Comparative Analysis of the Performance of Expert Systems and Machine Learning Models in the Context of the Islamic Stock Market

KAOUTAR ABBAHADDOU, MOHAMMED SALAH CHIADMI
Study and Research Laboratory in Applied Mathematics,
Mohammed V University in Rabat,
Mohammadia School of Engineering, Rabat,
MOROCCO

Abstract: - In this article, we will compare the performance of the autoregressive statistical methods of time series ARIMA-GARCH (Autoregressive Integrated Moving Average - Generalized Autoregressive Conditional Heteroscedasticity) and the machine learning methods, mainly ANN (Artificial Neural Networks) and SVM (Support Vector Machines). Different methods are suggested in the literature to enable the prediction of the direction of stock market returns. However, with recent improvements in technology, statistical and mathematical have been the most widely used. For this reason, our article focuses on their comparison to test the diverging results in literature when it comes to comparing their performance. The empirical study will rely on Islamic stock indexes as this area needs more research. Regarding the performance, it is evaluated based on two criteria based on calculating the Mean Absolute Percentage Error and the Root Mean Square Error. Hence, after the analysis of the results, we can confirm that neural networks are efficient compared to other methods.

Keywords: - Islamic finance, Stock price prediction, Machine Learning, Autoregression.

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1 Introduction

In finance, predicting the future performance of an index and knowing ahead of time the return on a security, is a major concern, even with limited precision. Hence, in reality, providing this kind of information is not easy. Markets have more than one dynamic behavior in practice. These observations, empirically prove the utility of considering complex, possibly non-linear models capable of modeling different dynamics from a single series. Thus, this kind of model should consider a limited number of underlying dynamics and model different phenomena causing behavior or another. Moreover, these models should be relatively simple to develop and adapted according to the available data.

Most investors who wish to engage in the stock market for the long term begin with fundamental analysis to evaluate a company, a stock, or the market as a whole. This form of study aims to identify a financial asset's theoretical worth to compare it to its current market value. Next, we have technical analysis (TA) which differs from fundamental analysis as it does not take into account theoretical value or other basic elements.

This third way to evaluate the market is through econometric models, which are probabilistic mathematical models that attempt to characterize the random relationships between the variables they include. They've been used to try to explain why time series of financial asset prices show positive autocorrelations.
The fourth way is artificial intelligence, which is a sort of knowledge gained by computers for them to function and react in the same way that people do. Machine learning is an area of artificial intelligence concerned with the design and development of algorithms that enable a computer (or a machine) to learn to do extremely complicated tasks without being explicitly programmed. This means that machine learning approaches seek to uncover links between data, extract knowledge from it, and apply it to new data, rather than an algorithmic system based on established rules that aim to duplicate or entirely reproduce the decision-making process of an expert.

In this paper, after going through the literature, different non-linear prediction methods will be presented and compared, namely autoregressive statical methods ad machine learning models as these are the most used and accurate methods in the current era. The basic idea is to take advantage of the information available in the data from the past evolution of the series and use it to determine, at least partially, its future evolution. These methods aim to show empirically, that a model covering several dynamics can predict financial series and affirm which one is the most productive.

2 Literature Review

The financial literature pays a lot of attention to the question of market efficiency. On the one hand, some defend the idea that financial asset prices vary randomly and independently from previous statements. Thus, they support the idea that generating more profit comes mainly from taking more risks. While, on the other hand, others argue that financial series are predictable and are not completely ruled by chance. In this sense, Louis Bachelier (1900) indicates that the trajectory of stock prices is only a succession of random steps [1]. Hence, this implies that the mathematical expectation of a speculator is zero. On the other hand, Fama in the year 1965 carried out an empirical study of market efficiency, where he concluded that the prices of stock market assets adjust instantly to the arrival of new information [2]. Next, Harry Roberts (1967) suggested dividing efficiency into three forms (weak, semi-strong, and strong) depending on the type of information that the market takes into consideration to reflect the current prices of securities [3]. However, Samuelson in the year 2016 shows that prices fluctuate randomly based on the concept of a martingale [4].

There are several approaches to analyzing and predicting market developments. First, we can find the sentiment analysis that considers non-quantifiable data in its approach and analyzes the public flow of information like articles and publications to get an overall insight into the trend of the stock market. On the other hand, we have the fundamental analysis which is based on studying microeconomic factors like debt levels and macroeconomic factors such as inflation to explain the change in prices in the medium to long term. In this respect, Cheung, Chung, & Kim, 1997, Chung & Kim, 2001 and Lo & MacKinlay, 2002 carried out a series of statistical analyzes over the period between 1988 and 2000 and concluded that the prediction of the intrinsic value of stocks is possible using models that rely on financial ratios and the cost of equity [5, 6, 7]. Next, we have the technical analysis that uses historical data of stock to help us get an idea about trends of future movements. This way, Lo, Mamaysky, & Wang, (2000) in their study confirmed the power of the technical analysis to predict the movements of financial assets by analyzing the results of technical analysis on US equity markets from 1962 to 1996 [8]. Also, Brock, Lakonishok, & LeBaron in the year 1992 showed that these rules were able to generate more profit than the market by analyzing a 90-year history of daily Dow Jones stock prices Besides, we have quantitative methods that will be subject to comparison in our article [9]. These methods use mathematical modeling, econometrics, and advanced computational techniques for the analysis and forecasting of movements in financial series. We can define an econometric model as a probabilistic mathematical model that attempts to describe the random relationships between the variables included in these models. They have been used in the finance market to try to explain the positive autocorrelations of the time series of financial asset prices.

Among the most used statistical methods, we have the family of ARIMA (Autoregressive Integrated Moving Average) approaches. The ARIMA model was introduced in 1970 by Box and Jenkins. It predicts the future values of a univariate time series [10]. This model includes an autoregressive (AR) part which describes the dependence between a current moment and past moments and a moving average (MA) part which captures the forecast error at past moments. This methodology was very used for short-term forecasting and quickly established itself as an essential base for comparison. Many extensions of this method have been suggested subsequently. The ARIMAX method makes it possible to integrate exogenous variables into the model. It is used in particular to integrate meteorological data into the forecast, but also information from data provided by a clustering algorithm. The Seasonal ARIMA (SA-RIMA) model is used to model the seasonality of data. A lot of studies fall into this scope, like the work of Hamilton in 1994 and Lo and Mackinlay in 2002 which describes all the econometric models and techniques used for the analysis and prediction of financial time series [11, 7]. Moreover, Jarrett, J., & Schilling, J. in 2008 concluded from their experience in the German market that autoregressive econometric models can predict the change in the returns of the stocks used [12].

Therefore, the majority of studies have shown the existence of positive autocorrelations for financial time series, which means that autoregressive models are useful for the prediction of these series. Today, the financial markets have access to other interesting measurement tools, rather than the statistical approaches that take into account the wide range of available information. This approach is artificial or machine learning, which is a field of artificial intelligence that studies algorithms or statistical models that allow a computer to perform a specific task without a set of explicit instructions, but by relying on the discovery of patterns and the principle of inference. The algorithm is presented with training data, from which it will learn a mathematical model allowing it to make decisions or make predictions without being explicitly programmed to perform this task. Following this learning phase, the learned model is used in a production phase to complete the task from new input data.

There are different types of machine learning, depending on the type of data used or the type of task being learned. Supervised learning algorithms build a mathematical model from labeled data, which contains the desired input and output of the model. The model can therefore be trained to reduce its error on the output examples. Unsupervised learning algorithms learn from input data and discover structure in that data, such as groups of similar inputs (clustering). These algorithms are not guided by labeled data describing the expected output for a given input. Reinforcement learning algorithms are concerned with the behavior of software agents, which can perform actions in an environment. The agent is rewarded (or punished) for the result of his actions and the goal is to learn how to maximize a notion of cumulative gain on his actions. Here also, several researchers have studied the effectiveness of these techniques. For example, Neely & Weller in the year 2001 used genetic programming to generate trading rules. These rules have shown a very strong performance in the exchange rate markets. Fernandez-Rodrıguez, Gonzalez-Martel, & Sosvilla-Rivero in the year 2000 in turn used machine learning, choosing neural networks as predictive models and technical indicators as input data and they found that this trading strategy outperforms the one of a passive strategy for bearish and stable markets, but not bullish ones [13].

Following this literature review, it is clear that we have many approaches for market analysis and prediction. Some attempts to reveal the most performant approaches were held. Turban in 1996, by using a sample of 58 companies, compared Multiple Discriminant analysis (MDA) predictions and artificial neural network (ANN) predictions and found that ANN is better than MDA and can improve the quality of communication. decision making of an investor [14]. However, these results do not allow us to say if ANN can make obtain exceptional gains. Similarly, Beyaz, Tekiner, Zeng & Keane (2018) compared the performance of fundamental analysis, technical analysis, and the combination of the two to predict the future price of stocks, applied to machine learning models [15]. They put together historical data from 140 S&P 500 companies. They decided to use the RMSE to measure the degree of error. Regardless of the period considered, fundamental analysis outperforms technical analysis because it offers a smaller Root Mean Square Error (RMSE). However, the combination of the two appears to reduce further this measure of the level of error. If we compare the performance of the two algorithms, regardless of the period or which metrics were used, the support vector regression (SVR) model offers the best predictions.

Nevertheless, as we can see the results differ and quantitative methods were rarely compared against each other. That’s why we will focus this study on comparing a statistical method ARIMA-GARCH and two machine learning methods that showed relevant results in price trend prediction from previous studies, namely artificial neural networks and support vector machines. The empirical study will be done on Islamic stock indexes because this market is often under-looked and present limited literature that focuses mainly on studying the performance of Islamic indexes like the one of Atta in 2000 who used weekly data from the DJIMI index from January 1996 until December 1999. The study concluded that the Islamic stock index outperforms its conventional counterpart. Ahmad and Ibrahim (2002) studied the Malaysian market from April 1999 to January 2002 [16]. In turn, they compared the daily returns of KLSI, the Islamic index of the Malaysian stock exchange, with its conventional benchmark with a risk-free rate. The results showed that Islamic indices fail to outperform the market as well as the absence of a significant difference in performance between Islamic stock indices and the benchmarks used. Hussein (2004) was interested in the English stock market and analyzed the monthly values of the Sharia index of the FTSE family from July 1996 to March 2000 (upward period), then from April 2000 to August 2003 (downward period) [17]. The results of his research corroborate those of Ahmad and Ibrahim (2002) [18]. In two subsequent studies, Hussein and Omran (2005) [19], as well as Girard and Hassan (2005) [20], found similar results in their study on DJIMI.

3 Data and Methodology

3.1 Data Preparation

To compare the performance of the classical statical model ARIMA-GARCH against two machine learning model artificial neural networks and support vector machines in the context of the Islamic stock market, we will use two Islamic indices:

- Morgan Stanley Capital International Islamic (MSCII) was launched in 2007 and covers 69 countries.

- Jakarta Islamic Index (JKII) started in 2000 and is composed of 30 companies specializing in the production and distribution of food.

Our dataset is made of the historical daily data of these two indices over 10 years and contains six characteristics (Open, High, Low, Close, Volume, and finally the Adj. Close).

In the context of studying data, the data typically needs to be manipulated before a prediction model can be used. We replaced data using different methods like suppression or replacing them depending on the nature of problems with the data, namely missing data, outliers, or duplicated data.

Machine learning models need to depend upon independent variables that we defined to be able to make an accurate prediction. Three variables were used for this matter. Mainly, the difference between the opening and closing price, the difference between the highest and lowest prices, and finally, the difference between the traded volume over two consecutive days.

A dependent variable should be defined as well in all cases and it represents the value the algorithms try to predict while relying on independent variables. Thus, the chosen variable in our case determines the price of the next day.

Separating the dataset is an essential step in building a machine learning model. In our case, 80% of the dataset will be used for training the model and 20% will be used to test their performance. Since the more data is afforded for training, the most robust our model will be.

3.2 Statistical and Machine Learning Models

In the context of this study, two machine learning algorithms and one statistical model were implemented. All algorithms were implemented in R.

Support Vector Machines (SVMs):

Support Vector Machines are a set of supervised learning techniques designed to solve ranking, classification, and regression problems. SVMs are a generalization of linear classifiers.

SVMs were developed in the 1990s from the theoretical considerations of Vladimir Vapnik on the development of a statistical theory of learning: the Vapnik-Chervonenkis Theory. SVMs were quickly adopted for their ability to work with large data, the low number of hyperparameters, the fact that they are well founded theoretically, and their good results in practice [21].

The basic principle of SVM is to reduce the problem of discrimination to a linear problem of finding an optimal hyperplane. Two principles make it possible to achieve this objective. The first consists of defining the hyperplane as a solution to an optimization problem under constraints whose objective function is expressed only using scalar products between vectors. Knowing that the number of active constraints or support vectors controls the complexity of the model. Secondly, the transition to the search for nonlinear separating surfaces is obtained by the introduction of a kernel function in the scalar product implicitly inducing a nonlinear transformation of the data using an intermediate space that we can call feature space. Hence, the commonly encountered name of the kernel machine. On the theoretical level, the kernel function defines a Hilbertian space, said to be self-reproducing and isometric by the nonlinear transformation of the initial space used to solve the linear problem.

We used the package 'e1071' for SVM in R to be able to implement SVMs. After testing the radial, linear and polynomial functions, the radial one was chosen as it has better precision as well the value of the cost was set to 128.

Artificial Neural Networks (ANN):

The origin of the development of neural network technology lies in the desire to develop an artificial system capable of performing intelligent tasks similar to those performed by the human brain. Neural networks are similar to the human brain when you consider their two properties. First, a neural network acquires knowledge through learning. Secondly, the knowledge of a neural network is stored in forces of inter-neuronal connection known as synaptic weights.

The real advantage of neural networks lies in their power, their ability to represent both linear and non-linear relationships, and their ability to learn these relationships directly from the modeled data series.

These networks are composed of Inputs (synapses), allowing them to receive external influences. Each input is characterized by a specific weighting coefficient (its synaptic weight W) which varies over time, depending on the inputs presented. The second component is a nucleus whose state is determined by the value of the input weighted by W. The last component is the output that reflects the influence of the neurons on the outside, its value depends on the state of the nucleus; it is linked to it by a function (filter) which is generally nonlinear and given by the following formula:

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

Where $A = \sum_{i=0}^{n} W_i Y_i$,

With W_i are Synaptic weights and Y_i the outputs of the predecessors of the neuron.

In our algorithmic implementation, we used 5 layers with 9 neurons on each layer, the activation function was the sigmoid one and we used the ‘neuralnet’ package in R for that purpose.

Autoregressive Integrated Moving Average - Generalized Autoregressive Conditional Heteroscedasticity (ARIMA-GARCH) :

ARIMA is composed of two main parts AR and MA which we are going to explain first.

An AR process stands for ‘autoregressive’. Concretely if we consider a stationary process X_t, this process is autoregressive of order p if we can give its value at time t using its previous p terms. Mathematically, it means that:

$$\forall t: X_t = \sum_{i=1}^{p} \alpha_i X_{t-i} + \varepsilon_t \quad (2)$$

with ε the error and (α_1, ..., α_p) are real numbers.

MA stands for ‘moving average’. If X_t is a time series, we consider that it is an MA process of order q if we can express its value at time t as a linear combination of random errors or what we call white noises. Mathematically we translate this by:

$$\forall t: X_t = \varepsilon_t + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \quad (3)$$

with ε the error and (β_1, ..., β_q) are real numbers.

If we combine these two processes, we obtain an ARMA model. This makes it possible to model more complex time series. An ARMA model of order (p, q) is therefore written mathematically in the form:

$$\forall t: X_t = \sum_{i=1}^{p} \alpha_i X_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \quad (4)$$

with ε the error, (α_1, ..., α_p) and (β_1, ..., β_q) are real numbers.

However, one of the limitations of this model is that it can only model stationary time series.

Thus, it cannot model a time series with an increasing linear trend. To overcome this problem, the ARIMA model was developed.

The I of the ARIMA model stands for 'integrated' for integration. Thus, it becomes possible to remove the trends in times series by calculating the difference to make them stationary. If we take the example of a time series with a linear trend of the form:

$$X_t = \alpha + \beta t + \varepsilon_t \quad (5)$$

$$X_t - X_{t-1} = \beta + \varepsilon_t - \varepsilon_{t-1} \quad (6)$$

So, by differentiating the series once, the linear time dependence is eliminated and the difference is stationary. Likewise, a quadratic trend can be eliminated by differentiating the series twice. Once the series is stationary, it is then possible to apply the ARMA model.

The ARIMA model is therefore a combination of this differentiation process and the classic ARMA process.

The ARIMA (Autoregressive Integrated Moving Average) processes were developed by BOX and JENKINS (1976) is the generalization of ARMA models for non-stationary, trend-admitting processes (ARIMA) [10].

The ARCH stands for Auto-Regressive Conditional Heteroskedacity and the GARCH stands for Generalized ARCH. This is a type of model that allows you to estimate and predict the volatility of a stock's price or short-term return based on the values that those prices or returns take a few periods before.

The term Autoregressive means that we regress the model from itself, that is to say, that the exogenous variables are the lags of the endogenous variable at order q. The term Heteroskedacity emphasizes the fact that the variance is not constant over time. We say that there is heteroskedasticity if there is in the time series one or more sub-periods whose variance is different from the variance of the other periods. In financial series, the variation in variance is often caused by a particular event that may arise in the market. Thus, if the variance is heteroscedastic, it is linked to market interactions.

The interesting thing in ARCH models is that it takes into account not only the value of the variable at different periods but also the change in the value of the variance during these periods.

Therefore, this contributes to greatly improving the forecast of volatility.
The ARCH model was introduced by Engle in 1982 [22]. An ARCH process of order p models a time series, if ε_t denoting the error is formed of a stochastic part z_t, representing a strong white noise and a standard deviation depending on time σ_t:

$$\varepsilon_t = \sigma_t z_t \quad (7)$$
$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \quad (8)$$

Where $a_0 > 0$, $a_i \geq 0$ and $i > 0$;
GARCH models follow the same principle as the ARCH model but adds a second member to the equation which is the moving average of order q. GARCH models of order p and q are written in this form:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} b_i \sigma_{t-i}^2 \quad (9)$$

Where $a_0 > 0$, $b_0 > 0$, $a_i \geq 0$, $b_i \geq 0$ and $i > 0$;
Finally, we can say that ARIMA-GARCH is a combination of ARIMA et GARCH. Mathematically, it is written as follows:

$$X_t = \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} + \varepsilon_t \quad (10)$$
$$\varepsilon_t = \sigma_t z_t, \quad (11)$$
$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} b_i \sigma_{t-i}^2 \quad (12)$$

Where $a_0 > 0$, $b_0 > 0$, $a_i \geq 0$, $b_i \geq 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$ and $i > 0$;

The main package used among others in this implementation is ‘rugarch’. We set the model to GARCH(1,1). Regarding, ARIMA(p,q,d), d is set to 0 and we implemented a function to search for the best combination of p and q where these orders can take values from 1 to 5.

3.3 Performance Evaluation

Our performance evaluation is based on measuring prediction errors. Let e_t the error on the prediction at period t, we define e_t as the difference between the estimated value of the prediction F_t and the real value D_t.

$$e_t = F_t - D_t \quad (13)$$

Let e_1, e_2, e_3, ..., be the error observed over the n periods considered. Then, the Mean Absolute Percentage Error (MAPE) will be:

$$MAPE = \left[\frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{D_i}\right|\right] * 100 \quad (14)$$

This criterion measures the importance of errors. The best model using this criterion will be the one giving the lowest value.
On the other hand, we have The Root Mean Square Error (RMSE) that will be:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {e_i}^2} \quad (15)$$

This criterion measures the deviation of error. The best model is the one giving a value close to zero.
We used the libraries ‘Metrics’ and ‘MLmetrics’ under R, to calculate these errors.

4 Empirical Results

We calculated MAPE and RMSE indicators to verify which model performs better.

Table 1. Calculation of MAPE

	MSCII	JKII
ANN	0,13	0,25
SVM	0,27	0,37
ARIMA-GARCH	0,41	0,39

Table 2. Calculation of RMSE

	MSCII	JKII
ANN	3,36	1,19
SVM	4,74	1,76
ARIMA-GARCH	6,13	1,90

Given that the results obtained are quite similar according to the used criteria used, we will focus first our attention on the MAPE (mean absolute percent error) which remains a widely accepted indicator for measuring the explanatory power of models. It shows how well the model fits the data in terms of absolute fit and how near the observed data points are to the model's predicted values. This accuracy metric can be expressed as a percentage and it is easier to understand than the other accuracy measures. For example, we can see that MAPE is 0,25 on JKII when we used ANN. It means that the forecast is improper by 25% percent on average. In our case, overall, we found that all of ANN's benchmarks were inferior to those of SVM and ARIMA-GARCH in MSCII and JKII cases.
However, we should note that even if the model fits the data well, we can observe some MAPE numbers are very high because we have data values that are close to zero. It is mainly related to the fact that the

metric divides by the absolute error by the actual data. Thus, we can say that values near 0 can dramatically inflate the MAPE.
On the other hand, we have the RMSE (root means square error), which can be considered as the standard deviation of a variance that is unexplained. It has the advantage to have the same unit as the predicted variable, which is useful. Lower RMSE values suggest a better match. Hence, we can say that the root means square error (RMSE) is a good indicator of how well the model predicts the response. Since the model's primary goal is prediction, this is the most significant fit criterion. In our case, we can say that the indicators show that most of the models perform well. We have mainly, the results of ANN are the smallest followed by SVM and finally ARIMA-GARCH for both indices.
We can confirm then that our neural networks can follow the evolution of the index and detect outliers better than the ARIMA-GARCH model and SVM which comes into the second position. Thus, we can say that globally, artificial intelligence models perform better than statistical models in our study.
These results are coherent because the artificial intelligence method can learn from the data series itself. Models can find relationships and trends in data that are often too complex to recognize just by modeling through mathematical formulas.
No matter the rigor of the method used, what interests the forecaster is to forecast the evolution of the stock market index, which calls for debates around the efficiency of the market.
In our case, it is difficult to forecast accurately by conventional statistical quantitative methods because these models predict hardly turning points and their performance decreases on long-term predictions. The artificial intelligence methods are thus more relevant. It is mainly possible to forecast the index from its historical values using ANN or SVM but it is not very reliable over the long term.
Indeed, the existence of anomalies reinforces the inefficiency of the stock market. They are linked to the microeconomic behavior of various stakeholders. These anomalies include irrationality, heterogeneity of information, or seasonal variations.

5 Conclusion

In recent decades, we have witnessed the spectacular development of quantitative methods applied to management in general and finance in particular. These methods can be defined as a set of formalized techniques aimed at providing decision support through the logical processing of a set of quantitative information. In this sense, the main goal of this study is to analyze how new mathematical and computational approaches such as artificial neural networks (ANN) or support vector machines (SVM) can contribute to a better forecast of stock market stock values compared to the methods usually used in this domain like the one used in our study ARIMA-GARCH. Starting from the comparison of the three methods applied to the analysis of time series on stock market values of two Islamic indices JKII and MCSII indices, we had significant results both on the predictive performance of the model and on its detection capabilities. We showed the outperformance of the new approaches mainly the ANN for a better forecast, obtained thanks to the great flexibility of these methods.

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