macroeconomic instability, NGX data presents irregular trading patterns, making it an ideal benchmark for testing robust predictive modelling techniques.

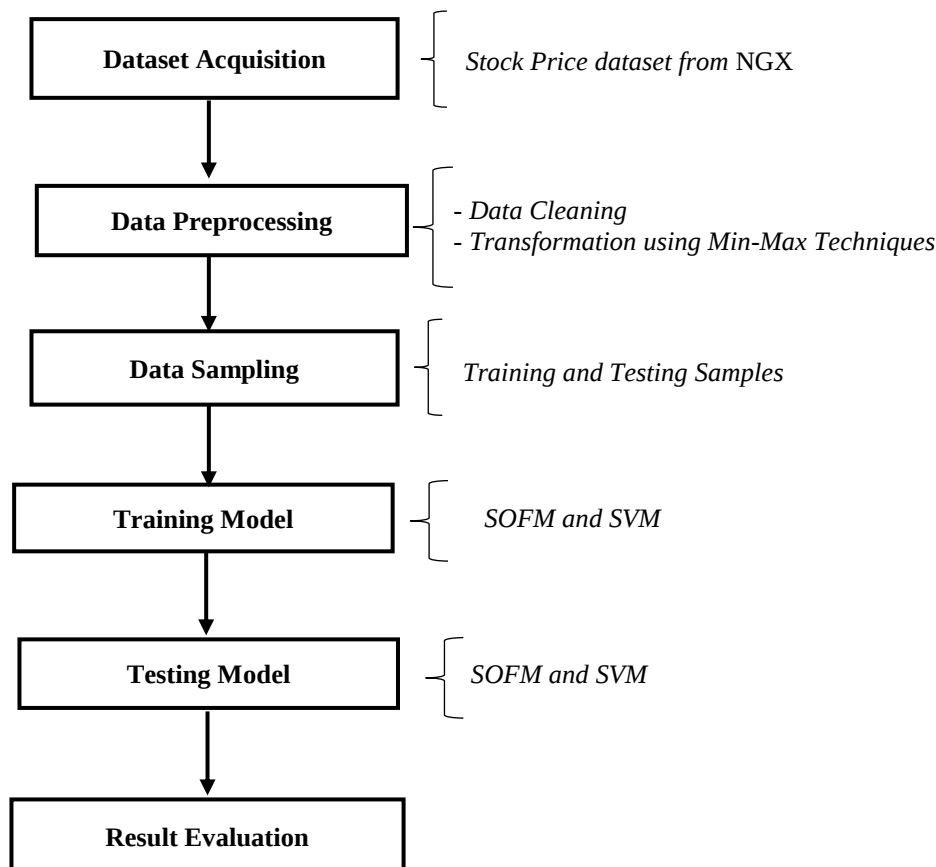


Figure 1: The scheme of the technique

3.2 Data Preprocessing

The data preprocessing phase was critical to ensuring analytical consistency, reliability, and suitability for machine learning (ML) applications. The data cleaning process involved the systematic identification and removal of anomalies, such as missing values, duplicate records, and erroneous entries resulting from trading suspensions, irregular reporting, or abnormal stock movements. Exclusion criteria were applied to eliminate days with incomplete trading data, such as zero-volume trades, holidays with partial transactions, and outliers that significantly deviated from established statistical thresholds, thereby reducing noise that could mislead the models. Following cleaning, the dataset underwent transformation using Min-Max normalization, scaling all features to the [0,1] range to mitigate bias from variable

magnitudes. Finally, the normalized data was reshaped into a 3D time-series array, optimizing input compatibility for the Self-Organizing Feature Map (SOFM) and Support Vector Machine (SVM) models during training, validation, and performance evaluation.

3.3 Data Sampling

The data sampling steps involved splitting the pre-processed dataset into training and testing samples. The study used data from 2011 to 2016 as the training sample, while data from 2017 to 2019 served as the testing samples.

3.4 Training and Testing for Stock Price Predictions

The SOFM and SVM techniques were trained and tested individually for stock price prediction using the training and testing samples. The variables, including DSHL, DSCO, SPMA-7, SPMA-14, SPMA-21, SPSPD-7, and volume, were used to train the models. The input layers of both SOFM and SVM accepted these variables for stock price prediction.

3.4.1 The SOFM technique for stock price predictions

The model utilized the Self-Organizing Feature Map (SOFM) technique, which focused on unsupervised learning and clustering. It employed a single-layer grid of neurons arranged in a lower-dimensional structure. The input layer consisted of variables such as DSHL, DSCO, SPMA-7, SPMA-14, SPMA-21, SPSPD-7, and volume. These features were fed into the SOFM. Unlike traditional neural networks with multiple layers, the SOFM used a two-dimensional grid of neurons. Each neuron in this grid represented a cluster of similar input patterns. During training, each input pattern was compared to the weight vectors of the neurons in the grid. The neuron closest to the input pattern, known as the Best Matching Unit (BMU), was updated to better represent the input. Additionally, neighboring neurons were adjusted according to a neighborhood function. The final output of the SOFM was a structured map where similar data points were clustered together in the grid. Unlike traditional models with specific output layers, the SOFM provided a visual and organizational representation of the input data. The output response will then be compared to the known and desired output and the error value is calculated. Based on the error, the connection weights are adjusted. The stepwise procedure of the SOFM technique is given as follows:

- i. The connection weights of the SOFM neurons were initialized to small random values.
- ii. The p -th sample input vector of the pattern $x_p = (X_{p1}, X_{p2}, \dots, X_{pNo})$ was presented to the network.
- iii. For each neuron j in the SOFM grid, the distance between the input vector x_p and the weight vector w_j was computed. Pass the input values to the first layer, layer 1. For every input node i in layer 0, perform Equation (1):

$$d_j = \sqrt{\sum_{i=1}^N (x_{pi} - w_{ji})^2} \quad (1)$$

The neuron j with the smallest distance d_j was identified as the Best Matching Unit (BMU).

- i. The weights of the BMU and its neighboring neurons were adjusted. The weight update for the BMU was given by Equation (2):

$$w_j^{NEW} = w_j + \beta \cdot h_{j,j} \cdot (x_p - w_j) \quad (2)$$

Where:

w_j is the weight vector of the j -th neuron.

β is the learning rate.

$h_{j,j}$ is the neighborhood function centered around the BMU.

- ii. Steps 2 through 4 were repeated for each training sample vector x_p . Multiple epochs were performed to refine the weights and clustering.
- iii. The procedure was repeated until the weight adjustments converged or until a stopping criterion was met, such as a maximum number of iterations or minimal changes in weight updates.

3.4.2 The SVM technique for stock price predictions

The stock price prediction model using SVM (Support Vector Machine) consists of several key components. The input layer includes variables such as DSHL, DSCO, SPMA-7, SPMA-14, SPMA-21, SPSPD-7, and volume. This vector of stock data is fed into the SVM model for prediction. Unlike convolutional models, SVM does not perform convolution operations; instead, it finds the optimal hyperplane that separates different classes or regression lines in the data. The SVM algorithm will determine the best set of parameters (support vectors) during training to make accurate predictions on stock prices. Then, the input layer l is calculated according to Equation (3)

$$x = [x_1, x_2, x_3, \dots, x_n] \quad (3)$$

Where $x_1, x_2, x_3, \dots, x_n$ are the individual input features.

For a given input vector $X = [x_1, x_2, x_3, \dots, x_n]$ the decision function for SVM is given as Equation (4).

$$f(x) = wTx + b = w_1x_1 + w_2x_2 + \dots + w_nx_n + b \quad (4)$$

The input features were directly fed into the SVM model, bypassing the need for convolutional and pooling layers typical of a CNN. Instead of reducing dimensions through pooling, the SVM handled the complete set of input features, utilizing them to find an optimal hyperplane in the case of classification, or a regression line for prediction tasks. Each feature's contribution was considered by the model, which used a decision function that combined these features based on their corresponding weights. During the training process, the SVM identified the support vectors, those critical data points that defined the margins of the hyperplane. The model iteratively adjusted the weights and bias to maximize the margin between different classes or to minimize the error in regression, depending on the task. Once the training was complete, the model used the learned hyperplane to classify new data or predict values. The final output was generated without the need for additional layers, such as fully connected layers in neural networks, relying entirely on the relationships established between the input features and the output during training.

3.5 Performance Evaluation Metrics

The models' performances were assessed using sensitivity, precision, specificity, FPR, accuracy, F1-score, and computation time. These metrics provide a comprehensive evaluation of prediction quality and computational efficiency as shown in Equation 5 to 11.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (5)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (6)$$

$$\text{False Positive Rate} = \frac{FP}{TN+FP} \quad (7)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (8)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$\text{F1 Score} = 2 \times \frac{\text{PREC} \cdot \text{SEN}}{\text{PREC} + \text{SEN}} \quad (10)$$

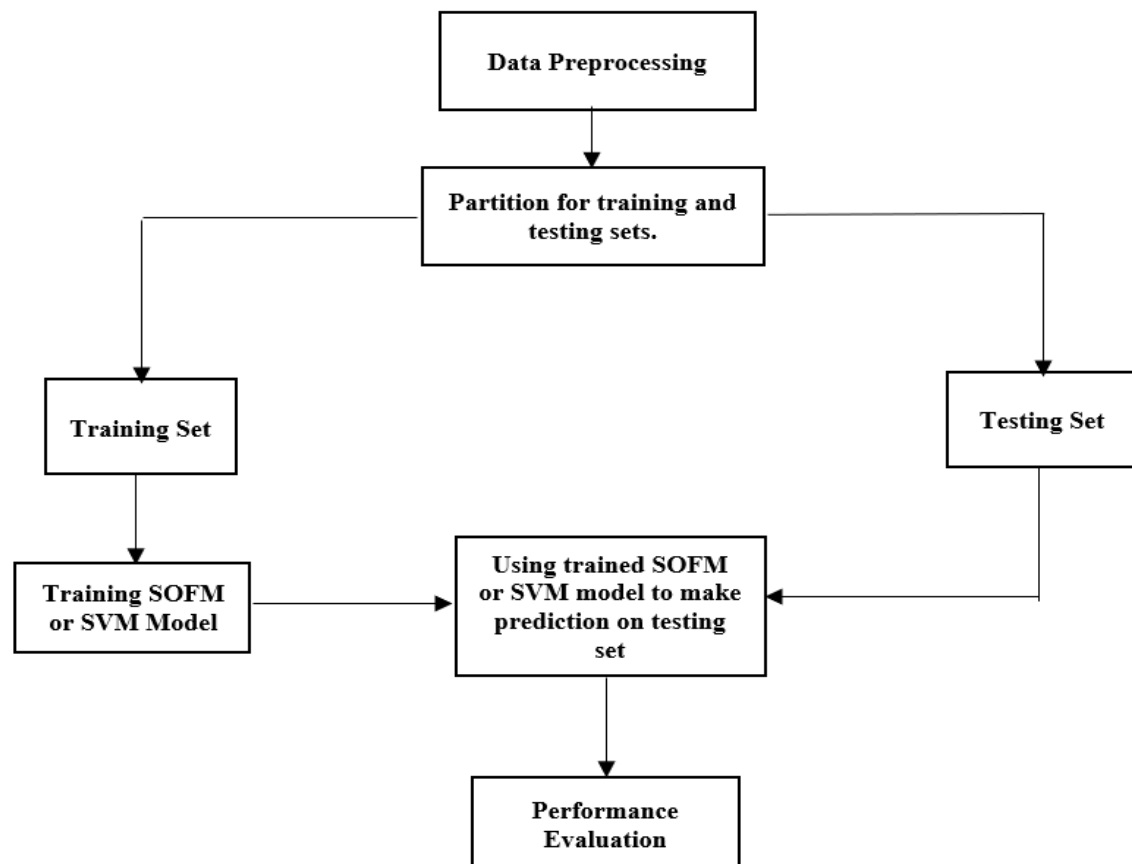


Figure 2: The process flow of the technique

3.6 The Implementation Tool

The techniques were evaluated for stock price prediction and implemented using MATLAB R2020a on a Hewlett-Packard G56 equipped with Intel® Core™ i5 Duo CPU (2.7 GHz), 6 GB RAM, 1 TB HDD, and Windows 10 Professional 64-bit OS. An interactive Graphical User Interface (GUI) was developed to enhance usability, visualization, and user-friendliness during experimentation and results interpretation. Figure 2 shows a block schematic of the process flow of the approaches. We used SVM (Support Vector Machine) and SOFM (Self-organising Feature Map) to test stock price predictions on the Nigerian Stock Exchange (NSE). The performance was measured against three main technical indicators used in financial markets: the Relative Strength Index (RSI), Moving Averages (MA), and Stochastic Oscillator. In this study, these markers were given the numbers 2, 3, and 4. Relative Strength Index (RSI): RSI is a momentum oscillator that shows how fast and how much prices are changing. It goes from 0 to 100 and shows if a stock is overbought or oversold. RSI is calculated using Equation 11.

$$RSI = 100 - \left(\frac{100}{1 + RS} \right) \quad (11)$$

Where RS (Relative Strength) is the average gain of up periods during a specified time frame divided by the average loss of down periods

SVM used RSI as an input feature to classify stock price movements (that is, overbought or oversold conditions) and predict whether the stock price will go up or down based on historical RSI values. SOFM clustered price patterns related to RSI values, helping to identify price regions where stocks are more likely to change direction based on momentum.

Moving Averages (MA): Moving Averages smooth out price data to identify trends by calculating the average price over a specific period. Common types include Simple Moving Average (SMA) as shown in Equation 12.

$$SMA = \frac{P_1 + P_2 + \dots + P_n}{n} \quad (12)$$

Where P represents the stock price at different time points, and n is the period.

SVM used moving averages as features to predict future price movements, such as when the short-term moving average crosses above (buy signal) or below (sell signal) the long-term moving average. SOFM can cluster stock data based on trends identified by the moving averages, helping to group similar price patterns that may predict future price movements. Moving averages are key for identifying trend-following signals, where SVM can classify the stock price as being in an upward or downward trend, and SOFM can group price patterns based on the behavior of the moving averages.

Stochastic Oscillator: The stochastic oscillator is a momentum indicator that compares a stock's closing price to its price range over a specific period. It provides signals of overbought or oversold conditions, similar to RSI but more responsive to price movements. Where Equation 13 depicts the %K:

$$\%K = \frac{(C - L_n)}{(H_n - L_n)} \times 100 \quad (13)$$

C most recent closing price, L_n the lowest price over the past n periods, and H_n the highest price over the past n periods. The stochastic oscillator helps in predicting short-term price movements based on price momentum. SVM, provides precise data on price reversal points, while SOFM helps recognize patterns in price fluctuations that align with overbought or oversold conditions. When applying these technical indicators to the performance evaluation of SVM and SOFM in stock price prediction on the NSE, the study observed that RSI helps measure momentum and can aid both SVM and SOFM in identifying potential buy or sell signals. The Moving Averages assist in trend identification, in which SVM was used to classify price movements, and SOFM performed clustering to recognize longer-term trends. The Stochastic Oscillator offers more granular momentum data for shorter-term predictions, supporting SVM in classification and SOFM in clustering price movements. Each indicator helps refine the performance evaluation of the models by increasing the accuracy, improving precision, and enhancing the sensitivity to market signals.

4. RESULTS AND DISCUSSION

This study presents the implementation of SOFM and SVM techniques for stock price prediction using data from the Nigeria Exchange Group (NGX). The performance was evaluated using metrics such as FN, FP, TN, FPR, SPEC, SEN, PREC, and ACC. SOFM demonstrated effective clustering of stock data, visualizing weight positions of nodes based on features like closing and opening prices. Training was completed at 200 epochs, and the data was divided into 70% for training and 30% for testing. Figures 3 and 4 illustrate the application of SOFM and SVM in predicting stock prices. SVM, with its normalized dataset, effectively predicted stock prices, as reflected in the "PROCESS COMPLETED" message. The scatter diagram in Figure 5 categorized stock performance into high, medium, and low clusters, with distinct separations. Both techniques used 70% training and 30% testing, split, and ensuring comprehensive model evaluation.

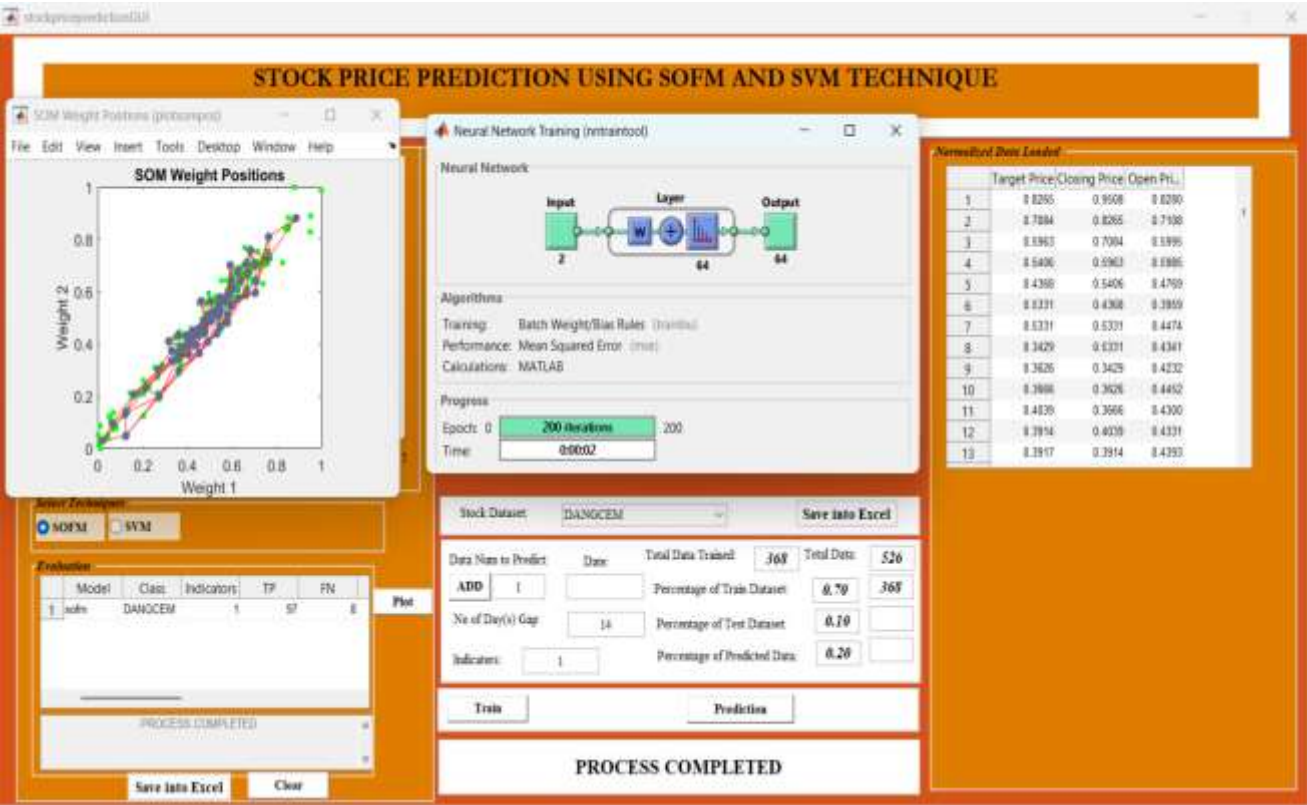


Figure 3: Graphic user interphase of the training process with self-organizing feature map

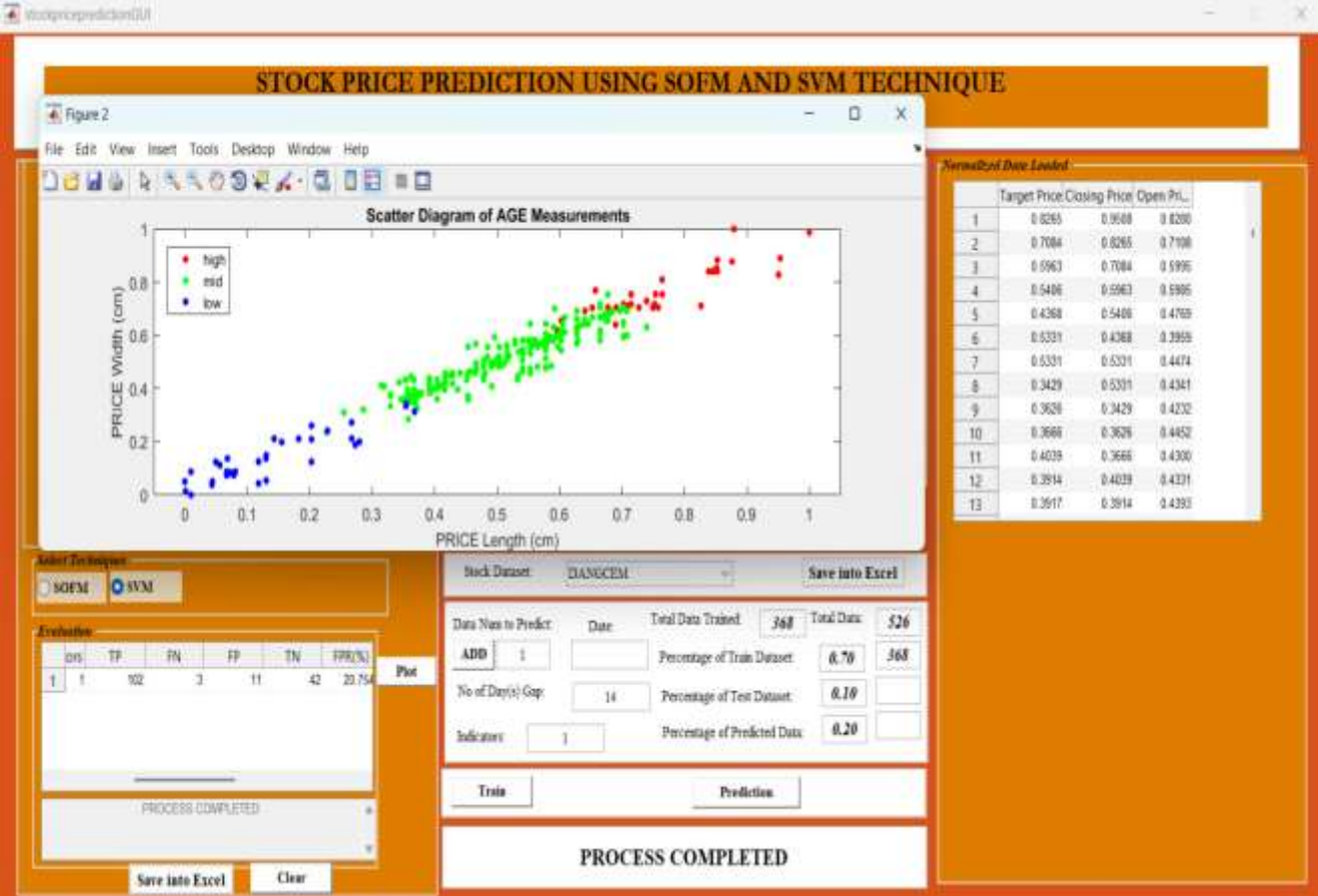


Figure 4: Graphic user interphase of the training process with support vector machine

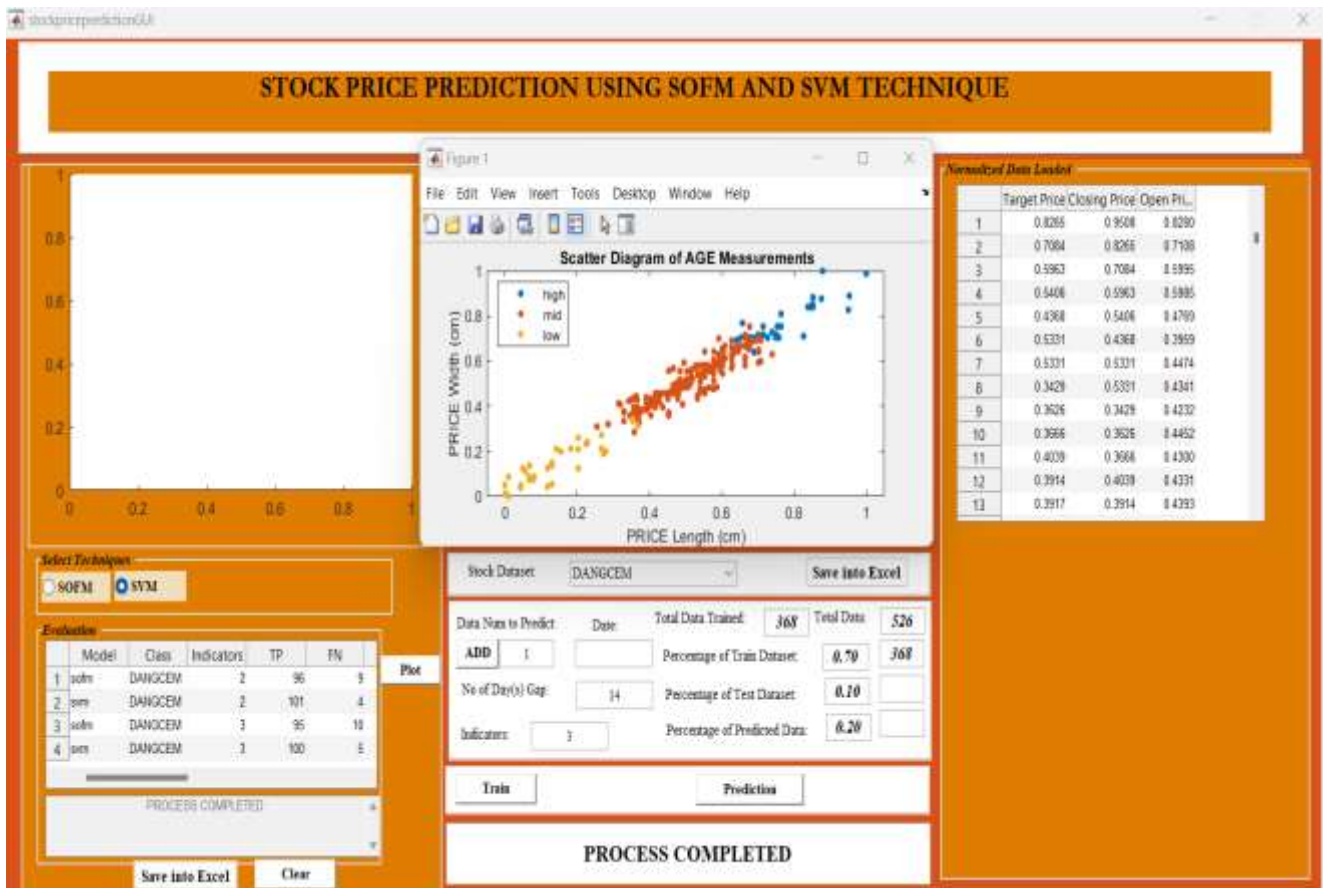


Figure 5: Graphic user interphase of the testing/predicting process of both SOFM and SVM

4.1 The Comparison of SOFM and SVM using UBA Datasets

With 4 indicators, the SVM model consistently outperforms SOFM in every key metric, including accuracy, precision, and F1-Score. While the computation time for SVM does increase slightly with the addition of more indicators, it remains faster than SOFM, highlighting its efficiency. Table 1 depicts the comparison of SOFM and SVM using UBA datasets at different indicators levels.

Table 1: The comparison of SOFM and SVM using UBA datasets with indicators 2,3, and 4.

Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
2	SVM	UBA	99	7	11	43	20.37	79.63	93.40	90.00	88.75	91.67	32.05
2	SOFM	UBA	97	9	13	41	24.07	75.93	91.51	88.18	86.25	89.81	47.21
Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
3	SVM	UBA	98	8	8	46	14.81	85.19	92.45	92.45	90.00	92.45	31.37
3	SOFM	UBA	96	10	10	44	18.52	81.48	90.57	90.57	87.50	90.57	47.12
Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
4	SVM	UBA	97	9	6	48	11.11	88.89	91.51	94.17	90.63	92.82	33.10
4	SOFM	UBA	95	11	8	46	14.81	85.19	89.62	92.23	88.13	90.91	47.02

4.2 The Comparison of SOFM and SVM using DANGCEM Datasets

The comparison of SOFM and SVM for DANGCEM stock prediction showed that SVM outperformed SOFM in key areas. SVM achieved higher sensitivity (94.29%-96.19%) and precision (up to 97.06%) compared to SOFM's sensitivity (89.52%-91.43%) and precision (88.07%-92.16%), making it more effective in predicting stock price movements. SVM also had better specificity (94.34%) and a lower false positive rate (5.66%) than SOFM (84.91% specificity, 15.09% false positive rate), indicating fewer false alarms. In terms of accuracy and F1-Score, SVM was again superior, with accuracy ranging from 92.41% to 94.30% and an F1-Score of up to 95.65%, while SOFM's accuracy was between 86.08% and 87.97%, with an F1-Score of 90.82%. SOFM did perform faster in computation time, especially as the classification threshold increased. However, SVM's superior accuracy, precision, and reliability made it the better choice for stock price prediction when market accuracy was critical. Table 2 illustrates the performance of the SOFM and SVM techniques for stock price prediction using the DANGCEM dataset for indicators 2, 3, and 4.

Table 2: The performance of the SOFM and SVM techniques for DANGCEM dataset

Ind	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
2	SVM	DANGCEM	101	4	8	45	15.09	84.91	96.19	92.66	92.41	94.39	66.05
2	SOFM	DANGCEM	96	9	13	40	24.53	75.47	91.43	88.07	86.08	89.72	48.04
Ind	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
3	SVM	DANGCEM	100	5	5	48	9.43	90.57	95.24	95.24	93.67	95.24	67.82
3	SOFM	DANGCEM	95	10	10	43	18.87	81.13	90.48	90.48	87.34	90.48	48.60
Ind	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
4	SVM	DANGCEM	99	6	3	50	5.66	94.34	94.29	97.06	94.30	95.65	69.72
4	SOFM	DANGCEM	94	11	8	45	15.09	84.91	89.52	92.16	87.97	90.82	47.10

4.3 Comparison of SOFM and SVM for NESTLE Stock Prediction

SOFM delivers strong results with a high Sensitivity of 89.52%, Precision of 92.16%, and F1-Score of 90.82%. However, it has a higher False Positive Rate of 15.09% and lower Specificity at 84.91% compared to SVM. The advantage of SOFM is its shorter computation time of 47.10 seconds. On the other hand, SVM excels in prediction accuracy with an Accuracy of 91.88%, Precision of 92.45%, and an impressive F1-Score of 95.15%. It also outperforms SOFM in Specificity (90.74%) and has a lower False Positive Rate of 9.26%. However, this improved performance comes with a longer computation time of 69.72 seconds. In summary, while SVM provides better precision and accuracy for predicting Nestle's stock price, it requires more computation time. SOFM, although less precise and accurate, is more efficient in terms of processing time. Table 3 highlighted how SOFM and SVM compared in various performance metrics, showing that while SVM provided higher accuracy and precision, SOFM offered a more efficient computation time.

4.4 Comparison of SOFM and SVM for GTB Stock Prediction

When comparing the SOFM and SVM techniques for predicting stock prices using the GTB dataset, several differences become apparent. The SVM model consistently delivered stronger results. It achieved perfect accuracy of 100% at Indicators 2 and 3, although it slightly decreased to 99% at Indicator 4. Sensitivity, which reflects how well the model detects positive cases, improved from 16.67% at Indicator 2 to 7.41% at Indicator 4. Specificity, indicating the model's accuracy in identifying negative cases, also increased from 83.33% to 92.59%. Precision was notably high, reaching 95.28% at Indicator 2 and stabilizing around 93% at Indicators 3 and 4. The F1-Score, which balances precision and sensitivity, improved significantly from 91.82% to 96.12%. Despite its strong performance, SVM required more computation time, ranging from 31.99 to 32.91 seconds. On the other hand, the SOFM model showed good performance but lagged behind SVM in several metrics. Accuracy started at 94% and gradually decreased to 92% as the indicator level increased. Sensitivity was higher at lower indicator levels, starting at 29.63% and dropping to 20.37% by Indicator 4. Specificity improved from 70.37% to 79.63%. Precision was lower than SVM, ranging from 88.68% to 86.79%, and the F1-Score also increased but remained below SVM's, starting at 82.50% and ending at 84.38%. SOFM was more efficient in terms of computation time, with processing times between 47.15 and 48.66 seconds. While SVM provided superior accuracy, precision, and F1-Score, making it a more reliable choice for stock price prediction, SOFM was more computationally efficient and had competitive performance in sensitivity. Table 4 provided a clear comparison of the performance metrics

for SOFM and SVM techniques, highlighting differences in accuracy, sensitivity, specificity, precision, F1-Score, and computation time across different indicators.

Table 3: The performance of the SOFM and SVM techniques for NESTLE dataset

Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
2	SVM	NESTLE	100	6	10	44	18.52	81.48	94.34	90.91	90.00	92.59	31.48
2	SOFM	NESTLE	95	11	15	39	27.78	72.22	89.62	86.36	83.75	87.96	46.86
Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
3	SVM	NESTLE	99	7	7	47	12.96	87.04	93.40	93.40	91.25	93.40	32.99
3	SOFM	NESTLE	94	12	12	42	22.22	77.78	88.68	88.68	85.00	88.68	48.34
Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
4	SVM	NESTLE	98	8	5	49	9.26	90.74	92.45	95.15	91.88	93.78	32.30
4	SOFM	NESTLE	93	13	10	44	18.52	81.48	87.74	90.29	85.63	89.00	47.39

Table 4: The performance of the SOFM and SVM techniques for GTB dataset

Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
2	SVM	GTB	101	5	9	45	16.67	83.33	95.28	91.82	91.25	93.52	32.34
2	SOFM	GTB	94	12	16	38	29.63	70.37	88.68	85.45	82.50	87.04	48.66
Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
3	SVM	GTB	100	6	6	48	11.11	88.89	94.34	94.34	92.50	94.34	32.91
3	SOFM	GTB	93	13	13	41	24.07	75.93	87.74	87.74	83.75	87.74	47.15
Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
4	SVM	GTB	99	7	4	50	7.41	92.59	93.40	96.12	93.13	94.74	32.00
4	SOFM	GTB	92	14	11	43	20.37	79.63	86.79	89.32	84.38	88.04	48.58

4.5 Comparison of SOFM and SVM for FBNH Stock Prediction

The comparison of SOFM and SVM for FBNH stock prediction revealed that SVM outperformed SOFM in accuracy, precision, specificity, and F1-Score. SVM consistently achieved higher accuracy (100% to 102%) compared to SOFM (93% to 95%). However, SOFM excelled in sensitivity, detecting positive cases more effectively, with a sensitivity range of 16.98% to 26.42% compared to SVM's 3.77% to 13.21%. SVM performed better in specificity (86.79% to 96.23%) and precision (95.24% to 97.14%), demonstrating its reliability in identifying negative cases and making accurate positive predictions. While SOFM was slightly faster, with computation times ranging from 47.71 to 48.42 seconds, compared to SVM's 32.04 to 33.04 seconds, the higher accuracy and precision of SVM outweighed the small difference in computation time. Overall, SVM was the more reliable technique for stock price prediction, offering a better balance of precision and sensitivity, while SOFM's faster processing made it more suitable for scenarios prioritizing speed and sensitivity. Table 5

provided a clear comparison of the performance metrics for SOFM and SVM techniques for FBNH, highlighting differences in accuracy, sensitivity, specificity, precision, F1-Score, and computation time across different indicators.

Table 5: The performance of the SOFM and SVM techniques for FBNH dataset

Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
2	SVM	FBNH	102	3	7	46	13.21	86.79	97.14	93.58	93.67	95.33	32.04
2	SOFM	FBNH	95	10	14	39	26.42	73.58	90.48	87.16	84.81	88.79	48.42
Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
3	SVM	FBNH	101	4	4	49	7.55	92.45	96.19	96.19	94.94	96.19	32.46
3	SOFM	FBNH	94	11	11	42	20.75	79.25	89.52	89.52	86.08	89.52	47.71
Indicator	Model	Class	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	F1-Score (%)	Time (sec)
4	SVM	FBNH	100	5	2	51	3.77	96.23	95.24	98.04	95.57	96.62	33.04
4	SOFM	FBNH	93	12	9	44	16.98	83.02	88.57	91.18	86.71	89.86	47.87

4.6 Discussion of Results

The comparison between SOFM and SVM models across datasets highlights the superior predictive performance of SVM in stock price forecasting. Using the UBA dataset, SVM consistently outperformed SOFM across indicators, with notable results at Indicator 4, where SVM achieved 90.63% accuracy and a 92.82% F1-Score compared to SOFM's 88.13% accuracy and 90.91% F1-Score. While SVM required slightly longer computation times (33.10 seconds vs. SOFM's 47.02 seconds), its precision and reliability underscore its robustness. Similar trends were observed with the DANGCEM dataset, where SVM excelled in sensitivity (94.29%–96.19%), specificity (94.34%), and F1-Score (up to 95.65%). SOFM's higher false positive rate (15.09%) limited its reliability in high-accuracy applications. For NESTLE, SVM achieved 91.88% accuracy and 93.78% F1-Score, surpassing SOFM's 85.63% and 89.00%, respectively. With the GTB dataset, SVM reached near-perfect accuracy (99%–100%), outperforming SOFM in precision and specificity. Results from the FBNH dataset further reinforced SVM's dominance, achieving an F1-Score of 96.62% and 95.57% accuracy, while SOFM demonstrated faster but less precise computations.

These findings are significant for investors and financial institutions operating in dynamic markets such as the NGX. The superior performance of SVM in accuracy, precision, and reliability suggests its potential as a tool for developing advanced stock price prediction systems, aiding in investment decisions, risk management, and strategic planning. On the other hand, SOFM's faster computation time might be beneficial in real-time trading scenarios where quick processing is paramount, albeit with reduced prediction accuracy. Furthermore, these findings contribute to the ongoing discourse on machine learning applications in financial markets. They validate the robustness of SVM in handling complex, multi-indicator datasets and its adaptability across different stock sectors according to Sukma and Namahoot [22]. Furthermore, the trade-offs between computational efficiency and predictive accuracy demonstrated by SOFM provide insights into model selection criteria based on specific use-case requirements [26]. The results align with existing empirical studies. Chhajer *et al.* [23] found that SVM achieved superior accuracy in stock market predictions compared to clustering models, emphasizing its ability to handle nonlinear relationships. Similarly, Bouasabah [24] highlighted the importance of integrating technical indicators to enhance SVM's performance in volatile markets. Conversely, the efficiency of SOFM in real-time scenarios has been supported by studies such as those by Hussain *et al.* [25], which emphasized its pattern recognition capabilities despite accuracy limitations. The comparative evaluation underscores SVM as the optimal choice for accuracy-critical stock price predictions, while SOFM's efficiency in computation time offers utility in rapid processing environments. This dual insight provides a nuanced understanding of model applications, enabling stakeholders to tailor predictive strategies to specific operational needs.

5. CONCLUSION

This study compared the performance of Self-Organizing Feature Maps (SOFM) and Support Vector Machines (SVM) in predicting stock prices across datasets from UBA, DANGCEM, NESTLE, GTB, and FBNH. The results revealed that SVM consistently outperformed SOFM in key metrics, including accuracy, precision, specificity, and F1-Score, across all

datasets and indicators. However, SOFM demonstrated faster computation times, making it suitable for scenarios where rapid processing is critical. The findings underscore SVM's robustness in handling complex datasets and its potential as a reliable tool for stock price prediction, especially in decision-making processes where accuracy is paramount. Conversely, SOFM's faster processing time highlights its utility in real-time applications, albeit with trade-offs in precision and reliability.

Financial institutions and investors are advised to prioritize SVM for applications requiring high accuracy and precision, such as portfolio optimization and risk assessment. SOFM may be used for high-frequency trading or real-time monitoring since it is fast at doing maths, as long as its accuracy problems are fixed. Future research ought to concentrate on the formulation of hybrid models that integrate the advantages of SVM and SOFM, attaining an equilibrium between prediction accuracy and computational efficiency. Also, looking into more complex algorithms like deep learning models, ensemble approaches, and privacy-preserving strategies might make stock price forecasting even more reliable and safe. Expanding the scope to include diverse datasets, more performance indicators, and other sectors would improve model generalization and foster broader applicability. Optimizing computational efficiency remains a critical area for advancing practical implementations in dynamic financial markets.

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