

Generating Trading Strategy Using Candlesticks Pattern with Machine Learning

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ABSTRACT

The proposed work considered to implementing a multiple-day trading strategy using ML algorithms that integrate candlestick patterns and technical indicators on the Nigerian Stock Exchange stock prices from 2013 to 2023. The results obtained from different models, including Linear Regression, Ridge Regression, Support Vector Regressor (SVR), K-Nearest Neighbors (KNN), and Decision Tree, were compared to find the best model with the highest potential to generalize well on future stock prices. The various algorithms were implemented in Python 3.10 alongside other important third-party packages such as Pandas, TA-Lib, Scikit-learn, and Skforecast. These packages were utilized for the various data tasks needed for this research. The data was cleaned and thoroughly explored before performing feature engineering, such as generating candlestick patterns and appending technical indicators like Simple Moving Average (SMA), Exponential Moving Average (EMA), and Volume Rate of Change (VROC). The data was split into train, validation, and test sets to avoid data leakage. Additionally, the various features underwent transformations, including standardization, before being passed to the algorithms for training and evaluation.

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INTRODUCTION

The origins of candlestick patterns can be traced to rice traders in 18th-century Japan, who invented these visual representations of price changes (Lin et al., 2021). The framework for comprehending how candlestick patterns could include important information about market emotion and future price reversals was laid by Munehisa Homma's groundbreaking work (Homma, 2017). Later contributions from Western analysts, most notably Steve Nison, helped candlestick analysis spread and become more widely used across cultures (Cagliero et al., 2020; Hu et al., 2015, 2018 & 2019). Analysing and forecasting the stock market is notoriously tricky due to the high degree of noise and semi-strong form of market efficiency, which is generally accepted. A reasonably accurate prediction may raise the potential of yielding benefits and hedging against market risks. However, financial

economists often question the existence of opportunities for profitable predictions. Technical analysis, also called candlestick charting, is one of the most common traditional analysis methods to predict the financial market (Hu et al., 2019).

Statement of the problem

Candlestick patterns are well-known as useful indications for trading decisions in the world of financial markets. These patterns, which graphically depict price changes over particular time periods, provide perceptions of probable market reversals, trends, and investor mood. However, the traditional method of using candlestick patterns in trading techniques mostly relies on human interpretation, which incorporates subjectivity, consistency, and emotional biases into the decision-making process. Because of the inherent limitations of human perception, it is extremely difficult for traders and investors to

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consistently spot and take advantage of good trading opportunities. Additionally, the characteristics of the financial markets are always shifting, causing trends, volatility, and susceptible to change quickly. Traditional candlestick pattern-based trading strategies frequently don't have the flexibility needed to react to these changeable market conditions efficiently, which results in subpar performance and missed chances. Utilizing machine learning's capabilities is crucial for overcoming these obstacles and improving the performance of candlestick pattern-based trading systems. Huge amounts of historical market data can be analyzed using machine learning algorithms, which have also shown the ability to spot trends and produce trading strategies that are informed by the analysis of the data. Machine learning can decrease subjectivity, increase consistency, and respond more quickly to shifting market dynamics by automating the process of recognizing and acting on candlestick patterns (Luca et al., 2023).

The problem at hand revolves around the need to develop a robust and reliable trading strategy that combines the insights from candlestick pattern analysis with the predictive power of machine learning algorithms. While Luca et al. (2023) proposed a method to filter machine learning-based recommendations using recognized graphical patterns for next-day stock trading, the study identifies a research gap in extending this approach to support multiple-day trading.

Aim and Objectives of the Study

The aim of this research is to design and implement a multiple-day trading strategy generation framework that integrates candlestick pattern with machine learning using the Nigerian stock market.

The aim of this study is to design a social media complaint management system that captures third party engagement. Objective of this study is to:

1. Identify and categorize a comprehensive set of candlestick patterns commonly used in technical analysis and use logistic regression,

random forest, and Gradient boosting models for pattern recognition and predictive modeling.

2. Improve the performance of the existing candlestick trading model by considering additional technical indicators (Moving Average, Volume rate, and Exponential Moving average).
3. Evaluate the proposed framework against the existing work using an accuracy and precision performance metrics.

CONCEPTUAL REVIEW

The research community has already investigated combining machine learning and pattern recognition to solve next-day stock price prediction in order to "take the best from the two worlds." For instance, Kamo and Dagli (2009) suggested a fuzzy logic-based gating network that accepts information regarding candlestick patterns as input. To train feed-forward neural networks and support vector machines, respectively, Jasemi et al. (2011) and Ahmadi et al. (2018) introduced approaches that extract features from candlestick charts. An auto-regressive time series forecasting model with ordered fuzzy candlestick patterns was integrated by Marszalek and Burczynski (2014). Hsu (2020) explored predictability in match outcomes using machine learning and candlestick charts, which have been used for stock market technical analysis. He compiled candlestick charts based on betting market data and considered the character of the candlestick charts as features in the predictive model rather than the performance indicators used in the technical and tactical analysis in most studies.

Lin et al. (2021) on the other hand used PRML, a novel candlestick pattern recognition model using machine learning methods to improve stock trading decisions. Four popular machine learning methods and 11 different feature types are applied to all possible combinations of daily patterns to start the pattern recognition schedule. Different time windows from one to ten days are used to detect the prediction effect at different periods. An investment strategy is constructed

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according to the identified candlestick patterns and suitable time window. We deploy PRML for the forecast of all Chinese market stocks from Jan 1, 2000, until Oct 30, 2020.

METHODOLOGY

This section proposes a comprehensive methodology for generating a trading strategy based on candlestick patterns using machine learning techniques. By fusing traditional technical analysis with advanced algorithms, the proposed approach aims to enhance trading decision-making, increase automation, and provide a

systematic framework for exploiting potential market inefficiencies. The research proposes a multiple day trading strategy and considers more technical indicators for efficiency as opposed to (Luca et al, 2021), who developed a trading strategy for the next day alone.

Methodology of the proposed framework

The proposed framework in generating a trading strategy using candlestick patterns with machine learning typically involves several key steps, here we shall be looking at the steps that would be adopted for this research:

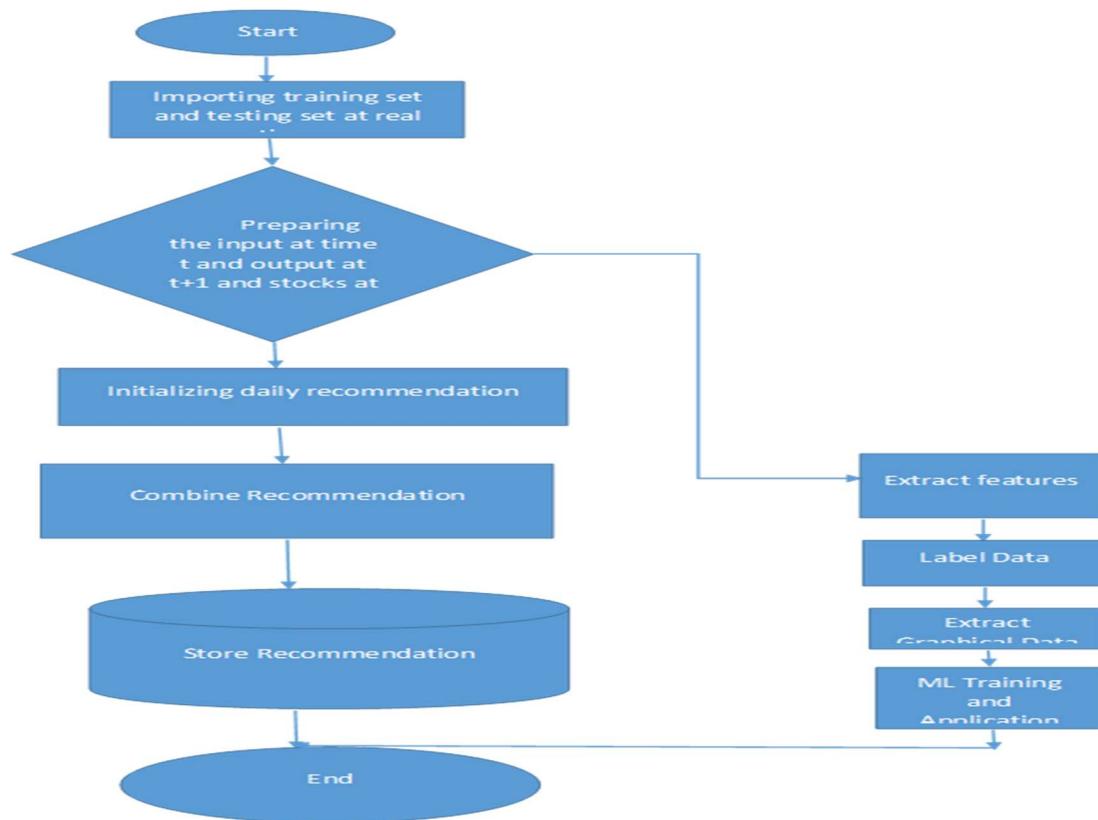


Figure 1: Proposed Flowchart

Candlestick Pattern Recognition

This module takes as input the daily candlestick chart representing the historical stock

prices. It generates per-stock direction recommendations (uptrend, downtrend, and flat) based on technical analysis fundamentals.

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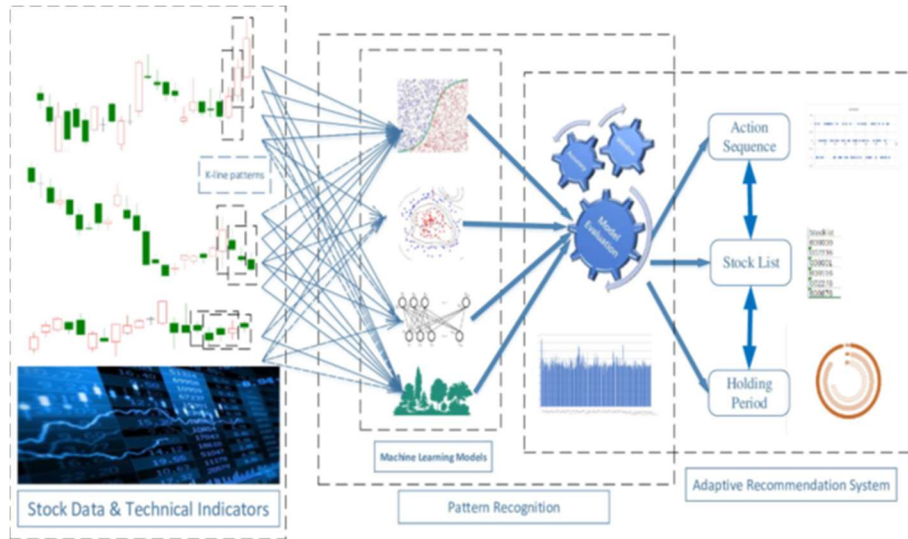


Figure 2: A schematic showing the flow of ML stock model. Source: (Lin et al.,2021)

Data Collection Technique

The initial step involves the collection and pre-processing of historical price data. This data includes open, high, low, and close prices for a given asset, typically represented as candlesticks. These candlesticks encapsulate valuable information regarding price trends, reversals, and market sentiment. The data is then cleaned, normalized, and transformed into appropriate input formats for machine learning models.

Dataset Splitting

The dataset will be Split into training, validation, and testing sets to evaluate model performance accurately.

Prediction models

We shall use Decision Tree, Ridge regression, SVR, Lasso and KNN models due to their robustness, flexibility, and ability to handle complex relationships in data. Although Luca et al.(2023) used SVM only, Random Forest, Logistic regression and Gradient Boosting models have been used in similar by Lin et al.(2021) for one day data and it gave good results Besides, using numerous models will give us the opportunity to choose the most effective one.

Training the Model

Train the machine learning model using the training dataset. Optimize hyper-parameters to enhance model performance.

Testing and Validation

Assess the model's performance on the testing dataset to simulate real-world trading conditions. Validate the trading strategy using out-of-sample data.

Moving average (MA)

A moving average (MA) is a calculation that examines data points by averaging numerous subsets of the entire data set. The formula for calculating (MA) is.

$$MA(t) = \frac{1}{m} \sum_{i=0}^{m-1} c_{i-1} \quad \dots (1)$$

Exponential moving average (EMA)

An exponential moving average (EMA) is a first-order infinite impulse response filter that applies weighting factors, which decrease exponentially. The calculation formula is:

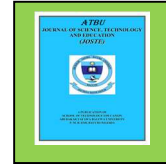
$$EMA(t) = \frac{2}{n+1} c_t + \frac{n-1}{n+1} EMA(t-1) \quad (2)$$

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Where n refers to the time interval

Volume rate of change

The volume rate of change (ROC) shows the changes in volume. The formula is given by;

$$ROC(t) = \frac{v_t}{\frac{1}{x} \sum_{i=0}^x v_{t-1}} \dots (3)$$

Where x refers to the time interval and V_t refers to the volume at time t .

Dataset Description

The data set in the appendix table are described below with the following such as dimensions, features and availability.

Dimensions:

The dataset has a time dimension, with each row representing a specific date. In this case, the time range is from January, 2013, to December, 2023.

Features:

Date: The date for which the stock prices are recorded.

Price: The closing price of Dangote Cement stock on the given date.

Open: The opening price of the stock on the given date.

High: The highest price reached by the stock during the trading day.

Low: The lowest price reached by the stock during the trading day.

Vol.: Volume, representing the total number of shares traded on the given date.

Change %: The percentage change in stock price compared to the previous day.

Features Availability:

1. Complete Data: the columns have complete data for each date, indicating that there are no missing values for the recorded features.

2. Variety of Information: The dataset includes information on stock prices (open, high, low, and closing), trading volume, and percentage change.

Additional Considerations:

Outliers: Check for any extreme values or outliers in the dataset that may affect the analysis.

Data Types: Ensure that the data types of each column are appropriate for analysis (e.g., dates as datetime objects, prices as floats, volume as integers).

Data Cleaning: this will be performed by cleaning the dataset before analysis.

Experiment Setup

The data preparation and analysis were conducted using Python version 3.10, along with other important third-party packages, such as Pandas, Pandas_ta, TA-Lib, Scikit-learn, and Skforecast. The Pandas library was used for data cleaning, manipulation and analysis, while Pandas_ta and TA-Lib were used for candlestick pattern detection and technical analysis. Scikit-learn were employed for machine learning modeling and evaluation, and Skforecast was used for multi-step recursive time series forecasting and prediction. The data preparation and analysis involved handling missing values and data normalization, generating candlestick patterns for prediction, calculating simple moving averages and other technical indicators, transforming data into suitable formats for modeling, and dividing the data into training and testing sets for model evaluation. This thorough data preparation and analysis enabled the effective preparation and evaluation of the models' performance.

Stock Analysis

Before conducting the experiment, the OHLC data was explored to gain valuable insights into the stock's behavior.



Figure 3: Daily Price Trend

Figure 3 displays the Open, High, Low, and Close prices for each trading day from 2013 to 2023. A visual examination of the data shows significant volatility in the stock price over this period, with a noticeable upward trend majorly

towards the end of the period. In 2023, the stock price experienced a sharp increase, with the High price reaching its highest level in the observed period.

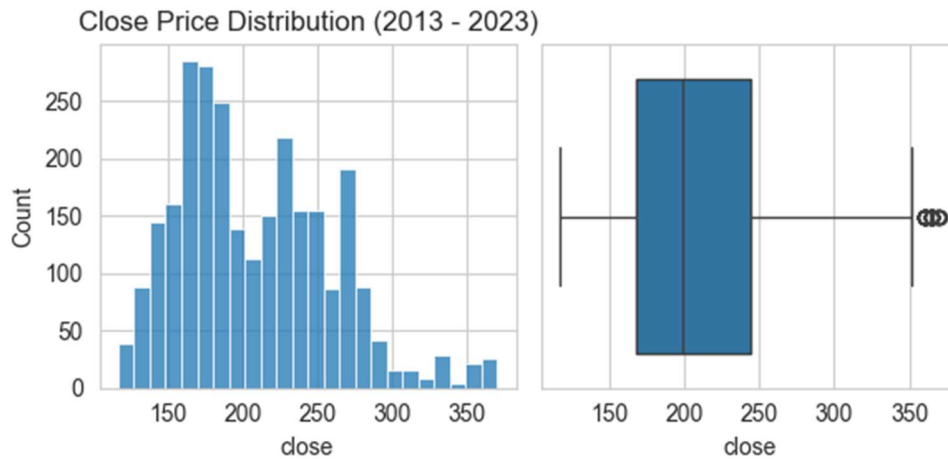


Figure 4: Close Price Distribution

Figure 4 shows the distribution of the stock's Close price over the same decade. The data reveals that the Close price rarely fell below 150 or above 350 during this period. However, there were a few instances where the stock price

closed within the range of 350 and above, indicating that prices in this range can be considered outliers.

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Candlestick Pattern Generation

Candlestick patterns were a crucial focus for training the machine learning algorithm. the ta-lib package, a Python wrapper for the TA-lib C library, and the pandas_ta library was used

to detect potentially 64 different candlestick patterns based on the current OHLC training data. After employing the ta-lib algorithm, 43 distinct candlestick patterns were successful identified.

Table 1: Candlestick Pattern

Candlestick Pattern	Detection
CDL_DOJI_10_0.1	105,800.0
CDL_SHORTLINE	37,800.0
CDL_LONGLEGGEDOJI	21,500.0
CDL_TAKURI	11,100.0
CDL_HANGINGMAN	11,100.0
CDL_DRAGONFLYDOJI	8,700.0
CDL_HAMMER	7,900.0
CDL_GRAVESTONEDOJI	6,500.0
CDL_CLOSINGMARUBOZU	5,200.0
CDL_MATCHINGLOW	2,900.0

Technical Indicators

In addition to candlestick patterns, three different technical indicators were incorporated as features for modeling, including Moving Average (MA), Exponential Moving Average (EMA), and Volume Rate of Change (VROC). These indicators are calculations based on past stock

price and volume data, aiming to capture trends, momentum, and volatility present in the data. These technical indicators provide insights into the underlying strength or weakness of a stock's price movement. (Figure 4.3) visualizes these technical indicators along a trend line chart for the period.

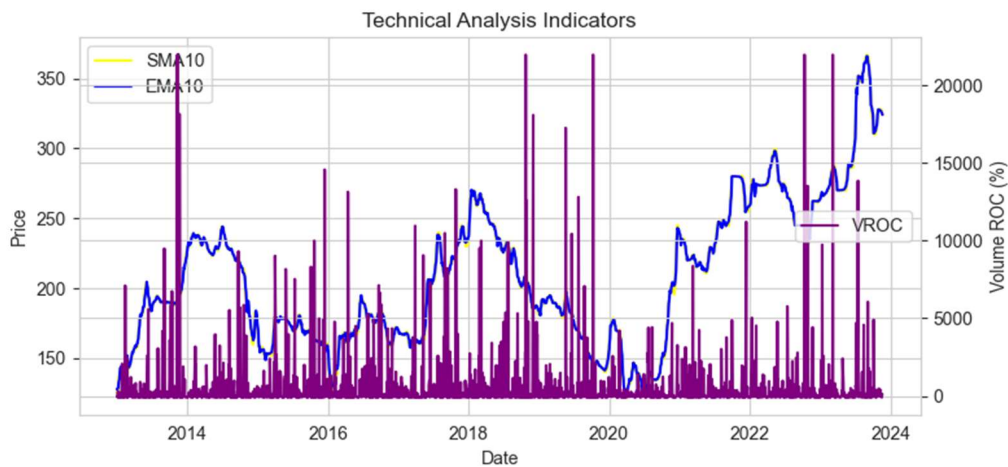


Figure 5: Technical Analysis Indicators

Feature Transformation

The project utilizes the Skforecast library, and several important transformation steps were involved to ensure the data fits the API

requirements. One crucial step was setting the date variable as the index, which helps the model efficiently access and manipulate data based on specific dates. Additionally, missing trading dates

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were added to the data to ensure all dates in the index have a corresponding data point. These new data points, initially represented as missing values (NaN), were filled using a technique known as linear interpolation, which creates a straight line between two known data points.

All features were standardized to have a mean of zero and a standard deviation of 1, primarily due to the high volatility present in the data. This process effectively centers the data and

reduces the impact of outliers. It also aims to preserve the original relationships between the features, especially between the candlestick patterns.

Data splitting

After completing feature engineering and transformation, the final OHLC data consisted of 51 features and 3,989 samples spanning a 10-year period.

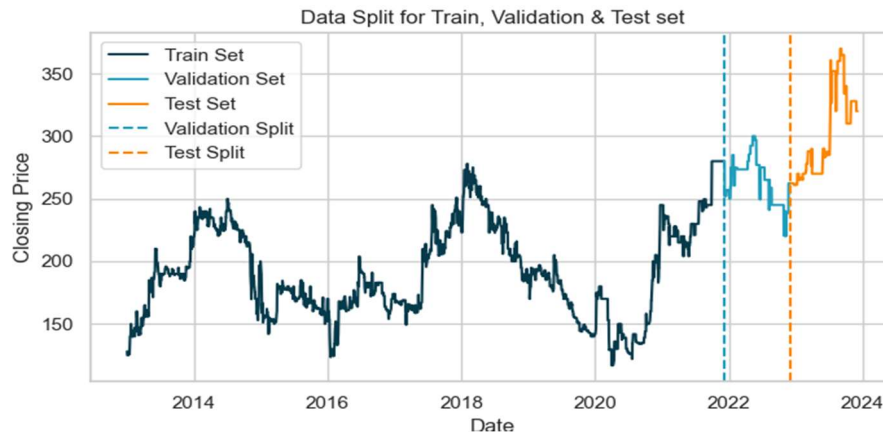


Figure 6: Data Split for Train, Validation & Test Set

The data was then split into training, validation, and testing sets. This data splitting strategy allowed for a robust evaluation of the model's performance on unseen data. The entire training set comprised 3,624 samples, ranging from 2013-01-02 to 2022-12-04. This was further

divided into a training set of 3,259 samples (2013-01-02 to 2021-12-04) and a validation set of 365 samples (2021-12-05 to 2022-12-04). The testing set also consisted of 365 samples, covering the period from 2022-12-05 to 2022-12-04.

Model Training

Default model parameters:

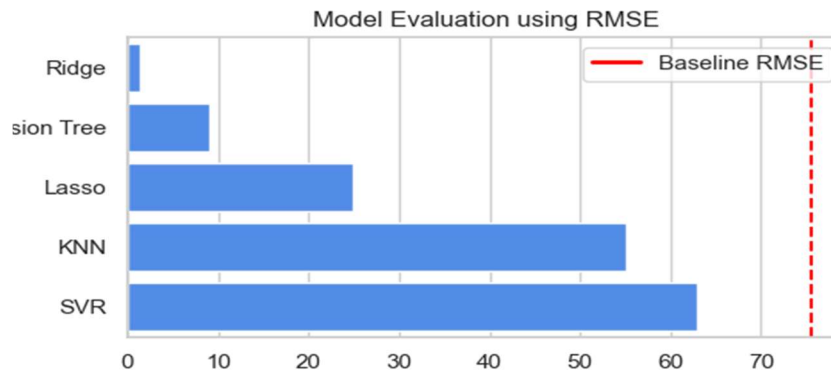


Figure 7: Model Evaluation Using RMSE

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Figure 7 shows the model performance using Root Mean Square Error (RMSE). The Ridge model performed best with an RMSE of 1.35, followed by the Decision Tree model with an

RMSE of 8.71. The Lasso, SVR, and KNN models performed poorly, with RMSE values of 24.94, 62.91, and 55.04, respectively.

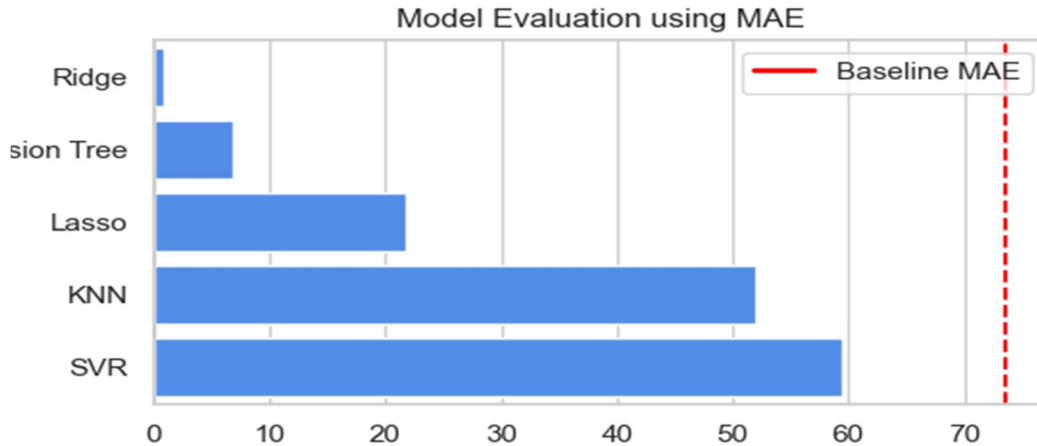


Figure 8: Model Evaluation Using MAE

The models were also evaluated using the Mean Absolute Error (MAE) metric as shown in (Figure 4.6) Again, the Ridge model performed best with an MAE of 0.76, followed by the

Decision Tree model with an MAE of 6.52. The Lasso, SVR, and KNN models performed poorly, with MAE values of 21.70, 59.45, and 51.95, respectively.

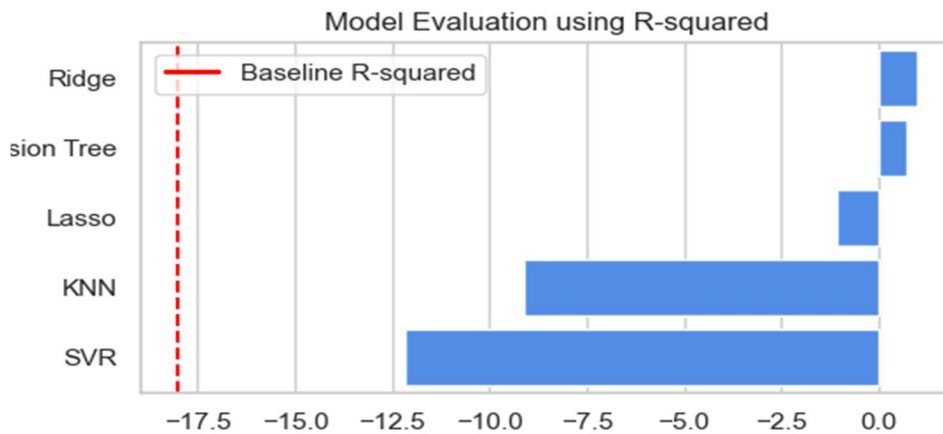


Figure 9: Model Evaluation Using R-squared

Finally, Figure 9 shows how well the models performed using the coefficient of determination (R2) metric. The Ridge model performed best with an R2 of 0.99. The Decision Tree model also performed well with an R2 of

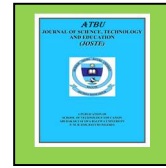
0.75. However, the Lasso, SVR, and KNN models performed poorly, with R2 values of -1.07, -12.18, and -9.09, respectively, indicating no predictive power.

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Tuned Hyperparameters

After training and evaluating the initial set of models, the Ridge and Decision Tree Regressors were selected for further hyperparameter tuning. The Ridge model was tuned using different alpha values [1.0, 5.0, 10.0], while the Decision Tree model was tuned using various parameters including:

- max_depth: [3, 5, 8, 10]

- min_samples_split: [3, 5, 10, 15]
- min_samples_leaf: [5, 10, 15]

The models were tuned using the Skforecast grid search forecaster on 365 lags for each grid of hyperparameters, and each combination was evaluated using time series back testing with the mean absolute error (MAE).

Table 2: Mean Absolute Error

Mean Absolute Error	Alpha
0.784333	1.0
1.112843	5.0
1.441036	10.0

The best parameters for the Ridge model were found to be alpha = 1.0, with an MAE score of approximately 0.784

Table 3: Best parameters for the ridge model

Mean Absolute Error	Max Depth	Min Samples Leaf	Min Samples Split
0.598966	10	5	15
0.625330	8	5	5
0.625330	8	5	10
0.625330	8	5	3
0.625330	8	5	15

From the table 3, The top 5 parameter sets for the Decision Tree model are shown, with the best parameters being max_depth = 10,

min_samples_split = 15, and min_samples_leaf = 5.

Table 4: Retraining and evaluating the models

model	MAE	R2	RMSE
Ridge	0.741932	0.998448	1.382513
Decision Tree	19.428687	0.199085	31.403256

From table 4, after retraining and evaluating the models using the best parameters, the results showed a more accurate representation of the models' generalization ability. However, while the Ridge regression model showed a slight improvement, the Decision

Tree model failed to generalize well on the test set (new data), with a significant reduction in the coefficient of determination (R2) from 0.75 to 0.20, and an increase in MAE and RMSE to 19.43 and 31.40 respectively

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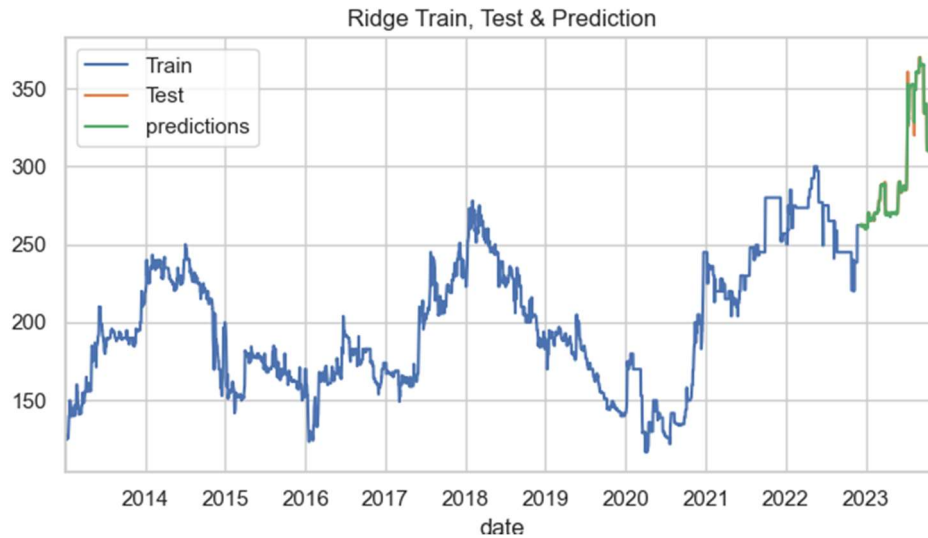


Figure 10: Ridge regression model

The Ridge regression model showed high performance based on the available OHLC data set, with its linear nature, regularization capabilities, and robustness, proves to be a suitable choice for the given OHLC dataset, demonstrating better generalization performance while incorporating candlestick and technical indicators.

Multi-day Price Forecast

Before the data was forecasted, it went through the same routine preprocessing steps as the OHLC dataset. Additionally, the data was carefully split during weekdays to properly evaluate the model and extract various trading signals, as the stock is only traded during weekdays.

The future stock price is forecasted using a multi-step recursive method, incorporating future exogenous features generated from lagged values of previous days. Lagged values are a reflection of potential future values because they

capture the historical patterns and dependencies in the stock price movement. By using lagged values as input features, the model can learn from past price behavior and make informed predictions about future prices. The model outputted an MAE of approximately 0.0366 and an RMSE of approximately 0.0367. These values indicate an improvement in performance compared to the previously tuned model.

Stock Trading System

The resulting predicted price output is passed to a custom trade signal generating function, which also takes the predicted price, as well as the actual price, a stop-loss percentage, and a position size as inputs. The stop-loss percentage is used to set the stop-loss level for each trade, effectively limiting the potential loss if the trade goes against the desired direction. The position size parameter allows for controlling the size of the position taken for each trade, enabling effective risk management.

Table 5: Price predictions

Date	Signal	Profit
2023-11-08	Buy	0.0
2023-11-09	Sell	0.0
2023-11-10	Sell	0.0

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Using a stop-loss percentage of 0.3 (i.e., 3%) and a position size of 0.5 (50%) to limit potential loss and control risk exposure, the trade signal generation function was applied to new unseen data. The results are observed in. This approach produced a buy strategy for the first day, given no profit or loss. However, the subsequent signals showed no sign of profit, and the trade signal function proposed to sell.

CONCLUSION

This research explored the application of machine learning algorithms, in predicting stock prices of Nigerian Stock Exchange from 2013 to 2023. The study aimed to develop a multiple-day trading strategy by incorporating candlestick patterns and technical indicators as features in the ML models. The integration of candlestick patterns and technical indicators, such as SMA, EMA, and VROC, provided valuable insights into the stock price movements and trends. These features enhanced the models' ability to learn from historical price behavior and make informed predictions. Furthermore, the research demonstrated the potential of using ML algorithms for multiple-day stock price prediction. The Ridge Regression model's ability to forecast stock prices with an MAE of 0.0366 over a three-day horizon demonstrate its potential for practical application in stock trading. This study demonstrated the potential of using machine learning models and candlestick patterns to predict multi-day stock prices. The Ridge regression model, with its robust performance and ability to generalize well, proved to be the most suitable model for this task. The study also highlighted the importance of thorough data preparation, feature engineering, and model tuning in achieving accurate predictions. However, the challenges encountered in developing a profitable trading system underscore the complexities of financial markets. While machine learning models can provide valuable insights and predictions, successful trading strategies require a holistic approach that considers various market factors and incorporates effective risk management practices. Future research could explore the integration of additional features, such as macroeconomic

indicators and sentiment analysis, to further enhance predictive accuracy. Additionally, more sophisticated trading algorithms and strategies could be developed to improve the profitability of trading systems based on machine learning predictions. This study contributes to the growing body of knowledge on the application of machine learning in financial markets. It demonstrates the feasibility and potential benefits of using advanced analytical techniques to predict stock prices, while also highlighting the challenges and complexities involved in developing practical and profitable trading systems.

RECOMMENDATIONS

The following recommendations are proposed for future research and practical implementation:

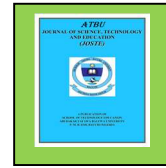
- i. Refinement of Feature Engineering: Further exploration and refinement of feature engineering techniques could improve model performance. This may include experimenting with additional technical indicators or alternative representations of candlestick patterns to capture more nuanced market dynamics.
- ii. Incorporating a more diverse dataset, including stocks from other sectors or markets, to assess the model's generalizability of the proposed approach.
- iii. Explore advanced ML techniques using deep learning algorithms, such as Long Short-Term Memory (LSTM), which have shown capabilities in capturing temporal dependencies and patterns in financial time series data.
- iv. Regularly retrain and update the model using new data to adapt to the changing market conditions and to also maintain predictive accuracy.
- v. Explore a wider range of technical indicators as well as oscillators to identify the most informative features for the model.
- vi. Model Selection and Tuning: While the Ridge regression model demonstrated

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- robustness, ongoing research into alternative models and hyperparameter tuning strategies may yield improvements. This could involve exploring ensemble methods or deep learning architectures tailored to financial time series data.
- vii. Risk Management Strategies: Given the challenges in translating model predictions into profitable trading strategies, developing robust risk management techniques is essential. This may involve refining stop-loss mechanisms, position sizing strategies, and incorporating market sentiment or external factors into trading decisions.
- viii. Continued Evaluation and Validation: Regular evaluation and validation of predictive models against new data are crucial to ensure ongoing performance and adaptability. This includes monitoring model drift, recalibrating parameters as market conditions evolve, and conducting out-of-sample testing to validate model generalization.
- ix. Interdisciplinary Collaboration: Collaboration between domain experts, data scientists, and financial analysts can foster interdisciplinary insights and enhance model interpretability. This collaborative approach may uncover new features, refine model assumptions, and facilitate more informed trading strategies.
- x. Continuous Learning and Adaptation: The dynamic nature of financial markets requires a mindset of continuous learning and adaptation. Staying abreast of emerging research, market trends, and technological advancements is essential to remain competitive and effectively leverage predictive modeling techniques.
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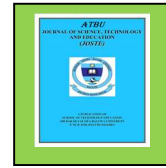
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