Do Artificial Neural Networks Provide Improved Volatility Forecasts: Evidence from Asian Markets

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Abstract

Forecasts of stock market volatility is an important input for market participants in measuring and managing investment risks. Thus, understanding the most appropriate methods to generate accurate is key. This paper examines the ability of Machine Learning methods, and specifically Artificial Neural Network (ANN) models to forecast volatility. The ANN models are compared against traditional econometric models for ten Asian markets across 24 years of daily data. The empirical results for ANN models are promising. Out-of-sample forecast evaluation reveals that ANN models are superior for each index compared to benchmark GARCH and EGARCH models. In addition to standard statistics forecast metrics, we consider risk management measures including the value-at-risk (VaR) average failure rate, the Kupiec LR test, the Christoffersen independence test, the expected shortfall (ES) and the dynamic quantile test. The findings again provide general support for the ANN and suggest that this may be afruitfull approach for risk management.

Keywords: Volatility, Forecasting, Neural Networks, Machine Learning, VaR, ES
JEL Codes: C22, C58, C63, G12, G17

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1. Introduction.

Stock market volatility remains a core issue in the empirical finance literature. While impetus to earlier work began with the stock market crash of October 1987 (known as Black Monday), where twenty-three major world markets experienced substantial single day collapses.[1] Repeated market events serve to highlight the importance of understanding volatility. This includes the global financial crisis (GFC) that began in 2007, where the S&P500 saw its then worst weekly drop of more than 20% and, most recently, the Covid-19 pandemic where March 2020 which saw global stock markets fall dramatically. The DJIA index slumped more than 26% in four trading days, while the price of WTI crude oil fell into negative territory for the first time in recorded history. The global stock markets lost over US$16 trillion within 52 days. This history indicates the need to forecast market swings and to develop models that can be applied to mitigate risk and understand crises, tail events and systematic risks.

The first general approach for this task within the academic literature is the genre of GARCH models (Engle, 1982; Bollerslev, 1986), while from the practitioner viewpoint the RiskMetrics variance model (also known as Exponential Smoother) is introduced by JP Morgan in 1989. Subsequent to this, the volatility index (VIX) is developed (in 1993) by the Chicago Board Options Exchange (CBOE) to measure stock market expectations and based on S&P 500 index options. The VIX index often referred as a fear gauge by market participants, while similar indexes have been developed for a range of markets.

These noted models, and their extensions, receive notable attention by both financial academics and practitioners with a large amount of related published work. Nevertheless, combined with the characteristic constraints on historical volatility models and the growing technological transformation of financial markets, this suggests that similarly new technologies might be needed to improve volatility modelling. Machine learning models based on Artificial Intelligence (AI) technology has significantly improved in recent years and provides fertile ground to examine the accuracy of AI based volatility models against those traditionally considered.

Brav and Heaton (2002) argue that traditional market theories and methods are incompatible and inadequate with the sophistication of modern financial analysis. In recent years, Machine Learning methods have been used broadly for stock market forecasting given their flexibility and feasibility (Bebarta et al., 2012). As these models are capable of learning non-linear patterns and functions, they have also been demonstrated as universal function

[1] According to Schaede (1991), the total estimated worldwide loss was US$1.71 trillion.

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approximators (Hornik et al., 1989; Kasko and Toms 1993). Therefore, this paper aims to contribute to the literature by applying neural network and deep learning techniques to Asian stock market volatility and considering the volatility forecasts, including economic-based implications, against traditional benchmark econometric models. Data from ten emerging and developed Asian stock markets over 24 years of daily data frequency is utilised. Several ANN (artificial neural network) models are chosen among the broad range of AI family, including those based on static, dynamic and supervised learning techniques. These models are compared against GARCH models in a volatility forecasting exercise.

2. Literature Review.

Volatility forecasting is an important area of empirical finance research and is one that have been extensively analysed. This review focuses on work that include AI models, while a review of the econometric models can be found in Bollerslev et al. (1994).

Yoon and Swales (1991) examine the stock market data of 58 widely followed companies in Fortune 500 and reveal that a neural network model is able to provide accurate forecasts for returns. Wong et al. (1992) note weakness in the neural network approach and study fuzzy neural systems to predict stock market returns as well as assessing country risk and rating stocks. Donaldson and Kamstra (1996) examine the applicability of the ANN approach using time series data on four developed stock markets. They conduct out-of-sample forecasts and revealed that ANN is superior compared to traditional linear models given its flexibility with complex nonlinear dynamics. Ormoneit and Neuneier (1996) study the German DAX index using minute data for the month of November 1994. They compare the Multilayer Perceptron method (MLP) with the Conditional Density Estimating Neural Network (CDENN) and reported that CDENN outperforms MLP for the high-frequency data. Jasic and Wood (2004) analyse the statistical significance and potential profitability of one-step-ahead forecasts for DAX, FTSE, S&P 500 and TOPIX indices using univariate neural network methods on daily closing prices. The results reveal that neural network methods are more successful in terms of predictability compared to a benchmark AR(1) model. Kim and Lee (2004) propose the feature transformation method based on the Genetic Algorithm (GA) model and compare it with two conventional neural network methods. The results indicate that the GA method improves prediction capability for financial market forecasting. Altay and Satman (2005) implement ANN methods on the Istanbul Stock Exchange using daily, weekly and monthly data. They compare out-of-sample forecasting results with linear regression models and report that ANN is superior only for weekly forecast results, while underperforming for daily and

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monthly data. Cao et al. (2005) studied ANN methods to predict firm-level stock prices that trade on the Shanghai stock exchange. They compare univariate and multivariate ANN models with linear models, with the results indicating superiority of the neural network models in predicting future price changes. On the other hand, Mantri et al. (2014) investigate the two Indian benchmark indices (BSE SENSEX and NIFTY) from 1995 to 2008 by comparing GARCH, EGARCH, GJR-GARCH, IGARCH and ANN models. The authors report that the prediction ability of the ANN model offers no improvement over the statistical forecast models. Dhar et al. (2010) construct an ANN model to predict National Stock Exchange of India (NSEI) and the results indicate supportive prediction results.

Fernandez-Rodriguez et al. (2000) investigate the potential profitability of the ANN model for the Madrid Stock Exchange. Out-of-sample forecasts are conducted for three different periods that represents bear, stable and bull markets. The empirical results revealed that, in absence of trading costs, the ANN model provides superior predictions for stable and bear markets, although underperforms during bull markets. Perez-Rodriguez et al. (2005) analyse daily returns for the Ibex-25 index from 1989 to 2000. One-step and multi-step ahead forecasts are conducted for six competing models, including linear and non-linear as well as AI models. The results suggest that ANN models provide better fit for the one-step-ahead forecasts but not multi-step.

A number of studies also investigate the performance of different class of ANN models and hybrid models. Roh (2007) proposes a hybrid model between ANN and time series models for KOSPI Index, with forecast results supporting the accuracy of the hybrid model for volatility forecasting. Unlike Roh (2007), Guresen et al. (2011) analyses daily NASDAQ return but finds that hybrid models are not as successful as standard ANN models. Kristjanpoller et al. (2014) propose ANN-GARCH hybrid models to predict three emerging Latin American stock markets and conclude that hybrid models improve prediction ability over conventional time series models. Further studies related to hybrid models are undertaken by Leigh et al. (2002), Chakravarty and Dash (2009), Wei et al. (2011), Rather et al. (2015), Mingyue et al. (2016), Kim and Won (2018), and Hao and Gao (2020). Adebiyi et al. (2012) combine technical and fundamental analysis with ANN and provide results suggesting that this improves prediction, consistent with the findings of Yao et al. (1999) and Sezer et al. (2017). However, Lam (2004) reports mixed results in terms of forecasting ability of integrated ANN with fundamental and technical analysis models. Although, the results show that the integrated model works well when the economy is in recession.

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Several researchers experiment with neuro fuzzy and neuro evolutionary methods in stock market forecasting exercises. Quah (2007) used DJIA index data spanning from 1994 to 2005 to compare the applicability of MLP, ANFIS and GGAP-RBF models. Using several benchmark metrics, including generalize rate, recall rate, confusion metrics and appreciation, the study shows that ANFIS provide more accurate results while GGAP-RBF underperforms in all selected criteria. In similar work, Yang et al. (2012) find a fuzzy reasoning system can be used to predict stock market trends. Li and Xiong (2005) argue that neural networks have limitations in dealing with qualitative information and suffers from the 'black box' syndrome and propose a neuro fuzzy inference system to overcome these drawbacks. The Shanghai stock market is chosen for prediction where they find the suggested fuzzy NN is superior to standard NN methods. Mandziuk and Jaruszewicz (2007) present a neuro-evolutionary method to predict the change of closing price on the DAX index for the next day. The results reveal that the proposed model produces high accuracy for the market in both directions. Garcia et al. (2018) implement a hybrid neuro fuzzy model to predict one-day ahead direction of the DAX Index. They conclude that the integration of traditional indicators with ANN may enhance predictive accuracy of the model, although may also generate noise in the prediction model. Further discussion on this issue is considered by Gholamreza et al. (2010), D'Urso et al. (2013), Vlasenko et al. (2018) and Chandar (2019).

The above discussion demonstrates that the present state of the literature does not suggest a clear superiority either within the different ANN models, or over conventional forecasting methods. However, as discussed in Ravichandra and Thingom (2016) Chopra and Sharma (2021), AI models do possess superior capabilities and the potential for more accurate volatility forecast and thus, worthy of further research. Furthermore, to the best of our knowledge, there are few studies that compare across standard NN, Neuro-Fuzzy, and Deep Learning techniques with a wide range of emerging and developed markets. Moreover, in contrast to previous studies, this paper adopts and builds advanced neural network architectures for each selected model with improved learning rule and optimized hyperparameters. Moreover, we also not only conduct a comprehensive comparison between traditional forecasting methods and ANN models, but also examine the economic implications of these models by assessing measures relevant for risk management practice.

3. Empirical Methodology.

3.1. Benchmark Models

Naïve Forecast

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Naïve forecasts are the most basic and cost-effective forecasting models that provide a benchmark against more complex models. This technique is widely used in empirical finance, especially for time series that have difficult to predict patterns. Forecasts are calculated based on the last observed value. Hence, for time t, the value of observation in time $t-1$ are considered the best forecast:

$$\hat{y}_t = y_{t-1} \tag{1}$$

The Moving Average Convergence Divergence Indicator (MACD)

MACD is a technical indicator designed by Gerald Appel in the late 1970s to reveal changes in the strength, momentum and trend of stock prices. The standard MACD is calculated by subtracting the 26 period Exponential Moving Average (EMA) from the 12 period EMA as:

$$MACD = 12\, period\ EMA - 26\, period\ EMA \tag{2}$$

$$Signal\ Line = 9\, period\ EMA\ of\ the\ MACD \tag{3}$$

When MACD falls below the signal line, it is a bearish signal and indicates a sell. Conversely, when MACD rises above the signal line, the indicator gives a bullish signal and indicates a buy.

GARCH Family Models

The GARCH approach forms the baseline models for this study. While there are over 300 GARCH-type models, we consider two of the most widely used, the GARCH and EGARCH (Nelson, 1991) models. Moreover, as these are widely known, we provide only a brief description. The return specification is given by:

$$r_t = \mu + \varepsilon_t \tag{4}$$

where r_t is the return series, μ is the constant mean and $\varepsilon_t = h_t z_t$ refers the returns of residual with 0 mean and 1 variance *(i.i.d.)*. The conditional variance specifications of the chosen models are as follow:

$$\text{GARCH:}\ \ h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta\, \mathrm{h}_{t-1}^2 \tag{5}$$

$$\text{EGARCH:}\ \ \ln\left(h_t^2\right) = a_0 + \beta_1 \ln(h_{t-1}^2) + a_1 \left\{ \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} \tag{6}$$

where h_t^2 is the time-dependent conditional variance and α_0, a_1, β and γ are the parameters estimated using the maximum likelihood method.

3.2. Artificial Neural Networks

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Artificial Neural Networks (ANNs) are one of the most widespread applications in machine learning. ANN is a brain-inspired model which imitate the network of neurons in biological brain so that the computer will be able to learn and make decisions in a human-like manner.

Multi-Layer Perceptron (MLP)

A multi-layer perceptron (MLP) is a feed-forward (where the information moves forward from input to output nodes) artificial neural network (ANN) and one of the most known and used neural network architectures in financial applications according to Bishop (1995). The basic feed-forward ANN model with a one hidden layer is given as follow:

$$n_{k,t} = w_{k,0} + \sum_{i=1}^{i} w_{k,i} x_{i,t} \quad (7)$$

$$N_{k,t} = L(n_{k,t}) = \frac{1}{1 + e^{-n_{k,t}}} \quad (8)$$

$$Y_t = \lambda_0 + \sum_{k=1}^{k} \lambda_k N_{k,t} \quad (9)$$

where i shows the number of input data (x) and k represents the number of nodes (neurons). The activation (transfer) function is chosen as logistic sigmoid function due to its convenience and popularity which is represented by $L(n_{k,t})$ and defined as ${}^{1}/{}_{1 + e^{-n_{k,t}}}$.

The training process starts with the input vector $x_{i,t}$, weight vector $w_{k,i}$, and the coefficient variable $w_{k,0}$. Combining these input vectors with the squashing function log-sigmoid, forms the neuron $N_{k,t}$, which then serves as an exogenous variable with the coefficient λ_k and the constant λ_0 to forecast output Y_t. This network architecture with the logarithmic sigmoid transfer function is one of the most popular method to forecast financial time series data (Dawson and Wilby, 1998; Zhang, 2003).

Recurrent Neural Network (RNN)

A Recurrent Neural Network (RNN) is a class of artificial neural network that allows the process of sequential information. In the RNN architecture, previous outputs can be used as inputs while having hidden states. The main difference between basic feedforward networks and RNN is that RNNs can impact on the process of future inputs. In other words, feedforward networks can only 'remember' things that they learnt during training, while RNNs can learn during training, in addition, they remember things learnt from prior input while generating output. As in the moving average model where endogenous variable Y is a function of

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exogenous variable X and error term ε in the equation; likewise, nodes in the RNN are a function of input data and its previous value from $t-1$. The equation of RNN is given as follow:

$$n_{k,t} = w_{k,0} + \sum_{i=1}^{i} w_{k,i} x_{i,t} + \sum_{k=1}^{k} \varphi_k n_{k,t-1} \tag{10}$$

$$N_{k,t} = \frac{1}{1 + e^{-n_{i,t}}} \tag{11}$$

$$Y_t = \lambda_0 + \sum_{k=1}^{k} \lambda_k N_{k,t} \tag{12}$$

The advantages of RNNs, which include having short term 'memory' and the ability to process sequential datasets, has attracted broad attention among financial researchers and various applications have been conducted (Rather et al., 2015; Gao 2016, Samarawickrama and Fernando, 2017; and Pang et al., 2020). However, the difficulty of training and the requirement of additional connections are major drawbacks for RNN architectures. RNNs are also prone to the problem of gradient vanishing, which is the phenomena of difficulty in capturing long term dependencies. It occurs when more layers using certain activation functions are added to network, which causes the gradients of the loss function to approach zero, making the network hard to train. To overcome of this issue Hochreiter and Schmidhuber (1997) proposed the Long Short-Term Memory (LSTM) networks. LSTMs are proficient in training about long-term dependencies. They are not a different variant of RNNs, yet improved transformation with additional gates and a cell state.

The structure of LSTMs are slightly different than conventional RNNs where RNNs have standard neural network architecture with a feedback loop, LSTMs contain three memory gates namely input gate, output gate and forget gate as well as a cell. The purpose of these gates are:

- The input gate states which information to add to the memory (cell)
- The output gate specifies which information from the memory (cell) to use as output
- The forget gate describes which information to remove from the memory (cell)

LSTMs are considered 'state of the art' systems in forecasting time series data, pattern recognition and sequence learning.

Modular Feedforward Networks (MFNs)

Modular Feedforward Networks (MFNs) are an extension of typical feedforward NN architectures that are designed to reduce complexity and enhance robustness. The issues of

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learning weights and slow convergence in standard NN designing motivated researchers to study new designs to generate more efficient results.

The MFNs have a number of different networks that function independently and perform sub-tasks. These different networks do not interact with or signal each other during the computation process. They work independently towards achieving the output (see Tahmasebi and Hezarkhani, 2011).

Generalized Feedforward Networks (GFNs)

Generalized Feedforward Networks (GFNs) are a subclass of Multi-layer Perceptron (MLP) networks that enable connections to jump over one or more than one layers. The direct connections between two separate layers provide raw information for the output layer along with the usual connection via the hidden layer.

The most prominent feature of GFN is providing capability to send linear connections if the underlying elements consist of linear component. But, if the underlying elements require non-linear connectivity, then the jump function is not needed. Theoretically, MLP can provide solutions to every task that GFN architecture can overcome. However, practically GFNs offer more accurate and efficient solutions compared to standard MLP networks. The GFNs are applied in many areas, including time series forecasting, data processing, pattern recognition and complex engineering problems. For further information, see Arulampalam and Bouzerdoum (2003), Teschl et al. (2007), Celik and Kolhe (2013).

Radial Basis Function Networks (RBFNs)

Radial Basis Function Networks (RBFNs) are a three-layered feedforward network that use radial basis function as activation function. The architecture was developed by Broomhead and Lowe (1988) to increase speed and efficiency of Multi-Layer Perceptron Networks as well as reducing the parameterization difficulty.

The standard RBFN process is given by McNelis (2005) as follow:

$$Min_{<\omega,\mu,\tau>} \sum_{t=0}^{T} (y_{t-} \hat{y}_t)^2 \tag{13}$$

$$n_t = w_0 + \sum_{i=1}^{i^*} w_i x_{i,t} \tag{14}$$

$$R_{k,t} = \phi(n_t; \mu_k) \tag{15}$$

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$$= \frac{1}{\sqrt{2\pi\sigma_{n-\mu_k}}} exp\left(\frac{-[n_t - \mu_k]}{\sigma_{n-\mu_k}}\right)^2 \quad (16)$$

$$\hat{y}_t = \lambda_0 + \sum_{k=1}^{k^*} \lambda_k N_{k,t} \quad (17)$$

where:

x = the set of input variables

n = the linear transformation of the input variables

w = weights.

The parameter k^* shows the number of centres for the transformation function of radial basis $\mu_k, k = 1,2, \dots\ k^*$ compute the error function generated by the separate centres μ_k, and obtains the k^* separate radial basis function, R_k. These parameters are then estimate the output $\hat{y}_t$ with weights λ via the linear transformation. Finally, the RBFN optimization occurs, which includes determination of parameters w, λ with k^* and μ.

Probabilistic Neural Networks (PNNs)

Probabilistic Neural Networks (PNNs) developed by Specht (1990) to overcome the classification issue caused by the applications of directional prediction. The structure of PNNs is formed of four layers which are the input layer, the pattern layer, the summation layer and the output layer.

The linear and adaptive linear prediction designs of PNNs are the most popular functions in forecasting exercises of time series. The main advantages of PNNs compared to MLPs are requiring less training time, providing more accuracy and being relatively less sensitive to outliers. The main disadvantage of the PNNs is requirement of more memory space to store the model.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a subclass of ANNs introduced by Jang (1993). According to Yager and Zadeh (1994), the model is considered one of the most powerful hybrid models, since it is based on two different estimators, namely Fuzzy Logic (FL) and ANN, which are designed to produce accurate and reliable results by justifying the noise and ambiguities in complex datasets. The ANFIS architecture is based on the Takagi-Sugeno inference system, which generates a real number as output. The structure of the model is similar

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to a MLP network with the difference on flow direction of signals between nodes and exclusion of weights.

The simulation of the ANFIS model and the function of each layers is presented as follow:

Layer 1: Selection of input data and process of fuzzification

In this step input parameters are chosen and the fuzzification is initialized by transforming crisp sets into fuzzy sets. This process is defined as follow:

$$O_{1i} = \mu A_i(x_1), \qquad O_{2i} = \mu B_i(x_2), \quad for \;\; i = 1,2 \tag{18}$$

where x_1 and x_2 are input parameters, A_i and B_i are linguistic labels of input parameters, O_{1i} and O_{2i} are membership grades of fuzzy set A_i and B_i.

Layer 2: Computation of firing strength

This layer is also called as rule layer and the outcome of this layer is known as firing strength. The nodes in this layer are fixed and represented by Π. These nodes are responsible for receiving information from previous layer and the output of this nodes is obtained by the following equation:

$$w_i = \mu A_i(x_1)\mu B_i(x_2) \quad for \;\; i = 1,2 \tag{19}$$

Layer 3: Normalization of firing strength

Each node is fixed in the 3rd layer and defined as N. The nodes in this layer receive signals from each nodes in previous layer and calculate the normalized firing strength by given rule:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad for \;\; i = 1,2 \tag{20}$$

Layer 4: Consequent Parameters

The nodes in this layer are adaptive and process the information from 3rd layer by a given rule as follow:

$$\overline{w}_i f_i = \overline{w}_i(p_i x_1 + q_i x_2 + r_i) \qquad for \;\; i = 1,2 \tag{21}$$

where $\overline{w}_i$ is the normalized firing strength and p_i, q_i, r_i are the parameter(s) set that can be determined by the method of least squares.

Layer 5: Computation of overall output

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This layer is labeled as Σ and contains only a single node which calculates the overall ANFIS output by aggregating all the information received from 4th layer:

$$y = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{22}$$

The mathematical details of ANFIS training procedure can be obtained in the studies of Jang (1993), Jang et.al. (1997), Nayak et al (2004), and Tahmasebi and Hezarkhani (2011).

Co-Active Neuro-Fuzzy Inference System (CANFIS)

The Co-Active Neuro-Fuzzy Inference System (CANFIS) is an extended version of ANFIS architecture and was introduced by Jang et al. (1997). The main advantage of CANFIS is the ability to deal with any number of input-output datasets by incorporating the merits of both neural network (NN) and fuzzy inference system (FIS) (Mizutani and Jang, 1995; Aytek, 2009). The main distinctive elements of CANFIS are the fuzzy axon (a) which applies membership functions (all the information in fuzzy set) to the inputs and a modular network and (b) that applies functional rules to the inputs (Heydari and Talaee, 2011).

As in the ANFIS system, the CANFIS system is also based on Sageno function. The main contribution of CANFIS model is to provide multiple outputs, while the two biggest drawbacks of the system are (a) problem with dealing extreme values and (b) requirement of large dataset to train the model.

Forecast Combination

The combination of forecasts is generally considered a useful tool to improve performance of individual forecasts. The arithmetic average method can be used with various forecasting models, which provides robustness and accuracy to the overall results. This method is applied as follows:

$$Cf_t^{NN} = (f_t^{NN1} + f_t^{NN2} + \cdots + f_t^{NNm})/m \tag{23}$$

where Cf is the forecast combination, $f_t^{NN}$is the Neural Network forecast at time t and m is the number of forecasts.

4. Data

The sample period covers 25 years, with Table 1 reporting the selected markets (and indices) and sample sizes (including out-of-sample forecast period) for each market, respectively. Table 2 presents the key descriptive statistics of total data sample for each index. The mean fluctuates

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between 0.004651 and 0.044841 for daily returns. Indonesia outperforms other markets while the Thai stock market performs worst. The return distribution is not symmetrical, with the series exhibiting skewness. The values in Table 2 suggest that half the markets present negative skewness, while the other half indicate positive skewness.[2] The results also suggest the presence of excess kurtosis, which suggests a larger number of extreme shocks (of either sign) than under a normal distribution. Of further note, China has the highest maximum value, while Singapore and Taiwan have the lowest maximum values. The greatest single-day increase is in China's SSE of 26.99% and the biggest drop occurs in Malaysia's KLCI with -24.15%. Singapore's STI and Taiwan's TAIEX Indices have the smallest gap between daily minimum and maximum values of -8.70% and 7.53% and, -6.98% and 6.52% respectively. This result indicates lower volatility compared to others, which is also seen in the standard deviation values.[3]

5. Neural Network Methodology and Forecast Evaluation.

5.1 Neural Network Implementation

In implementing neural network estimation, several additional considerations are required.

Hidden Layers

The learning process of a neural network is performed with layers and where the hidden layer(s) plays a key role in connecting input and output layers. Theoretically, a single hidden layer with sufficient neurons is considered capable of approximating any continuous function. Practically, single or two hidden layers network is commonly applied and provides good performance (Thomas et al., 2017). Therefore, this study follows the maximum of two hidden layers approach for each NN model.

Epochs

The number of epochs is a hyperparameter that defines the number times that the learning algorithm will work through the entire training dataset (Brownlee, 2018). The default number of 1000 epochs is used for training the data, but early stopping is applied if there is no improvement after 100 epochs to prevent overfitting (Prechelt, 2012).

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[2] Eastman and Lucey (2008) suggest that in the event of negative skewness, most returns will be higher than average return, therefore market participants would prefer to invest in negatively skewed equities.

[3] The Jarque-Bera statistic is significant at the 1% level for all series. Unit root rests support stationarity for returns.

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Weights

Weights are the parameters in a neural network system that transforms input data within the network's hidden layers. A weight decides how much influence the input will have on the output. Negative weights reduce the value of an output. The reproduction phase of the models are performed based on two modes of weight update, which are online weighting and batch weighting. In batch mode, changes to the weight matrix are accumulated over an entire presentation of the training data set, while online training updates the weight after presentation of each vector comprising the training set.

Activation Function

The activation function (also known as the transfer function) determines the output of a neural network by a given input or set of inputs. The use of the activation function is to limit the bounds of the output values which can "paralyze" the network and the prevent training process. The activation functions can be divided into two groups of linear and non-linear activation functions. As Hsieh (1995) and Franses and Van Dijk (2000) state, the fact that financial markets are non-linear and exhibit memory, non-linear activation functions are more suitable for forecast tasks. While there are various types of non-linear transfer functions, this study adopts the tanh activation function as such:

$$y_i(t) = f(x_i(t), w_i) \tag{24}$$

where $y_i(t)$ is the output, $x_i(t)$ is the accumulation of input activity from other components and w_i is the weight, with:

$$\tanh(x) = f\left(x_i, w_{,}\right) = \begin{Bmatrix} -1 & x_i < -1 \\ 1 & x_i > 1 \\ x_i & else \end{Bmatrix} \tag{25}$$

The tanh function is extensively used in time series forecasting as it delivers robust performance for feedforward neural networks, see Gomes et al. (2011), Zhang (2015) and Farzad et al. (2019).

Learning Rule

The learning rule in neural network is a mathematical method to improve ANN performance via helping neural network to learn from the existing conditions. The Levenberg-Marquardt (LM) algorithm, used in this study, is designed to work specifically with loss functions. This method, developed separately by Levenberg (1944) and Marquardt (1963), provides a numerical solution to the problem of minimizing a non-linear function (Yu and Wilamowski,

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2011). It is one of the faster methods to train a network and has stable convergence, making it one of the more suitable higher-order adaptive algorithms for minimizing error functions.

5.2. Forecast Evaluation

We utilise a range of well-known forecast evaluation metrics. This includes the mean absolute error (MAE), mean absolute percentage error (MAPE), mean squared error (MSE), root mean squared error (RMSE) and Quasi-Likelihood Loss Function (QLIKE):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|\sigma_t^2 - \hat{\sigma}_t^2| \tag{26}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|\sigma_t^2 - \hat{\sigma}_t^2|}{\sigma_t^2} \tag{27}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(\sigma_t^2 - \hat{\sigma}_t^2)^2 \tag{28}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\sigma_t^2 - \hat{\sigma}_t^2)^2} \tag{29}$$

$$QLIKE = \frac{1}{n}\sum_{t=1}^{n}\left(\log(\hat{\sigma}_t^2) + \left(\frac{\sigma_t^2}{\hat{\sigma}_t^2}\right)\right) \tag{30}$$

In each case where n denotes the number of forecasted data points, σ_t^2 is the true volatility series which is obtained by the squared return series and $\hat{\sigma}_t^2$ is the forecasted conditional variance series at time t. Of note, Patton and Sheppard (2009), Patton (2011), and Conrad and Kleen (2018) argue that the MSE and QLIKE are more reliable in volatility forecasting.

Value at Risk (VaR) and Expected Shortfall (ES)

We also consider economic loss functions. Value at Risk (VaR) measures and quantifies the level of risk over a specific interval of time. Jorion (1996) defines VaR as the worst expected loss over a target horizon under normal market conditions at a given level of confidence. Due to its relative simplicity and ease of interpretation, it has become one of the most commonly used risk management metrics. However, VaR has several drawbacks including the issue that it does not measure any loss beyond the VaR level, which is also referred to as 'tail risk' (Alexander, 2009; Danielsson et al., 2012). To overcome this, Artzner et al. (1999) introduce Expected Shortfall (ES), which is also known as conditional Value at Risk (CVaR), average

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value at risk (AVaR), and expected tail loss (ETL). Expected Shortfall measures the conditional expectation of loss exceeding the Value at Risk level. Where VaR asks the question of "How bad can things get?", ES asks "If things get bad, what is our expected loss?". We evaluate he forecast models using both of these metrics.

VaR is defined as:

$$VaR = \mu_t + \sigma_t N(\alpha) \tag{31}$$

where μ_t is the mean of the logarithmic transformation of daily return series at time *t*, σ_t is predicted volatility, and $N(\alpha)$ is the quantile of the standard normal distribution that corresponds to the VaR probability.

The Expected Shortfall (ES) equation is given as:

$$ES = \mu_t + \sigma_t \frac{f(N(\alpha))}{1-\alpha} \tag{32}$$

where μ_t and σ_t are defined as above and $f(N(\alpha))$ is the density function of the α^{th} quantile of the standard normal distribution. For further discussion see, Hendricks (1996), Scaillet (2004), Alexander (2009), Hull (2012), Fissler and Ziegel (2016), Taylor (2019).

To test the accuracy and effectiveness of the VaR model, we use three appropriate tests, the Kupiec, Christoffersen and Dynamic Quantile (DQ) tests. The Kupiec (1995) unconditional coverage test is a likelihood ratio test (LR_{UC}) designed to assess whether the theoretical VaR failure rate given by the confidence level is statistically consistent with the empirical failure rate and is given by:

$$LR_{UC} = 2\log{(1 - N_0/N_1)^{N_1 - N_0}} (N_0/N_1)^{N_0} - 2\log{(1-\phi)^{N_1 - N_0}} \phi^{N_0} \tag{33}$$

where $p = E(N_0/N_1)$ is the expected ratio of VaR violations obtained by dividing the number of violations N_0 to forecasting sample size N_1 and, ϕ is the prescribed VaR level. The Kupiec test is asymptomatically distributed ($\sim X^2(1)$) with one degree of freedom.

Although the Kupiec test is widely used, one of its disadvantages is that it only focuses on the number of violations, i.e., when the loss in the return of an asset exceeds the expected value of the VaR model. However, it is often observed that these violations occur in clusters. Clustering of violations (and hence, losses) is something that risk managers would ideally like to be able to determine. Thus, the conditional coverage test of Christoffersen (1998) is proposed to examine not only the frequency of VaR failures but also the time and duration between two violations. The model adopts the similar theoretical framework to Kupiec, with the extension of and additional statistic for the independence of exceptions, as such:

$$LR_{CC} = 2\log{((1-p_{01})^{n_{00}}\, p_{01}^{n_{01}} (1-p_{11})^{n_{10}} p_{11}^{n_{11}})} - 2\log{((1-p_0)^{n_{00}+n_{10}} {p_0}^{n_{01}+n_{11}})} \tag{34}$$

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where p_{ij} is the expected ratio of violations on state i, while j occurs on the previous period, and n_{ij} is defined as the number of days $for\ (i,j = 0,1)$. For the detailed procedure and further information see; Christoffersen (1998), Jorion (2002), Campbell (2005), and Dowd (2006).

In addition to the Kupiec and Christoffersen tests, we use the Dynamic Quantile (DQ) test proposed by Engle and Manganelli (2004). The DQ test is based on a linear regression model to measure whether the current violations are linked to the past violations. The authors define a demeaned process of violation as:

$$Hit_t(a) = I_t(a) - a = \begin{cases} 1 - a, & if\ x_t < VaR_t(a), \\ -a, & otherwise. \end{cases} \tag{35}$$

where $Hit_t(a)$ is the conditional expectation and equal to $1 - a$ if the observed return series is less than the VaR quantile, and $-a$ otherwise. The sequence assumes that the conditional expectation of $Hit_t(a)$ must be zero at time $t - 1$ (see Giot and Laurent, 2004). The test statistic for the DQ is given as follow:

$$DQ = \frac{\hat{\psi}' Q' Q \hat{\psi}}{a(1-a)}, \tag{36}$$

where Q denotes the matrix of explanatory variables and $\hat{\psi}$ indicates the OLS estimator. The proposed test statistic follows a chi-squared distribution X_q^2, in which $q = rank(X_t)$.

6. Empirical Results.

Table 3 demonstrates the forecasting performance for daily return series based on the calculation of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), Quasi-Likelihood (QLIKE) and Mean Squared Error (MSE). The out-of-sample forecasts are obtained using the ten ANN models and four benchmark models as discussed above.

The overall results suggest that the benchmark models provide superior forecasts based on the MAE criterion for seven of the ten indices, with the only exception of STI, KLCI and JCI indices. The result for the KLCI index is consistent with the study of Yao et al. (1999). According to the MAPE criterion, ANN models clearly outperform the benchmark models. Notably, the RNN, RBFN and PNN models provide the lowest MAPE values across multiple indices. In terms of the RMSE loss function, the EGARCH model achieves the best results in KLCI and TAIEX indices, whereas the GARCH model performs the worst among all. LSTM model tends to provide more accurate forecast result compared to other models. This contrasts with the work of Selvin et al. (2017), although supports the findings of Chen et al. (2015) and Nelson and Pareira (2017). The QLIKE and MSE error criteria find substantial support for the

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prediction power of ANN based models with the exception of STI, KLCI and TAIEX indices, for which they provide either mixed results or favour traditional forecasting models. The adaptive and coactive network based hybrid models of ANFIS and CANFIS indicate lowest prediction errors specifically in HANG SENG, TAIEX and PSE indices, which supports Chang et al. (2008), Boyacioglu and Avci (2010), and Kristjanpoller and Michell (2018).

The comparative predictive performance of standard NN, neuro-fuzzy and deep learning models indicate robust results compared to conventional methods for more occasions than the reverse. More specifically, the LSTM provides superior forecasts for six of the ten markets based on the MSE criterion, which justifies its favoured role in long term time series predictions given its memory cell properties (Kim and Kang, 2019). Other deep learning models, such as RNN, MLP and RBFN, are superior in three, three and four occasions respectively. In addition to the findings of Yap et al. (2021) on using deep learning models for predicting short-term movements and market trends in Asian tiger countries, the present results show that deep learning models are preferred in forecasting a wider range of markets. Furthermore, neuro-fuzzy models are favoured specifically for the NIKKEI, HANG SENG, SSE, TAIEX and PSE indices, although clearly underperforming for the remaining markets. Although Atsalakis et al. (2016) state that Neuro-fuzzy models are more preferred for turbulent times and shorter term predictions given their rapid learning capabilities, these results show that neuro-fuzzy models also offer promising results over longer term periods. GFN, MFN and PNN models indicate outperformance in seven, five and two occasions respectively. Notably, the MFN is clearly preferred for KLCI index where four out of five loss functions indicate preference. The GFN model reports lowest errors based on RMSE, QLIKE and MSE for JCI index. The PNN model is the weakest among all ANN models with it only preferable based on MAPE criterion for TAIEX and HANG SENG indices. This result supports the view of Chen et al. (2003) for Taiex index where PNN also produces enhanced predictive power compared to parametric benchmark models. However, as indicated by Wang and Wu (2017), the overall weaker performance of PNN might be due to its high computational complexity in the standard architecture that causes difficulties in the estimation of parameters.

Table 4 below presents the daily VaR and Expected Shortfall statistics as well as the corresponding test results. Examining Table 4, the lowest average VaR failure rate at the 1% level is mainly achieved by the hybrid models of ANFIS and CANFIS, while the benchmark models of GARCH and EGARCH report lowest values in KLCI and SET indices. The PNN model provides the preferred average failure rate for KOSPI index, while the RBFN and PNN models are preferred for the SSE index. In contrast, the LSTM, RNN and MLP models fail to

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provide minimum VaR rates for any of the selected indices and for which they tend to underestimate potential risks. As recently proposed by Basel Committee in 2017, there is a move regarding quantitative risk measures from VaR to ES (Expected Shortfall). In forecasting ES, the MLP model is preferred at 1% and 5% levels for the SSE, PSE, STI and HANG SENG indices. Furthermore, the RBFN, MFN and PNN models are preferred in both confidence levels for NIKKEI, KLCI and KOSPI indices. Accordingly, it can be inferred that the ANN models are the most suitable across all competing models in terms of Expected Shortfall at all selected confidence levels. The accuracy and reliability of the VaR forecasts are also tested as proposed by Basel I and Basel II . On the basis of the testing results of Kupiec, Christoffersen and DQ, the results report that none of the models reject the null hypothesis of expected VaR violation (Kupiec's unconditional coverage test), the independence exceptions of VaR (Christoffersen's conditional coverage test), and violations of VaR occurred correlated (Dynamic Quantile).

Overall, the results highlight the accuracy of the ANN class of models for volatility forecasting both in terms of statistical measures and economic, VaR and ES, metrics across a range of Asian stock markets. Notably, while there are exceptions, the results, similar to Zhang et al. (1998) and Cao and Wang (2020), suggests that the class of ANN models outperforms traditional forecasting methods across the statistical and economic measures.

7. Summary and Conclusion.

Stock volatility forecasting is highly important for both practitioners and policymakers, and which can allow for improved decision making and portfolio building, especially during periods of financial turbulence. This paper evaluates different Machine Learning methods to forecast the volatility of ten Asian stock market indices, with the results compared against benchmark models. The empirical results of the ANN models are promising. Out-of-sample forecast evaluation results show that ANN models are superior in each index compared to the GARCH and EGARCH models. Notably, the results show that neural network prediction models exhibit improved forecasting accuracy across both statistical and economic based metrics and offer new insights for market participants, academics and policymakers.

The contribution of this paper to the field of empirical finance and existing literature is three-fold. First and foremost, this study explores all key relevant machine learning models to address the problem of financial volatility forecasting. Previous studies tend to evaluate small sets of neural network methods. Using a wider range of ANN architectures has different advantages. For example, in stock market prediction exercises, the recurrent ANNs are recommended due to their memory component features that increase prediction accuracy.

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Second, comprehensive performance measures for model evaluation are utilized, namely, both a range of statistical measures (RMSE, MAE, MAPE, MSE and QLIKE) and economic based ones (VaR and ES). Third, a wide range of Asian markets are studied in order to have an in-depth examination for an extended set of volatility models across markets that are less studied.

To extend the study, it could explore a further diverse set of ANN architectures. For example, according to Partaourides and Chatzis (2017), further regularizations methods may increase the capacity of the machine learning systems. Moreover, hidden layers can be extended over two, more data frequencies can be added, and alternative input variables and activation functions can be studied. The value of such novel developments remains to be examined in future research endeavours.

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Table 1: Sample Sizes and Out-of-sample Forecasting Period for Daily Return Series in Selected Markets

Country	Estimation Period	Estimation Size	Forecast Period	Forecast Size	Full Sample Size
Japan	12/09/1994 - 8/11/2006	2874	8/14/2006 - 5/02/2018	2876	5750
Singapore	8/31/1999 - 12/30/2008	2344	12/31/2008 - 5/02/2018	2346	4690
Hong Kong	1/10/1995 - 8/29/2006	2874	8/30/2006 - 5/03/2018	2877	5751
Malaysia	1/10/1995 - 9/04/2006	2871	9/05/2006 - 4/30/2018	2869	5740
Indonesia	1/11/1995 - 8/25/2006	2847	8/28/2006 - 4/26/2018	2841	5688
Thailand	1/11/1995 - 8/24/2006	2855	8/25/2006 - 4/25/2018	2848	5703
China	1/10/1995 - 9/11/2006	2828	9/12/2006 - 5/03/2018	2829	5657
Taiwan	1/11/1995 - 3/23/2006	2997	3/24/2006 - 5/02/2018	2895	5892
South Korea	1/10/1995 - 5/02/2006	2970	5/03/2006 - 5/02/2018	2973	5943
Philippines	1/11/1995 - 7/17/2006	2875	7/18/2006 - 5/02/2018	2853	5728

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Table 2: Summary of Descriptive Statistics for Daily Return Series

	NIKKEI	STRAITS TIMES INDEX	HANG SENG INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SET INDEX	SSE INDEX	TAIEX	KOSPI	PSE INDEX
Mean	0.0294	0.0105	0.024194	0.012354	0.044841	0.004651	0.028739	0.015257	0.015445	0.015835
Median	0.030928	0.02846	0.0511	0.025455	0.090305	0.015914	0.065357	0.043451	0.050211	0.021669
Maximum	13.23458	7.531083	17.2471	20.81737	13.12768	11.34953	26.99277	6.52462	11.28435	16.1776
Minimum	-12.11103	-8.695982	-14.73468	-24.15339	-12.73214	-16.06325	-17.90509	-6.975741	-12.8047	-13.08869
Std. Dev.	1.504108	1.141326	1.60473	1.267938	1.52564	1.526721	1.761533	1.36745	1.66492	1.393054
Skewness	-0.300663	-0.266133	0.064089	0.502157	-0.19832	0.049086	0.195354	-0.182956	-0.291322	0.162169
Kurtosis	8.540723	8.37642	13.32528	65.37193	11.58383	10.95738	18.86232	5.815682	8.152126	14.21301
Probability	0.000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	5748	4689	5750	5740	5688	5703	5656	5892	5942	5728
Sample	12/09/1994 5/03/2018	8/31/1999 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018	1/11/1995 5/03/2018	1/11/1995 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018

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Table 3: Comparison of Forecast Performance Measures for Daily Return Series

NIKKEI INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.32	6.66	0.46	0.18	**0.21**
RNN	0.31	5.69	0.47	0.22	0.22
MLP	0.35	6.63	0.51	0.55	0.26
RBFN	0.32	6.56	0.48	0.21	0.23
ANFIS	0.27	**5.43**	0.51	**0.11**	0.28
CANFIS	0.33	5.44	0.46	0.13	**0.21**
PNN	0.40	6.54	0.60	5.74	0.36
GFN	0.32	7.06	0.46	0.18	**0.21**
MFN	0.32	6.53	**0.45**	0.18	**0.21**
ANN Fc	0.33	6.28	0.49	0.83	0.24
GARCH(1,1)	0.34	10.49	0.69	1.56	0.48
EGARCH(1,1)	**0.25**	10.56	0.69	1.54	0.47
MACD	0.55	13.50	1.27	1.56	0.59
NAIVE	0.41	6.59	0.73	5.71	0.34

HANG SENG INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.29	7.10	0.44	**0.15**	**0.19**
RNN	0.30	5.44	0.46	NA	0.21
MLP	0.37	9.48	0.54	1.31	0.29
RBFN	0.34	10.93	0.46	0.45	0.21
ANFIS	0.33	6.76	**0.39**	0.19	0.28
CANFIS	0.37	6.55	**0.38**	0.22	0.33
PNN	0.39	**5.42**	0.61	6.83	0.37
GFN	0.30	7.38	0.45	**0.15**	0.20
MFN	0.34	9.71	0.46	0.16	0.21
ANN Fc	0.34	7.64	0.47	1.18	0.25
GARCH(1,1)	0.26	10.32	0.73	1.46	0.53
EGARCH(1,1)	**0.25**	10.23	0.70	1.46	0.48
MACD	0.91	9.80	1.01	1.91	0.29
NAIVE	0.42	7.81	0.56	6.89	0.38

STRAITS TIMES INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	**0.19**	4.81	0.26	0.33	0.07
RNN	**0.19**	4.82	0.26	0.32	0.07
MLP	0.23	6.66	0.28	**0.26**	0.08
RBFN	**0.19**	**4.34**	0.26	1.66	0.07
ANFIS	0.44	4.57	0.35	0.44	0.13
CANFIS	0.29	5.33	0.28	0.52	0.11
PNN	0.24	4.90	0.35	3.65	0.13
GFN	0.21	6.12	0.27	0.29	0.07
MFN	0.20	5.32	0.26	0.31	0.07
ANN Fc	0.24	5.21	0.29	0.86	0.09
GARCH(1,1)	0.91	9.68	0.20	0.50	**0.04**
EGARCH(1,1)	0.91	9.50	0.20	0.49	**0.04**
MACD	0.80	10.20	0.44	1.94	0.26
NAIVE	0.30	5.94	**0.09**	4.77	0.19

SET INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.37	0.60	0.46	**0.06**	0.21
RNN	0.24	0.80	**0.38**	0.17	**0.15**
MLP	0.31	**0.15**	0.43	0.84	0.18
RBFN	0.25	0.80	**0.38**	0.55	**0.15**
ANFIS	0.24	0.33	0.54	0.47	0.19
CANFIS	0.27	0.28	0.57	0.41	0.22
PNN	0.34	4.51	0.51	3.34	0.26
GFN	0.27	0.60	**0.38**	0.07	**0.15**
MFN	0.26	0.61	**0.38**	0.08	**0.15**
ANN Fc	0.28	0.96	0.45	0.67	0.18
GARCH(1,1)	**0.19**	10.53	0.67	1.21	0.45
EGARCH(1,1)	**0.19**	10.51	0.67	1.15	0.45
MACD	0.55	9.80	0.67	2.03	0.67
NAIVE	0.39	4.50	0.47	3.55	0.34

KUALA LUMPUR COMPOSITE INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.18	5.77	0.23	0.54	**0.05**
RNN	0.14	6.11	0.23	0.52	0.05
MLP	0.24	4.53	0.31	0.58	0.09
RBFN	0.21	6.28	0.28	0.32	0.08
ANFIS	0.17	3.33	0.29	0.42	0.09
CANFIS	0.18	3.89	0.37	0.45	0.10
PNN	0.19	4.04	0.29	2.39	0.09
GFN	0.16	6.07	0.23	1.21	**0.05**
MFN	**0.15**	**1.42**	**0.22**	0.84	**0.05**
ANN Fc	0.18	4.60	0.27	0.81	0.07
GARCH(1,1)	0.68	10.00	0.23	0.06	**0.05**
EGARCH(1,1)	0.67	10.05	**0.22**	**0.05**	**0.05**
MACD	0.44	10.21	0.57	1.92	2.40
NAIVE	0.27	4.42	0.66	3.04	0.22

JAKARTA COMPOSITE INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.29	6.37	**0.40**	**0.01**	**0.16**
RNN	0.30	6.68	0.41	**0.01**	0.17
MLP	0.33	6.09	0.47	0.80	0.22
RBFN	**0.27**	4.35	**0.40**	1.06	**0.16**
ANFIS	0.37	7.43	0.57	0.26	0.24
CANFIS	0.48	8.55	0.41	0.18	0.23
PNN	0.35	3.95	0.54	7.65	0.29
GFN	0.28	6.23	**0.40**	**0.01**	**0.16**
MFN	0.29	6.60	0.41	0.02	0.17
ANN Fc	0.33	6.25	0.45	1.11	0.20
GARCH(1,1)	0.29	10.94	0.42	0.72	0.24
EGARCH(1,1)	0.29	10.99	0.42	0.76	0.23
MACD	0.37	10.75	0.93	2.03	6.62
NAIVE	0.38	**3.59**	0.80	2.64	0.35

SSE INDEX

TAIEX INDEX

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Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.40	6.50	0.53	0.29	0.28
RNN	0.40	6.44	0.52	0.27	0.27
MLP	0.40	4.90	0.58	0.31	0.34
RBFN	0.34	4.29	0.51	0.33	**0.26**
ANFIS	0.37	8.43	0.49	**0.25**	0.29
CANFIS	0.36	7.56	0.57	0.28	**0.26**
PNN	0.45	4.90	0.66	5.36	0.43
GFN	0.34	4.04	0.51	0.30	**0.26**
MFN	0.38	5.91	0.52	**0.25**	0.27
ANN Fc	0.38	5.89	0.54	0.85	0.30
GARCH(1,1)	0.34	10.47	0.69	1.70	0.48
EGARCH(1,1)	**0.33**	10.52	0.69	1.69	0.48
MACD	1.12	**1.29**	0.97	1.74	1.33
NAIVE	0.47	7.51	**0.36**	6.64	0.52

KOSPI INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.25	4.89	0.34	0.11	0.12
RNN	0.26	5.17	0.35	0.08	0.12
MLP	0.30	6.44	0.38	**0.01**	0.15
RBFN	0.25	4.52	0.35	0.54	0.12
ANFIS	0.36	4.77	**0.31**	0.29	0.12
CANFIS	0.48	6.49	0.37	0.43	**0.10**
PNN	0.33	**4.34**	0.47	8.15	0.22
GFN	0.26	5.37	0.35	0.09	0.12
MFN	0.26	5.53	0.35	0.08	0.12
ANN Fc	0.31	5.28	0.36	1.09	0.13
GARCH(1,1)	**0.16**	9.98	0.32	1.03	**0.10**
EGARCH(1,1)	**0.16**	9.84	**0.31**	1.02	**0.10**
MACD	0.64	10.25	0.68	1.75	0.17
NAIVE	0.39	5.89	0.71	4.09	0.30

PSE INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.24	9.12	0.36	**0.03**	**0.13**
RNN	0.28	5.97	0.38	0.07	0.14
MLP	0.27	12.97	0.40	1.23	0.16
RBFN	0.39	6.14	0.46	0.07	0.21
ANFIS	0.76	9.76	0.56	0.28	0.31
CANFIS	0.63	10.19	0.74	0.44	0.34
PNN	0.34	7.23	0.50	0.14	0.25
GFN	0.26	6.24	0.37	0.09	0.14
MFN	0.25	6.49	0.36	0.10	**0.13**
ANN Fc	0.38	8.23	0.46	0.27	0.20
GARCH(1,1)	**0.18**	10.06	0.49	1.01	0.24
EGARCH(1,1)	**0.18**	10.09	0.48	1.00	0.23
MACD	0.73	10.20	1.44	1.70	0.24
NAIVE	0.45	**4.62**	**0.35**	3.71	0.43

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.25	9.53	0.37	**0.01**	**0.13**
RNN	0.27	10.27	0.38	0.03	0.14
MLP	0.27	9.80	0.40	0.07	0.16
RBFN	0.27	5.44	0.41	0.03	0.17
ANFIS	**0.18**	5.54	0.18	0.07	0.19
CANFIS	0.19	5.61	**0.12**	0.09	**0.13**
PNN	0.34	8.41	0.50	0.06	0.25
GFN	0.26	10.11	0.37	**0.01**	0.14
MFN	0.28	11.81	0.38	0.03	0.15
ANN Fc	0.26	8.50	0.35	0.04	0.16
GARCH(1,1)	**0.18**	9.82	0.51	1.24	0.26
EGARCH(1,1)	**0.18**	9.73	0.50	1.22	0.25
MACD	0.41	10.42	0.88	1.63	0.24
NAIVE	0.36	**5.42**	**0.12**	4.47	0.30

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Table 4: Summary of Risk Management Analysis and Backtesting Results for Daily Return Series

NIKKEI INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0289	ALL	ALL	ALL	0.2503	0.2660
RNN	0.0287	ALL	ALL	ALL	0.1923	0.2216
MLP	0.0290	ALL	ALL	ALL	0.0266	0.1105
RBFN	0.0271	ALL	ALL	ALL	**-0.0367**	**0.0058**
ANFIS	0.0211	ALL	ALL	ALL	0.0313	0.0424
CANFIS	**0.0124**	ALL	ALL	ALL	0.0114	0.0193
PNN	0.0271	ALL	ALL	ALL	**-0.0367**	0.0058
GFN	0.0290	ALL	ALL	ALL	0.2278	0.2594
MFN	0.0308	ALL	ALL	ALL	0.2748	0.3143
GARCH(1,1)	0.0269	ALL	ALL	ALL	0.0916	0.0983
EGARCH(1,1)	0.0262	ALL	ALL	ALL	0.0783	0.0900

HANG SENG INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0290	ALL	ALL	ALL	0.1619	0.1899
RNN	0.0290	ALL	ALL	ALL	0.1085	0.1463
MLP	0.0303	ALL	ALL	ALL	**-0.5117**	**-0.2608**
RBFN	0.0288	ALL	ALL	ALL	0.0511	0.1019
ANFIS	**0.0254**	ALL	ALL	ALL	0.0448	0.0822
CANFIS	0.0258	ALL	ALL	ALL	0.0535	0.0998
PNN	0.0288	ALL	ALL	ALL	0.0511	0.1019
GFN	0.0294	ALL	ALL	ALL	0.1444	0.1817
MFN	0.0308	ALL	ALL	ALL	0.2386	0.2724
GARCH(1,1)	0.0313	ALL	ALL	ALL	0.0568	0.0634
EGARCH(1,1)	0.0314	ALL	ALL	ALL	0.0241	0.0293

STRAITS TIMES INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0277	ALL	ALL	ALL	0.2526	0.2618
RNN	0.0279	ALL	ALL	ALL	0.1608	0.1854
MLP	0.0265	ALL	ALL	ALL	**-0.0213**	**0.0269**
RBFN	0.0276	ALL	ALL	ALL	0.1051	0.1358
ANFIS	0.0277	ALL	ALL	ALL	0.1148	0.1225
CANFIS	0.0270	ALL	ALL	ALL	0.1053	0.1090
PNN	0.0276	ALL	ALL	ALL	0.1051	0.1358
GFN	0.0270	ALL	ALL	ALL	0.1467	0.1660
MFN	0.0272	ALL	ALL	ALL	0.1078	0.1360
GARCH(1,1)	**0.0241**	ALL	ALL	ALL	0.0352	0.0384
EGARCH(1,1)	0.0242	ALL	ALL	ALL	0.0313	0.0349

SET INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0291	ALL	ALL	ALL	0.3235	0.3341
RNN	0.0293	ALL	ALL	ALL	0.1908	0.2216
MLP	0.0301	ALL	ALL	ALL	**-0.1459**	0.0803
RBFN	0.0291	ALL	ALL	ALL	0.1702	0.2003
ANFIS	**0.0258**	ALL	ALL	ALL	0.1445	0.1839
CANFIS	0.0270	ALL	ALL	ALL	0.1735	0.2998
PNN	0.0291	ALL	ALL	ALL	0.1702	0.2003
GFN	0.0284	ALL	ALL	ALL	0.2142	0.2328
MFN	0.0297	ALL	ALL	ALL	0.2528	0.2770
GARCH(1,1)	**0.0258**	ALL	ALL	ALL	0.0698	**0.0753**
EGARCH(1,1)	**0.0258**	ALL	ALL	ALL	0.0669	0.0759

KUALA LUMPUR COMPOSITE INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0256	ALL	ALL	ALL	0.0534	0.0668
RNN	0.0256	ALL	ALL	ALL	-0.0282	0.0091
MLP	0.0288	ALL	ALL	ALL	0.0423	0.1834
RBFN	0.0270	ALL	ALL	ALL	0.0321	0.0880
ANFIS	0.0263	ALL	ALL	ALL	0.0422	0.0624
CANFIS	0.0275	ALL	ALL	ALL	0.0375	0.0524
PNN	0.0270	ALL	ALL	ALL	0.0321	0.0880
GFN	0.0280	ALL	ALL	ALL	0.2437	0.2574
MFN	0.0246	ALL	ALL	ALL	**-0.1234**	**-0.0736**
GARCH(1,1)	**0.0241**	ALL	ALL	ALL	0.0255	0.0280
EGARCH(1,1)	**0.0241**	ALL	ALL	ALL	0.0205	0.0243

JAKARTA COMPOSITE INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0282	ALL	ALL	ALL	0.2712	0.2811
RNN	0.0287	ALL	ALL	ALL	0.1276	0.1646
MLP	0.0288	ALL	ALL	ALL	**-0.0162**	0.1190
RBFN	0.0297	ALL	ALL	ALL	0.1536	0.2131
ANFIS	0.0255	ALL	ALL	ALL	0.2213	0.2464
CANFIS	**0.0249**	ALL	ALL	ALL	0.1745	0.1930
PNN	0.0297	ALL	ALL	ALL	0.1536	0.2131
GFN	0.0289	ALL	ALL	ALL	0.1979	0.2298
MFN	0.0286	ALL	ALL	ALL	0.2169	0.2427
GARCH(1,1)	0.0266	ALL	ALL	ALL	0.0687	0.0735
EGARCH(1,1)	0.0265	ALL	ALL	ALL	0.0503	**0.0595**

SSE INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0320	ALL	ALL	ALL	0.5068	0.5175
RNN	0.0280	ALL	ALL	ALL	0.0475	0.0866
MLP	0.0295	ALL	ALL	ALL	**-0.5657**	**-0.3355**
RBFN	**0.0264**	ALL	ALL	ALL	-0.1772	-0.1306
ANFIS	0.0284	ALL	ALL	ALL	0.1945	0.2675
CANFIS	0.0293	ALL	ALL	ALL	0.1424	0.1505
PNN	**0.0264**	ALL	ALL	ALL	-0.1772	-0.1306
GFN	0.0286	ALL	ALL	ALL	0.1222	0.1504
MFN	0.0275	ALL	ALL	ALL	-0.0416	0.0011
GARCH(1,1)	0.0282	ALL	ALL	ALL	0.0875	0.0930
EGARCH(1,1)	0.0286	ALL	ALL	ALL	0.0817	0.0924

TAIEX INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0287	ALL	ALL	ALL	0.2679	0.2827
RNN	0.0286	ALL	ALL	ALL	0.2473	0.2686
MLP	0.0283	ALL	ALL	ALL	0.0608	0.1483
RBFN	0.0278	ALL	ALL	ALL	**0.0484**	0.0895
ANFIS	**0.0228**	ALL	ALL	ALL	0.1124	0.1639
CANFIS	0.0247	ALL	ALL	ALL	0.1336	0.1469
PNN	0.0278	ALL	ALL	ALL	**0.0484**	0.0895
GFN	0.0285	ALL	ALL	ALL	0.1938	0.2184
MFN	0.0276	ALL	ALL	ALL	0.1582	0.1846
GARCH(1,1)	0.0254	ALL	ALL	ALL	0.0927	0.0980
EGARCH(1,1)	0.0253	ALL	ALL	ALL	0.0770	**0.0846**

KOSPI INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)

PSE INDEX

	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)

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LSTM	0.0283	ALL	ALL	ALL	0.1768	0.1915	**LSTM**	0.0284	ALL	ALL	ALL	0.2154	0.2363
RNN	0.0282	ALL	ALL	ALL	0.2137	0.2343	**RNN**	0.0298	ALL	ALL	ALL	0.2344	0.2892
MLP	0.0288	ALL	ALL	ALL	-0.0790	0.0801	**MLP**	0.0296	ALL	ALL	ALL	**-0.3932**	**-0.1490**
RBFN	0.0280	ALL	ALL	ALL	0.1519	0.1794	**RBFN**	0.0254	ALL	ALL	ALL	-0.1084	-0.0704
ANFIS	0.0274	ALL	ALL	ALL	0.0327	0.0744	**ANFIS**	0.0249	ALL	ALL	ALL	-0.0233	-0.0361
CANFIS	0.0269	ALL	ALL	ALL	0.0459	0.0844	**CANFIS**	**0.0244**	ALL	ALL	ALL	-0.0124	-0.0487
PNN	**0.0150**	ALL	ALL	ALL	**-1.9910**	**-1.9910**	**PNN**	0.0254	ALL	ALL	ALL	-0.1084	-0.0704
GFN	0.0292	ALL	ALL	ALL	0.1974	0.2260	**GFN**	0.0270	ALL	ALL	ALL	0.0539	0.1022
MFN	0.0298	ALL	ALL	ALL	0.2767	0.2995	**MFN**	0.0301	ALL	ALL	ALL	0.3178	0.3458
GARCH(1,1)	0.0261	ALL	ALL	ALL	0.0772	0.0825	**GARCH(1,1)**	0.0271	ALL	ALL	ALL	0.0653	0.0722
EGARCH(1,1)	0.0260	ALL	ALL	ALL	0.0683	0.0807	**EGARCH(1,1)**	0.0259	ALL	ALL	ALL	0.0440	0.0580

Notes: Avg.FR indicates the failure rate of VaR at 1% significance level. LRcc and LRuc show the signifance of the conditional (Christoffersen) and unconditional (Kupiec) coverage tests at 1%level of siginifance, respectively. Sig. DQ Test denotes the signifance of the Dynamic Quantile and ES shows the Expected Shortfall at 1% and 5% confidence levels for the selected index.

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