Jurnal Ekonomi Syariah Teori dan Terapan p-ISSN: 2407-1935, e-ISSN: 2502-1508.
Vol. 11 No. 1, Februari 2024: 86-104.; DOI: 10.20473/vol11iss20241pp86-104.

Predicting Shariah Stock Market Indices with Machine Learning: A Cross-Country Case Study

Prediksi Indeks Pasar Modal Syariah dengan Machine Learning: Studi Kasus Antar Negara

Dini Anggreini Khairunnisa, Ahmad Rodoni, Ali Rama
Master of Sharia Economics, Faculty of Economics and Business, Universitas Islam Negeri Syarif Hidayatullah, Jakarta, Indonesia
dini.anggreini22@mhs.uinjkt.ac.id, ahmad.rodoni@uinjkt.ac.id, rama@uinjkt.ac.id

ABSTRACT

Numerous factors influence stock prices, including policy adjustments, economic conditions, and international developments. As a result, accurately forecasting stock price trends remains a significant challenge for economists. Compared to the traditional financial sector, the Islamic financial industry experiences fewer shocks, enabling investors to anticipate the performance of Islamic indices. This study aims to predict the Islamic stock market indices in six countries, including Indonesia, Thailand, Malaysia, Pakistan, the United Arab Emirates, and Qatar, using the Autoregressive Integrated Moving Average (ARIMA) model. Monthly data from 2013 to 2023 sourced from investing.com and Yahoo Finance are analyzed using R machine learning. This study aims to provide accurate forecasts for the next 25 months and insights into potential price movements. Overall, this research also sheds light on the dynamics of the Islamic market in Indonesia, Thailand, Malaysia, Pakistan, the United Arab Emirates, and Qatar, which adhere to the Efficient Market Hypothesis (EMH) due to historical data predictability of index prices.

Keywords: Forecasting, R-Studio, ARIMA, Islamic Stock Market, Machine Learning, R-Programming

ABSTRAK

Harga saham dipengaruhi oleh banyak faktor, termasuk penyesuaian kebijakan, kondisi ekonomi, dan perkembangan internasional. Oleh karena itu, memprediksi tren harga saham dengan akurat telah menjadi tantangan signifikan bagi para ekonom untuk mempelajarinya. Industri keuangan Islam mengalami lebih sedikit goncangan dibandingkan dengan sektor keuangan tradisional, yang memungkinkan investor untuk memperkirakan kinerja indeks Islam. Studi ini bertujuan untuk memprediksi indeks pasar saham Islam di enam negara, termasuk Indonesia, Thailand, Malaysia, Pakistan, Uni Emirat Arab, dan Qatar, menggunakan model Autoregressive Integrated Moving Average (ARIMA). Data bulanan dari tahun 2013 hingga 2023 yang berasal dari investing.com dan Yahoo Finance dianalisis menggunakan pembelajaran mesin R. Tujuan dari studi ini adalah untuk memberikan prediksi yang akurat untuk 25 bulan mendatang dan menawarkan wawasan tentang pergerakan harga yang potensial. Secara keseluruhan, penelitian ini juga memberikan cahaya tentang dinamika pasar Islam di Indonesia, Thailand, Malaysia, Pakistan, Uni Emirat Arab, dan Qatar, yang mengikuti Hipotesis Pasar Efisien (EMH) karena dapat diprediksi oleh data historis..

Kata Kunci: Prediksi, R-Studio, ARIMA, Indeks Pasar Modal Syariah, Machine Learning, R-Programming

Article History
Received: 29-12-2023
Revised: 24-01-2024
Accepted: 28-02-2024
Published: 29-02-2024

[*)]Corresponding Author:
Dini Anggreini Khairunnisa

I. INTRODUCTION

Islamic stock indices offer a unique investment opportunity for individuals seeking to align their financial goals with ethical principles (Supriani et al., 2022). These indices track the performance of companies that comply with Islamic law (Sharia), which prohibits interest-bearing activities and investments in industries deemed harmful or unethical. Investing in Islamic stock indices allows individuals to participate in the growth of companies operating within a framework of ethical and sustainable practices (Rizvi et al., 2014). Additionally, compared to conventional indices, these indices often exhibit lower volatility, potentially offering stability for investors seeking long-term wealth creation. Islamic stock indices provide a compelling and growing investment avenue for investors seeking to align their financial goals with their values.

The Islamic finance market has witnessed significant growth in recent years, driven by rising demand from Muslim investors and increasing interest from ethical investors globally. This surge has fueled the creation of numerous Islamic stock indices across various regions, offering investors a diverse range of ethical investment options. Popular examples include the Dow Jones Islamic Market World Index, Jakarta Islamic Index, and S&P 500 Shariah Index, each providing exposure to distinct markets and sectors. This expansion caters to the evolving needs of investors seeking ethical and Sharia-compliant financial instruments.

The expansion of investment opportunities aligned with Sharia principles is evident across diverse geographical regions in various countries, encompassing nations with significant Muslim populations as well as some non-Muslim societies (Boukhatem & Moussa, 2018; Tatiana et al., 2015). This growth in Sharia-compliant investment is propelled by a multitude of factors, including considerations of risk management, equitable profit-sharing rates, the intrinsic motivation to uphold the principles of Maqasid Sharia, levels of financial literacy, and prevailing perceptions regarding the ethical and financial advantages of such investments (Abdullah, 2015; Yesuf & Aassouli, 2020). Alongside the demographic growth of the global Muslim community, research findings corroborate the notion that assets structured in accordance with Sharia guidelines offer a superior diversification effect compared to their conventional counterparts. This suggests that embracing Sharia-compliant assets within investment portfolios not only adheres to ethical principles but also enhances risk management strategies and potentially improves overall portfolio performance (Hkiri et al., 2017; Saiti et al., 2014).

As stock market efficiency evolves, investors may adjust their expectations regarding the performance of different sectors. In terms of portfolio management, an effective strategy involves considering a diversification approach that takes into account variations in the current efficiency levels of different sectoral markets. This approach recognizes that markets may exhibit different degrees of efficiency due to a dynamic structure over time (Arashi & Rounaghi, 2022). Investors aim to optimize their portfolios and manage risk more effectively by strategically diversifying across sectors with varying efficiency states. As mentioned earlier, investors must stay vigilant and adapt their investment strategies based on the changing market efficiency landscape, considering the many external factors that influence stock market movements. This adaptive approach enhances the potential for achieving robust and resilient investment portfolios in the face of evolving market conditions (Abraham et al., 2022; Deswal et al., 2023).

This growth in Islamic financial sectors allows many investors to invest for diversification purposes. Because investors and other financial surplus units in the economy seek investment opportunities with minimal shocks and predictable impacts, the Islamic financial industry experiences fewer shocks than the traditional financial sector, and investors can predict the performance of the Islamic index (Sahabuddin et al., 2023). Because investors are increasingly interested in Islamic equities to diversify their portfolios, it is necessary to forecast Islamic stock performance.

Predicting the movements of stock market indices has always been a formidable challenge due to the intricate interplay of economic, geopolitical, and social forces. While traditional econometric models have historically been the go-to approach, machine learning techniques have ushered in a new era of financial forecasting. These advanced algorithms boast superior predictive power and the ability to adapt to complex, nonlinear relationships within vast datasets, offering a significant leap forward in navigating the ever-evolving financial landscape (Demirel et al., 2021).

Using machine learning techniques allows researchers to improve stock price forecasts and gain a deeper insight into the correlations among index prices across different countries (Cao, 2023). Previous academic studies on stock markets have predominantly employed intricate methods to predict stock price fluctuations, considering the factors influencing them and the intricate nature of financial markets (Xiao et al., 2021). While these sophisticated trading models have enhanced theoretical understanding of finance, their complexity poses risks for investors who lack familiarity with stock movements, potentially leading to losses in the stock market. Therefore, using machine learning in stock price prediction is increasingly essential, particularly with the growing number of stocks entering the market (Cao, 2023).

However, stock index forecasting is extremely difficult but worthwhile for investors and businesses because there are numerous social and economic factors (e.g., economic conditions, investor interest, and government strategies, among others) that influence stocks and their returns (Barak et al., 2017; He et al., 2016). Because of the influence of so many factors, time series data on stock prices exhibit nonstationary and nonlinear patterns. Analyzing such a trend in stock price time series without accurate information is extremely difficult. Furthermore, poor signal-to-noise ratios present significant challenges for stock index forecasting, making previous stock values less productive for future value. This is particularly relevant in the market context, where past events and data somewhat influence future events (Demirel et al., 2021) rather than being entirely random (Du, 2018; Fantin & Junior, 2021.).

For efficient market theory by Fama (1965, 1970, 1998) which stands as a significant proposition in finance, all relevant information must be reflected in efficient stock markets and adjust promptly to new information. According to this theory, investors cannot gain an advantage solely through existing information, as all stocks are deemed fairly priced. In weak-form market efficiency, the prices of stocks reflect all information about past prices. In a semi-strong market efficiency form, the prices of stocks reflect all of the available public information. Consequently, the hypothesis contends that consistently outperforming the market to achieve abnormal profits is not feasible, given the efficient pricing mechanism. We employ uptrend forecasting, which contrasts with market efficiency as it includes real-time information that does not mirror the theoretical conditions (Abraham et al., 2022; Feuerriegel & Gordon, 2018; Rodoni et al., 2022).

The ability to forecast stock market indices has become a focal point for both financial professionals and academics. These predictions hold immense value, influencing national economic decisions and shaping investment strategies for brokers (Do & Van Trang, 2020; Sun, 2020). However, achieving accurate forecasts consistently proves to be a formidable task. The inherent complexity, dynamism, and inherent chaotic nature of the stock market present significant challenges, making precise predictions elusive (Do & Van Trang, 2020; Fu et al., 2020; Kenrick & Yanti, 2022). Forecasting Islamic stock indices across multiple countries is crucial for diversification, risk management, and understanding global economic interdependencies. It helps identify opportunities in diverse markets and mitigates adverse events in single markets. Forecasting also allows for comprehensive policy and regulatory analysis and better capital allocation and asset allocation across borders. It also helps researchers better understand similarities and differences within Islamic finance markets. Multinational corporations also benefit from forecasting, enabling them to anticipate market fluctuations and make strategic decisions.

While significant strides have been made in financial forecasting, there remains a noticeable gap in the literature concerning the application of machine learning techniques to forecast Islamic stock indices across multiple countries. Existing studies predominantly focus on traditional econometric models or limit their scope to single-country analyses, overlooking the potential cross-country dynamics inherent in Islamic finance markets. Furthermore, the few studies that do explore the forecasting of Islamic stock indices often employ rudimentary machine-learning algorithms or fail to provide comprehensive evaluations of model performance. Thus, there is a clear need for research that not only harnesses the predictive power of advanced machine learning methodologies but also examines the cross-country variations and unique characteristics of Islamic stock markets. Addressing this research gap is imperative for enhancing our understanding of the factors driving the performance of Islamic stock indices and for developing robust forecasting frameworks that can assist investors and financial institutions in making informed decisions across diverse geographical contexts.

Several studies have explored stock price forecasting and demonstrated varying levels of success. Do & Van Trang (2020) posited that there are two distinct categories of forecasting models for time series data: 1) statistical-based models and 2) machine learning models (ML). Statistical time series forecasting models use mathematical equations and traditional statistical theories to anticipate future values. Most successful time series analysis models In the previous literature, the aforementioned classical statistical time series models are used to forecast stock prices time series data but fail to predict performance perfectly (Kazem et al., 2013). Kocak (2017) and Wang et al., (2018) utilized an ARMA model. Adebiyi et al., (2014); Kamalakannan et al., (2018); and Du (2018) using ARIMA model. Generalized autoregressive conditional heteroskedastic (GARCH) by Y. Lin et al., (2020) and Mantri et al., (2010).

smooth transition autoregressive model (STAR), linear regression (LR), linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) (Ou & Wang, 2009), support vector machines (SVM) by Ballings et al., 2015 and Huang et al., (2005). ARMA-GARCH by Arashi & Rounaghi (2022) and so on.

Unlike classical time series, ML models make data-driven predictions by learning from input time series signal instead of following predesigned static rules and instructions (Provost & Kohavi, 1998). In the literature, many ML models have proved to have better forecasting accuracy (Ravi et al., 2017; Pradeepkumar & Ravi, 2017). Such as Artificial Neural Networks (ANN) by Kazem et al., (2013); Moghaddam et al., (2016); Fantin & Junior (2021); Rather et al., (2015); and Xi et al., (2014) for forecast analysis. Lin & Gong (2017) developed a forecast model using BP Neural Network and Convolutional Neural. Ali et al., (2021) used an artificial neural network (ANN) and support vector machine (SVM).). Jia & Yang, (2021) used deep neural network (DNN) and long short-term memory (LSTM) models. Genetic Algorithm (GA) (Rahman et al., 2015). Hidden Markov Model (HMM) (Hassan et al., 2007). Decision Tree (DT) (Hu et al., 2015). Rough Set Theory (Nair et al., 2010). Bayesian Analysis (BA) (Miao et al., 2015). K-Nearest Neighbors (KNN) (Nayak et al., 2015; Teixeira & Oliveira, 2010). Particle Swarm Optimization (PSO) (Zhang & Shen, 2009). Deep Learning architectures, i.e. Multilayer Perceptron (MLP) (Guresen et al., 2011), Recurrent Neural Networks (RNN) (Rout et al., 2015). Long Short-Term Memory (LSTM) (Baek & Kim, 2018; J. Cao et al., 2019; Y. Lin et al., 2021). Convolutional Neural Network (CNN) (Selvin et al., 2017). And the like.

In Islamic stock indices, the application of machine learning algorithms presents a promising avenue for improving forecasting accuracy and efficiency. By leveraging vast amounts of historical data, machine learning models can identify intricate patterns and trends that may not be discernible through conventional methods. Moreover, the flexibility of machine learning frameworks allows for incorporating diverse data sources, including economic indicators, sentiment analysis of news articles, and geopolitical events, which may significantly impact the performance of Islamic stock indices.

Islamic indices have played a crucial role in Islamic finance in recent years. These unique indexes describe the universe of assets available for investment and help Islamic investors measure market performance. This research aims to fill the gap in understanding Islamic indices by incorporating machine learning techniques and adopting a cross-country approach. It explores complex, nonlinear relationships in Islamic finance markets, offering a novel perspective on forecasting Islamic indices. The study includes multiple countries, comprehensively examining cross-country dynamics and identifying commonalities and divergences across different regions. This contributes to advancing our understanding of Islamic finance and enhancing predictive analytics. Filling this gap in this study, use of R in machine learning is still relatively uncommon for predicting stock market indices, particularly in the context of Islamic stock market indices. Several studies by Angadi & Kulkarni (2015); Kenrick & Yanti (2022); and Targa Sapanji et al., (2023) on stock prices using R have not addressed the Shariah stock market index. Furthermore, they have not combined it with ARIMA but have utilized other approaches, such as SVM.

This study aims to forecast Islamic stock market indices in multiple countries, including Indonesia (JKII), Thailand (FTSE SET), Malaysia (FTFB MHS), Pakistan (KMI), the United Arab Emirates (TASI), and Qatar (QERI), utilizing R machine learning techniques, specifically employing the ARIMA model. ARIMA, or Autoregressive Integrated Moving Average, is a popular time series forecasting method that captures both autoregressive and moving average components, making it well-suited for predicting stock market indices, which often exhibit time-dependent patterns. The data consists of monthly data from 2013 to 2023 from investing.com and Yahoo Finance. This data will be processed using the ARIMA model in R-Studio. The results of this data analysis will indicate predictions for Shariah stock index prices for the next 25 months in the form of the highest and lowest prices.

Forecasting Islamic stock indices across countries using machine learning offers exciting possibilities for investors and the market. This approach can empower investors with more accurate forecasts, enabling them to make informed decisions and manage risk effectively. Additionally, it can contribute to increased market efficiency and transparency by providing valuable insights, facilitating fairer price discovery, and potentially detecting fraudulent activities. Ultimately, machine learning-powered forecasting holds the potential to propel the Islamic finance sector towards sustainable growth and broader adoption.

II. LITERATURE REVIEW

Efficient Market Hypothesis

Rossi & Gunardi (2018) state that one of the most important principles used in measuring market efficiency is the ability of prices to reflect all the information available today. The Efficient Market Hypothesis (EMH) posits that current stock prices fully reflect all available information about the value of a company, making it impossible to gain surplus profits using this information (Ali et al., 2021; Jawadi et al., 2015; Rossi & Gunardi, 2018). Fama (1970) defined an efficient market as a market whose price always reflects all available information quickly and accurately. When a market (the stock market or the money market) is considered efficient, there should be no anomaly. Such anomalies can allow market operators or investors to obtain abnormal returns. In other words, investors can obtain unusual returns in an efficient market in any form when there is an anomaly (Elango & Macki, 2008; Kasidi & Banafa, 2022; Surachmadi et al., 2021).

Rodoni & Yong (2002) stated that market anomalies were primarily found in market efficiency forms of weak/weak forms (prices in the past cannot be used to predict current or future prices) and semi-strong forms (Agustin, 2019; Elangovan et al., 2022; Faisal et al., 2022; Khan et al., 2021). At least four types of anomalies occur in the market: corporate, event, seasonal, and accounting (Barberis et al., 2021; Elango & Macki, 2008; Keloharju et al., 2014; Koesoemasari et al., 2018; Ain et al., 2021).

Forecasting

Forecasting theory is based on the concept that current and historical information can be used to predict the future. Particularly for time series, there is a view that it is possible to find patterns in historical values and successfully implement them in predicting future values. However, precise forecasting of future values is not expected. Instead, an expected value (often referred to as a point forecast), a prediction interval, a percentile, and the whole prediction distribution are among the several alternatives for forecasting a single time series at a future time period. This set of outcomes could be considered “the forecast” as a whole. A forecasting procedure can have a lot of other possible results. The goal may be to foresee an occurrence, such as equipment failure, and time series may play only a minor role in the forecasting process. Forecasting processes work best when they are related to a problem that will be solved in practice. The theory can then be constructed by first comprehending the main elements of the situation. As a result, theoretical findings can lead to better practice (Clement & Tse, 2003; Mallikarjuna & Rao, 2019; Petropoulos et al., 2022).

A forecasting method is described as a preset sequence of processes that results in forecasts for future time periods. Many, but not all, forecasting approaches have matching stochastic models that yield the same point forecasts. In addition to point forecasts, a stochastic model provides a data generation mechanism that may be utilized to construct prediction intervals and whole prediction distributions. Every stochastic model makes assumptions about the process and the associated probability distributions. A stochastic model is not always unique, even when it underlies a forecasting technique. Several stochastic models, such as state space models that might or might not be homoscedastic (i.e., have constant variance), are available for the simple exponential smoothing method. Combining forecasts from many methodologies has been demonstrated to be a highly effective forecasting method. If there are any similar stochastic models, their combination constitutes a model in and of itself. Forecasts can be generated by combining new and/or existing forecasting methods/models. These more complicated processes would also predict methods/models (Deswal et al., 2023; Lv et al., 2022).

The variables’ nature and role in the forecasting process must be considered. Forecasts for a single time series are created utilizing information from the time series’ historical values in univariate forecasting. Other time series variables, such as time series regression, produce multivariate forecasts. Interventions (e.g., special promotions and extreme weather) may be possible with univariate and multivariate forecasting. Relationships between variables and other input types might be linear or nonlinear (for example, market penetration of a new technology). When no clear functional form is available, approaches such as simulation or artificial neural networks may be used. Theories from economics, epidemiology, and meteorology can help build these linkages. Multivariate forecasting could also refer to forecasting many variables simultaneously (e.g., econometric models) (Chang et al., 2009; Katterbauer et al., 2022; Sun, 2020).

Data or observed values for time series can take several forms, which might limit or affect the choice of a forecasting approach. There may be no historical observations for the item of interest when using judging approaches (e.g., time required to finish building a new airport). Because of the nature of the data, a new forecasting method may be required. The frequency of observations might range from every minute to hourly, weekly, monthly, and yearly (for example, the energy business must anticipate demand loads at hourly intervals and long-term demand for ten or more years ahead). The data could consist of anything from a single significant time series to billions of time series. Economic analysis frequently comprises several variables, many of which interact with one another. For enterprises, time series are likely to be essential at many distinct levels (e.g., stock keeping unit, common ingredients, or common size container) and, as a result, form a time series hierarchy. Some or all values may be zero, causing the time series to be intermittent. The number of data forms available is nearly limitless (Petropoulos et al., 2022; Phua et al., 2003).

The data may need to be pre-processed before applying a forecasting method. There are some basic details, such as checking for accuracy and missing numbers. Other issues may arise before deploying the forecasting approach or being integrated into the methods/models. The treatment of seasonality is one such example. Some forecasting methods/models require de-seasonalized time series, whereas others address seasonality inside the methods/models. Some governmental data organizations generate projections to extend time series into the future while estimating seasonal elements (i.e., X-12 ARIMA), making it less evident when seasonality is included relative to a forecasting method/model (Angadi & Kulkarni, 2015; Du, 2018).

III. RESEARCH METHODS

This research employs a quantitative approach, utilizing primary data for analysis. The study requires monthly closing price data for stock indices, including Indonesia (JKII), Thailand (FTSE SET), Malaysia (FTFB MHS), Pakistan (KMI), the United Arab Emirates (TASI), and Qatar (QERI) spanning from 2013 to 2023. Data for this period can be sourced from financial platforms such as investing.com and Yahoo Finance. The analysis will use the Autoregressive Integrated Moving Average (ARIMA) model, a time series forecasting technique implemented through R machine learning tools. This methodological framework allows for examining trends, patterns, and potential relationships within the stock markets of the selected countries over the specified timeframe.

The data sample for this research consists of monthly closing price data for stock indices from six countries: Indonesia (JKII), Thailand (FTSE SET), Malaysia (FTFB MHS), Pakistan (KMI), the United Arab Emirates (TASI), and Qatar (QERI). The time span for the data ranges from 2013 to 2023, providing a comprehensive view of stock market performance over a significant period. The sampling technique employed in this research is non-probabilistic convenience sampling. Convenience sampling involves selecting data points that are readily available and easily accessible. In this case, the researchers have chosen to focus on monthly closing prices of the selected stock indices, as this information is commonly available on financial platforms such as investing.com and Yahoo Finance. Convenience sampling is often used in studies where access to the entire population or a random sample is impractical or not feasible, but the available data is still representative enough for the research objectives.

While convenience sampling may introduce some bias due to the non-random selection of data points, it is justified in this context by the practical considerations of data availability and accessibility. Additionally, the large sample size spanning a decade helps to mitigate potential biases and increases the robustness of the analysis. The selected data sample and sampling technique are appropriate for conducting a quantitative study of stock market performance using the ARIMA model with R machine learning tools (Zhao & Chen, 2022).

The choice of the Autoregressive Integrated Moving Average (ARIMA) model for this research is based on its suitability for analyzing time series data, particularly in forecasting future values based on past observations. ARIMA is a widely used statistical method for capturing complex temporal patterns and trends in financial data, making it particularly relevant for studying stock market dynamics. ARIMA models can incorporate autocorrelation (the relationship between a variable's current and past values) and seasonality (patterns that repeat at regular intervals) into the analysis. This is crucial for understanding the behavior of stock prices, which often exhibit both short-term fluctuations and longer-term trends.

Furthermore, ARIMA models are flexible and can adapt to different types of time series data, making them suitable for analyzing financial data from various markets and regions (Kenrick & Yanti, 2022). Employing ARIMA within the context of this research allows for the extraction of valuable insights into the historical performance of stock markets in Indonesia, Thailand, Malaysia, Pakistan, the United Arab Emirates, and Qatar. It provides a basis for forecasting future trends and patterns within these markets.

Empirical modeling involves constructing mathematical or statistical models based on observed data to understand and explain real-world phenomena. In this research, empirical modeling refers to the development and application of the ARIMA model to analyze the monthly closing price data of stock indices from Indonesia, Thailand, Malaysia, Pakistan, the United Arab Emirates, and Qatar. ARIMA is a forecasting model that relies on the analysis of patterns in historical data. This approach utilizes past and present data as independent variables without considering other factors that might influence the movement of time series data. ARIMA comprises the autoregressive (AR) component and the moving average (MA) component (Angadi & Kulkarni, 2015; Du, 2018; Rodoni et al., 2022; Staffini, 2022).

The Auto-Regressive Integrated Moving Average (ARIMA) model (Box and Jenkins, 1976) is based on the theory of stochastic processes. It has the benefits of needing little data, being easy to understand, and being able to be modelled quickly. Additionally, ARIMA models can handle nonstationary time series. In the context of recent advances in machine learning for forecasting, the strengths of ARIMA include requiring a small amount of data, simplicity, speed, flexibility, and adaptability to various types of time series (Adebiyi et al., 2014; Du, 2018; Kenrick & Yanti, 2022; Targa Sapanji et al., 2023). On the flip side, the weaknesses of ARIMA are its inability to model nonlinear patterns in time series and its inapplicability to multivariate cases.

The equations of the AR components can be denoted as follows:

$$Y_t = \varphi_0 + \varphi_0 Y_{t-1} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t \quad (1)$$

While the equation of the MA component can be denoted as follows:

$$Y_t = \omega_0 + \varepsilon_t - \omega_1 \varepsilon_{t-1} - \cdots - \omega_p \varepsilon_{t-p} \quad (2)$$

Therefore, the general equation of the ARIMA model is as follows:

$$Y_t = Y_{t-1} + \varphi_0 + \varphi_1 (Y_{t-1} - Y_{t-2}) + \cdots + \varphi_p \left(Y_{t-p} - Y_{t-p-1}\right) - \omega_1 \varepsilon_{t-1} - \cdots - \omega_q \varepsilon_{t-q} + \varepsilon_t \quad (3)$$

The R function auto.arima() employs a modified version of the Hyndman-Khandakar algorithm (Hyndman & Khandakar, 2008). This algorithm integrates unit root tests, minimization of the AICc, and Maximum Likelihood Estimation (MLE) to derive an ARIMA model. The parameters for auto.arima() offer numerous options to customize the algorithm. The default behavior described here represents its standard operation: Determining the number of differences ($0 \leq d \leq 2$) involves repeated KPSS tests. Subsequently, the values of p and q are selected by minimizing the AICc after applying differencing d times to the data. Instead of exhaustively exploring every possible combination of p and q, the algorithm employs a stepwise search to navigate the model space. Four initial models are fitted: ARIMA (0, d, 0), ARIMA (2, d, 2), ARIMA (1, d, 0), ARIMA (0, d, 1). A constant is included unless d = 2. If $d \leq 1$, an additional model is fitted: ARIMA (0, d, 0) without a constant. The model with the smallest AICc value among these initial models is designated the "current model." Variations on the current model are then considered: Vary p and/or q from the current model by ±1 and Include/exclude c from the current model. The best model among these variations, whether the current model or one of its variations, becomes the new one.

The default approach incorporates certain approximations to expedite the search process. These approximations can be bypassed by setting the argument approximation=FALSE. The minimum AICc model might not be discovered due to these approximations or the utilization of a stepwise procedure. A significantly larger set of models will be explored when the argument stepwise=FALSE is employed. For a comprehensive description of the arguments, refer to the help file.

In this study, R, a powerful machine learning tool, was used for analysis. Machine learning techniques have become increasingly prevalent in forecasting Islamic indices. By analyzing historical data, identifying patterns, and considering various factors, machine learning aids in making accurate predictions. Data on Islamic indices, including price movements, were sourced from reputable platforms such as investing.com and Yahoo Finance. Subsequently, meticulous data pre-processing techniques were employed to cleanse the data, handle missing values, and standardize features, ensuring compatibility with machine learning algorithms. To ensure robustness, stationarity tests were conducted across all models. Once the models demonstrated stationarity, unit root tests were performed to determine the appropriate level for ARIMA modeling. Afterwards, the optimal ARIMA model was meticulously selected. Furthermore, the chosen ARIMA model underwent a thorough assessment for normality. Subsequently, the ARIMA model was employed to forecast the Shariah capital market index.

IV. RESULTS AND DISCUSSION

Results

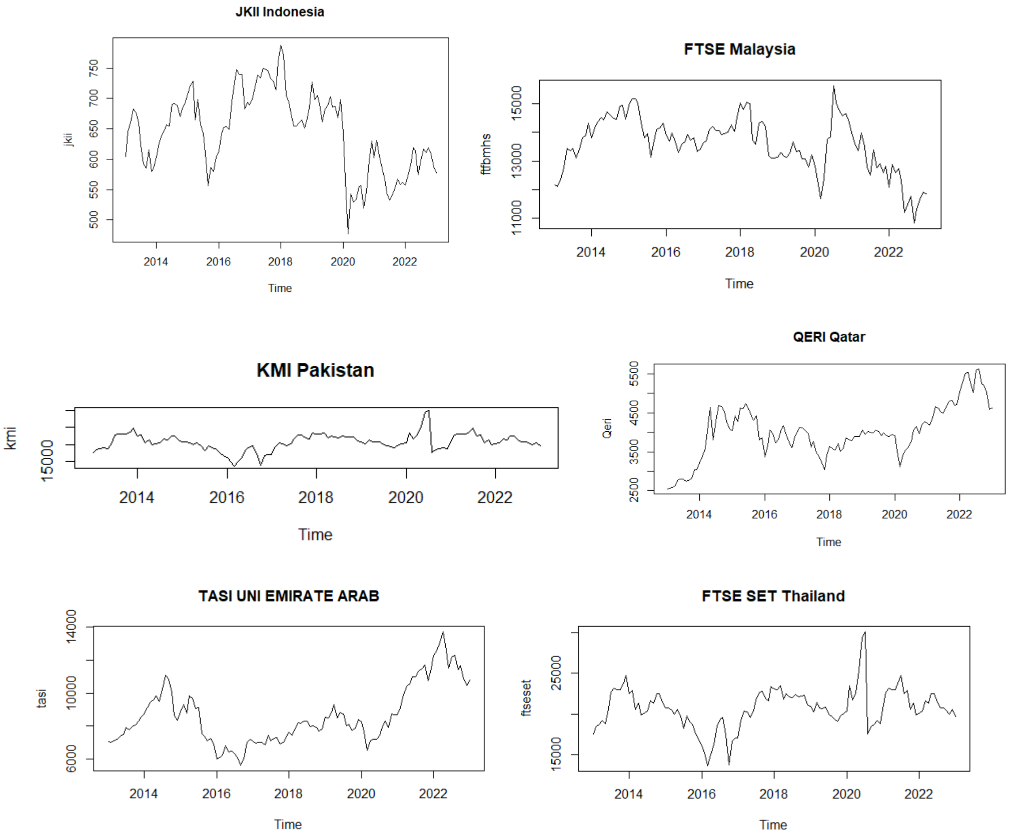


Figure 1. Time Plot Islamic Stock Index from 2013-2023

The time plot shows some sudden changes, particularly the significant drop in 2020. These changes are due to the COVID-19 pandemic. Otherwise, there is nothing unusual about the time plot, and there appears to be no need to make any data adjustments.

Table 1. BoxCox Lambda

Series	BoxCox Lambda	Result
JKII	1.937012	Stationary
FTFBMHS	1.999924	Stationary
KMI	1.189747	Stationary
QERI	0.2609835	Stationary
TASI	0.0391389	Stationary
FTSESET	1.898852	Stationary

The stationarity test is conducted using Box-Cox Lambda. The data is considered stationary if the Box-Cox Lambda result falls between -2 and 2. In the above Box-Cox Lambda results, all series can be considered stationary.

Table 2. Unit Root Test

Series	Level	First Difference
JKII	0.555	0.01
FTFBMHS	0.575	0.01
KMI	0.549	0.01
QERI	0.766	0.01
TASI	0.756	0.01
FTSESET	0.549	0.01

The Augmented Dickey-Fuller Unit Root Test at the level level did not pass the test (>α 0.05), so it needs to be retested at the first difference level. The result is that all series pass the unit root test at the first difference level. Subsequently, the testing script will use the data diff(variable).

Table 3. Best Model ARIMA

Series	Best Model	AIC
JKII	0, 1, 0	1130.097
FTFBMHS	0, 1, 0	1808.538
KMI	0, 1, 0	2120.898
QERI	0, 1, 0	1645.343
TASI	1, 1, 1	1826.311
FTSESET	0, 1, 0	2120.898

To determine the automatic ARIMA model using the script auto.arima(series, trace=TRUE), the results are as follows: All five series, namely JKII, FTFBMHS, KMI, QERI, and FTSESET, use the model (0, 1, 0), while TASI uses the model (1, 1, 1).

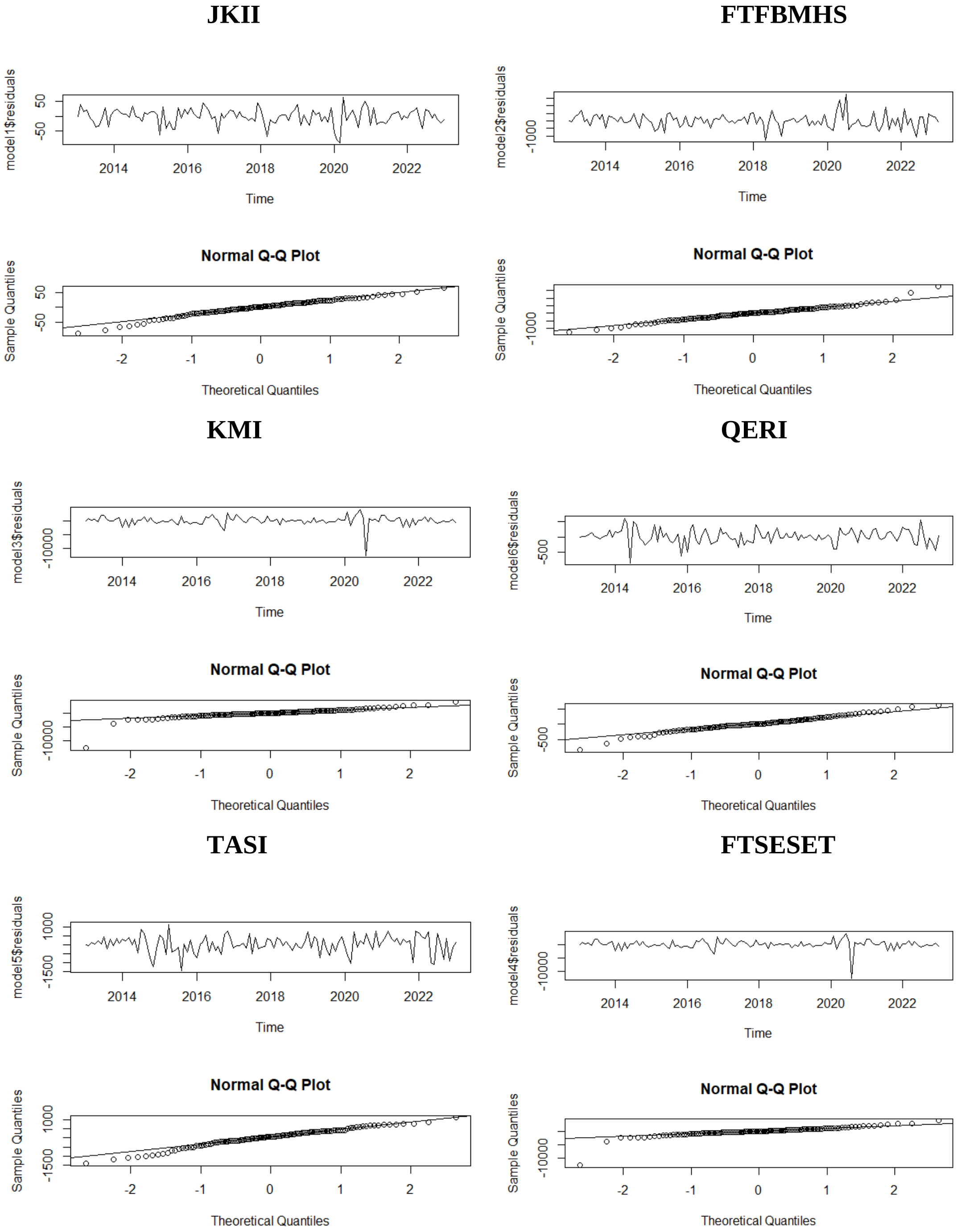


Figure 2. Normality Test Q-Plot ARIMA Chosen Model

Figure 2 shows the results of the normality test through a Q-plot. Visually, all series are considered normal, as seen from the normal QQ plot distribution within the lines.

Table 4. Forecasting Price 12 Months Model 1 (0, 1, 0) JKII

	Point Forecast	**Lo 95**	**Hi 95**
Jan 2024	577.58	396.8787	758.2813
Feb 2024	577.58	389.5002	765.6598
Mar 2024	577.58	382.4003	772.7597
Apr 2024	577.58	375.5499	779.6101
May 2024	577.58	368.9242	786.2358
Jun 2024	577.58	362.5025	792.6575
Jul 2024	577.58	356.2671	798.8929
Aug 2024	577.58	350.2026	804.9574
Sep 2024	577.58	344.2957	810.8643
Oct 2024	577.58	338.5347	816.6253
Nov 2024	577.58	332.9093	822.2507
Dec 2024	577.58	327.4104	827.7496
Jan 2025	577.58	322.0298	833.1302
Feb 2025	577.58	316.7602	838.3998
Mar 2025	577.58	311.595	843.565
Apr 2025	577.58	306.5281	848.6319
May 2025	577.58	301.5543	853.6057
Jun 2025	577.58	296.6685	858.4915
Jul 2025	577.58	291.8662	863.2938
Aug 2025	577.58	287.1434	868.0166
Sep 2025	577.58	282.4961	872.6639
Oct 2025	577.58	277.9209	877.2391
Nov 2025	577.58	273.4145	881.7455
Dec 2025	577.58	268.9739	886.1861
Jan 2026	577.58	264.5962	890.5638

Table 4 shows represents the price prediction for JKII for the next 25 months. In ARIMA modeling using R Studio, a “point forecast” refers to the predicted value for a specific point in the future. It represents a single, best estimate of the future value of the time series at a particular time. In this context, the term “point” signifies a specific data point in the time series sequence. It can be observed that the Lo 95 (lower bound) and Hi 95 (upper bound) are used to see the lowest and highest price predictions with a 95% confidence interval for the forecast. Upper and lower bounds are the maximum and minimum values a number could have had before it was rounded. They can also be called limits of accuracy. For Model 1 (0, 1, 0), the maximum lower bound is 396.8787, while the minimum lower bound is 264.5962. The maximum upper bound is 890.5638, and the minimum upper bound is 758.2813. Because index prices can be predicted, it can be stated that historical data can be used as a predictive tool for the Shariah capital market index in Indonesia (JKII), thus directly indicating Indonesia’s compliance with the Efficient Market Hypothesis (EMH).

Table 5. Forecasting Price 12 Months Model 2 (0, 1, 0) FTFBMHS

	Point Forecast	**Lo 95**	**Hi 95**
Jan 2024	11849.61	8797.197	14902.02
Feb 2024	11849.61	8672.558	15026.66
Mar 2024	11849.61	8552.627	15146.59
Apr 2024	11849.61	8436.909	15262.31
May 2024	11849.61	8324.987	15374.23
Jun 2024	11849.61	8216.512	15482.71
Jul 2024	11849.61	8111.183	15588.04
Aug 2024	11849.61	8008.741	15690.48
Sep 2024	11849.61	7908.962	15790.26
Oct 2024	11849.61	7811.647	15887.57
Nov 2024	11849.61	7716.623	15982.6
Dec 2024	11849.61	7623.736	16075.48
Jan 2025	11849.61	7532.846	16166.37
Feb 2025	11849.61	7443.831	16255.39
Mar 2025	11849.61	7356.58	16342.64
Apr 2025	11849.61	7270.991	16428.23
May 2025	11849.61	7186.972	16512.25
Jun 2025	11849.61	7104.441	16594.78

Jul 2025	11849.61	7023.321	16675.9
Aug 2025	11849.61	6943.543	16755.68
Sep 2025	11849.61	6865.04	16834.18
Oct 2025	11849.61	6787.756	16911.46
Nov 2025	11849.61	6711.633	16987.59
Dec 2025	11849.61	6636.622	17062.6
Jan 2026	11849.61	6562.676	17136.54

Table 5 represents the price prediction for FTFBMHS for the next 25 months. For Model 2 (0, 1, 0), the maximum lower bound is 8797.197, while the minimum lower bound is 6562.676. The maximum upper bound is 17136.54, and the minimum upper bound is 14902.02. Given the predictability of index prices, it's reasonable to assert that historical data is a valuable predictive tool for the Shariah capital market index in Malaysia (FTFBMHS), thereby directly suggesting Malaysia's adherence to the Efficient Market Hypothesis (EMH).

Table 6. Forecasting Price 12 Months Model 3 (0, 1, 0) KMI

	Point Forecast	**Lo 95**	**Hi 95**
Jan 2024	19695.49	8478.5379	30912.44
Feb 2024	19695.49	8020.5161	31370.46
Mar 2024	19695.49	7579.7970	31811.18
Apr 2024	19695.49	7154.5563	32236.42
May 2024	19695.49	6743.2694	32647.71
Jun 2024	19695.49	6344.6465	33046.33
Jul 2024	19695.49	5957.5854	33433.39
Aug 2024	19695.49	5581.1348	33809.85
Sep 2024	19695.49	5214.4671	34176.51
Oct 2024	19695.49	4856.8571	34534.12
Nov 2024	19695.49	4507.6650	34883.31
Dec 2024	19695.49	4166.3230	35224.66
Jan 2025	19695.49	3832.3242	35558.66
Feb 2025	19695.49	3505.2142	35885.77
Mar 2025	19695.49	3184.5835	36206.4
Apr 2025	19695.49	2870.0618	36520.92
May 2025	19695.49	2561.3126	36829.67
Jun 2025	19695.49	2258.0293	37132.95
Jul 2025	19695.49	1959.9315	37431.05
Aug 2025	19695.49	1666.7619	37724.22
Sep 2025	19695.49	1378.2839	38012.7
Oct 2025	19695.49	1094.2793	38296.7
Nov 2025	19695.49	814.5461	38576.43
Dec 2025	19695.49	538.8973	38852.08
Jan 2026	19695.49	267.159	39123.82

Table 6 represents the price prediction for KMI for the next 25 months. For Model 3 (0, 1, 0), the maximum lower bound is 8478.5379, while the minimum lower bound is 267.159. The maximum upper bound is 39123.82, and the minimum upper bound is 30912.44. Considering the predictability of index prices, it's plausible to argue that historical data functions as a significant predictive instrument for the Shariah capital market index in Pakistan (KMI), thus strongly indicating Pakistan's alignment with the Efficient Market Hypothesis (EMH).

Table 7. Forecasting Price 12 Months Model 4 (1, 1, 1) TASI

	Point Forecast	**Lo 95**	**Hi 95**
Jan 2024	10731.27	7158.257	14304.27
Feb 2024	10726.95	7008.099	14445.81
Mar 2024	10730.24	6869.313	14591.16
Apr 2024	10727.74	6731.061	14724.41
May 2024	10729.64	6600.739	14858.55
Jun 2024	10728.19	6471.858	14984.52
Jul 2024	10729.30	6348.728	15109.87
Aug 2024	10728.45	6227.457	15229.45
Sep 2024	10729.10	6110.528	15347.67
Oct 2024	10728.61	5995.597	15461.62
Nov 2024	10728.98	5884.074	15573.89

Dec 2024	10728.70	5774.537	15682.86
Jan 2025	10728.91	5667.772	15790.05
Feb 2025	10728.75	5562.906	15894.59
Mar 2025	10728.87	5460.362	15997.39
Apr 2025	10728.78	5359.595	16097.96
May 2025	10728.85	5260.824	16196.88
Jun 2025	10728.8	5163.699	16293.89
Jul 2025	10728.84	5068.321	16389.35
Aug 2025	10728.81	4974.463	16483.15
Sep 2025	10728.83	4882.158	16575.5
Oct 2025	10728.81	4791.252	16666.37
Nov 2025	10728.83	4701.744	16755.91
Dec 2025	10728.81	4613.526	16844.1
Jan 2026	10728.82	4526.578	16931.07

Table 7 represents the price prediction for TASI for the next 25 months. For Model 4 (1, 1, 1), the maximum lower bound is 7158.257, while the minimum lower bound is 4526.578. The maximum upper bound is 16931.07, and the minimum upper bound is 14304.27. Given the predictability observed in index prices, it's reasonable to contend that historical data plays a pivotal role as a predictive tool for the Shariah capital market index in the United Arab Emirates (TASI), thereby strongly suggesting the UAE's adherence to the Efficient Market Hypothesis (EMH).

Table 8. Forecasting Price 12 Months Model 5 (0, 1, 0) QERI

	Point Forecast	Lo 95	Hi 95
Jan 2024	4629.35	3082.924	6175.776
Feb 2024	4629.35	3019.778	6238.922
Mar 2024	4629.35	2959.019	6299.681
Apr 2024	4629.35	2900.393	6358.307
May 2024	4629.35	2843.691	6415.009
Jun 2024	4629.35	2788.734	6469.966
Jul 2024	4629.35	2735.372	6523.328
Aug 2024	4629.35	2683.473	6575.227
Sep 2024	4629.35	2632.922	6625.778
Oct 2024	4629.35	2583.620	6675.080
Nov 2024	4629.35	2535.479	6723.221
Dec 2024	4629.35	2488.420	6770.280
Jan 2025	4629.35	2442.373	6816.327
Feb 2025	4629.35	2397.276	6861.424
Mar 2025	4629.35	2353.072	6905.628
Apr 2025	4629.35	2309.71	6948.99
May 2025	4629.35	2267.145	6991.555
Jun 2025	4629.35	2225.333	7033.367
Jul 2025	4629.35	2184.235	7074.465
Aug 2025	4629.35	2143.817	7114.883
Sep 2025	4629.35	2104.046	7154.654
Oct 2025	4629.35	2064.892	7193.808
Nov 2025	4629.35	2026.327	7232.373
Dec 2025	4629.35	1988.324	7270.376
Jan 2026	4629.35	1950.861	7307.839

Table 8 represents the price prediction for QERI for the next 25 months. For Model 5 (0, 1, 0), the maximum lower bound is 3082.924, while the minimum lower bound is 1950.861. The maximum upper bound is 7307.839, and the minimum upper bound is 6175.776. Considering the observed predictability in index prices, it is logical to argue that historical data is a crucial predictive tool for the Shariah capital market index in Qatar (QERI), thus strongly indicating Qatar's adherence to the Efficient Market Hypothesis (EMH).

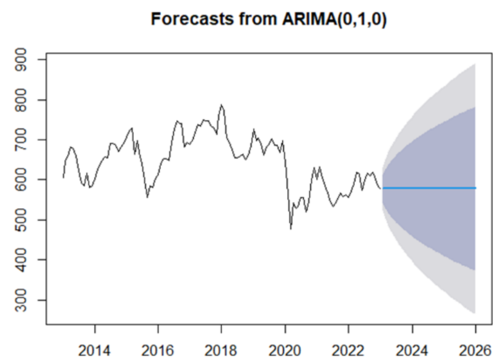
Table 9. Forecasting Price 12 Months Model 6 (0, 1, 0) FTSESET

	Point Forecast	Lo 95	Hi 95
Jan 2024	19695.49	8478.5379	30912.44
Feb 2024	19695.49	8020.5161	31370.46
Mar 2024	19695.49	7579.7970	31811.18
Apr 2024	19695.49	7154.5563	32236.42

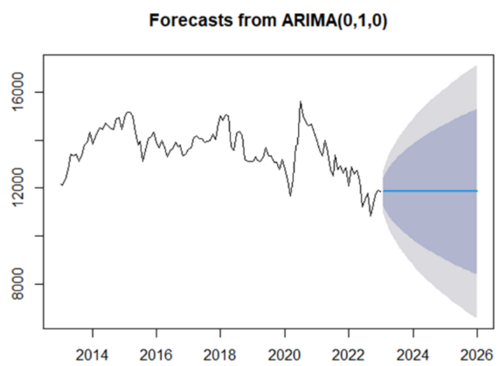
May 2024	19695.49	6743.2694	32647.71
Jun 2024	19695.49	6344.6465	33046.33
Jul 2024	19695.49	5957.5854	33433.39
Aug 2024	19695.49	5581.1348	33809.85
Sep 2024	19695.49	5214.4671	34176.51
Oct 2024	19695.49	4856.8571	34534.12
Nov 2024	19695.49	4507.6650	34883.31
Dec 2024	19695.49	4166.3230	35224.66
Jan 2025	19695.49	3832.3242	35558.66
Feb 2025	19695.49	3505.2142	35885.77
Mar 2025	19695.49	3184.5835	36206.4
Apr 2025	19695.49	2870.0618	36520.92
May 2025	19695.49	2561.3126	36829.67
Jun 2025	19695.49	2258.0293	37132.95
Jul 2025	19695.49	1959.9315	37431.05
Aug 2025	19695.49	1666.7619	37724.22
Sep 2025	19695.49	1378.2839	38012.7
Oct 2025	19695.49	1094.2793	38296.7
Nov 2025	19695.49	814.5461	38576.43
Dec 2025	19695.49	538.8973	38852.08

Table 9 represents the price prediction for FTSESET for the next 12 months. For Model 6 (0, 1, 0), the maximum lower bound is 8478.5379, while the minimum lower bound is 538.8973. The maximum upper bound is 38852.0, and the minimum upper bound is 30912.44. Given the predictability observed in index prices, it is scientifically justifiable to assert that historical data functions as a fundamental predictive instrument for Thailand's Shariah capital market index (FTESET), thus strongly suggesting Thailand's alignment with the Efficient Market Hypothesis (EMH). This observation holds particular significance, considering Thailand's status as a non-predominantly Muslim-majority country.

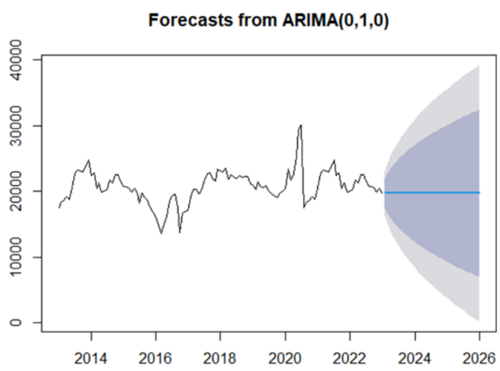
JKII



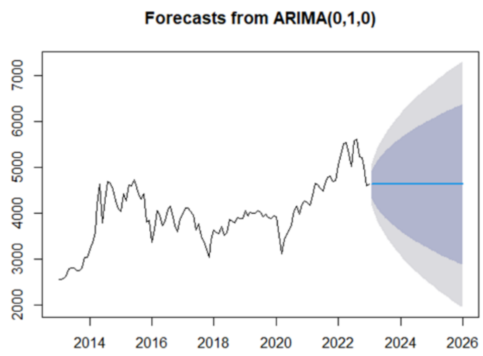
FTFBMHS



KMI



QERI



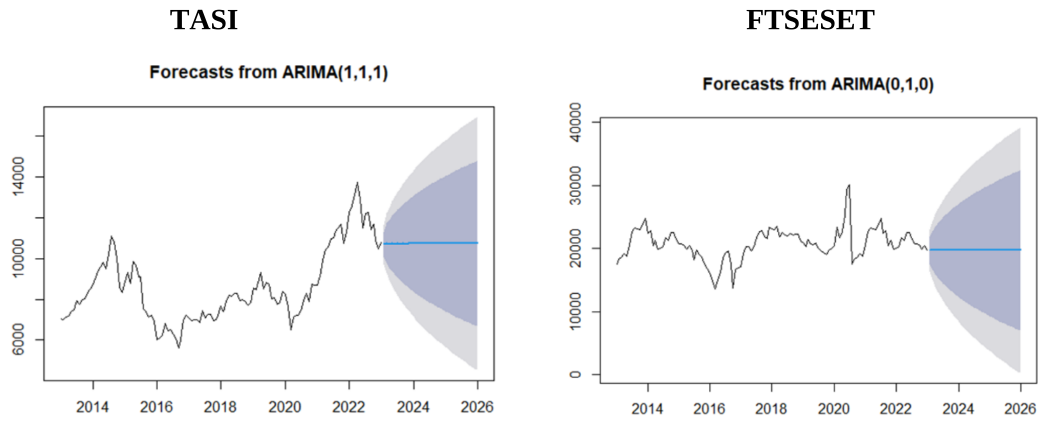


Figure 3. Forecast for the adjusted Islamic Stock Index

The `forecast()` function is used to make forecasts or predictions for a certain number of future time points. The arguments provided in the function are data, model, and h. The specified model is selected from the diagnostic model, and h is used to determine how many predictions are desired.

Discussion

The findings of this study shed light on the complexities inherent in predicting the monthly closing prices of Islamic stock indices across six countries. Despite demonstrating accuracy within a specific timeframe, the implications of these predictions warrant careful consideration in light of the Efficient Market Hypothesis (EMH) (Marwala & Hurwitz, 2017). EMH posits that stock prices reflect all available information, rendering it impossible for investors to outperform the market consistently. Therefore, the success of the predictions challenges the fundamental assumptions of EMH within the context of Islamic stock indices (Elangovan et al., 2022). The accuracy of the predictions suggests the potential presence of market inefficiencies or anomalies, which contradicts the notion of market efficiency espoused by EMH. This discrepancy prompts further exploration into the applicability of EMH to the unique dynamics of Islamic financial markets. Additionally, it underscores the need for a nuanced understanding of how predictive modeling intersects with established financial theories, highlighting the complexity of market behavior and the potential for divergence from traditional frameworks. Further research in this area can provide valuable insights into the interplay between predictive modeling, market efficiency, and the distinctive characteristics of Islamic finance.

Applying the Efficient Market Hypothesis (EMH) in this prediction study aligns with other findings that have indicated that predictions can be made if the market index has a market efficiency status that matches EMH. Several previous studies (Faisal et al., 2022; Hadianto et al., 2021; Jawadi et al., 2015; Kasidi & Banafa, 2022; Rodoni et al., 2022; Rossi & Gunardi, 2018; Santoso & Ikhsan, 2020) have also supported the idea that the possibility of accurate prediction can be obtained from an efficient market according to EMH. One of the implications of EMH is that if the market has been efficient, then all relevant information has already been reflected in the stock price, thus making price predictions more reliable. These findings are consistent with previous studies that show that in efficient markets, predictive models such as those used in this study have the potential to deliver accurate results.

Furthermore, the relevance of this model with previous research and the relevancy of the ARIMA model in predicting the price of the Islamic stock index by reference to prior research, as mentioned in the study by (Rodoni et al., 2022). The research results show that using the ARIMA model has a solid theoretical basis and supports the idea that this model is an appropriate and reliable approach to predicting Islamic capital markets. This reinforces the belief that the model can be used as an effective tool in analyzing and predicting the price of the Islamic stock index, thereby adding value to investors and stakeholders in the capital market. The use of the ARIMA prediction model in this study shows consistency with previous findings, as demonstrated in the prior study (Agustin, 2019). This provides additional support for the reliability and accuracy of the ARIMA model in predicting the Islamic Stock Price Index. As a result, technical analysis remains a useful tool for investors as a guide in conducting transactions in Islamic capital markets. The findings give investors confidence that the ARIMA model is reliable in producing accurate predictions of Islamic stock prices, which can help them make better investment decisions.

Although the model used is successful in predicting prices accurately, it is important to remember that the ARIMA model only takes historical price data into account. EMH, especially in strong form, assumes a perfect integration of information, including economic indicators, company news, and investor sentiment. By considering only historical prices, the model may not effectively take into account the incomplete integration of all relevant information by market participants.

Although the study shows the potential of models to predict short-term prices on Islamic stock indices, the findings do not directly contradict EMH. The limitations of information inserted by the model and the focus on short-term predictions suggest that markets may show partial efficiency, in which such imperfections can be exploited in the short term but then disappear with complete information integration in the long term. Further research that extends the scope of market data and analyzes long-term predictions can provide a more thorough understanding of the relationship between Islamic stock indices and EMH.

V. CONCLUSION

In conclusion, this study utilizes the ARIMA model to analyze monthly data from 2013 to 2023 to provide accurate predictions for Islamic stock market indices. By leveraging autoregressive and moving average components, the ARIMA model generates forecasts that offer valuable insights into potential price movements, thereby presenting significant opportunities for investors and contributing to market efficiency and transparency. The success of these predictions prompts a critical examination of their implications within the context of the Efficient Market Hypothesis (EMH), which questions the feasibility of consistently outperforming the market. While the accuracy of the predictions may indicate market inefficiencies, further research is necessary to explore the relationship between predictive modeling and market efficiency in Islamic finance. Furthermore, the study’s reliance on the ARIMA model aligns with prior research, affirming its theoretical foundation and effectiveness in predicting Islamic stock market indices. The consistency of findings across previous studies reinforces the reliability of the ARIMA model, instilling confidence in its utility as a predictive tool for investors. However, it is important to acknowledge the limitations of the ARIMA model, including its dependence on historical price data and potential oversight of other relevant information. Despite highlighting the potential for short-term predictions, additional research is warranted to analyze long-term trends and the interaction between Islamic stock indices and EMH. In summary, this study contributes valuable insights to the growing body of research in forecasting Islamic stock market indices, shedding light on market dynamics and the applicability of predictive modeling techniques. Continued research and refinement of predictive models will further enhance our understanding of market behavior and guide investment strategies in Islamic finance.

ACKNOWLEDGEMENT

We extend our heartfelt gratitude to all individuals and institutions whose contributions were vital to the completion of this study. Their unwavering support and invaluable assistance played a crucial role in conducting the research and analyzing the data. We would like to express our sincere appreciation to our colleagues at the UIN Syarif Hidayatullah Jakarta postgraduate program, whose expertise and guidance were instrumental in shaping this work.

REFERENCES

Abraham, R., El Samad, M., Bakhach, A. M., El-Chaarani, H., Sardouk, A., El Nemar, S., & Jaber, D. (2022). Forecasting a Stock Trend Using Genetic Algorithm and Random Forest. *Journal of Risk and Financial Management*, 15(5), 188. doi:10.3390/jrfm15050188

Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics,* 1–7. doi:10.1155/2014/614342

Agustin, I. N. (2019). Testing weak form of stock market efficiency at the Indonesia Sharia Stock Index. *Muqtasid: Journal of Islamic Economics and Banking*, 10(1), 17. doi:10.18326/muqtasid.v10i1.17-29

Ali, M., Khan, D. M., Aamir, M., Ali, A., & Ahmad, Z. (2021). Predicting the direction movement of financial time series using artificial neural network and support vector machine. *Complexity*, 2021. doi:10.1155/2021/2906463

Angadi, M. C., & Kulkarni, A. P. (2015). Time series data analysis for stock market prediction using data mining techniques with R. *International Journal of Advanced Research in Computer Science*, 6(6), 104–108. doi:10.13140/RG.2.1.1347.3360

Arashi, M., & Rounaghi, M. M. (2022). Analysis of market efficiency and fractal feature of NASDAQ stock exchange : Time series modeling and forecasting of stock index using ARMA - GARCH model. *Future Business Journal*, 8(1), 1–12. doi:10.1186/s43093-022-00125-9

Baek, Y., & Kim, H. Y. (2018). ModAugNet: A new forecasting framework for stock market index value with an overfitting prevention LSTM module and a prediction LSTM module. *Expert Systems with Applications*, 113, 457–480. doi:10.1016/j.eswa.2018.07.019

Ballings, M., Van den Poel, D., Hespeels, N., & Gryp, R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert Systemns with Applications*, 42(20), 7046–7056. doi:10.1016/j.eswa.2015.05.013

Cao, J., Li, Z., & Li, J. (2019). Financial time series forecasting model based on CEEMDAN and LSTM. *Physica A: Statistical Mechanics and Its Applications*, 519, 127–139. doi:10.1016/j.physa:2018.11.061

Cao, M. (2023). Retracted : Predicting the Link between Stock Prices and Indices with Machine Learning in R Programming Language. *Hindawi Journal of Mathematics*, 2021. doi:10.1155/2021/1275637

Chang, J., Wei, L., & Cheng, C. (2009). Anfis-based adaptive expectation model for forecasting stock index. *International Journal of Innovative computing, information, & control: IJICIC*, 5(7), 1949-1958.

Clement, M. B., & Tse, S. Y. (2003). Do investors respond to analysts' forecast revisions as if forecast accuracy is all that matters? *The Accounting Review*, 78(1), 227–249. doi:10.2308/accr.2003.78.1.227

Demirel, U., Cam, H., & Unlu, R. (2021). Predicting Stock Prices Using Machine Learning Methods and Deep Learning Algorithms: The sample of the Istanbul Stock Exchange. *Gazi University Journal of Science*, 34(1), 63–82. doi:10.35378/gujs.679103

Deswal, V., Kumar, D., & Suman. (2023). Stock Market Price Prediction using Machine Learning Techniques: A Review. *Proceedings of International Conference on Computational Intelligence and Sustainable Engineering Solution, CISES*, 693–698. doi:10.1109/CISES58720.2023.10183507

Do, Q. H., & Van Trang, T. (2020). Forecasting Vietnamese stock index: A comparison of hierarchical ANFIS and LSTM. *Decision Science Letters*, 9(2), 193–206. doi:10.5267/j.dsl.2019.11.002

Du, Y. (2018). Application and analysis of forecasting stock price index based on combination of ARIMA model and BP neural network. *Proceedings of the 30th Chinese Control and Decision Conference, CCDC 2018*, 2854–2857. doi:10.1109/CCDC.2018.8407611

Elangovan, R., Irudayasamy, F. G., & Parayitam, S. (2022). Testing the market efficiency in Indian stock market: Evidence from Bombay Stock Exchange broad market indices. *Journal of Economics, Finance and Administrative Science*, 27(54), 313–327. doi:10.1108/JEFAS-04-2021-0040

Faisal, F., Majid, M. S. A., & Rakhmawati, L. (2022). Testing weak form of efficient market hypothesis before and during covid-19 pandemic periods: Evidence from Indonesia. *2022 International Conference on Sustainable Islamic Business and Finance, SIBF 2022*, 125–129. doi:10.1109/SIBF56821.2022.9940133

Feuerriegel, S., & Gordon, J. (2018). Long-term stock index forecasting based on text mining of regulatory disclosures. *Decision Support Systems*, 112, 88–97. doi:10.1016/j.dss.2018.06.008

Fu, Y., Su, Z., Xu, B., & Zhou, Y. (2020). Forecasting stock index futures intraday returns: Functional time series model. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, 24(3), 265–271. doi:10.20965/jaciii.2020.p0265

Guresen, E., Kayakutlu, G., & Daim, T. U. (2011). Using artificial neural network models in stock market index prediction. *Expert Systems with Applications*, 38(8), 10389–10397. doi:10.1016/j.eswa.2011.02.068

Hadianto, B., Hendrik, H., & Yuwana, T. (2021). Does the efficient market theory in the weak form exist? Evidence from Indonesia. *Jurnal Manajemen Indonesia*, 21(2), 183-190. doi:10.25124/jmi.v21i2.2703

Hassan, M. R., Nath, B., & Kirley, M. (2007). A fusion model of HMM, ANN and GA for stock market forecasting. *Expert Systems with Applications*, 33(1), 171–180. doi:10.1016/j.eswa.2006.04.007

Hu, Y., Feng, B., Zhang, X., Ngai, E. W. T., & Liu, M. (2015). Stock trading rule discovery with an evolutionary trend following model. *Expert Systems with Applications*, 42(1), 212–222.

doi:10.1016/j.eswa.2014.07.059

Huang, W., Nakamori, Y., & Wang, S. Y. (2005). Forecasting stock market movement direction with support vector machine. *Computers & Operations Research*, 32(10), 2513–2522. doi:10.1016/j.cor.2004.03.016

Jawadi, F., Jawadi, N., & Cheffou, A. I. (2015). Are Islamic stock markets efficient? A time-series analysis. *Applied Economics*, 47(16), 1686–1697. doi:10.1080/00036846.2014.1000535

Kamalakannan, J., Sengupta, I., & Chaudhury, S. (2018). Stock market prediction using time series analysis. *IADS: International Conference on Computing, Communications & Data Engineering*, 1(3), 1–5.

Kasidi, K., & Banafa, A. (2022). Efficient market hypothesis and market anomalies: Empirical evidence from Nairobi Securities Exchange. *SSRN Electronic Journal*. doi:10.2139/ssrn.4270987

Katterbauer, K., Syed, H., Cleenewerck, L., & Genc, S. Y. (2022). Robo-Sukuk pricing for Chinese equities. *Borsa Istanbul Review*, 22(5), 854–860. doi:10.1016/j.bir.2022.06.002

Kazem, A., Sharifi, E., Hussain, F. K., Saberi, M., & Hussain, O. K. (2013). Support vector regression with chaos-based firefly algorithm for stock market price forecasting. *Applied Soft Computing*, 13(2), 947–958. doi:10.1016/j.asoc.2012.09.024

Kenrick, J., & Yanti, Y. (2022). Prediction calculation of PT. Indofood Sukses Makmur Tbk. Stock using R Studio with Autoregressive Integrated Moving Average (ARIMA) Method. *Journal of Software Engineering, Information and Communication Technology (SEICT)*, 2(2), 65–76. doi:10.17509/seict.v2i2.41552

Kocak, C. (2017). ARMA (p,q) type high order fuzzy time series forecast method based on fuzzy logic relations. *Applied Soft Computing*, 58, 92–103. doi:10.1016/j.asoc.2017.04.021

Lin, J., & Gong, Z. (2017). A research on forecasting of shanghai zinc futures price based on artificial neural network. *The Theory and Practicce of Finance and Economics*, 38(2), 54–57.

Lin, Y., Xiao, Y., & Li, F. (2020). Forecasting crude oil price volatility via a HM-EGARCH model. *Energy Economics*, 87. doi:10.1016/j.eneco.2020.104693

Lin, Y., Yan, Y., Xu, J., Liao, Y., & Ma, F. (2021). Forecasting stock index price using the CEEMDAN-LSTM model. *The North American Journal of Economics and Finance*, 57. doi:10.1016/j.najef.2021.101421

Lv, P., Wu, Q., Xu, J., & Shu, Y. (2022). Stock index prediction based on time series decomposition and hybrid model. *Entropy*, 24(2), 146. doi:10.3390/e24020146

Mallikarjuna, M., & Rao, R. P. (2019). Evaluation of forecasting methods from selected stock market returns. *Financial Innovation*, 5(1). doi:10.1186/s40854-019-0157-x

Mantri, J. K., Gahan, P., & Nayak, B. (2010). Artificial neural networks–an application to stock market volatility. *International Journal of Engineering Science and Technology*, 2(5), 1451–1460.

Marwala, T., & Hurwitz, E. (2017). Efficient market hypothesis. In: Artificial intelligence and economic theory: Skynet in the market. *Advanced Information and Knowledge Processing*, 101–110. doi:10.1007/978-3-319-66104-9_9

Miao, J., Wang, P., & Xu, Z. (2015). A Bayesian dynamic stochastic general equilibrium model of stock market bubbles and business cycles: Stock market bubbles and business cycles. *Quantitative Economics*, 6(3), 599–635. doi:10.3982/QE505

Moghaddam, A. H., Moghaddam, M. H., & Esfandyari, M. (2016). Stock market index prediction using artificial neural network. *Journal of Economics, Finance and Administrative Science*, 21(41), 89–93. doi:10.1016/j.jefas.2016.07.002

Nair, B. B., Mohandas, V. P., & Sakthivel, N. R. (2010). A decision tree-rough set hybrid system for stock market trend prediction. *International Journal of Computer Applications*, 6(9), 1–6. doi: 10.5120/1106-1449

Nayak, R. K., Mishra, D., & Rath, A. K. (2015). A Naïve SVM-KNN based stock market trend reversal analysis for Indian benchmark indices. *Applied Soft Computing*, 35, 670–680. doi:10.1016/j.asoc.2015.06.040

Fantin, C. O., & Junior, E. H. (2021). Stock price forecast, with multi layer perceptron artificial neural networks. *International Journal of Sciences: Basic and Applied Research*, 60(5), 62–77.

Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M. Z., Barrow, D. K., Ben Taieb, S., Bergmeir, C., Bessa, R. J., Bijak, J., Boylan, J. E., Browell, J., Carnevale, C., Castle, J. L., Cirillo, P., Clements, M. P., Cordeiro, C., Oliveira, F. L. C., De Baets, S., Dokumentov, A., Ellison, J., & Ziel, F. (2022).

Forecasting: Theory and practice. *International Journal of Forecasting*, 38(3), 705–871. doi:10.1016/j.ijforecast.2021.11.001

Ou, P., & Wang, H. (2009). Prediction of stock market index movement by ten data mining techniques. *Modern Applied Science*, 3(12), 28-42. doi:10.5539/mas.v3n12p28

Phua, P. K. H., Zhu, X., & Koh, C. H. (2003). Forecasting stock index increments using neural networks with trust region methods. *Proceedings of the International Joint Conference on Neural Networks*, 1, 260–265. doi:10.1109/ijcnn.2003.1223354

Rahman, H. F., Sarker, R., & Essam, D. (2015). A genetic algorithm for permutation flow shop scheduling under make to stock production system. *Computers & Industrial Engineering*, 90, 12–24. doi:10.1016/j.cie.2015.08.006

Rather, A. M., Agarwal, A., & Sastry, V. N. (2015). Recurrent neural network and a hybrid model for prediction of stock returns. *Expert Systems with Applications*, 42(6), 3234–3241. doi:10.1016/j.eswa.2014.12.003

Rizvi, S. A. R., Dewandaru, G., Bacha, O. I., & Masih, M. (2014). An analysis of stock market efficiency: Developed vs Islamic stock markets using MF-DFA. *Physica A: Statistical Mechanics and Its Applications*, 407, 86–99. doi:10.1016/j.physa.2014.03.091

Rodoni, A., Djauhari, H., Rahma, Y., & Alhassan, A. A. (2022). Comparative analysis of efficient market for sharia and conventional stocks in ASEAN countries. *Al-Iqtishad: Jurnal Ilmu Ekonomi Syariah*, 14(1), 1–22. doi:10.15408/aiq.v14i1.25025

Rossi, M., & Gunardi, A. (2018). Efficient market hypothesis and stock market anomalies: Empirical evidence in four European countries. *Journal of Applied Business Research*, 34(1), 183–192. doi:10.19030/jabr.v34i1.10111

Rout, A. K., Dash, P. K., Dash, R., & Bisoi, R. (2015). Forecasting financial time series using a low complexity recurrent neural network and evolutionary learning approach. *Journal of King Saud University- Computer and Information Sciences*, 29(4), 536–552. doi:10.1016/j.jksuci.2015.06.002

Sahabuddin, M., Islam, M. A., Tabash, M. I., Alam, M. K., Daniel, L. N., & Mostafa, I. I. (2023). Dynamic conditional correlation and volatility spillover between conventional and islamic stock markets: Evidence from developed and emerging countries. *Journal of Risk and Financial Management*, 16(2), 111. doi:10.3390/jrfm16020111

Santoso, E. B., & Ikhsan, M. (2020). Efficient Market Hypothesis in Indonesia Stock Exchange 2019. *Proceedings of The Annual International Conference on Accounting Research (Aicar 2019)*, 51–53. doi:10.2991/aebmr.k.200309.012

Selvin, S., Ravi, V., Gopalakrishman, E. A., Menon, V. K., & Soman, K. P. (2017). Stock price prediction using LSTM, RNN and CNN-sliding window model. *International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, 1643–1647. doi: 10.1109/ICACCI.2017.8126078

Staffini, A. (2022). Stock price forecasting by a deep convolutional generative adversarial network. *Frontiers in Artificial Intelligence*, 5, 1–16. doi:10.3389/frai.2022.837596

Sun, Z. (2020). Comparison of trend forecast using ARIMA and ETS models for S&P500 close price. *ACM International Conference Proceeding Series*, 57–60. doi:10.1145/3436209.3436894

Supriani, I., Herianingrum, S., Ninglasari, S. Y., & Budi, R. S. (2022). Islamic stock market performance pre-covid-19: Empirical evidence from Jakarta Islamic Index. *Jurnal Ekonomi dan Bisnis Islam (Journal of Islamic Economics and Business)*, 8(2), 267–287. doi:10.20473/jebis.v8i2.37789

Targa Sapanji, R. A. E. V., Lestari, S., Murnawan, M., & Samiharjo, R. (2023). Prediksi indeks Bursa Efek Indonesia 2023 pendekatan ARIMA, Machine learning dengan R programming. *Jurnal Manajemen Informatika (JAMIKA)*, 13(2), 163–177. doi:10.34010/jamika.v13i2.10777

Teixeira, L. A., & Oliveira, A. L. I. ´ de. (2010). A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert Systems with Applications*, 37(10), 6885–6890. doi:10.1016/j.eswa.2010.03.033

Wang, S., Wang, J., & Li, G. (2018). Research and prediction of high frequency intraday yield of the CSI 300 index futures based on ARMA Model. *Journal of North China Electric Power University (Social Sciences)*, 3, 71–79.

Xi, L., Muzhou, H., Lee, M. H., Li, J., Wei, D., Hai, H., & Wu, Y. (2014). A new constructive neural network method for noise processing and its application on stock market prediction. *Applied Soft Computing*, 15, 57–66. doi:10.1016/j.asoc.2013.10.013

Xiao, N., Xinyi, R., & Xiong, Z. (2021). A diversity-based selfish node detection algorithm for socially aware networking. *Journal of Signal Processing Systems*, 93(7), 811–825.

Zhang, Y., & Shen, W. (2009). Stock yield forecast based on LS-SVM in Bayesian Inference. *ETP International Conference on Future Computer and Communication*, 8–11. doi:10.1109/FCC.2009.34

Zhao, Y., & Chen, Z. (2022). Forecasting stock price movement: new evidence from a novel hybrid deep learning model. *Journal of Asian Business and Economic Studies*, 29(2), 91–104. doi:10.1108/JABES-05-2021-0061