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# Deep learning with small and big data of symmetric volatility information for predicting daily accuracy improvement of JKII prices

Mohammed Ayoub Ledhem
*Department of Economics, University Centre of Maghnia, Maghnia, Algeria*

## Abstract

**Purpose** – The purpose of this paper is to predict the daily accuracy improvement for the Jakarta Islamic Index (JKII) prices using deep learning (DL) with small and big data of symmetric volatility information.

**Design/methodology/approach** – This paper uses the nonlinear autoregressive exogenous (NARX) neural network as the optimal DL approach for predicting daily accuracy improvement through small and big data of symmetric volatility information of the JKII based on the criteria of the highest accuracy score of testing and training. To train the neural network, this paper employs the three DL techniques, namely Levenberg–Marquardt (LM), Bayesian regularization (BR) and scaled conjugate gradient (SCG).

**Findings** – The experimental results show that the optimal DL technique for predicting daily accuracy improvement of the JKII prices is the LM training algorithm based on using small data which provide superior prediction accuracy to big data of symmetric volatility information. The LM technique develops the optimal network solution for the prediction process with 24 neurons in the hidden layer across a delay parameter equal to 20, which affords the best predicting accuracy based on the criteria of mean squared error (MSE) and correlation coefficient.

**Practical implications** – This research would fill a literature gap by offering new operative techniques of DL to predict daily accuracy improvement and reduce the trading risk for the JKII prices based on symmetric volatility information.

**Originality/value** – This research is the first that predicts the daily accuracy improvement for JKII prices using DL with symmetric volatility information.

**Keywords** Deep learning, Jakarta Islamic Index (JKII), NARX neural network, Small and big data, Symmetric volatility information, Training algorithm

**Paper type** Research paper



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## 1. Introduction

The predicting of the movement of the stock market index is termed to be a rather critical goal in the financial world, given that a reasonably precise forecast has the potential to gain profit in the stock market, deliver higher financial benefits and hedge against market risks (Livieris *et al.*, 2019). The stock market is notorious for its intense uncertainty and instability, and investors are still looking for an efficient and accurate way to direct stock investing (Wang *et al.*, 2020). Certainly, the area of financial analysis has changed radically from a more qualitative science to a more quantitative science, which is also based on the extraction of knowledge from databases. Over the last few years, machine learning, artificial intelligence and deep learning (DL) have become effective analytical methods for the forecasting process through evaluating and leveraging the information gained from financial data (Jannes, 2018; Livieris *et al.*, 2019).

According to Aslam *et al.* (2020) and Jannes (2018), the use of artificial intelligence, machine learning and DL in predicting the stock index movements of Islamic capital markets became essential for making the right trading decisions by investors, particularly for the Jakarta Islamic Index (JKII) in the Indonesian Islamic stock market which witnessed deep volatilities and unstable movements as stated by Irsalinda *et al.* (2020).

In the last decade, the Indonesian Islamic stock market became one of the most global developed Islamic stock markets that offer great profit opportunities (Ledhem, 2020; Qizam *et al.*, 2020). According to Subekti *et al.* (2020), the structure of Islamic capital markets in Indonesia became large, investments in the Islamic capital markets were introduced first in 1997; then in 2000, the JKII has appeared to encourage investors who want to gain profits from the financial opportunities in Islamic capital markets (JKII is the first Islamic stock index established on July 3rd, 2000, which included 30 liquid stocks from the Indonesian capital market). There are similarities between the Islamic capital markets and the conventional ones in the practice of Islamic capital investment, the difference is that the mechanism and effect of trading do not violate the Islamic law principle which prohibits the interest rates (Subekti *et al.*, 2020). The JKII has its own characteristics as any other Islamic stock index that differ from the conventional one in terms of risk, profit and loss sharing, and informational efficiency. Regarding risk, on one hand, Islamic stock indexes are seen to be riskier than their conventional equivalents owing to the deficiency of diversification (Albaity and Ahmad, 2008). On the other hand, Al-Zoubi and Maghyereh (2007) demonstrated that the Islamic stock index is less risky than the standard because of the profit and loss sharing concept in Islamic finance. In addition, Ben Rejeb and Arfaoui (2019) demonstrated that Islamic stock indices are more efficient than conventional ones in terms of informational efficiency. However, Ben Rejeb and Arfaoui (2019) proved that Islamic stock indices are more volatile than their conventional equivalents in terms of volatility. Since this research is focussing on the factor of volatility in the JKII, Irsalinda *et al.* (2020) showed that the JKII is highly volatile and witnessed unstable movements.

According to Irsalinda *et al.* (2020) and Ledhem (2021), there is a lack of using modern statistical techniques in the Indonesian Islamic capital markets and particularly in predicting the JKII price movements, and since the JKII was witnessing volatilities and unbalanced movements, investors were obliged to employ the modern methods like artificial intelligence, machine learning and DL in predicting the JKII prices.

Therefore, the objective of this paper is to provide an effective DL model among artificial neural networks (ANNs) to predict daily accuracy improvement for JKII daily prices and support both the individual and the institutional investors in the Islamic capital markets to achieve their investment goals and make the accurate investment decision.

According to Floros (2009), Caporin *et al.* (2013), and Moon and Yu (2010), the appropriate technique for understanding the behaviour of the capital stock volatility structure is to identify it in terms of its information distribution function over a conditional variance examination. In fact, information is the ultimate driver of asset pricing volatility in the capital stock market (Caporin *et al.*, 2013; Floros, 2009; Moon and Yu, 2010). This information can reach the market in a linear or non-linear form, and it is supposed to be either negative or positive information with serious impacts on the asset price volatility (Caporin *et al.*, 2013; Floros, 2009; Moon and Yu, 2010). According to Moon and Yu (2010), volatility of the stock market is symmetric information with the capability to be maintained in the future. As well, symmetric volatility is considered to be more sensitive to its previous (lagged) values relative to the current market value shock (Floros, 2009; Moon and Yu, 2010; Caporin *et al.*, 2013; Othman *et al.*, 2020). Thus, in this study, the symmetric volatility structure of the JKII is used for predicting its daily price future movement based on symmetric information (that illustrates the information of supply and demand) which can be calculated through four input price features such as open price (OP), high price (HP), low price (LP) and close price (CP).

Hence, the objective of the current study is to provide an accurate and ethnic method, such as the ANNs to predict the JKII daily prices as an accuracy improvement to support both institutional and individual investors to achieve their investment objectives by reducing trading risk and to make the precise investment decision. As reported by Peng and Tang (2020), one of the modern ANNs that employed exogenous factors of the symmetric volatility as inputs to predict daily stock prices is the nonlinear autoregressive exogenous (NARX) neural network. As well, Wibowo *et al.* (2017) determined that the NARX neural network provided high accuracy in predicting the capital market movements in Indonesia. Therefore, this study is using the NARX neural model to predict JKII prices based on symmetric volatility information.

As well, big data which has brought notable attention among financial researchers and investors are also effective in the prediction process of economic and stock market indicators because big data hold large information about volatilities (Kapetanios and Papailias, 2018; Bok *et al.*, 2018; Sigo *et al.*, 2018). Conversely, Yudelson *et al.* (2014) and Faraway and Augustin (2018) demonstrated that small data outperforms big data in prediction accuracy because the high-quality small sample can generate superior inferences than the low-quality large sample. Therefore, for these reasons, this paper is using both small and big data of symmetric volatility factors as exogenous inputs within the NARX neural network for the prediction process to obtain a robust daily accuracy improvement for JKII prices.

Unlike the previous studies, the contribution of this current study is to predict the JKII prices using small and big data of symmetric volatility information as exogenous inputs inside the NARX neural network for improving the daily accuracy of the JKII. Since the prediction process under an ANN is built on the training algorithms within DL, it is suitable to choose the optimal DL training algorithm to get the best accuracy predicting score, this process is achieved by testing the optimum task for training based on the criteria of the lowest values in mean squared error (MSE) and correlation coefficient. Thus, this paper answers the following question, "What is the optimal training task of DL for predicting daily accuracy improvement for the JKII?"

The rest of this paper is framed as follows: the literature review and the research gap are addressed in the second section "Literature review". Data collection and DL tasks of analysis using NARX neural network are presented in the third section "Research methodology". Whereas the empirical outputs and discussion are then deliberated in the fourth section "Empirical outputs and discussion". To end with a conclusion and some practical implications are given in the fifth section "Conclusion".

## 2. Literature review

In the last few years, the use of ANNs in predicting prices and volatilities of capital markets has been emerged in many studies because of its significant efficiency (Livieris *et al.*, 2019;

Wang *et al.*, 2020; Yu and Yan, 2020). By reviewing the literature, one of the most effective methods of neural networks in predicting stock market prices is the NARX neural network. Gandhmal and Kumar (2020) predicted the daily stock prices of two companies (Relaxo Footwear and Reliance Communications) using NARX neural networks with chronological penguin Levenberg–Marquardt (CPLM) technique. Their findings indicated that the forecasting using the NARX model provides high-performance accuracy in terms of root mean squared error (RMSE) and mean absolute error. In another study, Peng and Tang (2020) predicted the quantitative stock investments of the Shanghai composite index using the NARX neural network. Their results showed that the NARX neural network provided an accurate predictive ability for the security market. Likewise, Alkhoshi and Belkasim (2018) predicted the Dow Jones stock market index using the NARX neural network based on a training algorithm of LM, their results showed that the predicted model using NARX neural network provides high prediction accuracy based on the MSE score. Also, Wibowo *et al.* (2017) predicted the price movement of the Indonesia composite index using the NARX neural network, their results showed that NARX neural network can be an alternative prediction model for investors and traders concerning the movements and dynamic variations of Indonesia composite index.

Correspondingly, Das *et al.* (2017) predicted the Dhaka stock price in the Malaysian stock market using the NARX neural model based on hybrid clustering, their results indicated that the NARX neural network was very efficient in predicting the Dhaka stock price by improving the error rate. Also, Indera *et al.* (2017) predicted the bitcoin prices using the NARX neural network based on the daily open, low, high and close prices by focussing on the closing price as the output target for forecasting. Their results indicated that the NARX neural network model provides high forecasting accuracy across the training and testing process. Consistently, Yassin *et al.* (2017) predicted the Apple Inc prices using NARX neural network based on weekly stock prices. Correlation tests and the one-step ahead method were used for validating the predictive model. Their results indicated that the predictive model offers high predictive ability while using generating the Gaussian residuals. Also, Ercan (2017) predicted the OMX Baltic Benchmark stock market prices using the NARX neural network. The predicted model used employed the EUR/USD exchange rate and the index value as exogenous variables. The results showed that the NARX neural network predicted efficiently the Baltic stock market index prices. As well, Shahbazi *et al.* (2016) predicted the Forex market movements using the NARX neural network, their results indicated that the NARX neural network is efficient in predicting the Forex market movements of the hourly foreign exchange rates (EUR/USD and GBP/USD).

Above and beyond, predicting the stock market prices and volatilities is gaining notable importance nowadays in capital markets around the world. For this purpose, in the last decade, ANNs have been widely used to predict stock market volatility. However, in the Islamic capital markets, the ANNs are not commonly used in predicting the prices and volatilities of Islamic financial indexes. To the best of the author's knowledge, there are limited studies that employed the ANNs for predicting price movements in the Islamic capital markets. One of the newest studies that applied ANNs in Islamic capital markets, a study by Aslam *et al.* (2020), predicted that daily closing prices of the Islamic securities (KMI-30) index using ANNs, their results showed that ANNs provided high accuracy in the prediction process. Correspondingly, Irsalinda *et al.* (2020) predicted the JKII using the neural networks based on the fuzzy feed-forward method, their results showed that the predicted model produced high prediction ability in reducing the error rate in the training and testing process.

Yet, generally, other traditional econometric techniques were employed in the Islamic capital markets for the forecasting processes, Rizwan and Khursheed (2018) predicted the volatility of the Islamic stock market index KSE-100 in Pakistan using the ARIMA and GARCH models. Besides, Nasr *et al.* (2016) predicted the Dow Jones Islamic stock market index volatility using the GARCH with a long memory and a short memory. Consequently, the forecasting in the Islamic capital markets is witnessing a lack of using ANNs which makes this is a gap in the literature. Therefore, to fill this gap and to enrich the literature, this paper employed one of the most effective ANNs models that use the exogenous inputs in forecasting price movements in capital markets which is the NARX neural network. Thus, this is the first study that uses the NARX neural networks in Islamic capital markets for predicting the daily accuracy improvement of the JKII prices.

Since the NARX neural network is based on exogenous inputs for targeting the output, this paper is following Othman *et al.* (2020), Floros (2009), and Moon and Yu (2010) when they employed the symmetric volatility information of prices as exogenous factors to improve the accuracy of predicting. Thus, this is the first study that uses the NARX neural networks based on symmetric volatility structure in forecasting the daily accuracy improvement for JKII prices.

One of the revolutionary data technologies in improving the prediction accuracy is the use of big data time series (Faloutsos *et al.*, 2019; Galicia *et al.*, 2019; Pérez-Chacón *et al.*, 2020; Singh, 2015; Singh and Yassine, 2018; Talavera-Llames *et al.*, 2018, 2019; Torres *et al.*, 2018a, b). As well, Sigo *et al.* (2018) predicted the stock price movements in India using ANNs based on big data time series for the best prediction accuracy. Conversely, Yudelson *et al.* (2014) and Faraway and Augustin (2018) demonstrated that small data outperforms big data in prediction accuracy because the high-quality small sample can generate superior inferences than the low-quality large sample. Therefore, to empower the prediction accuracy of the JKII in the Islamic capital market, this paper has used two samples of small and big data of the JKII symmetric volatility information. Consequently, to the best of the authors' knowledge, this research is the first that uses small and big data samples of symmetric volatility for the prediction of the daily accuracy improvement of JKII prices in the Islamic capital markets.

In conclusion, many researchers have applied artificial intelligence and machine learning in the capital markets especially predicting stock market volatility to make the right trading decisions. As well, all of them had determined the usefulness of these modern methods. However, to the best of the authors' knowledge, there is a lack of applying those modern methods in the Islamic capital markets, in which DL within neural networks methods was missed to be used in the Islamic capital markets. Thus, this research is filling this literature gap by employing neural networks using DL for predicting the daily prices of the JKII prices which is one the most common index in the Islamic capital market in Indonesia, this prediction process is conducted through using small and big data of symmetric volatility information as exogenous inputs within the NARX neural network. Additionally, following Othman *et al.* (2020), Floros (2009), and Moon and Yu (2010), this paper is using the symmetric volatility approach to predict the accuracy improvement information for the JKII prices, therefore, this paper is one of the limited studies that is using symmetric volatility information in the Islamic capital markets as exogenous factors within the NARX neural network model to predict the accuracy improvement for the JKII prices. Consequently, it is believed that this paper is making a substantial contribution to the related literature.

## 3. Research methodology

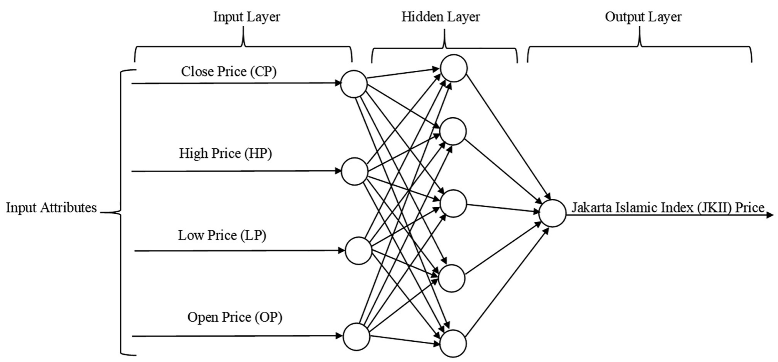
### *3.1 Data collection and pre-processing*

Indonesia is the prime country in Islamic Fintech (financial technology) that uses big data trials with 31 Islamic fintech firms, one of the biggest organizations which afford big data analytics under Islamic Fintech in the ASEAN is the Indonesian Financial Services Authority (OJK) (ISLAMIC FINTECH REPORT 2018, 2019; Ledhem, 2021). Therefore, big data became very important in the Islamic financial sector in Indonesia. By following the study of Singh and Yassine (2018) that used a big data sample for predicting the capital markets movements since big data are highly informative about the index volatilities, the current study used a big data sample of the daily basic symmetric volatility information for the JKII which contains the OP, HP, LP and CP spanning from the 6 October 2000 to 1 July 2021. Additionally, although small data of symmetric volatility information data can be more uniform with fewer volatilities (less extraordinary shocks), the small data sample can provide better inference than a big data sample due to the high quality as stated by Yudelson *et al.* (2014) and Faraway and Augustin (2018). Therefore, this study employs a small data sample of the daily basic symmetric volatility information for the JKII spanning from 04 January 2021 to 01 July 2021. Both small and big data samples of symmetric volatility information were collected from the respected financial platform database of "Investing.com" which affords financial investments analysis, portfolio and stock market quotes. From this basic information, four attributes are taken into account as input layers, which are the JKII daily OP, HP, LP and CP. The output layer comprises a single feature of the daily price index of the JKII. As well, for training the network, the data of each sample are divided into three subgroups, 70% for training, 15% in the validation process and the rest 15% in the testing process.

*3.2 The ANN framework of the current study*

This paper aims to predict the daily accuracy improvement for the JKII prices by using the volatility pattern of symmetric information of JKII using DL over the ANN which can model any connection amongst the data without statistical distribution assumptions (Othman *et al.*, 2020). In this study, the ANN framework consists of three main elements, including input layer (IL), hidden layer (HL) and output layer (OL), each with multiple neurons.

Following the study of Indera *et al.* (2017) that predicted the bitcoin prices using the NARX neural network based on the daily open, low, high and close prices, the IL in this study consists of four attributes as exogenous variables that construct basic symmetric volatility information for the JKII. Additionally, although stock volatility is affected by various parameters, the OP, HP, LP and CP which construct the symmetric volatility structure are the best parameters that illustrate the information of supply and demand for optimal informational efficiency (Othman *et al.*, 2020). Therefore, these four attributes of the JKII are used as exogenous variables in the IL. While the OL includes the target variable (daily JKII price) which is the close price of the JKII that reflects the standard benchmark for all trading activities of the JKII (Indera *et al.*, 2017), the HL in an ANN is a layer in-between the IL and OL. The typical ANN structure of the proposed model is therefore presented in Figure 1.




**Source(s):** Organized by authors

**Figure. 1.** The ANN structure for predicting the daily accuracy improvement for the JKII prices

*3.3 NARX neural network within deep learning methodology*

According to Lin *et al.* (1996), the nonlinear autoregressive with exogenous inputs (NARX) model is defined by the following equation:

$$Y(t) = F(Y(t-1), \ \ldots, Y(t-d), x(t), s(t-1), \ \ldots, x(t-d)) + \varepsilon(t) \tag{1}$$

The neural network predicts the time series' true value $Y(t)$, based on the prior $d$ values of the exogenous series, where $d \in \mathbb{N}, d \geq 1$ signifies the delay parameter, $Y(t-1), \ \ldots, Y(t-d)$ signify the feedback delays. The prediction aims to estimate the unknown nonlinear function $F$ as accurately as possible, using various approaches of the neural network. The last term of Eq (1), $\varepsilon(t)$, signifies the actual time series value approximation error (Lin *et al.*, 1996).

The optimization could be achieved by adjusting the weights and bias of the network, as well as testing with various numbers of neurons per layer and hidden layers. Through checking various parameters, one can achieve the optimal predictive accuracy of the neural network but, using this method, one must be aware that reducing too many neurons could decrease the computing capacity of the neural network, limiting generalization whereas increasing much more neurons increases the difficulty in the system. Therefore, this study employed three efficient DL techniques for the optimal testing and training process of the neural network as stated by Houssein *et al.* (2021), namely LM, Bayesian regularization (BR) and scaled conjugate gradient (SCG).

To develop several ANNs, this paper uses the LM as the first training algorithm based on the NARX model which is one of the utmost common ANNs algorithms with comprehensive applications in computing and mathematical fields (Levenberg, 1944). The LM method includes two optimization procedures, namely the Gauss–Newton and the gradient descent one (Marquardt, 1963). Provided that the LM algorithm incorporates the efficiency and functionality of its two component elements, it provides processors with various undeniable advantages. According to Beale *et al.* (2010), the LM algorithm has the advantage of taking less time for the training process, which automatically stops when generalization stops improving the MSE of the validation samples. However, the LM algorithm needs a larger memory capacity. Therefore, using the LM algorithm, this experimental study trains 15 predicting ANNs based on various architectures to get an optimal mix between the number of neurons from the hidden layer and the delay parameter. In this way, one neuron for the input data corresponding to the symmetric volatility information of JKII, $n$ neurons in the hidden layer, where $n \in \{6, 12, 24\}$, the delay parameter $d \in \{2, 5, 10, 15, 20\}$, one neuron for the output layer and one neuron for the output data (the predicted JKII daily price).

As well, this paper uses the BR training algorithm to construct various ANNs based on the NARX model. The BR algorithm uses a linear combination of squared errors and squared weights as an objective function, which is adjusted after the network's training process is completed to obtain a network with better generalization properties (MacKay, 1992; Foresee and Hagan, 1997). According to Beale *et al.* (2010), the BR algorithm has the advantage of providing good generalization for complex, small or noisy datasets in the training process, which automatically stops when based on adaptive weight minimization for the MSE in the validation samples. However, the BR algorithm needs more time for the training process. Using the BR algorithm, this research trains 15 predicting ANNs using the same procedure as in the LM algorithm case.

The third employed training algorithm in this paper is the SCG, a supervised learning algorithm that was implemented in 1993 and is valuable in the development of ANNs. It is built on the conjugate gradient process which incorporates the modelling and trust area solution of LM and the conjugate gradient one (Møller, 1993). According to Beale *et al.* (2010), the advantage of the SCG algorithm needs less memory capacity for the training process, which automatically stops when generalization stops improving the MSE in the validation samples. However, it requires more time for the training process.

Considering the benefits of the SCG method, this study aimed to evaluate how well-suited it is in predicting the JKII prices for achieving daily improvement accuracy based on symmetric volatility information. This research trains 15 predicting ANNs using the same procedure of testing and training as in the case of the LM algorithm and BR algorithm to achieve an optimal combination between the neurons number from the hidden layer and the delay parameter, therefore, the total developed ANNs is 45 for each data sample.

## 4. Empirical outputs and discussion

In this experiment research, the main process before the predicting is choosing the optimal developed ANN under the NARX model that affords the highest predicting accuracy score using the LM, BR and SCG algorithms for each data sample, this process within DL is called the training and testing process which generate the best solution for predicting the daily improvement accuracy of JKII prices. To execute DL procedures, this study implements the NARX neural network model using DL in the MATLAB NARX toolbox, because as stated by Paluszek and Thomas (2020), MATLAB is an advanced piece of software for DL. It includes deep belief networks, convolutional neural networks, and other neural net functions and provides DL tools for deep belief networks.

### *4.1 Training and testing the NARX neural network model using deep learning in MATLAB software*

In this process of training and testing, this study contrasts the best prediction accuracy among 45 developed ANNs within the LM, BR and SCG algorithms for each data sample as is shown in Tables 1 and 2, built according to the NARX model with different delays and

| *n* | *d* | 2 | 5 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|
| *The Levenberg–Marquardt training algorithm* | | | | | | |
| 6 | MSE | 43.50498 | 41.67759 | 41.98321 | 39.80425 | 36.83621 |
| | *R* | 0.999,604 | 0.999,624 | 0.999619 | 0.999637 | 0.999668 |
| 12 | MSE | 42.50559 | 40.32891 | 36.30088 | 36.01825 | 32.17813 |
| | *R* | 0.999619 | 9.999635 | 9.999675 | 0.999678 | 0.999707 |
| 24 | MSE | 39.35529 | 38.61868 | 34.48193 | 30.41023 | 30.69891* |
| | *R* | 0.999647 | 0.999649 | 0.999689 | 0.999723 | 0.999730* |
| *The Bayesian regularization training algorithm* | | | | | | |
| 6 | MSE | 44.44238 | 41.02784 | 39.82734 | 43.07897 | 41.43801 |
| | *R* | 0.999601 | 0.999630 | 0.999637 | 0.999604 | 0.999624 |
| 12 | MSE | 43.53416 | 42.56920 | 43.11142 | 41.53188 | 40.93640 |
| | *R* | 0.999607 | 0.999614 | 0.999610 | 0.999624 | 0.999629 |
| 24 | MSE | 42.51799 | 43.36059 | 42.65184 | 41.95487 | 40.88045 |
| | *R* | 0.999614 | 0.999608 | 0.999612 | 0.999620 | 0.999626 |
| *The scaled conjugate gradient training algorithm* | | | | | | |
| 6 | MSE | 45.94484* | 47.83143 | 51.92163 | 48.70105 | 53.78498 |
| | *R* | 0.999579* | 0.999562 | 0.999523 | 0.999557 | 0.999511 |
| 12 | MSE | 46.72128 | 47.13795 | 52.74485 | 49.92488 | 49.21687 |
| | R | 0.999582 | 0.999581 | 0.999524 | 0.999547 | 0.999550 |
| 24 | MSE | 47.16117 | 52.78176 | 47.92307 | 52.13024 | 58.59782 |
| | *R* | 0.999573 | 0.999525 | 0.999567 | 0.999530 | 0.999473 |

**Note(s):** * Refers to the optimal daily prediction accuracy
**Source(s):** Executed by authors using MATLAB DL toolbox

**Table 1.** The formulation of the experimental results when developing the ANNs predicting solution based on the NARX model using big data of symmetric volatility information

| n | d | 2 | 5 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|
| *The Levenberg–Marquardt training algorithm* | | | | | | |
| 6 | MSE | 31.28755 | 25.36937 | 0.0176856 | 0.00171828 | 0.0246743 |
| | R | 0.987904 | 0.991012 | 0.999994 | 0.999999 | 0.999992 |
| 12 | MSE | 22.32143 | 0.675699 | 0.00986436 | 0.00115437 | 0.00106328 |
| | R | 0.990935 | 0.999731 | 0.999996 | 0.999999 | 0.999999 |
| 24 | MSE | 11.67770 | 0.0352985 | 0.0187123 | 0.00372926 | 1.7247e−08* |
| | R | 0.995764 | 0.999997 | 0.999992 | 0.999999 | 0.999999* |
| *The Bayesian regularization training algorithm* | | | | | | |
| 6 | MSE | 41.02023 | 26.28571 | 9.06967 | 8.44309 | 7.87300 |
| | R | 0.985063 | 0.989586 | 0.996032 | 0.995629 | 0.996075 |
| 12 | MSE | 40.69494 | 26.43247 | 18.44209 | 4.33148 | 1.79139 |
| | R | 0.984555 | 0.989782 | 0.991830 | 0.997770 | 0.999071 |
| 24 | MSE | 38.06809 | 23.97588 | 18.22597 | 10.67097 | 2.62832 |
| | R | 0.985465 | 0.990684 | 0.991995 | 0.994947 | 0.998584 |
| *The scaled conjugate gradient training algorithm* | | | | | | |
| 6 | MSE | 45.79394 | 38.31102 | 37.43766 | 22.45958 | 19.59446 |
| | R | 0.980605 | 0.983947 | 0.98371 | 0.989267 | 0.990695 |
| 12 | MSE | 39.58193 | 33.93734 | 27.57546 | 21.41592 | 15.81079 |
| | R | 0.983823 | 0.986219 | 0.986459 | 0.989364 | 0.992591 |
| 24 | MSE | 37.76135 | 31.90750 | 24.66756 | 10.67672 | 5.84013 |
| | R | 0.984485 | 0.987827 | 0.989277 | 0.994058 | 0.996971 |

**Note(s):** * Refers to the optimal daily prediction accuracy
**Source(s):** Executed by authors using MATLAB DL toolbox

**Table 2.**
The formulation of the experimental results when developing the ANNs predicting solution based on the NARX model using small data of symmetric volatility information

neurons for choosing the optimal developed ANN that delivers the best accuracy results based on the criteria of MSE and the coefficient of correlation ($R$) between the targets and outputs networks where 70% of data are used for training, 15% in the validation process and the rest 15% in the testing process.

Analysing the outcomes in Tables 1 and 2, this research notices that the optimal daily prediction accuracy refers to the developed ANN using the LM training algorithm for both small and big data samples, however, the small data sample provides the best predicting accuracy which refers to a developed ANN based on the architecture of $n = 24$ neurons in the hidden layer and the delay parameter of $d = 20$ (20 days = 4 working weeks in the Islamic capital market), this optimal developed ANN delivers the lowest value of the MSE (MSE = 1.7247e−08, closer to 0) and the highest value of the correlation coefficient calculated for the entire dataset ($R = 0.999999 \approx 1$) (Table 3), this optimal ANN architecture is entitled NARX_LM_JKII (Figure 2). Additionally, the BR algorithm provides good accuracy results for the prediction in the case of using the small data sample as shown in Table 2 (the developed ANN with the architecture of $n = 12$ neurons in the hidden layer and the delay parameter of $d = 20$ that offers an MSE = 1.79139 and $R = 0.999071$), while the worst prediction accuracy refers to the SCG algorithm for both small and big data samples.

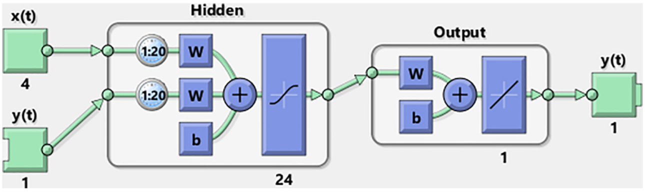
To analyse the training performance for predicting daily accuracy improvement for the JKII prices using the developed NARX model from the LM algorithm based on the small data sample, this study first plots the curves of the training, testing and validation process as is shown in Figure 3. In this case, this study has recorded the best training, testing and validation performance at the 2nd epoch, when the MSE has a value of 1.7247e−08 for the best training, 0.7053 for the best testing and 3.6151 for the best validation. By analysing the plot, the devised predicting solution (70% of data: training process, 15%: validation process and 15%: the testing process) is stable and provides good outcomes for the training process, therefore, the overfitting process does not occur, and the NARX_LM_JKII neural network delivers a high degree of performance and accuracy (Figure 3).

Afterwards, this study signifies the error histogram, when predicting daily accuracy improvement for the JKII prices for July 2021 (2 July 2021 until 12 July 2021) using the optimal developed ANN of the NARX_LM_JKII network (Figure 4).

| Deep learning techniques | LM training algorithm | | BR training algorithm | | SCG training algorithm | |
|---|---|---|---|---|---|---|
| Samples | MSE | *R* | MSE | *R* | MSE | *R* |
| Big data | 30.69891 | 0.999730 | 40.88045 | 0.999626 | 45.94484 | 0.999579 |
| Small data | 1.7247e−08* | 0.999999* | 1.79139 | 0.999071 | 5.84013 | 0.996971 |

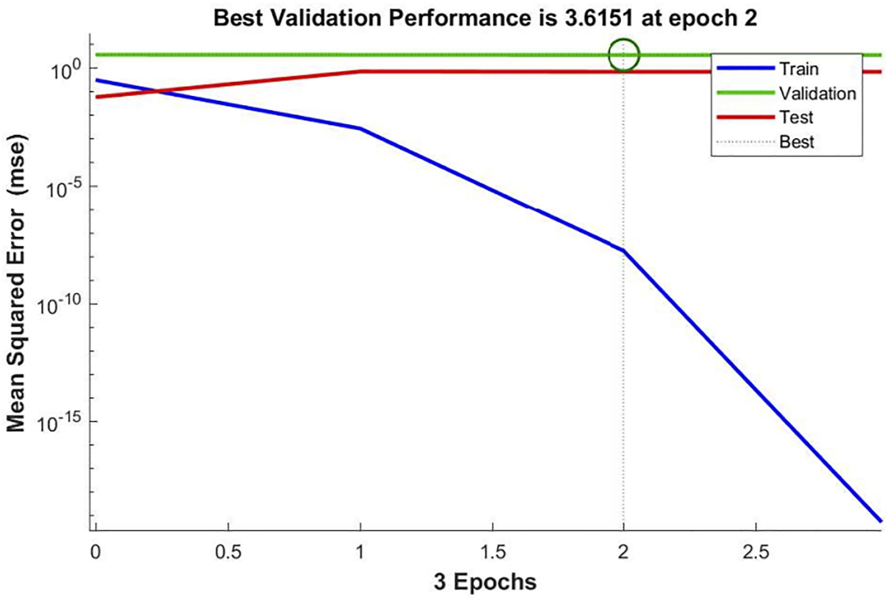
**Note(s):** * Refers to the optimal daily prediction accuracy
**Source(s):** Organized by authors

**Table 3.** The optimal accuracies of DL techniques for small and big data samples



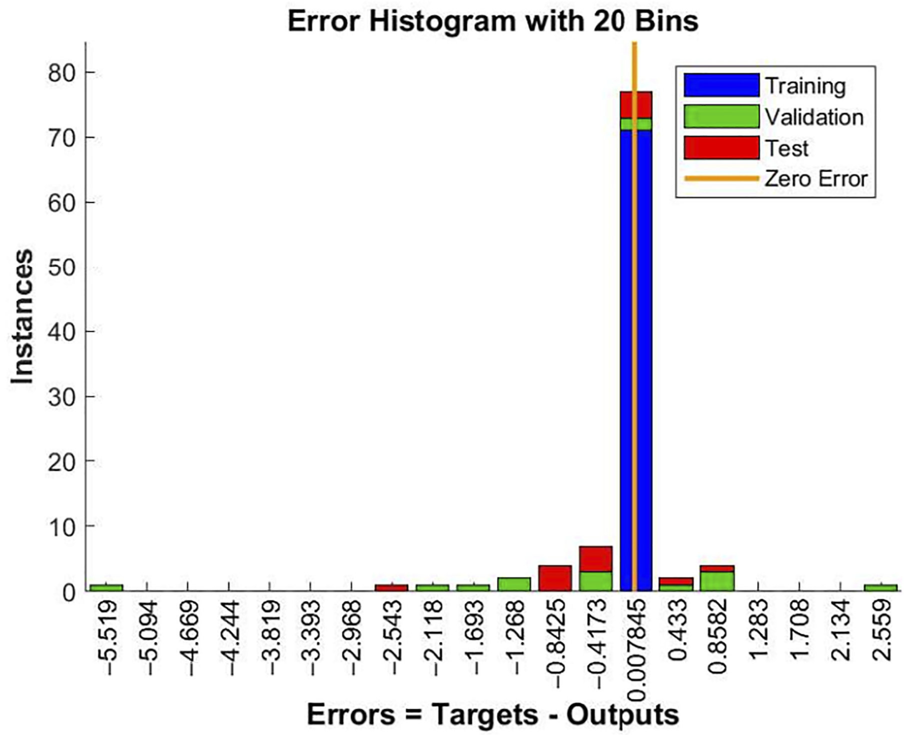

**Source(s):** Executed by authors using MATLAB deep learning toolbox

**Figure. 2.** The NARX_LM_JKII's architecture




**Source(s):** Executed by authors using MATLAB deep learning tool

**Figure. 3.** The best performance of training, testing and validation using the NARX_LM_JKII network




**Source(s):** Executed by authors using MATLAB deep learning toolbox

**Figure. 4.**
The error histogram while predicting the daily accuracy improvement for JKII prices using the NARX_LM_JKII network

Analysing the plot, this study notes that errors fall in 0.007845, a very small value. All the errors training points are close to this point. As a consequence, the error histogram in this context emphasizes extremely good outcomes.

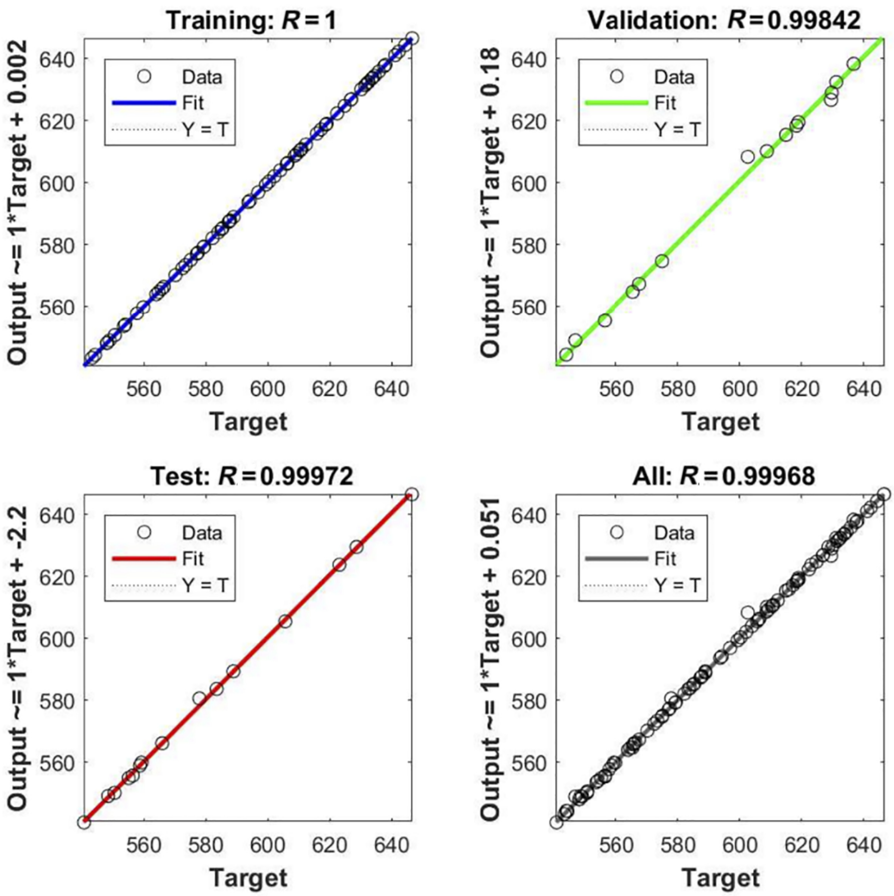
Afterwards, to analyse the prediction accuracy, this study calculates and represents one more important plot for the goodness of fit, the regressions between the outputs and network targets. This plot in Figure 5 shows that the correlation coefficient values are very close to 1, all of them is greater than 0.998. Thus, this experimental research attains very good fit outputs.

This study uses the error autocorrelation function to examine how the predicting errors are interconnected in time to verify the network's performance. Apart from the zero-lag correlation, most of the predicting errors fit inside the confidence limit around zero, confirming the efficiency of the predicting approach (Figure 6).

*4.2 Outputs discussion and visualization*

Finally, this experimental study compares the obtained predicted JKII prices (7 anticipated days starting from 2 July 2021 until 12 July 2021) with the corresponding real values provided by the respected website database of *Investing.com* as is shown in Table 4.

As well, this study plots the real daily prices of JKII and the predicted ones on the same graph for this purpose. Analysing the graph, this study notices that the two curves are very close to each other as Table 4 shows low absolute values of the differences (Δ = Real JKII prices – Predicted JKII prices) in most predicted days (2 July 2021, 6 July 2021, 7 July 2021, 8




**Source(s):** Executed by authors using MATLAB deep learning toolbox

**Figure. 5.** The regression between the network outputs and targets while predicting the daily accuracy improvement for JKII price using the NARX_LM_JKII network

July 2021, 9 July 2021 and 12 July 2021), a fact that demonstrates the high level of accuracy under the developed predicting solution for a whole five-day weak in the Indonesian Islamic capital markets (Figure 7).

## 5. Conclusion

In this paper, the experimental research aims to predict daily accuracy improvement of JKII prices based on small and big data of symmetric volatility information that consist of the OP, HP, LP and CP. The predicting solution has been developed using DL with small and big data over the LM, BR, SCG training algorithms within the NARX ANNs.

By testing various training algorithms of DL, choosing the optimal amount of hidden layer's neurons, the delay parameter and the network's weights, and comparing the outcomes, this study attains in each data sample (small and big data) the neural network that affords the best prediction accuracy. Subsequently, by evaluating the predicting performance of the chosen network (NARX_LM_JKII) which was emphasized by the MSE, correlation

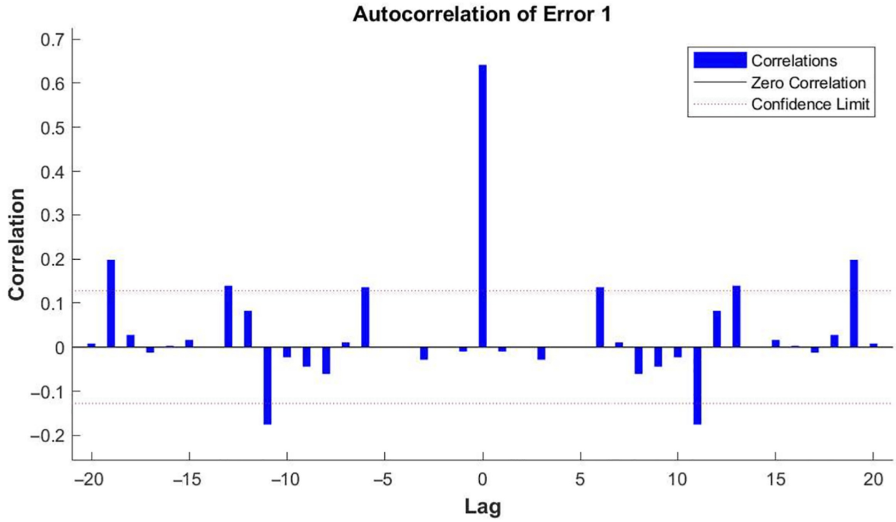



**Figure. 6.** The error autocorrelation function while predicting the daily accuracy improvement for JKII price using the NARX_LM_JKII network

**Source(s):** Executed by authors using MATLAB deep learning toolbox

**Table 4.** Comparison between real daily JKII prices and predicted daily JKII prices

| Days | 02 July | 05 July | 06 July | 07 July | 08 July | 09 July | 12 July |
|---|---|---|---|---|---|---|---|
| Real JKII prices (IDR) | 547.52 | 539.43 | 549.42 | 548.81 | 543.8 | 549.97 | 553.22 |
| Predicted JKII prices (IDR) | 548.210 | 555.768 | 550.061 | 544.215 | 548.933 | 555.770 | 554.700 |
| Δ = \|Real – NARX_LM_JKII\| | 0.690 | 16.338 | 0.641 | 4.595 | 5.133 | 5.800 | 1.480 |

**Source(s):** Organized by authors

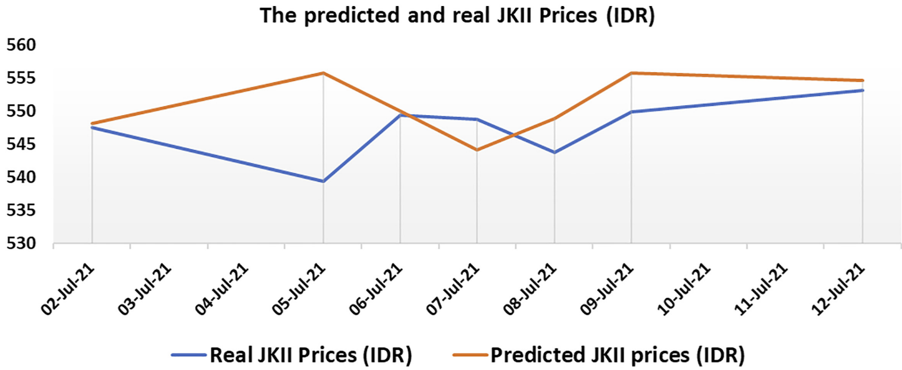



**Figure. 7.** Comparison between the predicted JKII prices with the corresponding real values

**Source(s):** Organised by authors using NARX_LM_JKII network

coefficient, the error histogram, the regression, the error autocorrelation chart, this study has determined that the best daily prediction accuracy for JKII prices under the NARX model is provided by the developed ANN using the Levenberg–Marquardt algorithm

(NARX_LM_JKII) in the case of using the small data sample, in which this developed ANN is built from exogenous variables of the OP, HP, LP and CP, with $n = 24$ neurons in the hidden layer and a delay parameter of $d = 20$ (NARX_LM_JKII).

To validate the predicting accuracy of the developed solution, this study has performed the final verification based on the real-world predicting scenario, through predicting the daily JKII prices using the developed ANN of NARX_LM_JKII provided by small data of symmetric volatility information and compared the obtained findings with the corresponding real values. Consequently, the daily JKII prices solution developed within this paper offers a high level of accuracy, having the potential of being useful tools for both the financial decision-makers and investors, offering them the means to attain appropriate management of portfolios, reduce the trading risk and make the right financial decisions in the Islamic capital markets.

Above and beyond, this study is enriching the literature by providing a new effective technique for predicting the JKII prices in the Islamic capital markets of Indonesia. It applied the DL techniques through the NARX neural network and chose the best training task based on the optimal accuracy score after learning processes. Consequently, to answer the main research question about the optimal training task of DL for predicting daily accuracy improvement for the JKII prices, the experimental results demonstrate that the LM algorithm is the most appropriate training task for predicting daily accuracy improvement for the JKII in Indonesia due to the optimal predicting accuracy according to the criteria of the lowest MSE and the highest correlation coefficient (*R*). In addition, this study accomplishes that using small data of symmetric volatility information is better than using big data sample, this result indicates that small data of symmetric volatility information is full of high-quality information for better prediction accuracy, therefore, this result is consistent with Yudelson *et al.* (2014) and Faraway and Augustin (2018) when they demonstrated that small data outperforms big data in prediction accuracy when small data generate superior inferences than the low-quality large sample. In conclusion, this paper supports the findings of Das *et al.* (2017), Wibowo *et al.* (2017), Alkhoshi and Belkasim (2018), Livieris *et al.* (2019), Aslam *et al.* (2020), Peng and Tang (2020), Wang *et al.* (2020), Irsalinda *et al.* (2020), Yu and Yan (2020), Gandhmal and Kumar (2020), and Peng and Tang (2020), in which modern techniques like machine learning, artificial intelligence and DL are effective tools in the capital markets by affording advanced knowledge to the financial investors for the well-organized managing of portfolios, to reduce trading risk and to make right financial decisions, which leads to the inevitability of using new technological techniques in Islamic capital markets due to the effectiveness of those modern techniques in the predicting process than other classical statistical tools which remained paralyzed to evaluate big data time series, this inevitability of updating the classical statistical tools obliges the financial investors and decision-makers to employ new techniques which only machine learning, artificial intelligence and DL can offer.

### *5.1 Practical implications for research and practice*

This paper has some implications for research and practice as the following:

(1) This study aims to apply DL for predicting daily accuracy improvement for the JKII prices using the NARX neural network model based on small and big data of symmetric volatility information. Therefore, this paper would fill the literature gap by providing a new efficient tool for predicting prices and volatilities in the Islamic capital markets.

(2) Due to the age of big data, DL is one of the effective techniques for financial analysers and decision-makers to evaluate and predict the volatilities in both Islamic and conventional capital markets. Consequently, although this paper is limited to an

Islamic stock index which is JKII, in terms of practical implication, this paper provides important evidence for researchers, financial investors and decision-makers across countries in the Islamic capital markets to the necessity of adopting DL due to high volatilities and unstable movements in Islamic stock indices, artificial intelligence, and machine learning as major tools in the age of big data technology and the emerging of Islamic fintech across the world. Thus, modern technological techniques can be beneficial in Islamic capital markets by ranking investments, assessing stock volatilities, reducing trading risk, managing portfolios strategies in Islamic financial environments and managing wise financial decisions to maximize financial investment profits.

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**Corresponding author**
Mohammed Ayoub Ledhem can be contacted at: ledhem.edu@gmail.com