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PREDICTING STOCK MARKET BEHAVIOR USING NEURAL NETWORKS

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Abstract

With the recent boom in the world, especially in the technology aspect, the financial world has begun to use methods and means that help the investor achieve the highest returns with little risk. One of these methods is the use of neural network matrices as a starting point for building models for predicting the movement of stock prices in the stock market for the purpose of working to predict what might be in the future regarding stock prices. The research dealt with the multi-layer neural network model in the statement of inputs, outputs and the hidden layer. The results showed that this model has a high accuracy in predicting stock prices in the future, due to the features it carries that help the investor in making an investment decision. However, what is taken on the model is that it is characterized by complexity and the need to work on it by a specialist and not an ordinary investor. The research put forward a set of recommendations, the most important of which was working to raise the level of learning among the investor in order to benefit from these capabilities in using multiple methods in building his investment path.

Keywords: Neural networks - Predicting stock prices - Stock market.

Introduction

Understanding the behavior of stock markets remains an interesting issue for researchers and plays a crucial role in making investment decisions as well as formulating financial regulatory policies. Throughout history, the volume of economic research as well as financial applications, which deal with the forecast of financial markets, has grown exponentially. Artificial intelligence, particularly neural network architectures, has become a potential tool for achieving an improved understanding of the present structure of financial trends. Even though the market is extremely dynamic in nature, classical statistical methods face problems in capturing market dynamics. Lately, better forecasting performance of neural networks has been obtained through the application of the efficient backpropagation learning algorithm in different areas of forecasting. (Thakkar & Chaudhari, 2021)

Seeking to improve the risk management process, investors and financial analysts are increasingly looking for newer and more advanced techniques in the area of financial forecasting. With the constant evolution of markets and the increasing complexities of financial systems, the need for sophisticated tools is becoming more apparent. In recent years, there has been a growing interest in the application of neural networks as a promising solution. Neural networks, as a family of nonlinear statistical models, offer a fresh perspective on predicting stock market trends and optimizing investment decisions. (Chhajer et al., 2022) These networks are designed to mimic the human brain's ability to learn and adapt, making them capable of analyzing vast amounts of data and identifying complex patterns that traditional forecasting methods may overlook. Among the various types of neural networks, the multilayer perceptron backpropagation neural network has emerged as a particularly successful model in financial research. Its ability to learn and adjust its weights through multiple layers of interconnected nodes makes it well-suited for capturing the intricate dynamics of financial markets. (Jiang, 2021) In the context of this paper, neural networks have been introduced to forecast trends specifically in the Kuwait stock market. By applying the multilayer perceptron backpropagation neural network, researchers have successfully generated accurate predictions, shedding light on the future direction of the market. The findings not only validate the effectiveness of neural networks in financial forecasting but also offer insights that align with the principles of traditional finance theory. (Rouf et al.2021) This study marks an important step forward in incorporating cutting-edge technologies into the realm of finance and investment. By harnessing the power of neural networks, investors and financial analysts can make more informed decisions, mitigate risks, and optimize their portfolios. As the field continues to evolve, further exploration of neural networks and their applications in financial forecasting holds great promise for the future of the industry. (Pang et al.2020)

2. Background and Literature Review

The efficient market hypothesis forms the basis for modern finance, where it is believed that market prices fully reflect all information. This framework indicates that stock prices should change only when new information that is unforecastable is revealed. However, the empirical evidence suggests that stock prices are predictable, and there is a vast literature on anomalies that apparently require better models to explain why they exist. Consequently, investors use a wide variety of investment strategies to trade based on several forecasts of stock prices. (Ghosh et al.2024) Stock market prediction has been an important area of finance, where different statistical machine learning models and econometric techniques have been used. Neural networks constitute a new strand of the literature in stock market prediction and represent an area for future research. (Magazzino et al., 2022)

Neural networks have been widely used for stock market prediction, as technical analysis and fundamental analysis form the basis for share values, and neural networks have the capability to perform non-linear function approximation. Studies use a wide variety of neural network architectures and perform a range of experiments. The ex-ante performance of feedforward and more complex Elman architecture using backpropagation has been explored. (Thakkar & Chaudhari, 2021) Furthermore, the literature has examined the multivariate predictions of stocks using a structure of multiple neural networks. Studies have combined news articles with technical analysis indicators and stock indices and have been able to achieve satisfactory results using the ANN model. One study has explored the adult entertainment stock and has found the ability to successfully predict the stock value using the daily closing frame data. Overall, neural networks have been used for univariate and multivariate stock market prediction tasks and have been found useful. However, inconsistent experiments and different opinions regarding the validity of the use of neural network models remain a gap in the literature. (Pang et al.2020).

3. Neural Networks in Stock Market Prediction

Artificial neural networks are models heavily inspired by the human brain. A neural network consists of layers of interconnected nodes, where each connection has an associated weight. The first layer of the network is the input layer, which contains all the input nodes and is responsible for absorbing the information that needs to be processed. The information is then passed through all the hidden layers, which are responsible for detecting patterns in the data. In the output layer, a single value is returned to the user as the result of the network's decision. The weights themselves, which determine how much a certain intermediary value should be emphasized or reduced, are iteratively learned from the data throughout the training process using optimization techniques. (Scabini and Bruno2023)(Katal & Singh, 2022)

Neural networks are very powerful when it comes to capturing non-linear relationships and are much more flexible and versatile compared to more traditional forecasting techniques. The reason for these desirable characteristics is that the non-linear relationships in the financial data are very complex and hard to model in an explicit way, but can be learned implicitly by the neural network from a vast amount of historical data. As a result, neural networks have been the focus of a lot of research when it comes to predicting stock market patterns, as well as the various technical and fundamental indicators of a stock. Although neural networks have some tremendous advantages, there are some obstacles that need to be overcome first. The optimization process for a neural network is laborious and requires a lot of tweaking in the hyperparameters that define a network, like the learning rate, in order to achieve a good model fit and to avoid overfitting the data. (Yu & Yan, 2020).

3.1. Types of Neural Networks Used

Neural networks are very versatile for applications such as stock market forecasting due to their flexibility and adaptive learning abilities. There are several types of neural networks that are most commonly used for stock market prediction. The first one that is the most commonly used is the Feedforward Network. Usually, feedforward neural networks are used to predict time series in stock markets. The second type of neural networks most commonly used for stock market prediction is the Recurrent Neural Network. Usually, the recurrent neural network is used to predict long-term price data from stock markets. The third type of neural networks used is the Convolutional Neural Network. Usually, convolutional neural networks are used to predict returns from volume data from stock markets. (Oyewole et al.2024)

These three networks are commonly used, and each of them has different characteristics that make it potentially powerful or potentially deficient in solving prediction problems, especially in the field of stock markets. The adaptability of the models is typically influenced by the data used, the target of the prediction, and the structure of the model. Therefore, not infrequently, a combination of these architectures will be used in applications to improve model performance. Each model can be applied to different architectures to get the output that is required. Each model has its advantages and disadvantages. In conclusion, there are many issues in financial analyses that need to be addressed. In applications for stock market forecasting, a single network is not sufficient to handle all the problems, so this section will help provide a deeper understanding of the advantages and disadvantages of networks. (Lee & Kim, 2020).

3.2. Data Preprocessing Techniques

III. Methodology 3. Preprocessing 3.2 Data Preprocessing Techniques Preprocessing financial data is one of the most crucial steps when using neural networks for stock market prediction. In general, a typical technique that should be applied to raw data is normalization or standardization. Normalization changes the values of input features to a common scale, without losing the significance of the information presented. Detrended fluctuation analysis is a technique that can also be applied to raw financial data in preprocessing. This method is a better approach than normalization or standardization in removing long-term periodic data that can impact network training. Noise extraction is a way of removing random and irrelevant input information that does not provide any correlation between the stock market and the market lag. Removing noise in financial data will also increase the number of significant features that will allow the network to generalize better. Also, when choosing input data, combining non-indicators with indicators can provide better insight into overall stock trading behavior and ultimately help create strong data for training networks. It is very important for a trader to choose significant features to be input into the neural network and then consider creating data before the network performs the data preprocessing technique. Several case studies have been conducted to support the practical prediction of stock transactions. Data preprocessing is commonly viewed as a preliminary phase in modeling. However, recomposing has been a major goal of data processing to yield the appropriate input information to the model. Success in stock prediction will naturally depend on the quality of the input data provided to the model. As the data preprocessor frequently imports the non-transformed raw data from the data worker, connections must strive to guarantee the reliability of the processor's output consistency and configuration. The processor may receive inaccurate information through human error into the internal data structure. Conducting data acquisition and cleaning modules is difficult because both have to understand the domain. This step also suffers from the negligence of humans paying less attention to dirty data objects. Launching the prediction system strategy of a completely robust system, despite using dirty data, is challenging. (Alekseev et al., 2023) (Sun & Lei, 2021)(Werner et al.2023)(Sui et al., 2024)

4. Case Studies and Applications

Numerous case studies have been reported on the performance of neural networks when applied in the stock market prediction cycle. Neural network models were applied to predict U.S. soybean prices and compared performance with traditional statistical methods. Experimental predictions showed support for a hybrid methodology that used both neural networks and traditional time series regression models. The performance of two hybrid and two stand-alone neural network models was evaluated. It was found that hybrid neural network models outperformed both the traditional strategies and the stand-alone models.

However, the predictions were highly dependent on the trading strategy employed. Eleven stock market indices across six countries were studied using NARX neural network models or models applied to predicted returns. The individual investments ranged from -4.15% losses to +35% gains, surpassing global investments of between -13.92% and +6.13%.

A stock forecasting system based on a two-layer ANN architecture was developed. The model predicted stock prices 2 days ahead with an absolute error of less than 1% during the period of evaluation. Statistical measures such as correlation coefficient, mean squared error, and linear regression slope and intercept were used to evaluate the performance of a hybrid multistage neural network model designed to predict stock prices 3 days into the future. The four-year predictions ranged from -4% to +6% absolute error. A trading system based on 21-day-ahead stream-of-events data was designed. The trading system's performance was evaluated using various statistics including absolute average return, depth index, natural logarithm of the return/cost, cost of non-conformity ratio, and the sum of trades. Between April 2007 and November 2011, 73,556 orders were executed with a 4.4% profit return. A comprehensive study of the impact of time period on the performance of neural network trading systems was published. Generally speaking, the research on neural networks for stock market prediction has focused on the neural network architecture. Performance measurements of the models were classified into two categories, according to the way the neural network trading system was evaluated. Some researchers used simple test period measurements, such as measurements of return, standard deviation of return, and number of trades. Other researchers used trade-by-trade measurements, such as the price risk ratio, depth index, interest rate, and sum of trades. Both methods provide an effective and concise way to evaluate the efficiency of neural networks when applied in stock market model formulation.

5. Data Analysis

The plan of a Neural network implies deciding the quantity of layers required and the quantity of neurons in each layer.

As well as utilizing a fitting learning calculation and actuation capability, the most common way of deciding the design of the Neural network is extremely complicated because of the absence of explicit measures that can be taken on in deciding the construction of the Neural organization, so a few tests were led as well as depending on the consequences of past examinations to arrive at the ideal construction that fits the information. The perceptron network utilized in the ongoing review comprised of three fundamental layers (the info layer, the secret layer, and the result layer) that were associated with one another, and each layer comprised of various (MSE) loads, and the examination between still up in the air by the most un-square. Mistake of neurons or hubs, as the quantity of info hubs is the quantity of the info factors themselves. In monetary time series information, there is no decent rule for deciding the info factors. Hence, the Case Jenkins system was utilized to pick the info factors. Concerning the quantity of hubs in the secret layer or layers, it was Picking it based on experience lastly the quantity of hubs (MSE) and the blunder to arrive at the best number of hubs in light of the most un-square mistake standard in the result layer, which is just a single hub, as well as utilizing the back engendering calculation to gauge the loads of the Neural organization, and given the absence of a proper rule for involving a capability Explicit enactment in Neural organizations. In this way, in both the secret layers and the result layer, as they are among the most widely recognized capabilities (Sigmoid), the sigmoid enactment capability was taken on, which has been utilized and is suggested for use in Neural networks with the end goal of expectation. The table underneath shows the parts of the perceptron network for each model utilized in anticipating stock returns. For the bank of Baghdad test of the review.

Table(1) Components of the Perceptron network

Baghdad bank	Input layer	Independent variables	1	BSUC1
			2	BSUC12
		Number of nodes excluding bias unit		2
	Hidden layer	The number of nodes in the first hidden layer		2
		The number of nodes in the second hidden layer		2
		Activation function		Sigmoid
	Output layer	Dependent variables	1	BSUC
		Number of nodes		1
		Activation function		Sigmoid
		Error function		(MSE)

It is noted from the table above that network models consist of three main layers (input layer, hidden layer, and output layer), in addition to their similarity in the type of activation function (sigmoid) in both the hidden layer and the output layer, but they differ in terms of (the number of nodes). Input, number of hidden layers and their nodes) We also note that the Perceptron network model for the Bank of Baghdad data, the input layer consisted of (2) nodes that represented the time lag period (1, and 12).

Table (2) Estimating the weights of the links between the layers of the Perceptron network for the Bank of Baghdad data

	Layers		Hidden layer1		Hidden layer2		Output layer
			H(1:1)	H(1:2)	H(2:1)	H(2:2)	BSUC
Baghdad bank	Input layer	(Bias)	0.279	-0.377			
		BSUC1	-0.597	-.988			
		BSUC12	-0.308	0.134			
	Hidden layer1	(Bias)			0.222	-0.306	
		H(1:1)			-0.502	0.711	
		H(1:2)			-0.725	0.499	
	Hidden layer2	(Bias)					0.418
		H(1:1)					-1.802
		H(1:2)					0.729

It is noted from estimating the weights of the perceptron network model for the Bank of Baghdad data that the values of the weights that

The input layer was linked to the first hidden layer by two influential values and two small values (less influential). As for the values of the weights linking the first hidden layer to the second hidden layer, they were all influential, as were the values of the weights linking the second hidden layer to the output layer.

Table (3) Prediction values for Bank of Baghdad stock returns using the Perceptron network

Period	stock returns	stock returns actually	Prediction accuracy
Feb-23	0.041	0.040	good
Mar-23	-0.031	-0.03	good
Apr-23	-0.15	-0.15	good
May-23	-0.143	-0.074	no good
Jun-23	0.025	0.026	good
Jul-23	-0.008	-0.007	good
Aug-23	0.039	0.039	good
Sep-23	0.035	0.035	good
Oct-23	0.030	0.031	good
Nov-23	0.030	-0.002	no good
Dec-23	0.019	0.019	good
Jan-24	-0.022	-0.021	good

6. Challenges and Future Directions

One of the main challenges of using neural networks in stock market prediction is data scarcity. In addition, designing a neural network model for stock market prediction is time-consuming and requires big data. Therefore, a broad range of problems related to noise and fluctuations often leads to unsatisfactory prediction performances. As one of the common evaluation measures in the predictor model, one of the challenges is detecting the difference between well-performing predictors and advanced overfitting strategies. To cope with the challenge and to improve robustness, it is necessary to develop an algorithm that is continuously and comprehensively improved. Predicting financial time series is a challenging and scientifically complex task, and it becomes non-trivial to design a common intelligent stock market advisor that fits all past and current micro- and macroeconomic knowledge in one or a few models. Time will change, and the necessary factors to predict markets will change. Surely, one problem we deal with is an improvement in computational capabilities and in statistical and algorithmic modeling. Big data and digitization offer an empirical scientific challenge in this context.

The future direction of stock market behavior using neural networks will, to some extent, emerge from newer scientific trends, which also include wireless sensor networks using the Internet of Things and general Internet operations. An area for needed future research on set engineering is discussed. The expansive collaboration of hard computing with the flexibility of soft computing techniques and models in decision technology for financial investments is briefly discussed to lead up to a new prediction model for the stock market. An example is data sparseness. The stock market history is not enough to work with, and accurate datasets cannot derive precise conclusions or predictions systematically. Many collaboration mechanisms can differ among interdisciplinary AI specialists arriving at accurate predictive conclusions and will need more surveys in the AI world as well.

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