International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Application of Artificial Neural Networks Compared to Machine Learning in Predicting Financial Prices

Baha Yahya

Department of Management Information System, Al Istiqlal University, Jericho P.O. Box 10, Palestine;
dr.baha@pass.ps

ABSTRACT

Predicting financial prices with accuracy is essential for sound decision-making in financial markets. Even as many new predictive models arise due to AI, there are still not very many statistical studies comparing Artificial Neural Networks (ANNs) to traditional machine learning (ML). This study tries to address these shortcomings by carefully comparing ANN with three popular machine learning methods such as Random Forest (RF), Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), using daily gold prices for 2019–2024 and daily MasterCard and Visa stock prices for the same years. Every model was programmed in MATLAB so that all execution, training and validation steps would be the same. Four evaluation metrics were applied: Avg. RMSE, Avg. R^2 and two data analysis techniques called ANOVA and F-test. Every time, RF and KNN outperformed ANN and SVM by many margins on both datasets. Regarding stock prices, RF did best with 0.0273 for Avg. RMSE and 0.9993 for Avg. R^2, while KNN ranked second with 0.0481 and 0.9987 respectively. The artificial neural networks (ANN) gave good results (RMSE = 0.0699, $R^2 = 0.9951$), but the support vector machine (SVM) performed worse. ANOVA analysis proves that these variations are highly significant ($F = 204.03$, $p < 0.000001$). Gold predicting too had RF and KNN as the leading methods, followed by ANN and SVM performed the least out of the four. It explains how, compared to ANN and SVM, using ML models such as RF and KNN tends to give improved results and adds more credibility to the findings in financial prediction for all types of assets.

Keywords: Artificial Neural Network (ANN), machine learning (ML) Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), financial prices.

1. Introduction

Particularly when it comes to the prediction of stock prices, bond prices, and index stock prices, forecasting financial prices continues to be one of the most complicated and challenging areas of research in the sciences of economics and finance. This is especially true when it comes to the prediction of stock prices. The highly dynamic, nonlinear, and usually unpredictable nature of financial markets has made it challenging for traditional statistical models to accurately describe the complexity of market behavior. This is owing to the fact that financial markets are exceedingly volatile. Since a considerable length of time ago, this has been the situation prevailing. On the other hand, the development of artificial intelligence, in particular methods that use Artificial Neural Networks (ANN) and Machine Learning (ML), has opened up exciting lines of inquiry for the purpose of improving the accuracy and flexibility of forecasting. Utilizing vast amounts of data and having higher processing capabilities, these strategies are utilized (Ayyildiz & et al, 2024).

Over the past several years, there has been a substantial amount of focus placed on the utilization of artificial neural networks as powerful tools for the analysis of financial data in order to discover previously concealed patterns. The ability of these models to learn complex, nonlinear connections between market inputs and future financial outcomes is made possible by the absence of the requirement for pre-specified functional forms. A few examples of market inputs are historical prices, trade volumes, and data on the macroeconomic environment. As an illustration, Hariyanti et al. (2024) proved that neural network models are capable of explaining complicated relationships between stock value, returns, and available market information, beyond the capabilities of standard statistical approaches (Hariyanti & et al, 2024). The ability of neural network models to explain was demonstrated, which allowed this to be accomplished.

While this is going on, typical machine learning techniques like Support Vector Machines (SVM), Random Forests, and Gradient Boosting have experienced tremendous progress, which has resulted in the building of models that are both robust and interpretable for the purpose of financial prediction. An important topic regarding the relative effectiveness of various algorithms in predicting the movements of stocks was posed by (Ayyildiz & et al, 2024). The results of their investigation brought to light the fact that the effectiveness of machine learning models is contingent on the context, in particular with regard to the quality of the data, the volatility, and the forecast horizon that was chosen. Furthermore, Jin and Xu (2024) applied machine learning methods in order to forecast scrap steel prices in Northeast China. This was done in a manner that was comparable. This research serves as an illustration of how these methodologies can be utilized in the process of putting commodity-specific financial modeling into action (Jin & et al, 2024). Observations have shown that the incorporation of deep learning architectures, such as Long Short-Term Memory (LSTM) networks and Transformer models, has led to a significant enhancement in the system's ability to make accurate predictions as presented in Figure 1. When applied to the context of financial time series data, these models are exceptionally well-suited to the challenge of capturing long-term temporal relationships as well as interactions that are not immediately visible with one another.

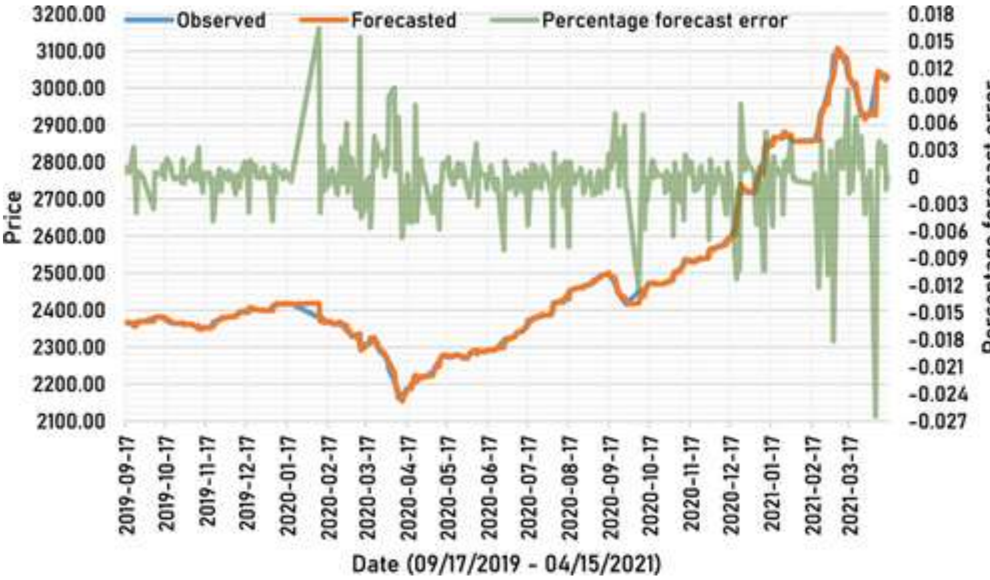
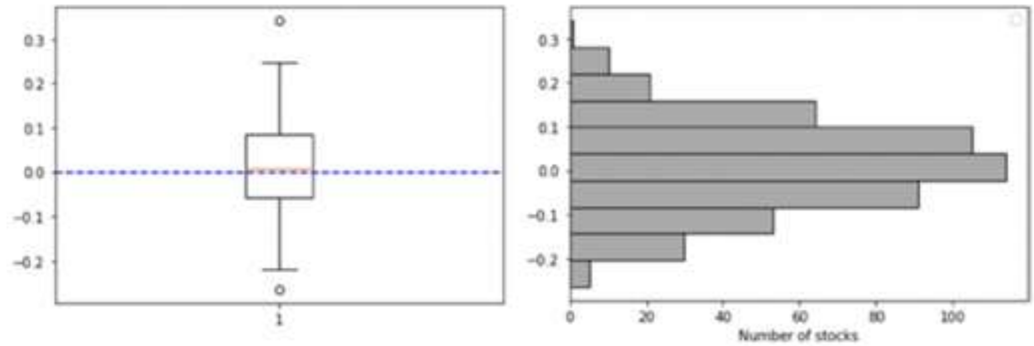


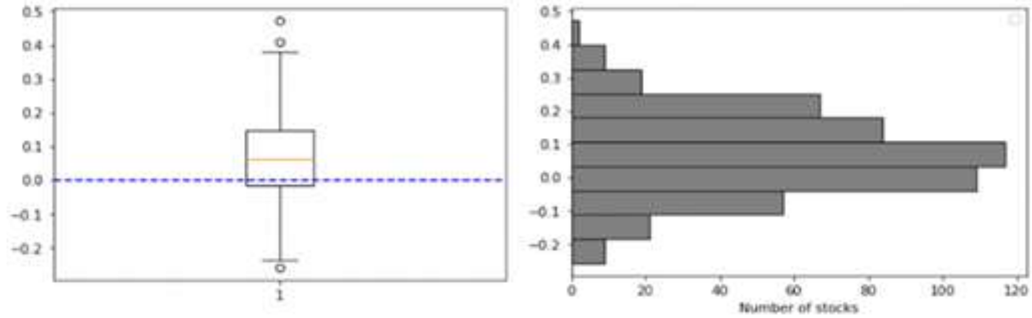
Figure 1. Out-of-Sample Forecast vs. Actual Prices and Error Rates according to (Jin & et al, 2024)

Wang et al. (2024) emphasized the benefits of LSTM networks in overcoming the vanishing gradient problem that is inherent in traditional Recurrent Neural Networks (RNNs), which ultimately led to more accurate stock trend forecasts. LSTM networks are able to overcome this difficulty so that they can forecast market trends more accurately (Wang & et al, 2024). It was at the same time period that Yañez et al. (2024) utilized Transformer neural networks, which were paired with frequency decomposition techniques, with the objective of enhancing the accuracy of market index forecasts (Yañez & et al, 2024). The sophisticated capabilities of modern deep learning technology are reflected in this methodology, which is a representation of those capabilities .The introduction of hybrid models is a result of recent innovations that have led to the introduction of hybrid models. The neural networks, signal processing, and feature extraction techniques are all incorporated into these models simultaneously. The SMP-DL model that was proposed by (Shaban & et al, 2024). Deep learning and financial signal processing are both components of this model, which was developed with the intention of improving one's comprehension of variations in the stock market. Yao (2025) has developed an updated Transformer model that is able to capture temporal and multidimensional information in stock prices. This model was successful in capturing this information (Yao, 2025). The fact that this is the case suggests that the model possess a greater capacity for prediction in complex market situations .Within a similar vein, the implementation of artificial intelligence has proven to be advantageous for the processes of risk assessment and derivative pricing. Specifically, Huang et al. (2024) conducted an examination into the ways in which deep learning and ensemble approaches could be applied to estimate and manage financial risk in derivative markets. This inquiry investigated the potential applications of these methods (Huang & et al, 2024). This study focused a particular emphasis on the scalability and robustness of models of this kind. By utilizing jump prediction models to monitor CDS (credit default swap) price fluctuations in systemically important financial institutions, Rao et al. (2024) established the potential of artificial intelligence in the monitoring of systemic risk. This was accomplished by demonstrating the potential of AI in the monitoring of systemic risk. These models were generated by the application of techniques within the field of machine learning. (Rao & et al, 2024) The aim of projecting relative returns inside equity markets has also received a significant amount of attention and effort throughout this time period. The results of a study that was carried out by Htun and et al (2024) demonstrated that machine learning has the ability to accurately predict the relative performance of companies that are included in the S&P 500 (Htun & et al, 2024). The significance of intelligent systems during the portfolio planning process is brought into focus by this discovery as presented in Figure 2. An expert system approach for portfolio forecasting that is based on deep learning was proposed by (Jeribi & et al, 2024).

Individuals are provided with enhanced investing decision-making capabilities through the utilization of this framework, which combines conventional financial insights with advanced artificial intelligence methodologies. It is becoming increasingly important to undertake a comprehensive comparison between traditional machine learning methods and artificial neural networks in light of the rapid advancement of technology and the growing body of empirical evidence supporting these methods. The objective of this attempt is to get a more in-depth grasp of their unique strengths and limitations, as well as the extent to which they are successful in predicting financial prices. In the next section, we will provide an overview of the relevant literature, focusing on the key contributions and empirical discoveries that have been derived from current research in this field. For the purpose of laying a solid groundwork for this comparison, which will be discussed in the subsequent section, this will be carried out.



(a)



(b)

Figure 2. Comparative Analysis of Precision and Recall Differences Between LSTM and RC Classifiers Across Multiple Stocks

2. Literature Review

Financial time-series forecasting has experienced big improvements from using ML and DL models together. There are many research studies on algorithms to describe the changing and volatile patterns found in stock and commodity prices.

They pointed out that Artificial Neural Networks (ANN), Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) methods are capable of predicting stock prices (Chhajer & et al, 2022). It was discovered that LSTM excels at handling time-based connections, but when it comes to accuracy and the cost of computing, ANN and SVM were still good picks. Additionally, in their study, (Mokhtari & et al, 2021) noticed that multiple ML models often do better than single algorithms, more noticeably when market conditions are volatile.

(RL & Mishra, 2021) found MLPs to deliver improved accuracy in forecasting spot prices when used in the agricultural commodity market compared to using traditional statistics. They found that architectures should be chosen attentively to match the nature of the data. (Sonkavde & et al, 2023) underlined that there is no one model that performs better than others in every market and this emphasizes why examining several models is necessary.

(Aldhyani & Alzahrani, 2022) suggested a model that uses LSTM and CNN with deep learning methods and found that it outperformed classical machine learning techniques. This approach only used information on fast trades which does not cover the daily level of financial markets. (Zhu & et al, 2024) built a neural network model that uses both machine learning and deep learning, showing better predictions for prices than simple machine learning models but not testing them against each other.

Using gold prices as an example, Tashakkori et al. (2024) tested the MLP which achieved better outcomes than linear regression. Their study, however, was limited to one asset class (gold) and one model type (ANN) (Tashakkori & et al, 2024). Song et al. (2024) designed an LSTM-based model for financial stock prediction, reinforcing the importance of time-awareness in modeling stock sequences (Song & et al, 2024). Zheng et al. (2024) extended this by applying ML time-series analysis to predict financial enterprise stocks and macroeconomic data, illustrating the scalability of such models across domains (Zheng & et al, 2024). Table 1 summarizes key studies and the algorithms they employed.

Table 1: Summary of Algorithms Used in Recent Financial Forecasting Studies

Study	**Algorithms Used**	**Domain**	**Findings**
Chhajer et al. (2022)	ANN, SVM, LSTM	Stock Market	LSTM best for time-sequence; ANN still effective
Mokhtari et al. (2021)	ML models (various)	Stock Market	Hybrid models outperform standalone ML
RL & Mishra (2021)	MLP, DL	Agricultural Prices	MLP outperforms linear models

Sonkavde et al. (2023)	ML & DL	Stock Prices	No universal best model
Aldhyani & Alzahrani (2022)	CNN, LSTM	Stock Market	Deep learning superior, but domain-specific
Zhu et al. (2024)	Hybrid NN + ML	Price Forecasting	Hybrid improves performance
Tashakkori et al. (2024)	MLP	Gold Prices	MLP effective, lacks comparative analysis
Song et al. (2024)	LSTM	Stock Prices	Captures temporal behavior well
Zheng et al. (2024)	ML + Time Series	Financial & Economic Data	Effective trend prediction across domains

Despite the fact that LSTM and certain hybrid networks have been proven reliable, a comparison of their performance with that of traditional machine learning techniques, specifically for gold and equity prices, is virtually unexplored. Studies carried out earlier usually deal with either just one model or one kind of asset class.

In addition, not many empirical research projects have compared ANN, Random Forest (RF), Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) in the same way, especially on MATLAB using datasets for gold and financial equities (MasterCard and Visa) as shown in Table 2.

Table 2: Gaps Identified in Reviewed Literature

Gap Identified	**Description**
Model Diversity	Lack of comprehensive comparison between ANN and traditional ML models like RF, SVM, KNN
Asset Class Diversity	Focused studies on either gold or stock, not both
Tool/Platform Standardization	Few studies using MATLAB as implementation platform
Temporal Range	Most studies limit data up to 2020 or focus on high-frequency data
Evaluation Framework	Inconsistent or limited evaluation metrics (e.g., lacking ANOVA-based comparisons)

This study aims to fill these gaps by thoroughly comparing ANN with three commonly used machine learning models—Random Forest, Support Vector Machine and K-Nearest Neighbors—on two datasets: gold prices from 2019-2024 and daily stock prices of MasterCard and Visa from 2008 to 2024. All simulations were conducted with MATLAB, guaranteeing that everything ran and was checked the same way. This study gives insights from real-world data about the usefulness of trading models across different assets and makes sure to use ANOVA to assess the models' results.

3. Methodology

This analysis will focus on how effective ANN is when measured against Random Forest (RF), Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) in predicting stock prices. There were two datasets used: daily gold prices over history and daily stock closing prices for MasterCard and Visa. Both modeling and evaluation steps in the project were done with MATLAB. Figure 3 shows this research Methodology.

A. Preparation and Collection of Data

The data was obtained in Excel format and imported into the program using readtable from (Kaggle_Datasets.com). MATLAB's datenum function was used to change the date column into a numerical time index to use as a continuous input feature. The predicted result we aimed for was the value of Y which was the closing price. Both the input and output data were normalized with z-score normalization to make machine learning models converge and be more stable. Missing values caused certain rows to be omitted to protect the quality of the input data as presented in Table 1.

Model building and testing was done separately for the data from the gold price dataset and the stock price data containing both MasterCard and Visa closing prices. Every target was addressed individually by using the same preparation and training methods.

Table 1. Summary of Datasets Used

Dataset Description	**Time Span**	**Frequency**	**Target Variable**
Gold Prices	2019–2024	Daily	Gold Closing Price
MasterCard/Visa Stock Prices	2008–2024	Daily	MasterCard / Visa Close

B. Modeling Framework

ANN, RF, SVM and KNN are the four algorithms used in the predictive modeling. The data was divided into five parts to perform a 5-fold cross-validation. In this method, one group served as the test set while the remaining groups were used for training in each of five iterations. Using this way makes the model perform consistently and reduces the probability of overfitting.

The artificial neural network included two hidden layers, each containing 10 and 5 neurons. The training used the Levenberg-Marquardt algorithm and the training window stayed turned off for automated methods. The regressor builds Random Forest out of 50 bootstrap-based decision trees. In the SVM regression model, RBF was selected as the kernel, but in KNN the parameter K was set to 5. Table 2 shows the parameters of this study models. In the first case, the KNN algorithm was hand-coded with distance calculations, while MATLAB's own fitcknn function was used in the second. All of the models were rated according to RMSE and R^2. To see if there were differences, an ANOVA test was also carried out on the RMSE values.

Table 2. Model Implementation of this study

Model	**Tool Used**	**Parameters**
ANN	Neural Network	Hidden layers: [10, 5]; Training: Levenberg-Marquardt
Random Forest	Ensemble Learning	50 trees; Bootstrap aggregation
SVM	Regression	Kernel: RBF; Automatic scaling
KNN	Regression	K = 5; Manual or automatic distance evaluation

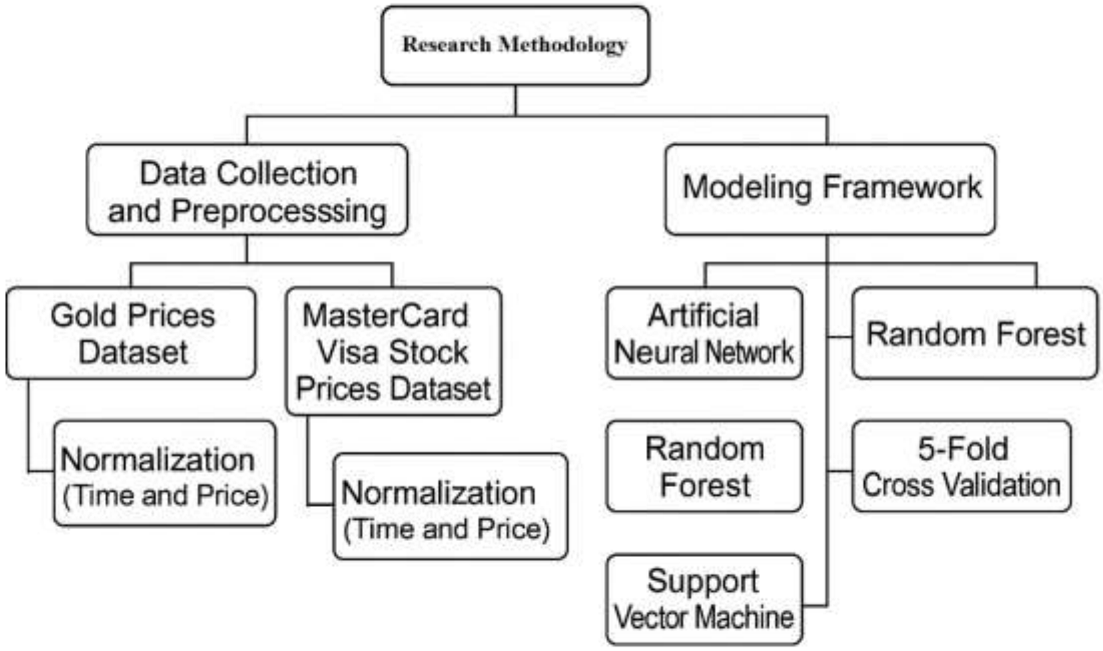


Figure 3. procedures of the proposed model

4. Results and Discussion

In this section, the complete results of the model training and evaluation are presented. Particular attention is paid to the progression of accuracy and loss over time, as well as final performance indicators such as validation accuracy, and a comparative study with earlier studies.

C. Application on ANN and ML using datasets of Stock Prices of MasterCard and Visa (2024-2008)

Five-fold cross-validation was used to assess the power of each of the machine learning models—ANN, RF, SVM and KNN—on the given dataset. Measures for the models included Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2). The following table gives the average values of RMSE and R^2 for each model in all the folds.

As illustrated in Table 1, the Random Forest model was the best among the models, earning the lowest RMSE of all (0.0273) and the highest R^2 value (0.9993). After SVM, the next model to perform well was KNN, mainly in terms of R^2. There were some minor issues with the ANN model outperforming the previous ones by a small amount. Alternatively, SVM returned an RMSE of 0.1131 and an R^2 of only 0.9873, meaning it struggled more to represent the main patterns in the data (See Figure 4).

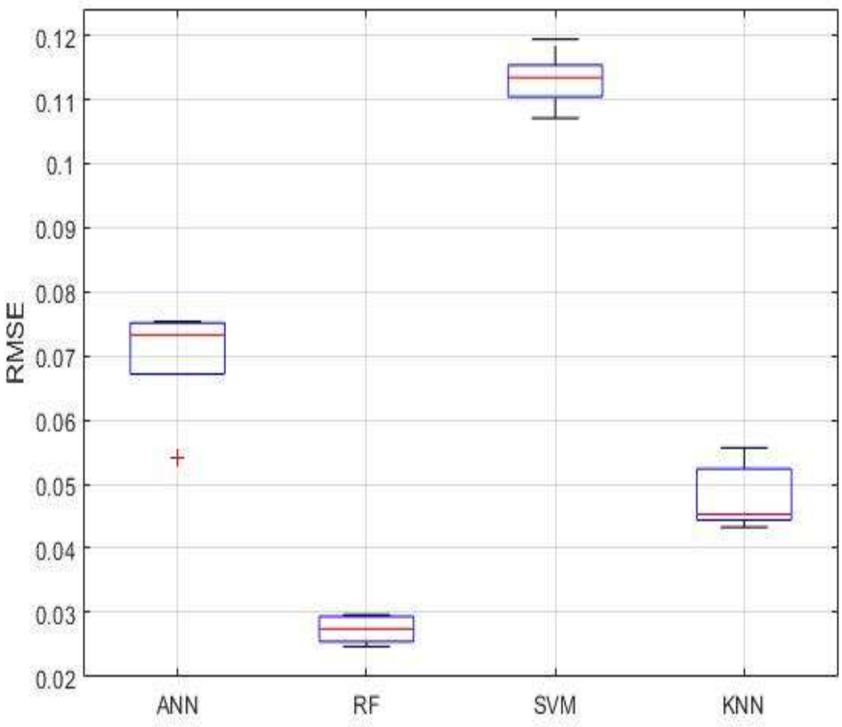


Figure 4: Plot box determined the Average Performance Metrics for Each Model

The comparison clearly demonstrates the overall performance of four predictive models through the Root Mean Squared Error metric. The Random Forest (RF) model performed best, with an average RMSE of 0.027 which demonstrates that it predicted values with the highest accuracy. Next, KNN reports a slightly larger error with RMSE of 0.048 and ANN has a value of 0.070. The SVM model returned an RMSE of 0.113, showing that it was not useful for this data and goal as presented in Figure 5.

Figure 5: Average RMSE values for ANN and Machine Learning (ML) Techniques.

Figure 6 displays how the Root Mean Square Error is distributed in the three folds. The boxplot makes it easier to visualize how the RMSE values change in the 5-fold cross-validation process. Both the lowest median RMSE and the narrowest IQR in the RF model suggest that it gives similar results when training on different data. KNN and ANN display stable behavior, however they seem to produce a little more error and more variability in results than RF. SVM has the highest median RMSE and the widest range of uncertainty which points to its being very sensitive to the data used and unable to accurately generalize.

Table 1: Average Performance Metrics for Each Model using datasets of Stock Prices of MasterCard and Visa

Model	Avg. RMSE	Avg. R^2
ANN	0.0699	0.9951
RF	**0.0273**	**0.9993**
SVM	0.1131	0.9873
KNN	0.0481	0.9987

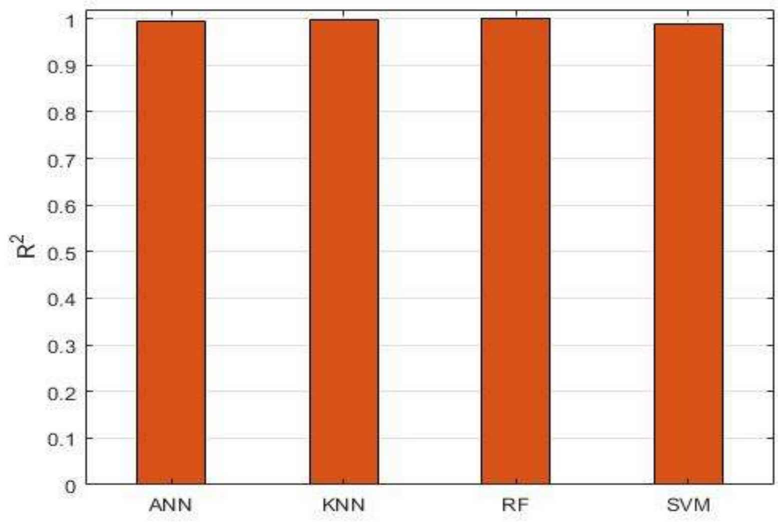


Figure 6: Average RMSE values for ANN and Machine Learning (ML) Techniques.

To find out if the observed discrepancy in RMSES between models was significant, a one-way ANOVA test was carried out. Table 2 shows the results of the analysis.

Table 2: ANOVA Results for RMSE Differences Between Models using datasets of Stock Prices of MasterCard and Visa

Source	SS	df	MS	F	p-value
Columns	0.0202	3	0.0067	204.03	5.85×10^{-13}
Error	5.29e-04	16	3.30e-05	—	—
Total	0.0207	19	—	—	—

For the ANOVA test, the F-statistic came out to be 204.03 and the p-value was 5.85×10^{-13} which is much less than the standard significance level of 0.05. From this result, we can tell that the changes in RMSE values among the models are statistically significant which means the choice of model plays a major role in predicting the results.

Figure 7 shows scatter plots that contrast between the model predictions and actual test values for four models: ANN, RF, SVM and KNN. Every plot displays a dashed red line that represents the perfect match between predicted and true data. Most of the points are found along the ideal line which means ANN produces reliable predictions. RF Performs similarly and its predicted values are usually quite close to the actual numbers, showing that it can predict well. There are several points in the SVM that vary from the main line which points to the fact that it may not handle some data points well. KNN provides an appropriate fit for the data, although it's less reliable in the predictions than ANN or RF. It seems that ANN and RF produce the most accurate outcomes by how their results match the real values.

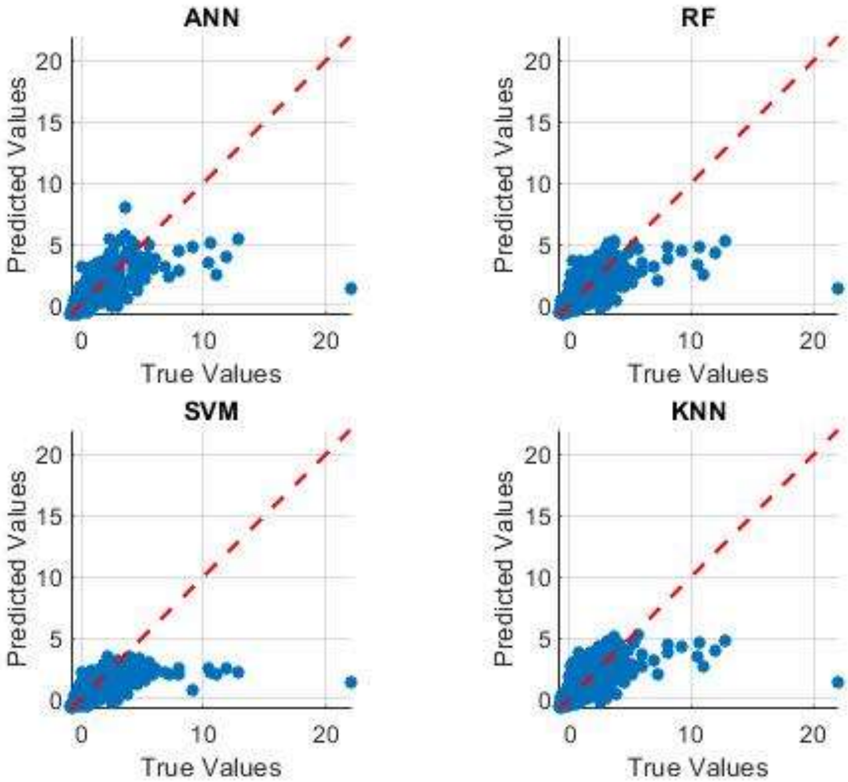


Figure 7: Scatter Plot: True vs Predicted for Four Approaches, ANN, RF, SVN, and KNN.

As a result, the reason for this is that from these comparisons, RF shows the best performance and stands out for its low error rate as well as impressive accuracy of prediction. It was also found that KNN introduced extra competition, as it met most of the performance standards as the RF model did. Both R^2 and MSE proved that the ANN performed well; however, the RMSE of the ANN was greater than those of the RF and the KNN.

D. Application on ANN and ML on Gold Prices datasets During (2019-2024)

By applying Four Techniques, KNN, RF, SVM, and ANN, it noted that among the models, KNN and RF get the best results, with average RMSE around 0.07 and R^2 more than 0.99, meaning they predict very accurately. Even though an Artificial Neural Network (ANN) works well, there are small discrepancies with a higher error and less R^2 as presented in Figure 8. The Support Vector Machine ranks as the worst because it has a high rate of error and a low value of R^2. A very small p-value from ANOVA (Prob > F ≈ 0) shows that the differences between the models' performances are not caused by luck; they are real and cannot be explained by randomness. All in all, KNN and RF offer the best results for this prediction task when measured by the given criteria as presented in Tables 3 and 4

Table 3: Model Performance of four models on gold prices datasets

Model	**Avg_RMSE**	**Avg_R2**
ANN	0.14092	0.98001
RF	0.07385	0.99461
SVM	0.30860	0.90637
KNN	0.07272	0.99479

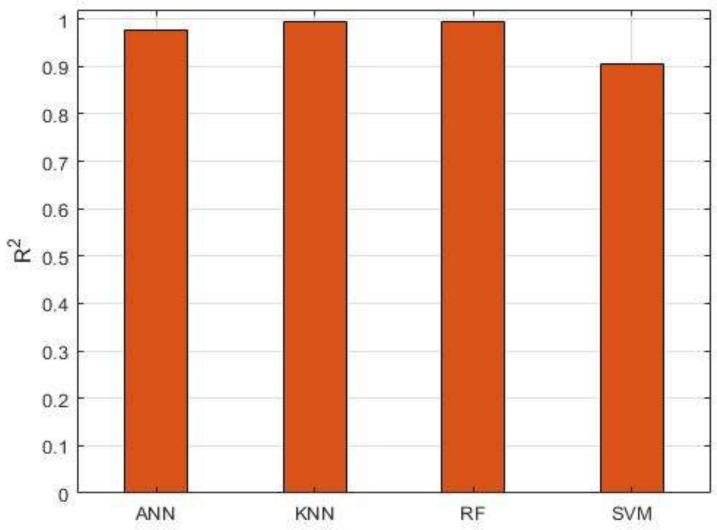


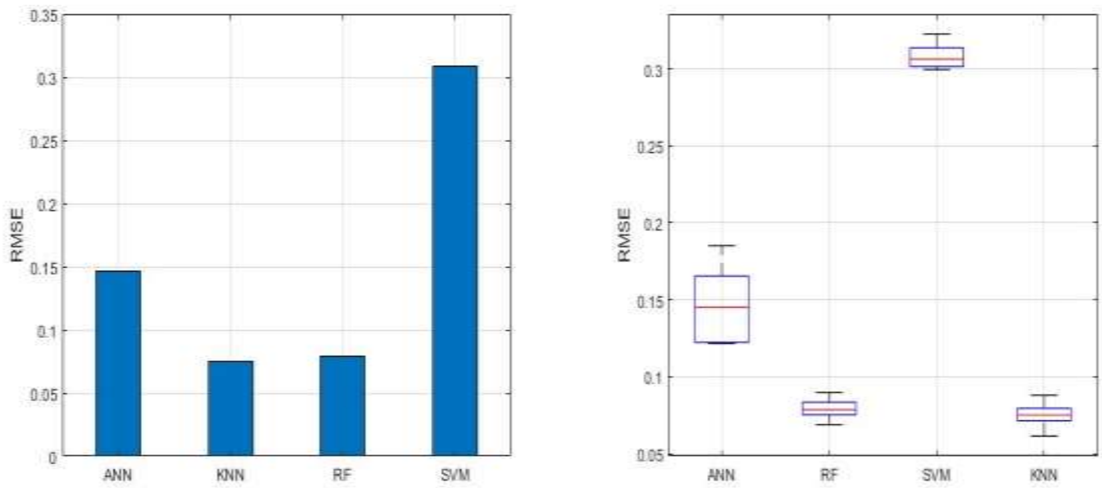
Figure 8: Average RMSE values for ANN and Machine Learning (ML) Techniques using Gold prices datasets.

Table 3: ANOVA Results for RMSE Differences Between Models on gold prices datasets

Source	**SS**	**df**	**MS**	**F**	**Prob > F**
Models	0.1850	3	0.0617	1371.3	1.6916×10^{-19}
Error	0.0007196	16	0.00004497		
Total	0.1857	19			

Figure 9.a represents the RMSE (Root Mean Square Error) for ANN, KNN, RF and SVM models through a bar chart. Lower RMSE shows that the models are more accurate in their predictions. RMSE shows that the Random Forest (RF) model gave the most accurate results in this task. Likewise, Support Vector Machine (SVM) reported the highest RMSE, meaning it performed the worst out of all the models.

In Figure 9.b, box plots show the RMSE values for the same models. The RMSE for each model is shown in terms of its distribution and variations. Box plot demonstrates that ANN and RF have median RMSE that is lower and variations that are narrower than KNN and SVM. In addition, SVM stands out by having the highest median and presenting the largest variety which points to inconsistent outcomes depending on the data. All in all, RF proves to be the most accurate model and SVM could be improved by adjusting some of its settings.



(a) **(b)**

Figure 9: Comparison of Model Performance Using RMSE Metrics

Accordingly, these findings ensured that Random Forest is better than other models in terms of accuracy and consistency. Although ANN and KNN perform decently, SVM does not do as well. These outcomes agree well with the results from statistics and suggest that Random Forest should be chosen for similar tasks.

The SVM model, using an RBF kernel, performed the weakest in this context—suggesting that either the kernel choice or the hyperparameter settings may not be optimal for this dataset. The ANOVA results reinforce the notion that not all models perform equally well, and choosing the right model is essential for ensuring accurate forecasting. The statistical significance in the differences supports the adoption of ensemble learning methods such as Random Forest in similar forecasting problems involving temporal financial data.

6. Conclusion

The study aimed to examine how accurately each of the four supervised learning models—ANN, RF, SVM and KNN—predicts financial prices. To bridge a research gap on this topic, the study compared how ANN and core machine learning algorithms fare at predicting prices of different assets, taking a statistical approach. Two sets of data were needed: the daily stock prices of MasterCard and Visa from 2008 to 2024 and daily gold prices from 2019 to 2024. All of the models used MATLAB to maintain consistency in how they were developed. RMSE and R^2 were used as important evaluation metrics and ANOVA tests were done to check whether the results were real. The research showed that certain trends were repeated. Almost every metric indicated that RF and KNN worked the best in both datasets. RF gave the best accuracy in the stock price dataset, with Avg. RMSE = 0.0273 and R^2 = 0.9993, almost equal to what KNN could manage. ANOVA found that model differences were different enough to be statistically significant (F = 204.03, $p \approx 5.85\times10^{-13}$). Compared to GBM and SVM, both RF and KNN again had the best results in gold price forecasting and their success was underlined by F (1371.3) and p (1.69×10^{-19}) from ANOVA, whereas R^2 values were very high at approx. 0.995 and errors were minimal at RMSE ≈ 0.07. Although ANN did well in almost all parts of the study, it usually did not surpass the performance of RF and KNN. In the two scenarios, SVM did not perform as expected. The study shows that RF and KNN models give better predictive results and can be more widely used than ANN and SVM in the financial sector. Results from these experiments provide good suggestions for financial analysts, investors and data scientists who want to increase the reliability of their forecasting. Future studies may use various models combined into one to make use of the strengths of the existing algorithms.

References

Aldhyani, & Alzahrani. (2022). Framework for predicting and modeling stock market prices based on deep learning algorithms, Electronics. 3149.

Ayyildiz, & et al. (2024). How effective is machine learning in stock market predictions?, Heliyon.

Chhajer, & et al. (2022). The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction, Decision Analytics Journal. 100015.

Hariyanti, & et al. (2024). The Application of Neural Network Models to Explain the Relationship Between Stock Value, Returns Value, and Information on Prices, Jurnal Informasi dan Teknologi. 23–28.

Htun, & et al. (2024). Forecasting relative returns for S&P 500 stocks using machine learning, Financial Innovation. 118.

Huang, & et al. (2024). Artificial Intelligence-Driven Risk Assessment and Control in Financial Derivatives: Exploring Deep Learning and Ensemble Models, Transactions on Computational and Scientific Methods.

Jeribi, & et al. (2024). A deep learning based expert framework for portfolio prediction and forecasting, IEEE Access.

Jin, & et al. (2024). Machine Learning-Based Scrap Steel Price Forecasting for the Northeast Chinese Market, International Journal of Empirical Economics.

Mokhtari, & et al. (2021). Effectiveness of artificial intelligence in stock market prediction based on machine learning, arXiv preprint arXiv:2107.01031.

Rao, & et al. (2024). Jump Prediction in Systemically Important Financial Institutions' CDS Prices, Spectrum of Research.

RL , & Mishra. (2021). Forecasting spot prices of agricultural commodities in India: Application of deep-learning models, Intelligent Systems in Accounting, Finance and Management. 72-83.

Shaban, & et al. (2024). SMP-DL: A novel stock market prediction approach based on deep learning for effective trend forecasting, Neural Computing and Applications. 1849–1873.

Song, & et al. (2024). LSTM-Based Deep Learning Model for Financial Market Stock Price Prediction, Journal of Economic Theory and Business Management. 43-50.

Sonkavde, & et al. (2023). Forecasting stock market prices using machine learning and deep learning models: A systematic review, performance analysis and discussion of implications. *International Journal of Financial Studies*.

Tashakkori, & et al. (2024). Forecasting gold prices with MLP neural networks: A machine learning approach, International Journal of Science and Engineering Applications (IJSEA). 13-20.

Wang, & et al. (2024). Predicting stock market trends using LSTM networks: Overcoming RNN limitations for improved financial forecasting, Journal of Computer Science and Software Applications. 1-7.

Yañez, & et al. (2024). Stock market index prediction using transformer neural network models and frequency decomposition, Neural Computing and Applications. 15777–15797.

Yao, Y. (2025). Stock Price Prediction Using an Improved Transformer Model: Capturing Temporal Dependencies and Multi-Dimensional Features, Journal of Computer Science and Software Applications.

Zheng, & et al. (2024). Predicting financial enterprise stocks and economic data trends using machine learning time series analysis, Applied and Computational Engineering. 26-32.

Zhu, & et al. (2024). Forecasting price in a new hybrid neural network model with machine learning, Expert Systems with Applications. 123697.