Study of the Use of Artificial Neural Networks in Islamic Finance

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Abstract
The need to find a relevant way to predict the next day price of a stock index is a real concern for many financial stakeholders and researchers. We have known across years the proliferation of several methods. Nevertheless, among all these methods, the most controversial one is a machine learning algorithm that claim to be reliable, namely neural networks. Thus, the purpose of this article is to study the prediction power of neural networks in the particular case of Islamic finance as it is an under-looked area. In this article, we will first briefly present a review of the literature regarding neural networks and Islamic finance. Next, we present the architecture and principles of artificial neural networks most commonly used in finance. Then, we will show its empirical application on two Islamic stock indexes. The accuracy rate would be used to measure the performance of the algorithm in predicting the right price, the next day. As a result, we can conclude that artificial neural networks are a reliable method to predict the next day price for Islamic indices as it is claimed for conventional ones.

Keywords: Islamic finance, Stock price prediction, Artificial neural networks.

JEL Classification

1. Introduction

Artificial neural networks were used since at least 20 years in science of management as a quantitative method of forecasting, next to classical statistical methods. They were used particularly in finance, but other fields of management were also concerned.

This connectionist approach differs from expert systems. In the latter, the user is required to build a knowledge base that contains the rules of deduction that must be applied. Building this base is often tedious and requires a long process of formalizing the expert's knowledge. While, the connectionist approach of neural networks is capable of learning the relationships between variables on their own and that what explains their appeal comparing to expert’s systems.

It is through algorithms that these systems learn on their own the relationships between variables from a set of data, much like the human brain would. Thus, neural networks are self-configuring from the examples provided to it.

In the financial field, these systems can be used to deal with various issues such as portfolio management, identification of arbitrage opportunities, technical analysis or even fundamental analysis.

The object of this article is to question the performance of these systems in predicting the performance of stock market indices, in particular in the case of Islamic indices.

2. Literature review

Since the beginning of the 1990s, financial applications implementing artificial neural networks become significant. First, Time series forecasting seems to be a privileged field of investigation today, to such an extent that Azoff in 1994 devotes an entire book to it [1]. Typically, in univariate forecasting, this involves using the past of a variable in order to extract relationships from it to predict its future value. Nevertheless, after assuming that these relations really exist, the most difficult problem to solve is to determine their form which is more often not linear. This has also led to the development of non-linear statistical forecasting models in recent years. yet, some researchers favour artificial neural networks, thanks to their ability to discover recurring forms in series in order to escape thi complexity in statistical models.

The arrival of this new analytical instrument makes it possible in particular to revive the question of market efficiency. In fact, it is legitimate to question the power of neural networks to highlight certain forms of inefficiency which, until now have not been highlighted by conventional analysis tools.

Tsibouris and Zeidenberg in 1995 recognize a certain predictive power in neural networks under test by using the the past rates of return of six American securities [2]. However, even if the results were good on the training sample, it was less acurate on the test sample. Next, Avouyi-Dovi and Caulet in 1995 compared traditional statistical models of ARMA type to the neural networks. The study was about the forecast of two stock market indices Deutscher Aktien Index and the french benchmark index CAC40, as well as the exchange rates Mark and Dollar. The neural networks showed relevant performances [3].

Later, Donaldson and Kamstra, 1996 showed that neural networks can better predict stock market volatility by multiplying the input variables [4]. An investment strategy simulation based on the results of the model would have made an average annual return of 1.60%.

Tests were also undertaken with some success with gold futures and the S&P index (Grudnitski and Osburn, 1993) using neural networks with contextual variables [5].

Finally, to stay in the area of financial markets, we should also point out studies that has focused on options. In particular, Hutchinson et al. in 1994 showed that neural networks trained on a sample of daily data observed over two years, finds the formula of Black and Scholes in 1973 [6].

Besides, the issue of forecasting exchange rates has also been explored on several occasions (Refenes et al., 1993; Azoff, 1994; Mehta, 1995; Avouyi-Dovi and Caulet, 1995) [3], [7], [1], [3]. In particular, an original work by Refenes and Zaidi (1995) shows how exchange rate forecasts can be improved by combining recommendations from methods conventionally used by professionals, in neural networks [7]. Thus, on the USD / DEM exchange rate, the application of the recommendations of the neural networks gives a profitability of 18% on an annual basis, when the moving average and average value strategies give returns of 12.3% and 13, 1%.

The ease of use of artificial neural networks, and their ability to recognize shapes after learning, make them tempting to test on problems usually handled by expert systems. If their predictive power were to prove satisfactory, this would be of considerable benefit as it would no longer be necessary to spend precious time developing the rule base which constitutes the heart of an expert system.

There are still relatively few studies that can be classified in this category. They relate to the forecasts of mergers and acquisitions of companies and especially to the rating of bonds. We have first Sen et al. (1995) that tested the predictive capacities of neural networks against those of a logistic regression using the variables usually found in the literature on the subject [8]. It appears that while neural networks mathematically fit the data better than logistic regression, it is just as incapable of correctly forecasting mergers and acquisitions.

Regarding the rating of bonds, a study was carried out to reproduce the ratings assigned by the American rating agencies, (Dutta and Shekar, 1988; Moody and Utans, 1995) [9], [10]. The systems built learn, from a sample, to reproduce the ratings of the experts. The results obtained were more encouraging than the field of mergers and acquisitions but they showed at the same time that the models still need to be refined.

On another side, a model integrating both neural networks and symbolic representation of the expert's knowledge was used at Nikko Securities since October 1992. This system would produce exact answers in 96% of the cases outside the training sample (Asakawa, 1993) [11].

From this literature review, it should be noted in particular that in these fields of research, only internal variables are mostly retained as they have a sufficient explanatory power. Nevertheless, the complexity of the decision-making processes would undoubtedly be improved by the introduction of contextual variables, including qualitative, like those usually integrated in expert systems. However, it is shown that neural networks are better than statistical analysis techniques to taking information into account overall. While many suggest future improvements in order to offer better results.

On the other hand, since our empirical study will focus on Islamic stock market indices, it is advisable to do a review of the literature and history concerning this area. Actually, one of the first Islamic stock market indices was the one of Dar al-Mal al-Islami (DMI 150), it was created by "Faisal Finance" in April 1998. After, the American bank Klein Maus and Shrine had launched, in November 1998, the SAMI stock market index "the Socially Aware Muslim Index" which noted the evolution of 500 companies where it was possible to invest in accordance with the Sharia. February 1999 saw the launch of the Dow Jones Islamic Market Index (DJIM Index), which was followed by the Global Islamic Index Series (GIIS) launched by FTSE in October of the same year.

After this wave of first indices, 2006 saw the launch of the Islamic version of the Standard and Poor's indices. During the same year, socially responsible indices and Islamic stock indices were brought together through the index: "islamic sustainability index" launched jointly by the Dow Jones Islamic and the SAM Sustainable Asset Management group. In 2007, Morgan Stanley Capital International established its own family of Sharia-compliant stock indexes. Next, the "Russel-Jadwa Shariah" index was launched on June 25, 2009, jointly by index provider Russel Investments and Saudi Arabian bank Jadwa Investment. The most recent is the Stoxx Europe Islamic index launched on February 23, 2011 by Six Group and Deutsche Börse and it is composed of the leading Islamic stock index in continental Europe. The literature on stock market indices in Islamic finance is not very extensive. Nevertheless, the outperformance or underperformance of these indices is subject to questions, for two reasons. First, it is assumed that Islamic stock indices are riskier than their conventional counterparts due to the lack of diversification (Ahmad and Albaity, 2006) [12]. On the other side, the fact that the companies included in Islamic indices have successfully passed the screening criteria makes this type of indices more profitable than conventional ones (Hussein and Omran 2005) [13]. Besides, we can find other studies confirming that the performance of Islamic indices is similar to their conventional ones (El khamlichi et al., 2014) [14].

Other research has concluded that Islamic stock indexes perform better in times of rising than in falling markets. Indeed, in times of decline, Islamic stock indexes may have lower risk-adjusted returns than their conventional counterparts due to the exclusion of companies operating in sectors such as alcohol, tobacco or gambling. These actions considered to be “sin stocks” actions (Hong, Harrison and Kacperczyk, 2009) are known to be more resistant in times of crisis, or “recession-proof” [15]. In addition, Islamic stock indexes often contain stocks of small cap companies, with little debt and which may have growth potential when the trend is up (Hussein and Omran, 2005) [16]. Differences in performance, if it exist, can also be attributed to differences in management style (Girard and Hassan, 2008) [17].

Given the literature review we can confirm that we are faced with the lack of unanimity among researchers on the subject of Islamic indices performance. Thus, carrying out an analysis seems essential to us. Moreover, we can see that none of the studies has included a data science perspective. Therefore, it shows that it is relevant to study the use of Artificial Neural Networks in the case of Islamic stock market performance.

3. Methodology

Our study is focused on Artificial neural networks that are inspired by the functioning of the brain and the nervous system or, more precisely, how we think.

There are two main categories of networks. First, supervised learning networks in which the system learns to recognize shapes from a learning sample that combines the modalities carried by variables to characterize a shape. Moreover, the results of all information given to the system are known on this sample. This is where the system is configured. Then, unsupervised learning networks, which are used when the user of neural networks are unable to present a sample to the system that matches a sum of information and the form it is supposed to represent. Neural networks self-organize themselves to discover recurring patterns in the information it receives, but it does so without outside help, unlike supervised learning networks. The best known of this category of networks is that of Kohonen (1984)

[18]. In finance, the first type of networks is the most commonly used, called also layered networks.

An artificial neural network is organized into layers, each of these layers comprising several neurons. Each of these neurons, which is presented as an autonomous computing unit connected to all or to certain neurons of the preceding layer or layers.

Neurons are linked together through synaptic weights, denoted $w_{i,j}$. The learning algorithm will have the task of evaluating these weights based on the data presented during the learning phase. Note that some more complex networks may add direct connections between the input layer and the output layer.

In the field that interests us, the neurons at the input layer receive the information supposed to explain the phenomenon to be analyzed. As regards to the detection of the rise or fall of the next day price of an index, for example. The output neuron will take a binary value, 1 or 0, depending on whether the price is rising or the opposite.

Each neuron collects the information provided by the neurons of the previous layer with which it is linked and then calculates its activation potential. This is then transformed by a function to determine the information sent to the neurons of the next layer (output potential).

The activation of a neuron is given by the sum of the output potentials of its predecessors, weighted by the synaptic weights. This activation potential is then transformed by a function to determine the output potential. In this context, several functions can be considered, but the most commonly used is the sigmoid function and whose analytical expression is as follows:

$$S = f(A) = \frac{1}{1 + e^{-A}}$$

Other forms of functions are sometimes used, such as binary threshold functions or linear threshold functions or even step functions.

Neural networks are set up using a learning sample, which associates presented shapes with a desired outcome. It is the learning algorithm that adjusts the synaptic weights seeking to minimize a cost function.

It was undoubtedly the discovery of the error gradient backpropagation algorithm by Rumelhart, Hinton and Williams in 1986 that marked the breakthrough in the application of artificial neural networks. It is still the most widely used in finance applications today [19]. The cost function E minimized by this algorithm is the sum of the squares of the errors produced by the network with regards to the desired result.

Thus, if the training sample is composed of s examples each described by an input vector of dimension m, $X_i = (x_{i,1}, x_{i,2}, \dots x_{i,m})$ and a vector output of dimension n, $D_i = (d_{i,1}, d_{i,2}, \dots d_{i,n})$, the function to be minimized is written:

$$E = \sum_{i=1}^{s} \sum_{j=1}^{n} \frac{(y_{i,j} - d_{i,j})^2}{2}$$

Where $y_{i,j}$ represents the outputs produced by the network while $d_{i,j}$ represents the desired outputs. The calculation of the quantity E, makes it possible to determine in a second step, the variation of the synaptic weights $w_{i,j}$:

$$\Delta w_{i,j} = -\frac{\partial E}{\partial w_{i,j}} - \mathcal{E}$$

Where $0 < \mathcal{E} < 1$, is a parameter to control the speed of convergence of the algorithm. After initializing the synaptic weights, a first calculation is performed in the topological order of the network. The resulting output is then compared to the desired output and the cost function, E is evaluated.

In order to measure the performance of neural networks we can use the confusion matrix. Let us take the example of a binary classifier, which predicts 2 classes denoted class 0 and class 1. To measure the performance of this classifier, it is customary to distinguish 4 types of classified elements for the desired class:

1. True positive TP: Element of class 1 correctly predicted
2. True negative TN: Element of class 0 correctly predicted
3. False positive FP: Element of class 1 poorly predicted
4. False negative FN: Element of class 0 badly predicted

This information can be gathered and visualized in a table form called confusion matrix. In the case of a binary classifier, we obtain:

Table 1: Example of confusion matrix

		Predicted class	
		Class 0	Class 1
Real class	Class 0	TN	FN
	Class 1	FP	TP

In particular, if the confusion matrix is diagonal, the classifier is perfect. Note that the confusion matrix is also generalizable when k> 2 classes to predict. It is possible to calculate several indicators summarizing the confusion matrix. For example if we want to count the quality of the prediction on class 1, we define precision as the oportion of well classified elements for a given class:

$$Precision = \frac{TP}{TP + FP}$$

In the general case this will give:

$$Precision = \frac{1}{k}\sum_{i=1}^{k}\frac{TP_i}{TP_i + FP_i}$$

4. Empirical results

In order to verify the performance of neural networks, we used for our study 2 stock market indices:

- MSCII (Morgan Stanley Capital International Islamic), that started in 2007 and it covers more than 60 countries.

- JKII (Jakarta Islamic Index) that started in 2000. It is focused on the industry of food and represent 30 companies.

We use historical daily data over 10 years starting. The dataset contains the following characteristics: Open, High, Low, Close, Volume and finally the Adj.Close. A data preparation was needed when it comes to missing values and outliers that we either deleted or replaced by the average for example, depending on the case.

The algorithm implementation was done using R using the "neuralnet" package. In this context, the dataset was dived in two part, 80% of data was intended for training the model and 20% to test the model.

Our algorithm is intended to calculate two signals from the input data, a high signal to indicate that the price trend will be higher in the next day or a low signal if the opposite occurs.

We calculated the confusion matrices as well as the precision of our algorithms for both indices that is recapitulated in the following table.

Table 2: Confusion matrices and precision calculations

	Indexes	MSCII		JKII	
	Signals	High	Low	High	Low
Confusion Matrix	High	223	170	33	36
	Low	55	57	185	244
Precision		55,25%		55,62%	

From the confusion matrices we can note the elements that were correctly classified. We can see that for MSCII, 280 elements were classified and 277 for JKII. We can see also that we have a similar precision around 55% that can be explained by the fact that some high signals were predicted as low signals and the opposite is also correct. Nevertheless, overall, we can say that the neural networks have a certain predictive power of the next day price trend for both indices, but at the same time the models still need to be refined to offer better results by introducing new variables for example.

5. Conclusion

At the end of this article, it appears that artificial neural networks are giving good results in finance applications. Mainly, predicting the trend of the next day price. However, they still have some limitations: building the network, reprocessing input variables, and adjusting learning parameters still need much human intervention. Moreover, they still have only reduced explanatory power. But all of these problems are now the subject of research which we can hope will provide satisfactory answers in the years to come.

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