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Financial market index prediction using machine learning

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Abstract: The present work aims to tackle the crucial objective of forecasting values for a range of financial market indices in order to maximize income while minimizing potential losses. This study utilizes a comparative analysis approach to examine the performance of artificial neural networks (ANNs) and decision tree models in predicting stock market movements in Saudi Arabia (KSA). The analysis is conducted using a daily database. The predictive models included in this study are constructed using historical stock market data, which encompasses the time period from January 1, 2013, to October 4, 2023. The primary objective of these models is to generate accurate projections specifically for the Tadawul Daily Index. The main objective of this study is to evaluate and contrast the effectiveness of artificial neural network (ANN) and decision tree models in predicting the performance of the stock market in Saudi Arabia. The analysis demonstrates that the decision tree model has a somewhat lower predictive capability when compared to the artificial neural network (ANN) model. The present study utilizes statistical metrics, namely root-mean-squared error (RMSE) and mean absolute error (MAE), to assess and quantify the accuracy of predictions.

Moreover, a thorough examination is undertaken, encompassing a range of relevant statistical indicators, and visually representing the data series using graphical means. The utilization of a diverse methodology serves to augment knowledge and facilitate a comprehensive grasp of the intrinsic daily patterns observed in the Tadawul Daily Index. The objective is to enhance the understanding and examination of the complexities of the stock market, so empowering investors and financial analysts to make educated choices that match with their strategic goals and risk management methods. The study's findings provide significant contributions to the field of financial market prediction, specifically in the Kingdom of Saudi Arabia.

Keywords: Machine Learning, Artificial Neural Network, Statistical Model, Decision Tree, Statistical Metric

1 Introduction

In recent years, there has been a notable increase in the interest around machine learning methodologies, primarily attributed to their ability to anticipate and forecast patterns within the financial market. This phenomenon can be ascribed to their innate capacity or capability. Presently, the field of financial market prediction extensively employs many techniques such as multi-layer feed-forward neural networks, support vector machines, reinforcement learning, relevance vector machines, and recurrent neural networks [1]. In contemporary times, intelligent systems that provide artificial intelligence functionalities frequently depend on the utilization of machine learning techniques. Machine learning refers to the ability of systems to acquire knowledge from training data that is relevant to a given problem. This knowledge acquisition enables the automation of the process of constructing analytical models and effectively addressing related tasks. Deep learning is a computational paradigm within the field of machine learning that is rooted on the utilization of artificial neural networks. In numerous areas, deep learning models have demonstrated superior performance compared to shallow machine learning models and conventional data analysis methodologies. This article provides a comprehensive overview of the fundamental principles of machine learning and deep learning, aiming to enhance readers' comprehension of the systematic foundations that underlie contemporary intelligent systems. This paper presents a conceptual differentiation between pertinent terms and concepts, elucidates the procedure of constructing automated analytical models using machine learning and deep learning techniques, and examines the difficulties encountered during the implementation of these intelligent systems in the domain of electronic markets and networked business. These phenomena extend beyond the realm of technology and bring attention

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to challenges in the interaction between humans and machines, as well as the process of integrating artificial intelligence into service-oriented systems.[2]. This research presents a comprehensive exploration of machine learning algorithms and statistical methodology with the objective of forecasting stock market data. The present study is organized in the following manner: Section 2 offers an extensive examination of the current body of literature. Section 3 provides an introduction to the Artificial Neural Network (ANN) methodology. Section 4 of the paper provides an in-depth analysis of the Auto-regressive Integrated Moving Average (ARIMA) model. Section 5 of the document provides an overview of the Data Analysis and Numerical Results. Section 6 presents a variety of comments.

2 literature review

In the study conducted by the authors of Paper [3], a machine learning information acquisition technique was employed to evaluate the associations between different financial and economic indicators, as well as their potential for predicting. The variables can be ordered by determining the information acquired for each model variable. A predetermined threshold is set to exclusively incorporate the most pertinent and influential elements into the forecasting models. This study examines the efficacy of artificial neural network (ANN) models in the tasks of level estimation and classification for the purpose of forecasting future values. Furthermore, the utilization of a cross-validation technique serves to enhance the generalization of diverse models. The results indicate that trading strategies based on categorization models provide higher risk-adjusted gains when compared to the buy-and-hold strategy, alternative neural network models, and linear regression models.In the paper, [4]Recurrent neural networks (RNNs) are a very effective collection of artificial neural network algorithms, particularly well-suited for the analysis and manipulation of sequential data, such as auditory, temporal, or linguistic information. Certain recurrent neural networks (RNNs), specifically the Long Short-Term Memory (LSTM) model, have demonstrated superior performance in the prediction of financial data, leading to their increased use in this domain. The paper characterizes recurrent neural networks as a powerful category of artificial neural network algorithms, specifically advantageous for the analysis of sequential data such as sound, time, or language. Recurrent neural networks (RNNs) are a kind of artificial neural networks that exhibit a unique ability to process sequential data by utilizing feedback connections. Some recurrent neural networks (RNNs) gained popularity because they were more effective at predicting financial data. The ANN can be trained using a variety of techniques, some of which are more effective than others at identifying the linear and nonlinear relationships as mentioned in the paper [5]. For the investigation of linear and nonlinear qualities, ANN employs two criteria. The quantity of layers has a significant impact on predictability. Using too many layers will complicate the structure and prevent the ANN from selecting the best option. Additionally, the ANN cannot locate the global solution or nonlinear relationships if there are too few layers. The researchers have looked for techniques that are quick, accurate, and have low error rates. Metaheuristic algorithms are employed as a result. These techniques are used to optimize networks and determine the optimal number of input and hidden layers. The ANN models outperform conventional statistical models at forecasting stock price, stock return, exchange rate, inflation, and imports. In a study conducted by Hulbert White [6], the closing values of IBM were predicted using a feed-forward neural network. The model incorporated an input layer, a hidden layer, and an output layer. Out of the total dataset of 5000 days, 1000 days were allocated for training the model, while the remaining 4000 days were designated for testing the model. The present study [7] examines the application of a multi-layer back-propagation (BP) neural network, a widely recognized technology in the field of neural networks, for the purpose of financial data mining. The proposed framework includes a modified neural network forecasting model and an intelligent mining system. The algorithm has the capability to predict buying and selling signals based on anticipated future stock market trends, thereby aiding stock investors in making informed decisions. Based on the findings from a seven-year simulation of the Shanghai Composite Index, it has been observed that the mining system yields a return that is roughly three times greater than that of the buy-and-hold strategy. This suggests that utilizing neural networks for forecasting financial time series can be advantageous, as it presents an opportunity for diverse investors to potentially benefit from it. The research [8] highlights the potential of Artificial Neural Networks (ANN) to identify hidden and unknown patterns within data, making them particularly effective in the field of stock market forecasting. If this initiative achieves success, it possesses the potential to yield benefits for investors and financial institutions, thereby making a substantial contribution to the economy. There exist several approaches that are utilized for the purpose of predicting returns in the Share Market.

3 An artificial neural network (ANN)

A model utilizing neural networks has been employed for the purpose of predicting stock market trends. One of the techniques employed in intelligent data mining is the utilization of artificial neural networks (ANN) [9]. The artificial neural network (ANN) is a computer model that draws inspiration from the structural and functional characteristics of biological neural networks seen in the human brain [10]. The aforementioned concept holds significant importance within the domains of machine learning and artificial intelligence. The fundamental principle underlying an artificial neural network encompasses the subsequent components:

1.Neurons, sometimes referred to as nodes or units, serve as the fundamental processing units within an artificial neural network [11]. Every individual neuron inside a neural network is capable of receiving many inputs, undergoing internal processing, and subsequently generating an output. Neurons exhibit a hierarchical arrangement, commonly comprising an initial layer for input, one or more intermediate layers known as hidden layers, and a final layer designated as the output layer [12].

2. In the context of neural networks, the weights assigned to each connection between neurons serve as indicators of the connection's relative strength. Furthermore, it is worth noting that every individual neuron possesses a bias term [13]. The weights and biases are acquired through the training procedure, and they govern the propagation of information throughout the network.

3.The activation function is commonly utilized by each neuron to process the weighted sum of its inputs in addition to its bias [14]. The incorporation of this activation function introduces non-linearity within the network, allowing it to gain an understanding of complex patterns and correlations inherent in the data.[15]. Frequently employed activation functions in neural networks encompass the sigmoid, ReLU (Rectified Linear Unit), and tanh (hyperbolic tangent) functions [16].

4. The feed-forward process involves the transmission of information inside the network, following a unidirectional path from the input layer, passing via the hidden layers, and ultimately reaching the output layer [17]. Every individual neuron inside a given layer has the task of processing the input it receives, then transmitting the outcome to the neurons situated in the subsequent layer.

5. Training: The process of training neural networks involves the utilization of labeled data, which is accomplished through a technique known as supervised learning [18]. During the training process, the neural network modifies its weights and biases by employing optimization algorithms, such as gradient descent, with the objective of minimizing the discrepancy between its predicted values and the true target values. This procedure entails the computation of gradients and the subsequent propagation of errors across the neural network [19].

6. A loss function is utilized to evaluate the degree of alignment between the predictions made by a neural network and the true target values. The objective during the training process is to minimize the aforementioned loss function [20].

7. Back-propagation refers to the computational procedure employed to calculate the gradients of the loss function in relation to the weights and biases of a neural network [21]. The gradients are employed to modify the weights and biases in a manner that is opposite to their gradients, resulting in a reduction of the loss and enhancement of the network's performance.

8. The architectural configuration of a neural network, encompassing factors such as the quantity of layers, the quantity of neurons inside each layer, and the interconnections between neurons, is contingent upon the specific problem for which the network is intended to address [22]. Deep neural networks consist of numerous hidden layers and possess the ability to acquire intricate representations. Artificial neural networks find application in diverse machine learning applications, encompassing image identification, natural language processing, speech recognition, and other domains [23]. The capacity to acquire intricate patterns from data renders them a potent instrument in contemporary AI applications [24]. Various neural network topologies have been created to cater to various jobs and data types. For instance, convolutional neural networks (CNNs) are designed for processing images, while recurrent neural networks (RNNs) are tailored for sequential data.

4. Decision trees

The Decision Tree technique is commonly employed in the domain of machine learning for the purposes of classification and regression applications [25]. The method in question is a supervised learning technique that constructs a hierarchical structure resembling a tree in order to facilitate decision-making or prediction. The fundamental concept of a Decision Tree encompasses the subsequent essential components [26]:
Nodes Serve as the primary components that comprise a Decision Tree. There exist two distinct categories of nodes.The root node is the highest-level node in the tree and serves as the starting point for making decisions or predictions[27].
Internal nodes in a given system are representative of intermediate decisions or conditions that are contingent upon input attributes. The child nodes are determined by the condition's outcome [28].
Edges, often referred to as branches, serve the purpose of connecting nodes within a system and symbolize the result of a decision or condition. Every edge within the context of an internal node represents a potential outcome of the linked condition.
Terminal nodes, also known as leaves, serve as the concluding points inside a Decision Tree, signifying the ultimate anticipated class or value. In the context of classification, every leaf node is associated with a specific class label, while in regression, each leaf node represents a predicted value [29].
Splitting refers to the procedure of partitioning the data at an internal node into multiple child nodes, utilizing a designated feature and threshold as the criteria for division. The selection of the feature and threshold is conducted with the objective of maximizing the differentiation between classes in classification tasks or minimizing the variance in regression tasks at

every node.

Criterion: decision trees employ many criteria to assess the efficacy of a split. Typical criteria encompass Gini impurity, employed in classification tasks, and mean squared error, utilized in regression tasks. These factors aid in the determination of the most suitable characteristic and threshold for the purpose of splitting.

Pruning is a methodology employed to decrease the intricacy of a Decision Tree by eliminating branches that possess negligible impact on the accuracy of the model. One of the advantages of using decision trees is their ability to mitigate the issue of over-fitting, which occurs when the tree becomes overly specialized to the training data and therefore exhibits subpar performance when presented with new, unseen data.

Decision rules are formed by each path from the root to a leaf in a Decision Tree. The aforementioned rules constitute a series of conditions derived from input features, which ultimately culminate in a conclusive judgement or prediction.

Classification: Decision trees have the capability to be employed in both classification and regression applications. In the context of data analysis, classification involves the assignment of a class label to each leaf node within a tree structure. On the other hand, regression pertains to the prediction of a continuous value within the same framework.

Entropy and Information Gain are commonly employed in classification tasks by Decision Trees to identify optimal splits [30]. Entropy is a metric used to assess the level of impurity or disorder inside a given data set. On the other hand, information gain is a measure that quantifies the extent to which entropy is reduced following a split operation [31].

The calculation of entropy for a data set S in the context of a binary classification problem, where there are two classes (e.g., 0 and 1), is as follows:

$$H(S) = -(p_1 \log_2(p_1) + p_2 \log_2(p_2)) \quad (1)$$

p_1 The ratio of occurrences belonging to class1 within data set S.

p_2 The ratio of occurrences belonging to class2 within data set S.

The logarithm is commonly computed with a base of 2, leading to the quantification of entropy in units of bits. Alternatively, it is possible to utilize alternative bases, such as the natural logarithm (ln), provided that a consistent approach is maintained throughout the computations.

The concept of Information Gain (IG) is employed to quantify the decrease in entropy, which represents the level of disorder, resulting from the division of a data set S into smaller subsets depending on a certain characteristic A . The quantification pertains to the amount of information received on the class labels when the attribute A is taken into account for the split.

$$IG\ (S, A) = H(S) - \sum \frac{|S_v|}{|S|} * H(s_v) \quad (2)$$

$IG\ (S, A)$ The calculation of the information gain of data set S resulting from the splitting on attribute A.

$|S_v|$ The cardinality of the subset $s_v$resulting from the partitioning of the data set based on attribute A.

$|S|$ The aggregate count of occurrences within data set S.

$H(S)$ The entropy of the original data set S.

$H(s_v)$ The entropy of each subset s_v that is formed as a result of the split.

The calculation of Information Gain involves determining the disparity between the entropy of the initial data set and the weighted average of the entropy of the subsets generated by the split. Attributes with higher Information Gain are considered more suitable for splitting since they effectively decrease the level of uncertainty, or entropy, inside the data set.

Tree depth: The concept of tree depth in the context of a Decision Tree pertains to the quantification of the number of levels or nodes that exist between the root node and the furthest leaf node[32]. A tree with more depth has the ability to capture intricate relationships within the data, however, it is susceptible to the problem of over-fitting.

Tree pruning: is a method employed to mitigate over-fitting by diminishing the dimensions of the tree [33]. The process entails the elimination of branches that do not yield a substantial enhancement in the model's performance on the validation data.

Decision trees provide the advantageous characteristics of interpret-ability and visualizability, rendering them a helpful instrument for comprehending and elucidating the decision-making mechanism within machine learning models. Ensemble methods such as Random Forests and Gradient Boosting frequently employ them, wherein many Decision Trees are combined to enhance forecast accuracy and robustness.

The accuracy measurement

The primary concept underlying accuracy evaluation is doing a comparative analysis between the original target and the projected outcome based on a predetermined set of criteria.

Metrics for model evaluation

Mean absolute percent error (MAPE) $= \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right|$ (3)

The Mean Absolute Percent Error (MAPE) is a quantitative measure employed to assess the precision of a forecasting or prediction model. There are various advantages associated with it.

Intuitive Interpretation: The Mean Absolute Percentage Error (MAPE) possesses a high level of comprehensibility. The forecasting model's accuracy is quantified using a percentage error, allowing for comprehensibility among individuals with varying technical backgrounds. A lower Mean Absolute Percentage Error (MAPE) value signifies a higher level of accuracy in the model.

Scale Independence: The Mean Absolute Percentage Error (MAPE) possesses the characteristic of being scale-independent. This attribute allows for the comparison of model performance across various datasets or industries, without being influenced by the scale of the data. This characteristic renders it a flexible instrument for the purpose of comparing forecasts across different domains.

The concept of symmetry in the context of Mean Absolute Percentage Error (MAPE) is characterized by its treatment of overestimation and underestimation in an equal manner.

Outlier Insensitivity: The Mean Absolute Percentage Error (MAPE) exhibits considerably lower sensitivity to outliers in comparison to alternative error metrics such as the Mean Absolute Error (MAE) or Mean Squared Error (MSE). The amplification of severe errors is not observed.

6. Data Analysis

In order to examine financial market indicators in the Kingdom of Saudi Arabia, we choose to employ artificial neural networks and decision tree approaches, in order to gain a comprehensive understanding of the suitable model for predicting the Saudi market index, for this purpose, we utilized a data set of 3482 observations. , statistical measures such as the mean, standard deviation, maximum value, and minimum value are utilized, The Tadawul Daily Index has a mean value of about 8320.42304, indicating the average value of the index across the full duration of the data set. The aforementioned feature serves as a focal point for assessing the performance of the index during this specific period. The standard deviation, estimated to be around 1548.50, quantifies the extent of dispersion or variability exhibited by the Daily Index values in relation to the mean. A larger standard deviation signifies increased volatility or variations in the index. In this particular scenario, the calculated standard deviation of 1548.50 indicates a level of volatility that may be characterized as moderate. The monitored time witnessed the Daily Index reaching its greatest peak, which was recorded as 13853.10, signifying the maximum value attained. This denotes the prevailing market conditions characterized by a highly optimistic sentiment or the pinnacle of the index's performance. The observed period witnessed the Daily Index reaching its lowest point, which was represented by the minimum value of 5416.50. This denotes the prevailing market circumstances characterized by a significant downward trend or the lowest recorded performance of the index. the data set was divided into training and testing sets. Cross-validation techniques are employed in order to guarantee the robustness of a model or method. The data set utilized in this study comprises daily observations of the TADAWUL Daily Index spanning from January 1, 2013, to October 4, 2023[34], as illustrated in Figure 1.

Fig. 1. The daily closing price index values series

Figure 1. The data set comprises the daily closing price index values ranging from January 2, 2010, to September 2, 2023

Multilayer Perceptron (MLP)

Table 1. Case Processing Summary

Case Processing Summary			
		N	Percent
Sample	Training	2417	69.4%
	Testing	1065	30.6%
Valid		3482	100.0%
Excluded		0	
Total		3482	

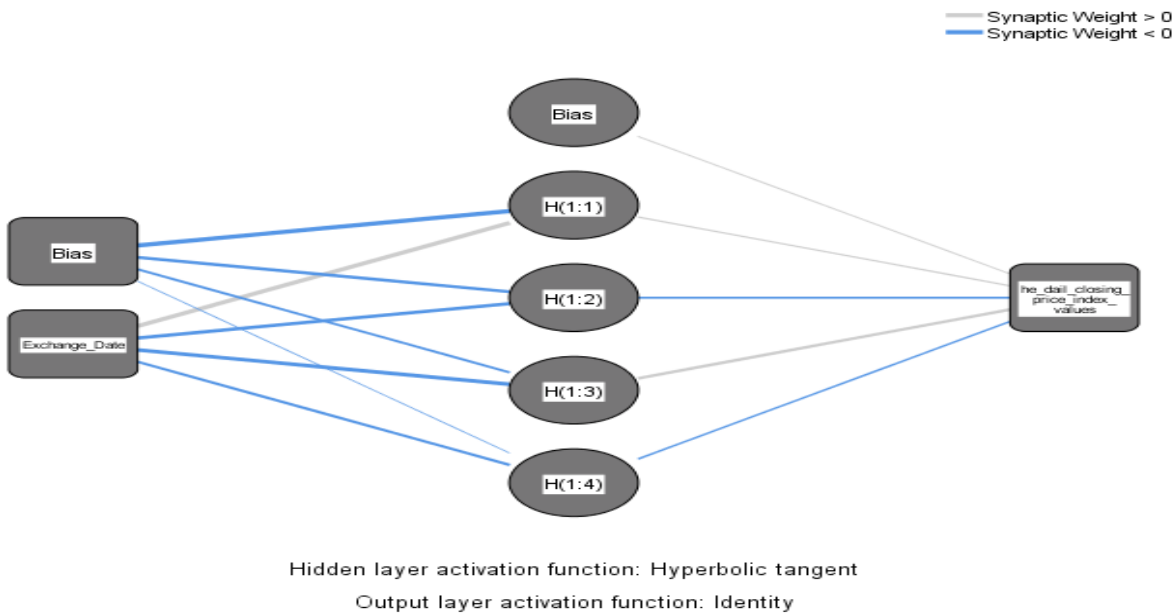

Fig.2.Feed-forward architecture with one hidden layer

In this figure, The research employs a feed-forward architecture with a solitary hidden layer, wherein data is transmitted unidirectional from the input layer to the hidden layer and then to the output layer, devoid of any feedback loops.

Decision Tree (DT)

Table 2. Response Information

Mean	Std. Deviation	Range	Minimum	Maximum
8320.42304	1878.93264	8497.08	5323.27	13820.35

As shown in Table 2. the mean value of the index for the entire lifetime of the data set is around 8320.42304, signifying the average value. The previously mentioned characteristic functions as a crucial element for evaluating the success of the index throughout this particular time frame.

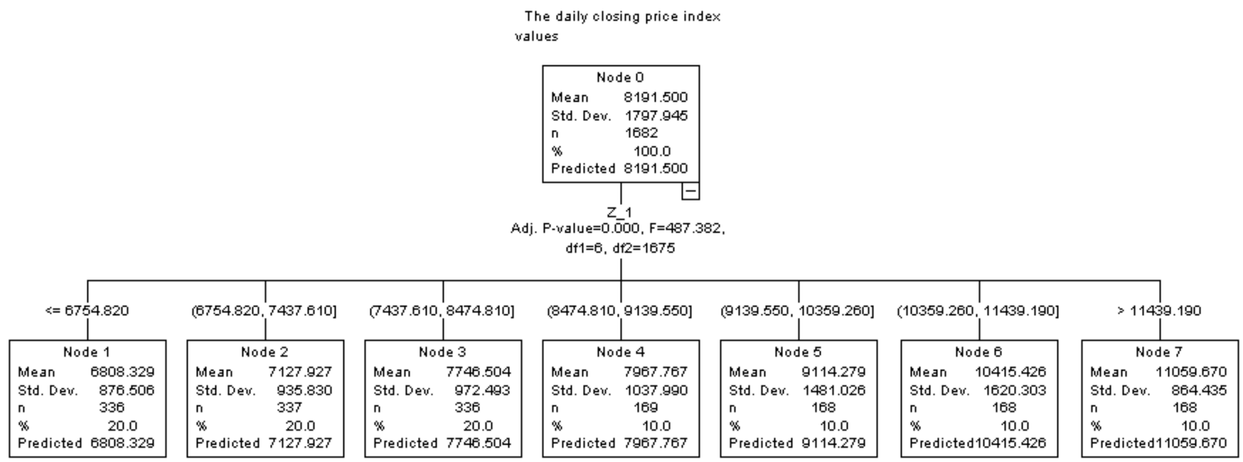

Fig.3 .Training Sample

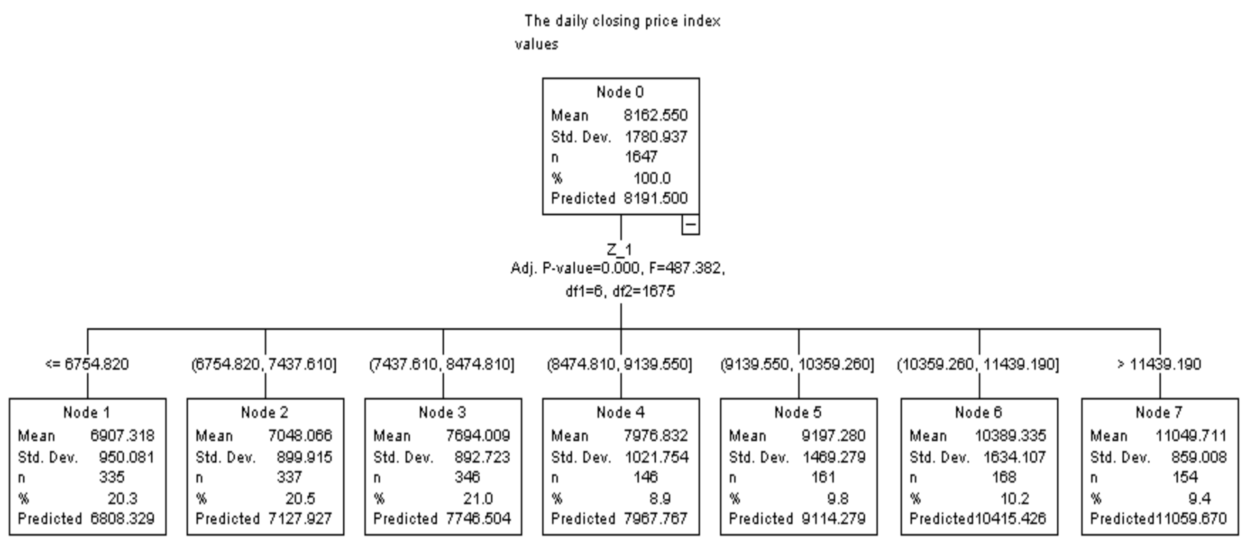

Fig. 4. Test Sample

The aggregate quantity of nodes is 7.

The Mean Absolute Percent Error (MAPE) of the Decision Tree (DT) model is calculated to be 0.108346389, whereas the MAPE of the Multi-Layer Perceptron (MLP) model is determined to be 0.04832612. The aforementioned statistics denote the percentage discrepancy between the predictions generated by each model and the actual data. A lower Mean Absolute Percentage Error (MAPE) value is indicative of a higher level of accuracy in the model. Therefore, based on the available information, it can be inferred that the MLP model demonstrates greater accuracy in the given context.

7. Conclusion

This study aims to provide a scholarly contribution to the field of forecasting the daily closing price index values in the Kingdom of Saudi Arabia by employing machine learning approaches. The presentation thoroughly examined the findings and their potential consequences in a manner that demonstrated expertise and authority. The utilization of artificial neural networks and decision tree techniques facilitated the development of models that exhibit high accuracy and are readily interpretable in relation to their predictive capabilities for the index. Based on the Mean Absolute Percent Error metric, it can be concluded that the multi-layer perceptron (MLP) method exhibits a higher level of prediction accuracy compared to the decision tree (DT) approach. The researchers employed a dataset comprising a cumulative count of 3582 individual observations. In order to further our understanding of the daily trading indicator's behavior, we incorporated statistical metrics including the mean, standard deviation, maximum value, and minimum value. The findings and viewpoints derived from this research may potentially provide valuable support to investors, financial analysts, and policy makers in Saudi Arabia as they navigate the dynamic Saudi financial environment and make well-informed decisions.

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References

[1] T. Francis & C. Lijuan. Application of support vector machines in financial time series forecasting. Omega, 29(4)., 309-317, (2001).

[2] H. Simon. Self-organizing maps. Neural networks-A comprehensive foundation, Prentice-Hall, (1999).

[3] E. David. & T. Suraphan. The use of data mining and neural networks for forecasting stock market returns. Expert Systems with applications, 29(4)., 927-940, (2005).

[4] G. Tingwe & C.Yueting. Improving stock closing price prediction using recurrent neural network and technical indicators. Neural computation, 30(10), 2833-2854, (2018).

[5] Y. Julian & M. Heather. A comparison of corporate failure models in Australia: hybrid neural networks, logit models and discriminant analysis, in International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, Berlin, Heidelberg: Springer Berlin Heidelberg,348-358, (2003).

[6] W. Halbert. Economic prediction using neural networks: The case of IBM daily stock In ICNN, 2, 451-458, (1988).

[7] D. Shubharthi, K.Yash, S. Snehanshu & B. Suryoday. Forecasting to Classification: Predicting the direction of stock market price using Xtreme Gradient Boosting. PESIT South Campus, 1-10, (2016).

[8] S. L. Pandhripande & D. Aasheesh. Prediction of 2 Scrip Listed in NSE using Artificial Neural Network. International Journal of Computer Applications, 134(2), 22-26, (2016).

[9] C. Parshv, S. Manan & K. Ameya. The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction. Decision Analytics Journal, 2, 100015, (2022).

[10] Z. Zhitua. Artificial neural network. Multivariate time series analysis in climate and environmental research, Springer, 1-35, (2018).

[11] I. Mohaiminul, C. Guorong & J. Shangzhu. An overview of neural network. American Journal of Neural Networks and Applications, 5(1), 7-11, (2019).

[12] T. Amey & K. Archit. Fundamentals of neural networks. International Journal for Research in Applied Science and Engineering Technology, 9, 407-26, (2021).

[13] S. Subana. Artificial neural network modelling: An introduction, Springer International Publishing, 1-14, (2016).

[14] B. Umair, H. Ehsan, A.Tariq &S. Chao. PINNeik: Eikonal solution using physics-informed neural networks. Computers & Geosciences, 155, 104833, (2021).

[15] A. Asif, B. Khan, A. Abdurahman. Modelling and computational experiment to obtain optimized neural network for battery thermal management data. Energies, 14(21), 7370, (2021).

[16] R.M. Qamar & K. Abbas. A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. Renewable and Sustainable Energy Reviews, 50, 1352-1372, (2015).

[17] L. Minhyeok. GELU Activation Function in Deep Learning: A Comprehensive Mathematical Analysis and Performance. arXiv preprint arXiv:2305.12073, (2023).

[18] A. Ganesh & B. Abdesselam. A generalized feed forward neural network architecture for classification and regression. Neural networks, 16(5-6), 561-568, (2023).

[19] B. Mahesh, Machine learning algorithms-a review. International Journal of Science and Research (IJSR). [Internet],

9(1), 381-386. (2020)

[20] A. Iscen, G.Tolias, Y. Avrithis, & O.Chum, Label propagation for deep semi-supervised learning. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 5070-5079).(2019).

[21] A. M.Roy, & J.Bhaduri, A fast accurate fine-grain object detection model based on YOLOv4 deep neural network. Neural Computing and Applications, 1-27. (2022).

[22] Z.Lyu, Y. Yu, B. Samali, M Rashidi, M, Mohammadi, T. Nguyen, & A.Nguyen, Back-propagation neural network optimized by K-fold cross-validation for prediction of torsional strength of reinforced Concrete beam. Materials, 15(4), 1477. (2022).

[23] S. Lari, J. Kim, & H. Kwon, Hybrid Neural Network Models for the Optimization of Induction Hardening Processes. Journal of Applied Artificial Intelligence, 4(1), 21-44. (2023)

[24] A. Goel, & A. Kumar, The role of artificial neural network and machine learning in utilizing spatial information. Spatial Information Research, 31(3), 275-285. (2023).

[25] B. Charbuty, & A. Abdulazeez, Classification based on decision tree algorithm for machine learning. Journal of Applied Science and Technology Trends, 2(01), 20-28. (2021).

[26] Dou, Q., Zhang, J., & Jing, B.A ML-based economic protection development level using Decision Tree and Ensemble Algorithms. Soft Computing, 1-19. (2023)

[27] S. Bruzzese, S. Blanc, & F. Brun, The Decision Trees Method to Support the Choice of Economic Evaluation Procedure: The Case of Protection Forests. Forest Science, 69(3), 241-253. (2023).

[28] J. Pearl, Fusion, propagation, and structuring in belief networks. In Probabilistic and Causal Inference: The Works of Judea Pearl (pp. 139-188). (2022)

[29] J. S. Kushwah, A. Kumar, S., Patel, R. Soni, A. Gawande, & S. Gupta, Comparative study of regressor and classifier with decision tree using modern tools. Materials Today: Proceedings, 56, 3571-3576. (2022)

[30] G. S. Reddy, & S. Chittineni, Entropy based C4. 5-SHO algorithm with information gain optimization in data mining. PeerJ Computer Science, 7, e424. (2021)

[31] Li, X., Yi, S., Cundy, A. B., & Chen, W. Sustainable decision-making for contaminated site risk management: A decision tree model using machine learning algorithms. Journal of Cleaner Production, 371, 133612. (2022)

[32] F.J. Shamrat, S. Chakraborty, M., M., Billah, P., Das, J. N.,Muna, & R Ranjan,. (2021, June). A comprehensive study on pre-pruning and post-pruning methods of decision tree classification algorithm. In 2021 5th International conference on trends in electronics and informatics (ICOEI) (pp. 1339-1345). IEEE. (2021, June).

[33] M. Bramer, Avoiding overfitting of decision trees. Principles of data mining, 119-134. (2007)

[34] https://www.google.com/search?q=Tadawul+All+Share+(TASI)&oq=Tadawul+All+Share+(TASI)&gs_lcrp=EgZjaHJvbWUyBggAEEUYOTIGCAEQRRhAMgoIAhAAGBMYFhgeMgoIAxAAGBMYFhgeMgYIBBBFGD0yBggFEEUYPdIBCjE0MzIzajBqMTWoAgCwAgA&sourceid=chrome&ie=UTF-8