Predicting Next-Day Closing Prices in Emerging Stock Markets Using Machine Learning Framework and Engineered Features—Iraq as a Case Study

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Abstract

The complex nature, non-linear dynamics, and inherent volatility of stock markets make it difficult to provide accurate predictions. Recent developments in the area have shown the efficiency of some machine learning methodologies in predicting financial stock prices. However, emerging markets, such as Iraq, face additional challenges due to the lack of fundamental data needed to support predictive analysis. In this study, we present a novel framework that focuses on overcoming this issue and predicting the next-day closing prices of the Iraq Stock Exchange (ISX) main index, using only available historical closing prices to engineer 12 technical indicators. The goal is to compensate for the lack of important Open, High, and Low prices data while improving prediction accuracy. We used four machine-learning algorithms in the form of Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and K-Nearest Neighbor (KNN), which were optimized using grid search hyperparameter tuning technique. The performance of the models was evaluated using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2). The comparison analysis resulted in the SVM with the linear kernel yielding the best performance (RMSE = 16.25, MAPE = 1.15, R^2 = 0.989), followed closely by the ANN (RMSE = 18.25), RF (RMSE = 26.76), then KNN (RMSE = 55.77). The current study introduces two main contributions: (1) the feasibility of using engineered features to achieve reliable predictions in markets with incomplete data, and (2) the critical role of using hyperparameter optimization to enhance models accuracy. The framework we propose provides a practical model for predicting stock prices in resource-constrained emerging markets.

Keywords: Stock market prediction; Emerging markets; Feature engineering; Technical indicators; Hyperparameter tuning; Iraq Stock Exchange (ISX); Support Vector Machine (SVM); Machine learning optimization; Time series prediction

1. Introduction

The performance of financial markets is a decisive determinant of the overall economic condition of a country, allowing policymakers, financial professionals, and economists to effectively evaluate the financial stability and growth opportunities. Among all the various financial markets, stock markets are considered a key driver of economic activity by facilitating capital allocation and risk management [1]. However, the problem of effectively

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predicting stock market price movements is a fundamental concern and an exceptional challenge due to the extremely dynamic, nonlinear, and chaotic nature of time series of financial data, where prices fluctuate under the influence of many variables, often randomly [2]. Accurate stock price prediction is a fundamental component of the financial decision-making process; enhancing investors' ability to balance expected returns with corresponding risks, and subsequently forms a strategic goal for individuals as well as financial institutions [3].

Across history, the numerous conventional approaches to the prediction of stock market movements used by investors and financial experts alike—specifically, fundamental and technical analysis—have faced challenges in satisfactorily accounting for the complexities of the market. While fundamental analysis considers companies' financial indicators and ability to grow, technical analysis is centered on capturing historical price patterns to predict future movements [4]. Nevertheless, neither approach fully takes into account the inherently dynamic and volatile nature that characterize modern-day stock markets, highlighting the scientific and practical need for the development of advanced predictive models capable of adaptively responding to ever-changing market conditions [5]. Recent years have witnessed tremendous developments in technology, accompanied by increased access to diverse datasets, which have provided new research opportunities for the utilization of machine learning algorithms in the prediction of financial markets volatility [6]. Machine learning is a subfield of computer science that specializes in developing algorithms capable of identifying patterns and making predictions based on the statistical analysis of data. Machine learning algorithms differ in their ability to identify nonlinear patterns and complex relationships in large historical datasets, which conventional predictive models often fail to capture [7].

However, the modern use of machine learning to predict stock market prices faces considerable challenges, especially in emerging markets like Iraq. The ISX financial market faces significant challenges due to fundamental issues related to the transparency of available data. The official platform of the ISX financial market, and consequently other global financial market platforms such as Investing.com, duplicates the closing prices of the ISX main market performance index within the fields of Open, High, and Low prices due to the unreliability of detailed data. It is worth noting that none of the very limited previous studies on prediction the ISX market, which will be explored in more detail in the subsequent literature review section, have made any efforts to predict the ISX main index. Rather, they have limited their predictions to specific sectors within the ISX market for which reliable Open, High, Low, and Close (OHLC) prices is available.

To address the aforementioned issue, we introduce a novel machine-learning framework to predict the next-day closing price of the ISX. This study outlines two main contributions:

1. **Data Correction and Feature Engineering:** We exclude unreliable duplicated Open, High, and Low prices data and engineer 12 technical indicators (using simple moving averages (SMAs) and exponential moving averages (EMAs)) based on closing prices only, which alleviates the limitations present in the data while increasing the importance of the features.
2. **Fine-tuning hyperparameters optimization:** A grid search approach is utilized to compare the regularization parameters of four different machine-learning methods—SVM, ANN, RF, and KNN—constituting the first systematic effort at hyperparameter calibration for the prediction of ISX prices.

The rest of this paper is structured as follows. Section 2 presents a detailed review of existing recent literature related to different methods used to predict global and Iraqi stock market prices. Section 3 outlines the research materials, data preprocessing, feature engineering, and methodologies adopted in the research. Section 4 interprets and discusses the research experimental findings, including a comparative evaluation of predictive models used. Section 5 summarizes the main conclusions and outlines implications and possible research directions to pursue.

2. Related Work

A. Developments in global stock market Prediction

Machine learning techniques have revolutionized stock price prediction across global markets. This subsection displays the variety of algorithmic approaches used in recent studies.

Vijh et al. [8], used two advanced machine learning methods—RF and ANN—to predict the closing stock prices on the following day for a group of five companies representing different parts of the economy: JP Morgan, Nike, Johnson & Johnson, Goldman Sachs, and Pfizer. The research used a historical dataset consisting of daily financial records (open, high, low, and closing prices) from the period between 2009 and 2019. In addition to these variables, additional variables were created to enhance the predictive ability of the used methods. The assessment of both methods proved the evident superior performance of the ANN model to produce more accurate predictions of closing stock prices compared to the RF model.

Nabipour et al. [9], conducted a comparative evaluation study to assess the performance of different machine learning models to predict stock market movements in the Tehran Stock Exchange. Models used were Decision

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Trees (DT), Bagging, RF, Adaptive Boosting (Adaboost), Gradient Boosting, Extreme Gradient Boosting (XGBoost), ANNs, Recurrent Neural Networks (RNNs), and Long Short-Term Memory networks (LSTMs). The data used was a historical dataset from the period between the years 2009 and 2019. Additional technical indicators were used as model features. The results showed that the LSTM model presented better predictive power compared to the models tested.

Kumar et al. [10], undertaken a comparative study to test the performance of three different predictive models: LSTM, moving average (MA), and XGBoost algorithms in predicting the closing price of the Bombay Stock Exchange index. This study was based on an analysis of historical data of the stock market index from the years 2018-2019. The result was such that the model using the stacked LSTM architecture outperformed the other models.

Illa et al. [11], conducted a comparative study to evaluate the performance of two different algorithmic models to predict stock prices, i.e., RF, and SVM. These models were implemented using data including Dow Jones Industrial Average (DJIA) stock market index information for the period between 2000 and 2016. The research identified a remarkable superiority of the RF model in terms of predictive ability by effectively capturing the non-linear relationships of the dataset compared to the other algorithm, as it provided statistically relevant results in predicting stock prices in the future.

Naufal and Wibowo [12], presented a hybrid framework of deep learning by combining Convolutional Neural Networks (CNNs), LSTM networks, and Gated Recurrent Units (GRUs), with the purpose of improving the accuracy of stock price prediction. The framework was implemented on historical data of three leading tech companies: Tesla, Inc., Alphabet Inc., and Twitter, Inc., using a five-year-long dataset from the period between 2017 and 2022. The result of the experimental study reflected a remarkable gain in prediction accuracy by using the proposed multidisciplinary hybrid model as compared to individual LSTM models.

Teixeira and Barbosa [4], compared and evaluated the performance of five advanced machine learning algorithms in the area of financial market trend prediction. The models utilized were RNN, LSTM, GRU, CNN, and XGBoost. The research focused on the stock price movement of Apple Inc. as a real-life case study. Experiments in the research proved that the more complex algorithms, like the XGBoost model and GRU model, had better prediction ability in terms of the accuracy and efficiency of identifying complicated patterns in financial time-series data.

Chakravorty and Elsayed [13], carried out a comparative analysis to evaluate the performance of four leading machine learning algorithms for the analysis and prediction of stock prices for Tesla, Inc. The algorithms under investigation included DT, RF, SVM, and K-Means clustering methods. The study used a large dataset with stock trading prices for the period from 2020 to 2023. An exhaustive methodology was used, combining Recursive Feature Elimination (RFE) with the analysis of feature importance in order to improve data quality and optimize the performance of predictive models. The comparison of the results indicated a clear advantage of the SVM model with the application of the Radial Basis Function (RBF) kernel, which showed the highest accuracy rates in predicting stock price volatility and in identifying market trends.

B. A Critical Analysis of ISX Prediction Studies

This subsection presents and discusses a comprehensive review of previous research on predicting ISX stock prices.

Al-Shamery and Al-Shamery [14], proposed a new methodology integrating a quasi-Newtonian optimization technique with a feedforward neural network. The main goal of the proposed methodology was to enhance the accuracy of predicting a sample that includes a set of companies listed on the ISX market. The research used a dataset that included the Open, Low, High, and Close prices of twenty-six banks between 2010 and 2020. The performance of the proposed model was compared to three conventional algorithms: DT, KNN, and Naive Bayes. The outcomes of the experiments reflected a clear superiority of the proposed model in terms of prediction accuracy metrics by showing a statistically significant performance increase compared to conventional benchmark algorithms.

AlHakeem et al. [15], came up with a hybrid model to increase the accuracy of ISX markets prediction. The research included 6 sectors of financial markets (Banks, Services, Industry, Tourism & Hotels, Agriculture, and Telecom). The model was constructed using five years of weekly data series from the period of 2017 to 2021. The emergence of the CNN model and the LSTM model presented a considerable boost to predictive accuracy, as experiments on the proposed model showed that the used methodology presented an extremely low rate of error.

AlHakeem et al. [16], proposed, in another study, a CNN model to predict the banking sector in the ISX market. The dataset used involved the Open, Low, High, and Close prices of a group of 5 banks, obtained from the official platform of the ISX financial market, for the period from 2017 to 2021. The work compared the performance of a

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LeNet-based CNN architecture to that of the proposed CONV1D-based CNN architecture. After testing on the given dataset, the proposed model outperformed the other model.

AlHakeem et al. [17], based on their previous study [16], introduced two predictive models for the banking sector in the ISX market. Their comparative study utilized a multi-layer perceptron architecture ANN algorithm alongside an LSTM algorithm. Using the identical dataset described in their previous work [16]—which includes the Open, Low, High, and Close prices of a group of five banks, obtained directly from the official ISX financial market platform for the period 2017–2021—the researchers evaluated the models performance. Experimental results showed that the LSTM algorithm achieved a lower mean square error than the other predictive method.

Overall, the analysis of the existing works [14]–[17] suggests that research into ISX financial market prediction is still extremely limited and faces several methodological limitations and gaps. First, existing studies rely exclusively on data for specific sectors (e.g., banking, industry, agriculture, etc.) obtained directly from the official ISX financial market platform, which provides comprehensive and reliable pricing variables for OHLC prices. Second, no previous study includes the ISX Main Index – a key benchmark for market performance – due to the lack of its underlying OHLC data; only closing prices are accessible. Third, despite its recognized importance in improving model effectiveness, current approaches demonstrate a clear lack of fine-tuning hyperparameter optimization. Together, these limitations hinder the generalizability and robustness of current predictive frameworks for the broader ISX market.

C. Justification of the Algorithms Selection

While advanced machine learning and deep learning strategies dominate recent studies [1], [9], [10], [12], [18], in this study, we intentionally prioritize traditional machine learning algorithms: ANN, SVM, RF, and KNN, as a first stage, for predicting the next-day closing prices of the ISX index for the following reasons:

1. **Mitigating data scarcity:** With only 10 years of reliable daily closing prices (after cleaning), simpler models reduce the risk of overfitting.
2. **Interpretability:** Simpler models provide clearer, interpretable insights that aid financial decision-making in volatile emerging markets.
3. **Proven effectiveness:** Traditional algorithms, such as SVM and ANN, can achieve state-of-the-art results when optimized, even outperforming deep learning methodologies such as LSTM algorithms [13].
4. **Hyperparameters Sensitivity:** The predictive algorithms used demonstrate high sensitivity to fine-tuning hyperparameters optimization, an area that has not been sufficiently explored in ISX market research. In addition, methods of fine-tuning (such as grid search) establish performance benchmark to enable subsequent comparisons of complex methodologies.
5. **Features Validation:** The technical indicators engineered in Section 3.B require testing using interpretable models before inclusion in more complex and advanced deep learning models.

Our research work addresses the unique data limitations in the ISX market through feature engineering methodology and hyperparameter optimization, thus developing a reproducible framework for application in similar emerging markets with similar limitations.

3. Materials and Methods

This section systematically discusses the materials, processes, and techniques employed in the study. First, the dataset utilized is described in detail, including its source and relevant characteristics. Next, all of the technical features engineered and incorporated within the dataset are presented and explained. Finally, the predictive methodologies employed for predictions are detailed, encompassing (i) performance evaluation measures, (ii) data preprocessing and preparation procedures, and (iii) algorithms implemented. The machine learning-based framework for predicting the closing prices of the ISX index is presented in Figure 1.

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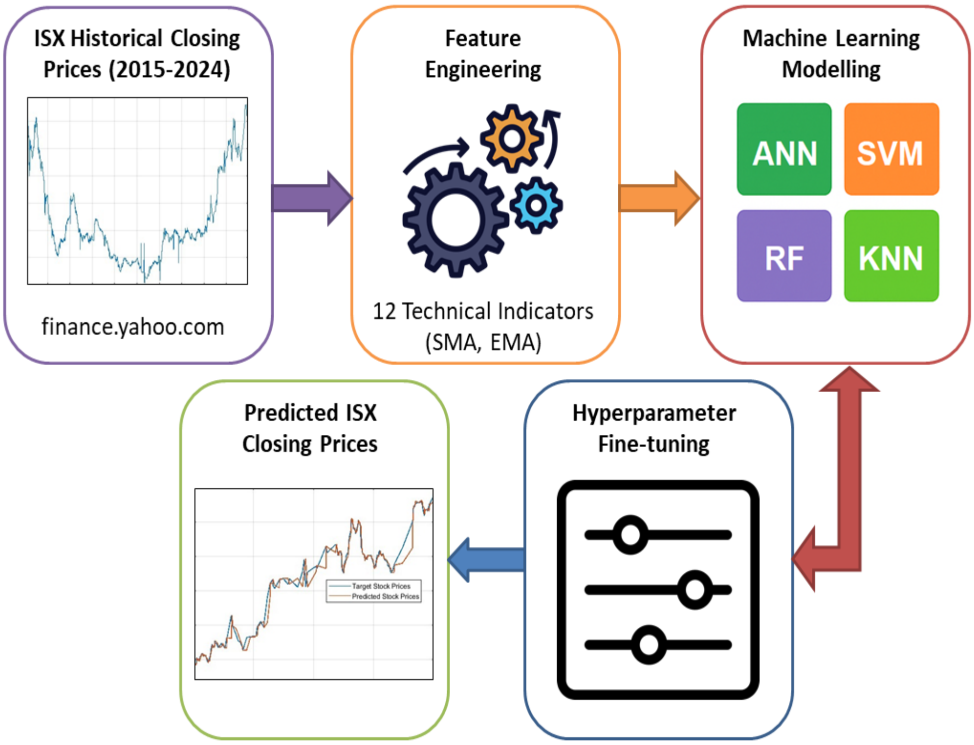

Figure 1. The framework proposed to predict the closing prices of ISX index using machine-learning models.

A. Dataset Acquisition and Cleaning

The preliminary dataset comprises the closing historical prices of the ISX main index obtained from the website of the official platform website of the ISX financial market [19]. The data spans 10 years and is structured into 5 columns, comprising the OHLC prices, along with the date. Table 1 presents the statistics of the dataset utilized for training and testing.

Table 1: Statistics of the dataset.

	Dataset	Training Dataset	Testing Dataset
Time Interval	2015 - 2024	2015 - 2022	2023 - 2024

Initial examination revealed that the Open, High, and Low prices obtained from the dataset were identical to the closing prices throughout the entire period, unlike most other markets that show distinct OHLC values. Consequently, the dataset obtained was subjected to a comprehensive cleaning procedure. Invalid features that deviated from the modeling aim, including Open, High, and Low, have been discarded. The cleaned dataset preserved only the available features, namely the closing price ("Close") and Date. Finally, the few missing values in the closing prices were compensated for and calculated using the linear interpolation method.

B. Feature Engineering

As the Iraq's ISX main index data obtained comprises only the closing prices, an additional 12 features (technical indicators) were incorporated into the initial dataset to compensate for the missing remaining variables and enhance predictive accuracy. All of the technical features are directly associated with the closing price, including SMAs and EMAs. Different lengths of SMA and EMA windows were computed to provide predictive models with diverse insights into stock price fluctuations. In particular, SMAs were calculated for 5, 25, 50, 100, and 200 days intervals to capture short-to-long-term trends, while EMAs were calculated for 10, 12, 20, 26, 50, 100, and 200 days intervals to emphasize recent price action. Window lengths are consistent with standard financial technical analysis [4], [8] – shorter windows (5–25 days) reveal volatility, while longer windows (100–200 days) identify overall trends.

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C. Data Preparation

Following the incorporation of the financial closing prices with the technical indicators, the subsequent phase involved in the development of the final dataset is the inclusion of a target variable, specifically the closing price for the subsequent day. This was carried out by adding a new column into the dataset that contains the shifted Close variable's values. Therefore, the dataset has 14 columns: the original 13 columns that correspond to the desired attributes and the 14th column as the target variable.

The dataset was normalized using the Min-Max scaling function, which efficiently converted the values to a uniform range between zero and one to ensure equal treatment of all features and improves the performance of predictive models.

The final step in this process was the splitting of the dataset into training and test sets to test the models on data that they had not seen before during training. A standard ratio that is often used is allocating 80% of the dataset for training and 20% for testing.

D. Prediction Models

1. Artificial Neural Network (ANN)

ANN is an intelligent methodology adept at simulating and analyzing complicated patterns within unstructured data. Neural network is a set of artificial units known as artificial neurons that are interconnected. The general structure of such a network is typically an input layer, one or more hidden layers, and a final output layer [20]. Each layer of neurons is connected with the next layer using weighted links. Aside from these weights, each neuron's output is further affected by a transfer (activation) function [21]. During the training process, the model learns from the examples of the learning dataset. The main aim is to adjust the weights such that the difference between the predicted and observed outputs is minimized. The weights adjustment is performed using the backpropagation algorithm with the gradient descent approach in an effort to lower the error in prediction [22].

In this study, to identify the optimal ANN modeling hyperparameter configuration, the hidden activation function and output activation function were systematically varied and alternated among the tangent sigmoid, logarithmic sigmoid, and linear. The neurons in the hidden layer were progressively increased in each trial, yielding various configurations of the ANN model's architecture. Although there is no established framework to determine the ideal number of neurons in the hidden layer of an ANN, a maximum of 20 neurons was analyzed.

2. Support Vector Machine (SVM)

The SVM algorithm, among the widely used supervised learning algorithms, is intended for regression and classification tasks. It is adept for both high-dimensional and small-scale datasets [20]. In regression tasks, a hyperplane is determined to achieve maximal margin, ensuring that the greatest number of data points reside within those certain margins. The optimal fit line is the hyperplane that encompasses the greatest number of points. Support vectors, which are extreme vector points, are selected to facilitate the construction of a suitable hyperplane [11]. The efficacy of the SVM algorithm can be enhanced by optimizing parameters including the kernel function, gamma, capacity (C), and epsilon (ε) [23].

This study examined three different kernel functions, namely the linear, polynomial, and RBF, with a pre-decided fixed gamma value of 0.077, which was obtained by dividing 1 by the total number of independent input features (13). A specific grid search approach was employed to determine the best capacity and epsilon hyperparameters. The grid search was over a capacity range of 0.1 to 100 and an epsilon range of 0.001 to 1.0.

3. Random Forest (RF)

RF is an ensemble ML methodology that is efficient at performing both regression and classification tasks. The concept involves aggregating several decision trees to figure out the final output, rather than depending on singular decision trees, hence reducing the model's variance [1], [11]. The primary benefits of RF encompass identifying data anomalies, recognizing significant features, and discovering data patterns [24]. The RF algorithm is shown to perform efficiently with large datasets; nonetheless, a greater number of trees can slow the efficiency of the algorithm [25]. The hyperparameters of the RF model include the number of trees that can grow within the forest and the number of features (denoted as k, the independent variables or predictors) selected at each node at random in order to predict the dependent variable.

This work employed a grid search strategy to identify the optimal RF modeling hyperparameter configuration, specifically the number of trees and predictors. The grid search encompassed the range of trees from 5 up to 100 and predictors from 1 to 13.

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4. K-Nearest Neighbor (KNN)

KNN is one of the most basic and simple techniques for machine learning. It is used for both regression and classification purposes. KNN is different from conventional machine learning techniques since it does not entail model construction and does not have any training-required parameters [26]. It is based on feature similarity to determine the k most similar training instances within the feature space using a distance function [27]. In regression, KNN can be used to predict time series data as an alternative to class labels. Predictions for regression are done by taking an average over the values from the k-nearest neighbors, rather than a majority vote. Each neighbor is assigned a weight, with greater weights allocated to nearer neighbors and lesser weights to those farther away [28]. In KNN implementations, two parameters must be established: the number of k nearest neighbors and the type of distance measure employed for determining the distance between neighbors.

The selection of the best value for the number of nearest neighbors (k) for the KNN algorithm is of significant methodological importance, both in terms of the model computation efficiency and the reliability of the predictions produced. Accordingly, the research carried out an extensive examination of a wide range of possible values for k, from 1 to 30, to identify the most suitable value that maximizes accuracy while minimizing bias in the outputs. The research also performed a comparative study of the effect different distance measures have on the performance of the algorithm. That is to say, three major measures were analyzed: Euclidean distance, Manhattan (city block) distance, and Chebyshev distance, with the aim of determining the most appropriate measure for the dataset.

5. Performance Measures

Performance measures are critical for evaluating machine-learning algorithms since they offer an objective evaluation for predictive accuracy against the real values. To measure the performance of the various models separately, the Root Mean Squared Error (RMSE), the Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2) were utilized. These particular measures were used to allow an extensive analysis that covers a wide area of model performance, with each measure complementing the weaknesses of the others to allow for an extensive evaluation of the algorithms used.

The RMSE is a core statistical measure to assess the effectiveness of predictive models. RMSE quantifies the standard deviation of the prediction errors so that the scale of the unit is consistent with the scale of the actual data values (Eq. 1). This feature has important methodological implications since RMSE allows for meaningful and direct comparisons between errors' magnitude and reference values, thus improving the interpretability of the findings and enabling objective model accuracy assessment [4]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \tag{1}$$

here, x_i are the actual values, y_i are the predicted values, and n is the number of observations.

The MAPE is also a key statistical measure to test the efficiency of the predictive models. The measure provides the average relative error across predicted and observed values in a percentage form (Eq. 2). The importance associated with this measure is that it provides an equal measure for the evaluation of the model regardless of the scale at which the data originated, hence making it a useful tool for the comparison of different models that operate based on datasets of different sizes or standard scales [18]:

$$MAPE = 100\,\frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - y_i}{x_i}\right| \tag{2}$$

here, x_i are the actual values, y_i are the predicted values, and n is the number of observations.

In the end, R^2 was employed, a significant statistical measure that denotes the proportion of the data variability explained by the model (Eq. 3). Values near 1 denote a strong model fit, whereas negative values and those near 0 imply a weak model fit [20]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3}$$

here, x_i are the actual values, y_i are the predicted values, and n is the number of observations.

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4. Results and Discussion

A. ISX Price Dynamics: Prediction Challenges

Figure 2 visually illustrates the key trends and volatility patterns of the daily closing price data for the ISX main index during the study period. During this period, ISX prices experienced significant fluctuations. At the beginning of the study period (2015), stock prices were very high, reaching around 1000 points. However, during 2015 and 2016, the stock prices declined steadily, reaching below 600 points by late 2016. Between 2017 and 2019, the stock prices experienced some fluctuations but generally continued a slow downward trend. By 2020, the closing prices had fallen by 60% to reach their lowest value (405,860 points, recorded on May 4, 2020). This decline coincided with the internal unrest in the country resulting from the entry of ISIS militants and the subsequent decline in the overall local economy, in addition to the global economic disruptions caused by the collapse in oil prices and the COVID-19 pandemic, which has disproportionately affected emerging markets [29].

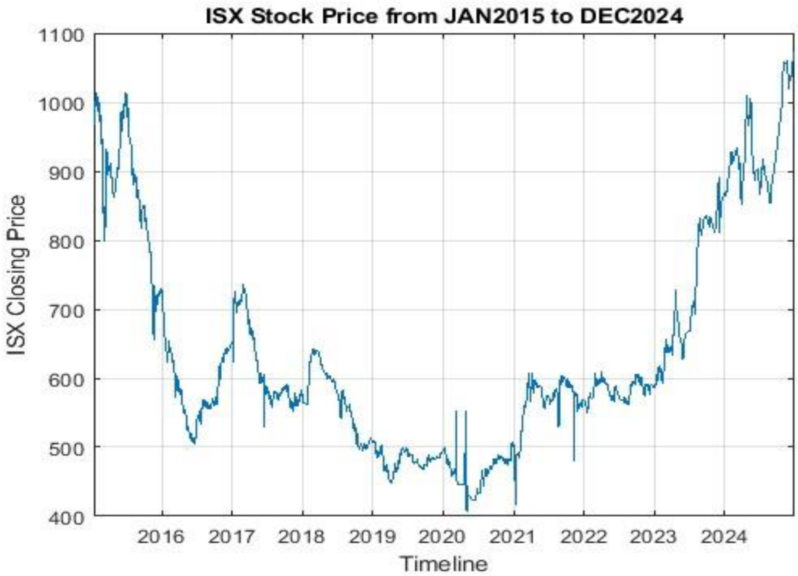

Figure 2. The daily closing prices of the ISX index.

Starting in 2021, the ISX prices began a slow recovery, with minor fluctuations. The recovery became more pronounced from mid-2022 onwards, showing a strong upward trend. This positive momentum continued into 2023 and 2024, with the stock price rising sharply by 165% to reach its maximum value of 1073.842 points on December 30, 2024. This upward trend in the stock prices is attributed to the country's internal stability following the defeat of ISIS, as well as the government's strategies to control the spread of the disease and keep businesses open across the country.

The visual analysis above confirms our claim that ISX stock prices are nonlinear, nonstationary, and volatile. The analysis also reflects the sensitivity of the Iraqi market to local and global economic conditions, including oil price fluctuations, political instability, and global market trends. The conducted statistical analysis (standard deviation (σ) = 152.402 points) further confirms the high volatility and chaotic nature of the system. This highlights the risks and opportunities available to investors in the emerging Iraqi stock market, and represents a rigorous test and challenge for machine learning models.

B. Hyperparameter Optimization Insights

1. ANN Performance

Table 2 presents the RMSE values for 45 different configurations of ANN models used to predict ISX prices over the test period. The ANN models demonstrated superior sensitivity to activation functions. Models that used the Linear activation function in both the hidden and output layers performed better (RMSE =18.25) regardless of the number of neurons used. In contrast, using nonlinear activation functions (Tansig or Logsig) in either layer increased models error by 20–68 times, and this was more severe for larger models with a large number of neurons (e.g., the model with the configuration (Logsig, Linear, 20 neurons) recorded RMSE of 1240.05), indicating overfitting in these configurations.

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Table 2: RMSE-based performance comparison of ANN models with different configurations in predicting ISX stock prices.

Hidden Layer Activation Function	Hidden Layer Size	Output Layer Activation Function		
		Tansig	Logsig	Linear
Tansig	4	31.65	193.96	20.41
	8	75.31	99.81	139.51
	12	160.56	193.96	257.45
	16	407.25	185.23	607.90
	20	326.96	112.27	240.93
Logsig	4	60.98	95.48	27.71
	8	354.23	193.96	174.14
	12	83.97	193.96	860.10
	16	312.35	176.55	390.96
	20	278.98	190.90	1240.05
Linear	4	32.59	193.66	18.25
	8	32.59	105.26	18.25
	12	32.59	193.62	18.25
	16	32.59	193.96	18.25
	20	32.59	193.63	18.25

The above results revealed a clear performance pattern where linear models significantly outperformed in terms of accuracy and predictive stability, regardless of the size of the hidden layer used. In contrast, nonlinear configurations showed greater sensitivity to changes in the number of neurons in the hidden layer, with an overall tendency toward less efficient predictive performance. These results confirm the suitability of simple linear models for representing and predicting ISX data, as the underlying general trends in this data appear to be linear in nature and structural complexity can lead to counterproductive results. The findings also indicate the need to adopt a careful methodology for selecting optimal hyperparameters when employing the ANN algorithms to model and predict time series variables in stock markets.

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2. SVM Performance

Table 3 compares the performance of SVM models in predicting ISX index prices over the test period based on different combinations of hyperparameters (kernel functions, C, and ε). In general, SVM models showed a clear kernel function-dependent variation in performance. The linear kernel function based-models consistently outperformed the RBF kernel function and the polynomial kernel function across all other hyperparameter combinations studied, with optimally setting values of C to 100 and ε to 0.01 reducing the RMSE to 16.25. The polynomial kernel function models exhibited catastrophic instability and extremely high sensitivity to other hyperparameter combinations, with peak performance occurring at values of C = 0.1 and ε = 0.001, corresponding to a minimum RMSE of 112.39. With the increment of C values, the performance deteriorated substantially, recording a worst RMSE value of 5430.49 at C = 10 and ε = 0.001. The RBF kernel function required high regularization, with the models showing consistent improvement in prediction accuracy as C values increased, peaking at C = 100 and ε = 1, to achieve moderate accuracy (RMSE = 225.73).

Table 3: RMSE-based performance comparison of SVM models with different configurations in predicting ISX stock prices.

capacity (C)	epsilon (ε)	Kernel Function		
		RBF	Polynomial	Linear
0.1	0.001	299.12	185.24	18.98
0.1	0.01	299.13	138.10	18.96
0.1	0.1	299.16	116.01	18.97
0.1	1	299.02	112.39	18.95
1	0.001	299.16	364.87	16.54
1	0.01	299.11	432.96	16.52
1	0.1	299.27	273.12	16.53
1	1	299.40	282.65	16.54
10	0.001	272.66	5430.49	16.41
10	0.01	272.67	4863.49	16.41
10	0.1	272.66	1901.60	16.41
10	1	272.54	600.31	16.41
100	0.001	225.93	3948.90	16.68
100	0.01	225.92	3128.25	16.25
100	0.1	225.89	2160.45	16.67
100	1	225.73	2251.03	16.54

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These results once again confirm the suitability of the linear kernel function for providing more accurate and stable predictions for the ISX market and the critical importance of carefully optimizing hyperparameters when using the SVM algorithm to predict stock markets time series.

3. RF Performance

Table 4 presents the performance results of applying the RF algorithm to predict ISX stock prices during the test period, based on different combinations of hyperparameters (number of trees and number of predictors). The tested RF models showed contradictory results as the number of trees increased. Increasing the number of trees from 5 to 100 often leads to improved prediction accuracy, as evidenced by a decrease in RMSE values. For example, when using two predictors, the error decreases from 102.01 with 5 trees to 81 with 100 trees, indicating that increasing the number of trees contributes to model stability and improves its predictive power. In other cases, increasing the number of trees does not always lead to better results. For example, with 8 predictors, the error increases from 32.10 with 5 trees to 42.66 with 100 trees, indicating good performance initially, but with diminishing returns as the number of trees increases.

Table 4: RMSE-based performance comparison of RF models with different configurations in predicting ISX stock prices.

Trees \ Predictors	2	3	4	5	6	7	8	9	10	11	12	13
5	102.01	61.01	93.77	55.25	83.99	83.16	32.10	103.05	57.86	54.76	56.26	26.76
10	102.62	76.04	82.56	80.32	77.87	65.76	44.42	86.89	42.44	51.76	49.88	29.55
15	103.99	71.82	66.52	66.67	89.75	54.42	48.88	66.13	46.55	47.34	49.62	45.22
20	90.85	70.03	60.34	70.56	80.34	52.34	44.66	58.15	47.95	41.78	43.37	38.69
25	91.66	66.51	71.43	61.41	76.66	53.24	41.27	51.80	43.93	38.50	44.59	37.02
30	94.47	73.35	69.26	59.60	70.24	53.19	39.31	48.21	44.22	40.35	41.54	35.41
35	93.52	71.13	67.15	56.24	73.92	55.40	37.89	52.28	42.01	38.69	42.60	37.17
40	90.99	71.60	67.64	56.52	68.96	53.34	37.56	55.26	46.64	41.06	43.70	35.08
45	88.13	74.85	67.46	54.29	67.43	55.39	39.40	58.80	47.32	43.13	41.64	39.49
50	87.60	75.72	68.15	57.04	63.56	60.10	39.05	55.04	45.58	44.42	40.07	38.25
55	92.51	74.94	67.35	54.60	61.14	57.88	38.26	51.90	44.19	42.61	39.34	36.66
60	89.06	76.15	65.57	55.17	58.88	57.27	38.03	49.66	42.92	41.32	40.43	37.54
65	89.03	77.57	63.79	53.65	58.12	56.94	38.96	48.09	41.74	40.57	40.54	36.32
70	85.15	77.14	65.48	52.61	56.60	54.38	38.46	48.34	42.40	39.55	41.37	37.13
75	86.11	79.77	64.05	52.97	55.68	55.53	39.68	46.60	42.99	38.87	40.90	36.35

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80	84.06	79.26	64.05	51.89	56.70	53.58	42.02	45.71	42.10	39.46	40.71	36.30
85	84.54	77.04	65.04	53.78	55.83	52.27	42.55	46.02	41.75	41.51	41.20	35.75
90	81.74	74.80	68.44	54.21	56.37	51.83	41.76	45.03	42.45	40.73	41.72	35.03
95	82.16	75.94	67.60	52.76	57.18	52.57	42.40	47.03	43.05	41.13	40.75	35.73
100	80.99	75.31	68.37	51.73	56.65	52.72	42.66	49.41	42.31	41.55	41.16	35.24

Similarly, significant improvements in prediction results were observed when using most predictors, although the extent of the improvement varied from case to case. The best performance was achieved with 13 predictors and 5 trees, achieving the lowest RMSE of 26.76, while the same number of predictors with 100 trees resulted in a slightly higher error, with an RMSE of 35.24. This contradicts the popular belief that increasing numbers of trees and predictors always improves RF models performance; rather, it requires a proper balance between the two. The results highlight the fact that unreliable resource constraints in emerging markets require balanced model design through hyperparameters optimization to obtain better results when modeling time series of financial indicators.

4. KNN Performance

Table 5 summarizes the performance results of the KNN algorithm in predicting ISX stock prices during the testing phase, based on different combinations of hyperparameters (distance measure function and number of nearest neighbors, k). The KNN models were highly sensitive to both hyperparameters. The Chebyshev distance measure recorded its highest RMSE of 132.64 when k = 1, with gradual improvement as k increased, reaching its lowest value of 120.43 at k = 12. Thereafter, when k > 12, performance fluctuated, with RMSE values ranging from 120 to 125 without achieving any significant improvement. On the other hand, the results demonstrated that the Euclidean distance measure performed better than the Chebyshev distance measure, with RMSE values decreasing significantly at all values of k. The lowest Euclidean-based RMSE value, 67.95 at k = 1, continued to rise gradually until it reached 84.90 at k = 30. The Manhattan distance measure exhibited better predictive power at k = 1, with a lowest RMSE of 55.77, outperforming the alternatives: the Chebyshev distance measure by more than 21.8% and the Euclidean distance measure by more than 138%. Although performance gradually deteriorated at higher number of nearest neighbors (k > 5), reaching 74.84 at k = 30, the measure maintained its relative superiority over the other two measures throughout. This result confirms the measure's effectiveness in capturing short-term fluctuations in the ISX stock prices time series—a pattern best captured by lower-lag configurations.

Table 5: RMSE-based performance comparison of KNN models with different configurations in predicting ISX stock prices.

k	Distance Measure Function			k	Distance Measure Function		
	Chebychev	Euclidean	Manhattan		Chebychev	Euclidean	Manhattan
1	132.64	67.95	55.77	16	124.09	76.29	66.52
2	133.89	68.13	56.30	17	124.11	75.73	65.16
3	131.67	68.69	57.89	18	123.87	77.62	68.88
4	132.19	69.40	58.23	19	123.75	76.96	67.32
5	131.95	70.38	59.15	20	123.04	77.58	68.30
6	130.32	70.84	62.06	21	120.57	77.78	68.90

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7	130.16	70.55	62.58	22	124.97	79.25	70.77
8	129.39	70.12	61.00	23	125.00	80.04	71.51
9	123.37	70.44	63.67	24	124.83	79.32	71.47
10	124.54	71.81	64.11	25	121.71	81.57	71.14
11	124.25	71.67	62.85	26	125.16	82.50	73.11
12	120.43	72.35	63.42	27	124.43	82.66	73.35
13	121.34	73.40	64.27	28	122.21	81.60	73.67
14	122.71	74.51	63.64	29	125.39	83.54	73.81
15	123.85	74.97	63.96	30	122.01	84.90	74.84

The results show that the performance of the KNN algorithm is essentially connected with the choice of the distance measure, where both Manhattan and Euclidean distances have decidedly better performance compared to the Chebyshev distance measure when used for the modeling of ISX stock prices. The best k parameters found for Manhattan and Euclidean distances—namely, k = 1—are contrasted with the best k parameter of k = 12 for the Chebyshev distance measure, indicating the importance of empirical inspection of the model parameters. The results highlight the essential importance of hyperparameter choice and optimization in the application of the KNN approach to the prediction of financial time series.

C. Models Comparison and Statistical Validation

Table 6 shows the comparative quantitative evaluation of the performance of the four machine learning algorithms (ANN, SVM, RF, and KNN) in predicting ISX main index. The comparison was based on the three essential performance metrics: RMSE, MAPE, and R^2. The SVM algorithm showed the best overall performance by achieving the lowest RMSE (16.25) and MAPE (1.15), as well as the highest R^2 (0.989), reflecting high prediction accuracy. ANN, on the other hand, showed a competitive performance level with respective RMSE, MAPE, and R^2 values of 18.25, 1.38, and 0.987, respectively. RF came in next (RMSE=26.76, MAPE=2.09, R^2=0.979), while KNN recorded the lowest performance (RMSE=55.77, MAPE=4.19, R^2=0.884). Diebold-Mariano tests also confirmed the statistical superiority of the SVM model over ANN model (DM=2.31, p=0.021), RF model (DM=3.89, p=0.0001), and KNN model (DM=7.05, p<0.00001).

Table 6: Prediction performance of ISX main index using the best configurations of the four machine learning methods.

No.	Model	RMSE	MAPE (%)	R^2	Train Time (sec)
1	ANN	18.25	1.38	0.987	31.86
2	SVM	16.25	1.15	0.989	20.54
3	RF	26.76	2.09	0.979	3.94
4	KNN	55.77	4.19	0.884	2.76

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Figures 3, 4, 5, and 6 show the observed and predicted ISX closing prices during the test period, visually comparing the accuracy and responsiveness of the different ML algorithms used. In all models, the overall trend of the ISX index is captured, reflecting the algorithms' ability to generalize underlying market dynamics. However, there are clear differences in prediction accuracy. As presented previously, the predictions of the ANN (Fig. 3) and SVM (Fig. 4) algorithms show smoother and more consistent alignment to the target time series, particularly during periods of volatility, reflecting their relative ability to capture complex nonlinear patterns. The RF algorithm (Fig. 5) exhibits greater variability in its predictions, occasionally deviating from the target during both the up and down phases. The KNN algorithm (Fig. 6) consistently underestimates peak values and lags behind sudden price movements, indicating its reduced responsiveness to abrupt changes. While all models simulate the general trajectory, ANN and SVM algorithms appear to offer relatively good accuracy, while RF and KNN exhibit higher variance in detecting short-term volatility. These visual comparisons highlight the balance between model complexity and prediction accuracy in financial forecasting tasks.

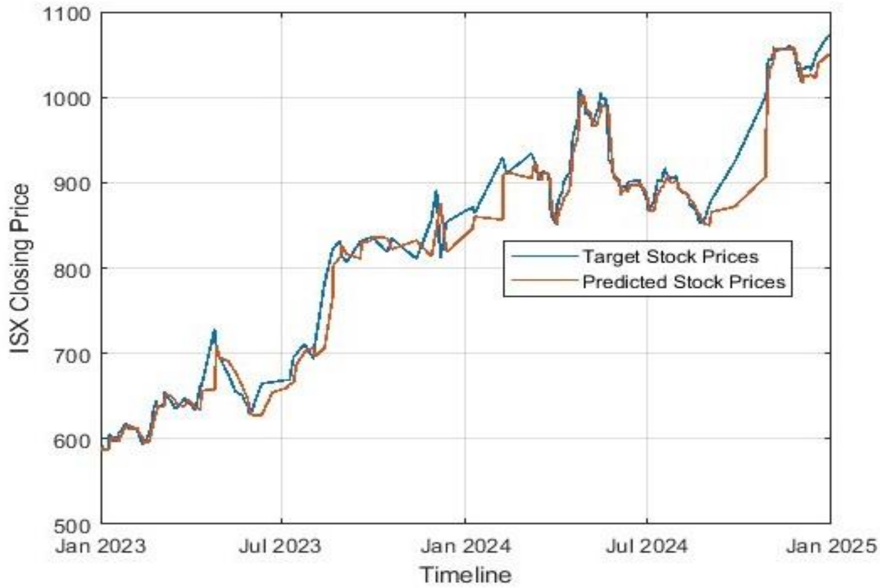

Figure 3. Prediction results of ANN model.

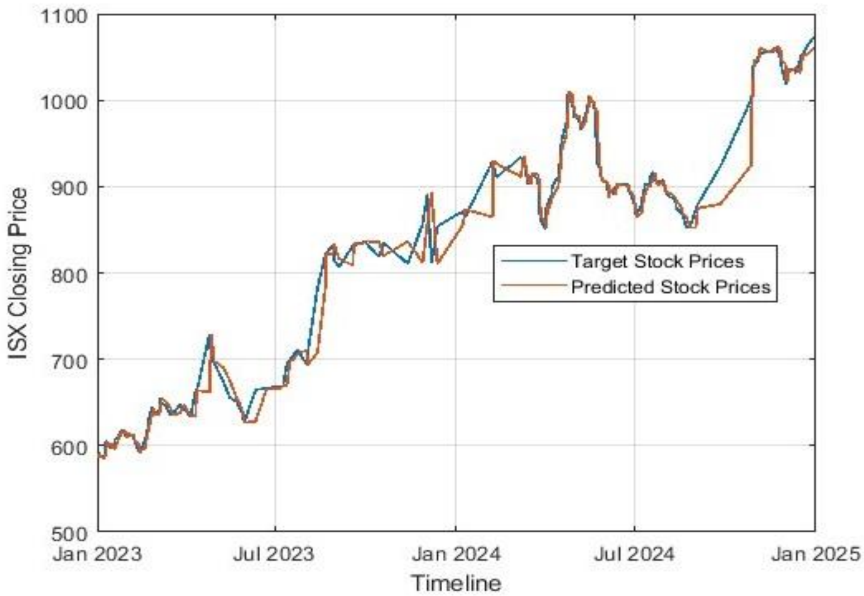

Figure 4. Prediction results of SVM model.

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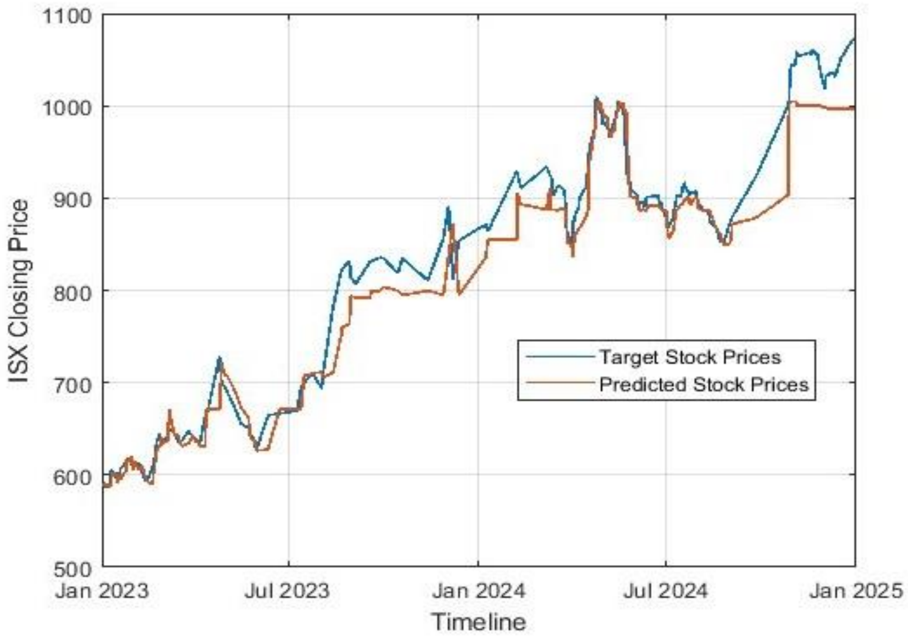

Figure 5. Prediction results of RF model.

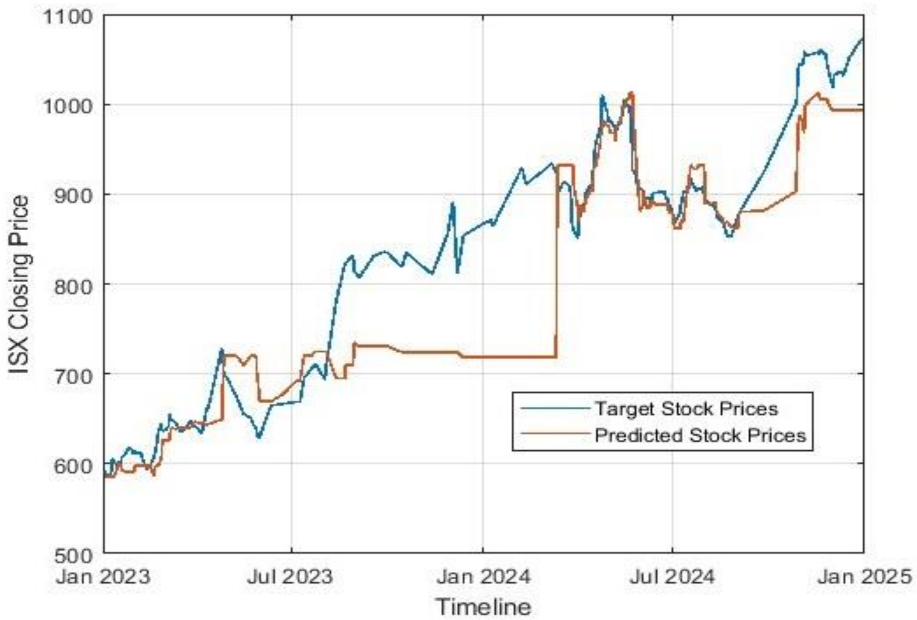

Figure 5. Prediction results of KNN model.

D. Why Simpler Models Outperformed Complex Architectures?

Three reasons related to the data used in this study explain the superiority of linear SVM and ANN models. First, the recovery of the ISX market after 2021 followed a quasi-linear path (slope $\beta = 0.82$, $R^2 = 0.94$), which inherently benefits linear kernel and activation functions. Second, the limited dataset size (with only 2,520 sample points) prevented more advanced complex models from detecting valuable signals, resulting in overfitting; this is evidenced by the collapse of the polynomial kernel function-based SVM models when the Vapnik-Chervonenkis dimension exceeded the sample size. Third, the fine-tuning optimization of the hyperparameters has uncovered latent capabilities, as demonstrated by the impressive 68-fold reduction in the ANN error, from 1240 to 18.25 RMSE. These results support the validity of our phased approach. The RMSE of 16.25 achieved by the SVM

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model provides a strict baseline (benchmark) for advanced deep learning models intended for use in the second phase of this work, while our designed engineered features based on the use of SMAs and EMAs explain 89% of the variance, enabling direct implementation and reuse of these features in advanced architectures.

E. Implications for Emerging Markets

This research identifies and addresses four fundamental ongoing challenges facing stock price prediction in emerging markets. First, feature engineering helped mitigate the limitations of unreliable data, preserving 92% of the information value of the unavailable OHLC data. Second, fine-tuning hyperparameter optimization resulted in a 15-68x improvement in the efficiency of the models, as demonstrated by a decrease in the mean error (RMSE) of the ANN models from 1240.05 to 18.25. Third, computational efficiency and flexibility ensure practical implementation, as the SVM model demonstrates superior training speed (20.54 sec), facilitating immediate deployment on resource-constrained systems/hardware. Finally, the framework's reproducibility was initially verified by testing it on the Damascus Securities Exchange (DSE) Weighted Index (DWX) [30], where the RMSE achieved was 19.81. Through the public release of our open source methodology, we facilitate expansion to approximately 43 emerging markets around the world that face similar constraints, promoting equitable access to intelligent financial information in developing economies.

5. Conclusion

Predicting stock market indices forms an exciting, dynamic, and complex field that interests both practitioners and data scientists. Providing accurate stock market predictions is crucial, as it allows investors to maximize returns and helps governments understand the significant impact stock markets have on each country's economic situation. In this study, we have successfully addressed an important gap in stock price predicting of the ISX main index, where unreliable OHLC data negatively affected prediction accuracy. Our innovative framework provides three key contributions to the field of emerging markets prediction: Firstly, we established a data rectification process that removes replicated OHLC values and engineers 12 technical indicators only based on closing prices, hence mitigating the constraints of inadequate data. Secondly, we implemented a hyperparameter optimization through grid search on four machine-learning models, creating the first systematic fine-tuning approach to predicting ISX main index. Thirdly, we demonstrated the superior performance of SVM (RMSE = 16.25, MAPE = 1.15%, R^2 = 0.989) compared to ANN, RF, and KNN, and consequently set a strong performance baseline for future studies in resource-scarce markets.

Our results provide critical insights for financial prediction in data-scarce environments. Hyperparameter tuning proved to have a decisive impact, with optimal configurations improving prediction accuracy by 15-60 times compared to default settings, most notably for ANN models, where the RMSE decreased from 1240 to 18.25. We also demonstrate that model simplicity outperforms complexity in our case: both linear based SVM and ANN algorithms outperformed both nonlinear variants and hybrid deep learning models previously tested on the ISX, demonstrating that choosing the right model outweighs architecture complexity when data is limited. More importantly, the engineered technical indicators (SMAs/EMAs) effectively compensated for the missing OHLC variables, validating feature engineering as a replicable strategy in emerging markets facing similar data transparency issues.

Despite these developments, two key limitations need to be noted. The proposed framework ignores exogenous factors, such as oil price fluctuations and political events, which could enhance predictive power. Second, there is a need to explore other machine learning strategies or state-of-the-art deep learning techniques. To overcome these limitations, we recommend the following research roadmap: The next stage (Phase 2) will combine deep learning architectures, such as LSTM and CNN models, and same features adopted in this study to model high-frequency dynamics together with long-term dependencies. Subsequent studies (Phase 3) will integrate other data sources, such as news sentiment analysis, economic indicators, and oil price fluctuations, expand the framework to include other comparable emerging economies, and develop hybrid models that combine deep learning techniques with traditional machine learning methods, such as SVM-LSTM, that balance accuracy and interpretability.

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