Is Artificial Intelligence the Oracle of Delphi for Stock Markets? Artificial Intelligence and Stock Market Predictability

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Abstract

This present study explores the use of Artificial Intelligence in stock market predictions. An accurate prediction of stock price movement may yield profits for investors. Due to the complexity of stock market data, development of efficient models for predicting is very difficult. However, recent literature has reported that Artificial Intelligence based models outperform traditional techniques for accurately predicting stock returns. This paper develops two efficient models and compare their performances in predicting the value and direction of the Philippine Stock Exchange indices. The models are based on the two most prominent classification techniques, artificial neural networks (ANN) and support vector machines (SVM). These models are trained on the eight Indices of the Philippine Stock Exchange: PSEi, All Shares, Financials, Industrial, Holding Firms, Services, Mining and Oil, and Property. Index values, technical and macroeconomic variables from 2010 to the first quarter of 2016 are used as input variables. Two comprehensive parameter setting experiments for both models are performed to improve their prediction performance. Subsequently, the study compares the performance of ANN and SVM in forecasting stock price and direction movement by using the Paired T-Test, RMSE/MAE/MAPE, Hit-Miss and Directional test. Although both models can adequately forecast the stock indices, ANN performs better than SVM. Experimental results show that average performance of ANN model (80.72%) is significantly better than that of SVM (74.49%). Finally, this study concludes that the Philippine stock market is indeed predictable and inefficient. Some sectors (Industrial and Financials) are more predictable compared to others, implying variation of predictability and subsequent inefficiency across sectors.

Key words: Philippine Stock Market, Artificial Intelligence, Artificial Neural Network, Support Vector Machine, Backpropagation, Efficient Market Hypothesis, Adaptive Market Hypothesis, Computational Learning Theory

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Mathematician Irving Good (1965):"The first ultra-intelligent machine is the last invention that man need ever make."

1. Introduction

Numerous studies in the past two decades have investigated the ability of financial variables such as the dividend-price ratio, the earnings-price ratio, and various measures of the interest rate to predict stock returns and its implications to the Efficient Market Hypothesis. See, for example, Campbell (1987), Campbell and Shiller (1988), Fama and French (1988, 1989), Fama and Schwert (1977), Hodrick (1992), and Keim and Stambaugh (1986). Other approaches include out-of-sample forecasting (Goyal and Welch, 2003) and Bayesian inference (Kothari and Shanken, 1997; Stambaugh, 1999).

Recent literature has established that stock markets are known to be dynamic, non-linear, and complicated resulting in a wider range of strategies and techniques utilized to obtain accurate predictions. Subsequently, soft computing techniques are perceived as viable candidates to predict stock market returns and indices. Primarily, since they can capture nonlinear characteristics of stock markets, especially, without prior knowledge of the statistical distributions of the input data/stock returns. Numerous studies have documented that Artificial Intelligence (AI) models such as Artificial Neural Networks[1] (ANN) and Support Vector Machines[2] (SVM) outperform traditional stock market forecasting models. However, few researchers focus on Artificial Intelligence models and even in the sparse existing literature there exist opposing views on which AI forecasting model is superior. Based on recent developments in the field of artificial intelligence (AI) this study attempts to provide a more suitable methodology to clarify contradictory opinions on the superiority of ANN and SVM. Given the school of thought that ANN and SVM show accurate results and better performance than traditional methods in forecasting, this study further aims to test both Artificial Intelligence models in the context of Philippines stock market setting (An emerging market). Moreover, this study aims to address the gap in prior literature on applying Artificial Intelligence techniques to predict stock market indices.

Despite, widespread research on stock return predictability for the US stock market, the existing literature on the predictability of stock returns of non-US markets, including the Asia-Pacific has not been that extensive. Philippines is one of the emerging stock markets in the Asia Pacific and the 10th fastest growing economy in the world.

[1]Several research studies utilized ANNs to predict stock returns in developed and emerging economies as its established that it can outperform traditional linear models such as linear regression, ARIMA, and exponential smoothing methods. (Karymshakov and Abdykaparov, 2012; Yao et al.,1999; Wijaya et al, 2010; Sterba and Hivlska, 2010; Gahanan, 2008; Hansen et al., n.d., Gardner, 2006; Enke & Thawornwong, 2004; De Faria, 2009). While ANN has become a dominant and popular type of AI forecasting model, there are some issues concerning this tool. ANN captures unwanted noise, which leads to poor performance of generalizations when it comes to training data. Thus, researchers explored a variety of alternative procedures that could improve the generalization ability of neural networks. Subsequently, in 1979, Vapnik introduced Support Vector Machines (SVM) to solve the issue on generalization (Cao & Tay, 2001).

[2]SVM is a specific type of learning algorithm, which is resistant to the overfitting problems found in other AI methods including ANN. Many research studies have shown that SVM achieves a higher accuracy in predicting stock returns, perform better than traditional forecasting models and even Artificial Neural Networks (Huang, Nakamori & Wang, 2004; Shen, Jiang & Zhang, 2012; Wang, 2004; Cao & Tay, 2001; Kumar & Thenmozhi, 2006; Chen et al., 2006).

The Philippine Stock Exchange is sub divided into eight different sectors, each with its corresponding index. Namely: PSEi, All Shares, Financials, Industrial, Holding Firms, Services, Mining & Oil, and Property (Lo, 2015). Prior research has been unable to reach a consensus regarding the efficiency of the Philippine stock market. Several prior literatures find the Philippine stock exchange to be unpredictable and efficient along with other Asian economies such as India, Indonesia and Malaysia (Lanaraja, Salve & Vasanth, 2014; Aquino, 2006; Poshakwale, 1996). However, in contrast, several studies states that the Philippine stock market is indeed predictable and inefficient (Chen & Diaz, 2014; Guidi & Grupta, 2011). Hence, it is important to conduct studies on the predictability of the Philippine stock markets' various index returns and efficiency. Moreover, this is the first study to utilize Artificial Intelligence techniques such as ANN and SVM models to test the predictability of the Philippine Stock Exchange.

Thus, this study poses the following questions: Can Artificial Neural Network (ANN) and Support Vector Machine (SVM) models forecast the value and direction of the Philippine Stock Exchange? If so, which model has better accuracy and consistent performance? Is there any variation of predictability across different sectors?

The study finds that ANN performs better in forecasting the value and direction of the next day's closing price compared to SVM. In addition, one-day ahead time window is a better forecasting period compared to other time windows. Moreover, ANN and SVM, respectively, have high accuracy of prediction with a forecasting error of less than 5%. Out of the three ANN models implemented, ANN30 performs better compared to other models with different time windows. Industrial, Financials, and Holding Firm indices show consistent predictability using ANN, while All Shares index, shows consistent predictability using SVM. Finally, this study concludes that the Philippine stock market is indeed predictable and inefficient. Some sectors (Industrial and Financials) are more predictable compared to others, implying variations of predictability and subsequent forms of inefficiency across different sectors.

The structure of the paper is as follows: Section II reviews the literature. Section III presents the data and empirical methodology of applying artificial intelligence techniques to predict stock market indices in the Philippine setting. Section IV provides empirical evidence of the predictability of the Philippine stock market indices using ANN and SVM models and the forecasting accuracy of the same. Section V concludes the study. Additional tables of descriptive statistics, forecasting accuracy and the forecasts of the ANN and SVM models for each index are provided in a separate appendix for brevity and is available upon request.

2. Review of Related Literature

This study contributes to several strands of literature on Stock market predictability and efficiency, computational and statistical learning techniques and finally applications of artificial intelligence models in Finance and Economics. The first part of this section reviews the prior literature on stock market predictability in general and the various theories involved. The second section focuses on Artificial Intelligence models and their applications to predicting stock returns. The final section reviews prior literature on the predictability and efficiency of the Philippine Stock market.

2.1 Stock Market Predictability and Related Theories

There is an extensive ongoing debate and a plethora of theoretical and empirical literature on stock return predictability and its subsequent efficiency. Campbell (1987) and Fama and French (1989), among many other studies, document that variables such as the dividend yield, the default premium, the term premium, and the short-term interest rate forecast excess stock returns. The primary focus in prior literature has been the predictability of excess aggregate stock market returns by lagged financial and macroeconomic predictive variables. However, Bossaerts and Hillion (1999), Ang and Bekaert (2001), and Goyal and Welch (2003) cast doubt on the in-sample evidence documented in prior literature, by showing that these variables have negligible out-of-sample predictive power.

Although most of research has concentrated on the U.S., there is an increasing string of research focusing on lead-lag relationships in international asset markets. Rapach et al. (2005) examine the predictability of stock returns in 12 industrialized countries and find that interest rates are the most consistent and reliable predictors of stock returns. In the same vein, Ang and Bekaert (2007) show that the dividend yields and short-term interest rates are robust predictors for the stock returns in the U.S., U.K., France, and Germany. Hjalmarsson (2010) examines return predictability in a larger dataset comprising 40 developed international stock markets. Similarly, Rapach et al. (2005) and Ang and Bekaert (2007) finds that the short-term interest rate as well as the term spread are generally superior predictors across countries. Wohar et al. (2005) examine return predictability using monthly macroeconomic variables data in 12 industrialized countries, using the data from the early to-mid 1970s to the late 1990s. They find that interest rates are the most consistent and reliable predictors of stock returns across countries, while the inflation rate also appears to have important predictive ability in certain countries. Schrimpf (2010) examines return predictability in five major international stock markets, using a monthly data set of nine financial and macroeconomic predictors, covering the period 1973-2007. He finds, adopting the ARM of Amihud et al. (2008), that interest-rate related variables are usually among the most prominent predictive variables, whereas valuation ratios perform rather poorly. Further, Schrimpf (2010) reports that the return predictability of international stock markets is not uniform across countries. Giot and Petitjean (2011) examine the predictability of stock returns in 10 international markets adopting the Stambaugh (1999) and Lewellen (2004) correction methods, using the data to 2005 and considering five traditional predictors.

Their out-of-sample analysis shows that the short-term interest yield is the most informative predictor of stock returns. Due to its major role in the world economy, investors are likely to focus on the U.S. markets, potentially creating spill overs of U.S. returns to other markets. Rapach et al. (2013) study the importance of the U.S. market movements in predicting international stock returns. Jordan et al. (2014b) analyse return predictability for 11 Asian countries over the period 1995-2011, using monthly data for three types of predictors (fundamental, macroeconomic and technical variables). They find that the performance of fundamental price ratios and macroeconomic variables as well as some technical variables shows evidence of predictability.

In addition, some emphasis has been given to predicting emerging stock market returns. Han-Kim and Singal (2000), Füss and Herrmann (2005), Bilson et al. (2002), Bacmann and Dubois (2002), Guermat et al. (2003) and Assaf (2006). Most of the surveyed papers focused on exploring the behaviour of stock returns with most authors studying a single stock market as in Kiricos and Terzakis (1999), Marcucci (2003), Pereira (2004), Danilov and Magnus (2004), Duker (1997), Berg (2003), Oomen (2001), Lee (2000), Park and Lee (2003), Stentoft (2005), Peters (2001), Eisler and Kertesz (2004). Several studies have tested the robustness of conventional techniques using multiple stock indices, as in Balaban et al. (2006), Fornari and Mele (1997), Balvers et al. (1990), Guo (2003), Assaf (2006), Yu and So (2003), Bacmann and Dubois (2002), Bilson (2001) and Griffin et al. (2004). Few studies, focused on individual major stocks from industrial companies (BWM, VODAFONE etc.) or mutual funds; Miyahara and Novikov (2002), Skaradzinski (2003), Dufrenot, et al. (2005), Sibbertsen (2004), Zontos et al. (2000). In what follows, I discuss the prominent theories that have implications on stock market predictability. Chaudhuri & Wu, 2003 finds that 10 out of 14 emerging markets rejected the random walk. Dupernex (2007) stated that the reactions of the investors to any informational advantages are instantaneous which results in elimination of profits. Oskooe (2011) documents that the Iranian Stock market returns follow a random walk and is most efficient in weak form. Nwidobie (2014) states that stock price movement in capital markets can either be in a random or non-random fashion.

Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) introduced by Eugene Fama suggests that it is unlikely to profit from the stock market through predicting stock price movements. EMH proposes that the current stock price reflects all market information and it is therefore impossible to beat the market using this information. The Efficient Market Hypothesis has three forms - depending on the type of information reflected in security prices. *Weak Form Efficiency* states that the current stock price fully incorporates all historical data. Thus, past price changes do not contain information that is able to predict future changes, suggesting that the market operates in a random walk. *Semi-strong Form Efficiency* states that the current price incorporates all publicly available information of a company. It also states that neither fundamental nor technical analysis could utilize the new information released because stock prices would rapidly adjust to the new publicly available information. *Strong Form Efficiency* states that the current stock price fully incorporates both public and private information.

Thus, making it impossible for anyone to earn excess returns including company insiders. Markets are said to be efficient if prices adjust rapidly and without bias to new information. EMH claims that no one can beat the market; Primary issue with EMH is that it assumes that all stock market participants are rational, meaning all of them expect the same future stock returns (homogeneous expectations).

Adaptive Market Hypothesis

Adaptive Markets Hypothesis (AMH) was developed to reconcile market efficiency with behavioural alternatives through the application of evolutionary principles. Principles such as competition, adaptation, and natural selection, in financial interactions. Market efficiency and environmental factors, which characterize market ecology such as number of competitors in the market, magnitude of profit opportunities available and adaptability of stock market participants, are related to each other. AMH postulates that investor behaviour (loss aversion, overconfidence and overreaction) and evolutionary models of human behaviour (competition, adaptation, and natural selection) are consistent with each other (Lo, 2004). Adaptive Market Hypothesis could resolve the flaw of Efficient Market Hypothesis. Aruwa S. and Musa A. (n.d.) stated that AMH covers market friction and claims that markets evolve over time, unlike EMH which assumes that the market is frictionless. Neely and Weller (2011) stated that using EMH is flawed as believed by technicians. Markets include short-lived inefficiencies that could only be resolved through technical analysis[3]. Todea, et al. (2009) showed that the degree of market efficiency differs in cyclical fashion over time since its profit opportunities exist from time to time. In the next section, I discuss the theories and literature related to predicting stock market returns using Artificial Intelligence techniques.

2.2 Artificial Intelligence (AI) Techniques for Stock Predictability

Both academic researchers and practitioners have made considerable progress so far in predicting stock returns and devising trading strategies to translate the forecasts into profits (Chen, Leung, & Daouk, 2003). However, several studies on stock return prediction models based on Artificial Intelligence(AI) have stated that they provide better performance than traditional forecasting methods. Primarily due to them being capable of analysing large amount of information and detect patterns between different variables. According to Trippi (2002), Artificial Intelligence is one of Wall Street's most promising new technologies. Consequently, there is a growing trend especially in the industry to use AI techniques to predict stock returns, highlighting the importance of research similar to this study. Research studies such as the following have used Artificial Intelligence methods such as Artificial Neural Network (ANN) and Support Vector Machines (SVM) in the field of finance and concluded that they can accurately forecast stock return movements (Wiyaya et al, 2010; De Faria, 2004; Lahmiri, 2011; Wang, 2014; Huang, Nakamori & Wang, 2004, Chen et al, 2006; Shen, Jiang, & Zhang, 2012).

[3] Technical Analysis is a method in security evaluation through analysing the statistics of market activities, such as past prices, volume, etc.

However, it has yet to be proven in the Philippine setting. From here on I discuss theories that are related to predicting stock returns using artificial intelligence techniques.

Rational Choice Theory

Rational Choice Theory defines the process of choosing the most preferred among available options (Levin & Milgrom, 2004). Browning, Halcli and Webster (2000) stated that this theory introduces the idea that all actions are rational. This theory began with considering the choice behaviour of individuals, most often by consumers and/or firms. The decision makers choose based on their customs or habits, randomly, as long as their choices best help their objectives, given all relevant and uncontrollable factors. The Rational Choice Theory of consumer behaviour is based on different axioms on consumer preferences. Green (2002) states that consumers choose the most preferred alternative among the available choices.

Statistical Learning Theory

The Statistical Learning Theory is one approach to understanding learning systems. It aims to analyse limits of new data performance, bounds that will hold for a training set, and bounds for the improvement of learning algorithms (Taylor, 2011). Its framework assumes that future observations are related to the past (training data), so that the data generating process is somewhat stationary. The core of this theory is a probabilistic model of the data generation process. It states that both past and future observations are sampled identically and independently according to the same distribution. New observations yield maximum information. Through this phenomenon, algorithms can be constructed that are consistent. Predictions of the algorithms get closer and closer to the optimal result as more and more data is collected.

Computational Learning Theory

Computational Learning Theory (also called Learning Theory) is a branch of theoretical computer science, which studies how capable computer programs can learn and identify computational limits of learning by machines (Goldman, 2002). This theory is a research field focused on studying machine learning algorithms, which aims to make accurate predictions based on observations.

Artificial Neural Network (ANN) as a Forecasting tool

Several prior literatures concentrate on predicting stock returns using artificial intelligence techniques. One of the methods that is slowly becoming prominent is the Artificial Neural Network (ANN) which can be used to predict indices. Neural networks are designed to imitate "the fault- tolerance and learning capacity of biological neural systems". This type of Artificial Intelligence technique also recognizes hidden functional relationships in data (Zhang, Patuwo, & Hu, 1998). Several studies used various types of ANNs to accurately predict stock price returns and the direction of its movements. Yao et al. (1999) concludes that ANN obtained better results than ARIMA models in predicting stock returns. ANN has been demonstrated to provide promising results in predicting the stock price returns by Avci, 2007; Egeli, Ozturan, & Badur, 2003; Karaatli, Gungor, Demir, & Kalayci, 2005; Kimoto, Asakawa, Yoda, & Takeoka, 1990; Olson & Mossman, 2003; White, 1988; Yoon & Swales, 1991.

Leung et al. (2000) stated that classification models (discriminant analysis, logit, probit and probabilistic neural network) outperform the level estimation models (adaptive exponential smoothing, vector auto regression with Kalman filter updating, multivariate transfer function and multi-layered feed forward neural network) in terms of predicting the direction of the stock market movements and maximizing returns from investment trading. Chen et al. (2003) predicted the direction of return on the Taiwan Stock Exchange Index using ANN. Diler (2003) presented that the direction of the ISE 100 Index could be predicted at a rate of 60 to 81 % using ANN. Altay and Satman (2005) found that neural network models are able to predict the direction of stock market indices more accurately. Cao, Leggio, and Schniederjans (2005) demonstrated the accuracy of ANN in predicting stock price movement for firms traded on the Shanghai Stock Exchange (SHSE). They compared the capital asset pricing model (CAPM) and Fama and French's 3-factor model to the predictive power of univariate and multivariate neural network models. Their results showed that neural networks outperform the linear models. Enke & Thawornwong (2004) found ANN to be better than Exponential Smoothing. Although both are adaptive in modifying their answers as the market modifies its behaviour, ANN can still perform better. Gahanan (2008) reported that ANN demonstrated better performance than ARIMA in value forecasting. Moreover, Hansen et al. (n.d.) compared the performance of ANN and ARIMA models on time series predictions, and showed that ANN outperformed the latter. De Faria (2009) predicted the principal index of the Brazilian stock market through neural networks and adaptive exponential smoothing methods (AES) and found neural networks to be more effective. Dase and Pawar (2010) states that the application of ANN in stock prediction is more efficient and faster than other models even for considerably larger datasets. Ahangar, Yahyazadehfar and Pournaghshband (2010) compare Linear Regression and Exponential Smoothing to neural networks and states that the latter is faster compared to other models. Wijaya et al. (2010) conducts a comparative study for both models based on the Indonesian stock exchange and finds that ANN outperforms ARIMA. This claim is further supported by the study of Sterba and Hilovska (2010) stating the same. Lahmiri (2011) conducts a comparison of ANN and SVM in prediction of S&P500 index returns and shows that ANN performs better with technical indicators, while SVM performs best with macroeconomic information.

In other fields such as science, Bandyopadhyay and Chattopadhyay (2007) states that ANN outperforms Linear Regression Models in forecasting series of ozone layer data. Bocco, Willington, and Arias (2010) documents that ANN is a better model compared to times series models for solar radiation prediction.

Several researches utilize hybrids of several artificial intelligence (AI) techniques to predict stock market returns (Baba & Kozaki, 1992; Chu, Chen, Cheng, & Huang, 2009; Hiemstra, 1995; Kim & Chun, 1998; Leigh, Purvis, & Ragusa, 2002; Oh & Kim, 2002; Pai & Lin, 2005; Saad, Prokhorov, &Wunsch, 1998; Takahashi, Tamada, & Nagasaka, 1998; Tan et al., 2007; Yudong & Lenan, 2009). Tsaih, Hsu, and Lai (1998) applies a hybrid AI approach to predict the direction of daily price changes in S&P 500 stock index futures.

Support Vector Machine as a Forecasting tool

Recently, support vector machines (SVM) have been applied to predict stock returns and index movements (Shah (2007). The Support Vector Machine (SVM) is a predominant approach in especially, stock market direction predictions. SVM is known for its pattern recognition characteristics in data. Cao and Tay (2001) concluded that SVM provided more forecasting accuracy compared to Backpropagation Neural Networks. Lin (2004) finds that the structural risk minimization principle used in SVM achieves better performance and lowers risk of overfitting compared to Artificial Neural Network (ANN). Kim (2003) use SVM to predict the direction of daily stock price changes in the Korean composite stock price index (KOSPI). Experimental results prove that SVM outperforms back-propagation neural network (BPN) and case-based reasoning (CBR) and provide a promising alternative for stock market predictions. Manish and Thenmozhi (2005) shows that SVM outperforms other traditional models. Huang, Nakamori, and Wang (2005), compare SVM's performance with those of linear discriminant analysis, quadratic discriminant analysis and Elman backpropagation neural networks. Their results show that SVM outperforms other classification methods. Chen et al (2006) states that SVM performs better than ANN as it could predict four out of seven indices of the Taiwan stock exchange. Msiza, Nelwamondo and Marwala (2007) concludes that ANN has better performance in forecasting than SVM. Hsu, Hsieh, Chih, and Hsu (2009) develops a two-stage architecture by integrating self-organizing map and support vector regression for stock price predictions. They examine seven major stock market indices. Their results suggest that the two-stage architecture provides a promising alternative for stock return predictions (see Atsalakis and Valavanis (2009)). Shen, Jiang and Zhang (2012) use SVM to predict the NASDAQ, S&P500 and DJIA index returns garnering an accuracy rate of 74.4%, 76.0% and 77.6% respectively. Das and Padhy (2012) also concludes that SVM performs better than ANN. Madge (2015) shows that SVM has a low accuracy in short term predictions but an acceptable accuracy when long term predictions. Hence, apart from SVM's superior performance compared to traditional forecasting models several studies conclude that SVM performs better than ANN. The final part of the literature reviews the predictability of the Philippine stock exchange.

2.3 Predictability and Efficiency of the Philippine Stock Market

Prior literature on the predictability and subsequently the efficiency of the Philippine stock market contradicts one another. On one hand, several studies documents that the Philippine stock market is in weak form efficiency while on the other hand others state that the market is inefficient. Poshakwale S. (1996) confirms that the Philippine market along with India, Malaysia and Thailand are efficient in weak form. Aquino (2006) states that from July 1987 to May 2004, the Philippine stock market has been in weak-form efficiency. Guidi and Gupta (2011) documents that the Philippine stock market is inefficient using unit root tests, variance ratio tests, non-parametric and co-integration tests. The study further states that the Philippine index exhibits a long-memory process.

Lingaraja, Selva and Vasanth (2014), assess the volatility and efficiency of emerging stock markets, specifically those that are in the Southeast Asia region including Philippines. However, Chen and Diaz (2014) shows that the Philippine stock market is inefficient.

3. Data & Empirical Methodology

This study tests whether Artificial Neural Network (ANN) and Support Vector Machine (SVM) can forecast the following day's direction and value of the Philippine Stock Exchange indices. In addition, I assess the ability of each model in forecasting the direction and value of the indices, and compare which method is more accurate. While the earlier section reviews the prior literature on stock market predictability, related theories and applications of Artificial Intelligence systems to predicting stock returns. This section provides the sources and definitions of the variables used and the empirical methodology followed to implement the artificial intelligence systems to predict stock indices.

3.1 Data Definitions

The stock market data is obtained from the Philippines Stock Exchange and the rest from Data stream. Specific attention is given to selecting the input variables for the forecasting process from a large number of candidates. The most commonly used inputs are the stock index opening or closing price, as well as the daily highest and lowest values. These inputs support the statement that soft computing methods use simple input variables to provide predictions. Majority of prior literature use stock, index prices or an indicator depending on it as input variables[4]. The daily opening/closing price, the daily minimum/maximum price and, in some cases, the transaction volume are also used as input variables[5] in prior literature. In addition, several studies use the daily closing price in combination with the closing price of previous trading days (usually up to a week)[6].

Indices of the Philippine Stock Exchange (PSE) involves 8 stock indices. PSEi, All Shares Index, Financials Index, Holding Firms Index, Property Index, Industrial Index, Mining and Oil Index and Services Index. Hence, this study considers four input variables for each index. Daily high and low values, daily open and close index price and several macroeconomic variables such as political attribute[7], gold price and USD to Peso exchange rate[8]. Hence, the Political attribute dummy would contain a value of either 1 or 0. Days starting from the first day of the filing of candidacy to one month after the actual elections are represented with a value of 1.

[4]Bames et al. (2000), Donaldson and Kamstra (1999), Halliday (2004), Tan, Prokhorov, and Wunsch (1995), Pai and Lin (2005), Pantazopoulos et al. (1998), Perez-Rodriguez et al. (2004), Rast (1999), Rech (2002), Walczak (1999), Wang and Leu (1996), Zhang et al. (2004) and Zhongxing and Liting (1993).
[5]Ajith et al. (2003a), Ayob et al. (2001), Chandra and Reeb (1999), Chen et al. (2005a), Chun and Park (2005), Doesken, Abraham, Thomas, and Paprzycki (2005), Thammano (1999), Wang (2002) and Zhang et al. (2002).
[6]Andreou et al. (2000), Fernandez-Rodriguez et al. (2000), Pan et al. (2005), Tang, Xu, Wan, and Zhang (2002) and Atsalakis and Valavanis (2006b).
[7]Local Government Units (LGU) elections for Governors, Congressmen, etc. occur every 3 years for Local Government Units (LGU), while national elections for Presidents, Vice Presidents, Senators, occur every 6 years. According to Mahmood, et al. (2014), political events such as elections influences the stock market. Furthermore, a study conducted by Aquino (2004), states that news regarding political events as well as economic events in the Philippines affect the stock market.
[8]Lu, et al. (2012) analyse the interrelationship between Philippine Stock Exchange Index (PSEi) and USD to Peso exchange and documents a stable long-term relationship based on co-integration tests.

The inputs from years 2015 to 1st quarter of 2016 are used for both training and testing. Although there are several studies stating that more inputs can help improve the performance of the model, having fewer variables may lead to a more accurate and robust prediction. Moreover, this can avoid over fitting and possibilities of weakened outcomes from the data set. In terms of the frequency of data, majority of prior studies use daily data[9].

The above mentioned seven independent variables are used as inputs for Artificial Neural Network (ANN) and the Support Vector Machine (SVM) models. Following the data training step to predict the pattern, the ANN and SVM programs will subsequently forecast the indices of the Philippine Stock Exchange. Training the data in artificial intelligence involves processing or learning of the data inputs by the Artificial Intelligence (ANN and SVM) systems. Windowing involves the number of input days to forecast the next day closing prices. ANN1 depicts the inputs used in forecasting the next day closing price of the index through ANN from the previous trading day; SVM1 depicts inputs used in forecasting the next day stock price index through SVM from the previous trading day; ANN5 depicts inputs used in forecasting the next day stock price through ANN from the past 5 trading days; SVM5 depicts inputs used in forecasting the next day stock price index through SVM from the past 5 trading days; ANN5 depicts inputs used in forecasting the next day stock price through ANN from the past 30 trading days; SVM30 depicts inputs used in forecasting the next day stock price through SVM from the past 30 trading days;

3.2 Empirical Methodology for the Artificial Intelligence Framework

This section explains the steps involved in implementing the ANN and SVM models to predict the index returns. The flow of the process, on a per index basis is as follows: 1. Data Collection. 2. Training of Data. 3. Forecasting/Testing of Data. 4. Results Analysis. Daily data from 2010-2015 is used to train the models, while data from first quarter of 2016 is used to test the trained models. Each model is assessed using one, five, thirty-day windows and forecasted on a one day ahead basis. In more detail, for ANN1, SVM1, ANN5, SVM5, ANN30 and SVM30, the inputs used in forecasting the next day stock price indices are from the previous day, past 5 days and past 30 days before the forecasting day respectively. Following the training and testing of the ANN and SVM models, the study analyse the results and move on forecasting accuracy.

Forecasting performance measures are generally categorized into statistical and non-statistical measures. Statistical measures include the root mean square error (RMSE), the mean absolute error (MAE) and the mean squared prediction error (MSPE). Non-statistical performance measures include the Hit-Miss and Direction Symmetry Test that measures the percentage of correct predictions and the direction of the same. This study implements the following tests to gauge forecasting model performance: Paired T-test, RMSE/MAE/MAPE, Hit-Miss and the Direction Symmetry Test.

[9]Chaturvedi and Chandra (2004) uses only 40 observations, Koulouriotis et al. (2005) uses 2000 observations, Thawornwong and Enke (2004) uses 24 years of data, Kanas and Yannopoulos (2001) uses 21 years of data and Atsalakis and Valavanis (2006a) uses 18 years of daily data.

The first three tests determine the accuracy of ANN and SVM in forecasting while the last test determine the accuracy of forecasting the direction of each index. For the Paired T-test, statistical insignificance is desirable as it shows more accuracy when significance is higher than 5%. For RMSE, MAE and MAPE, models with the least mean would provide the most accurate results and the opposite for Hit-Miss and Direction Symmetry Test. Following section discusses the training and testing of Artificial Neural Network (ANN) model followed by the Support Vector Machine (SVM).

Training and Testing of Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a computational model composed of artificial neurons, which are activated when they receive strong signals through synapses located on the membrane of the neuron. These signals are then emitted through the axons, and sent to another synapse that activates other neurons. The activation of the neuron is determined through a mathematical function which is computed by inputs (like synapses) multiplied by weights (strengths of the signals).

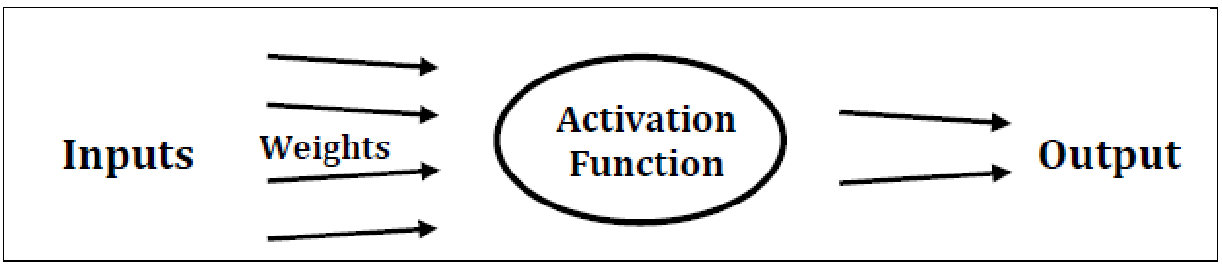

Figure 1

The strength of the input will be affected by how high the weight of an artificial neuron is – the higher (lower) the weight, the stronger (weaker) the input will be. However, negative weights can also exist which will cause the signal to be inhibited. The computation of the neurons is dependent on the weights. The outputs expected for specific inputs can be obtained by adjusting the weights of an artificial neuron. Since ANNs are composed of hundreds or thousands of neurons, identifying the necessary weight is complicated. Here in lies the primary reason to adjust the weights in algorithms, which is called learning or training. Backpropagation, one of the most common algorithms used in ANN is used in this study for learning the appropriate adjusted weights.

Backpropagation Algorithm for ANN

According to Rumelhart and McClelland (1986), backpropagation algorithms are used in layered feed forward Artificial Neural Networks. Backpropagation algorithms organize the artificial neurons in layers, sending signals “forward”, and then sending the errors backwards. The inputs are received by neurons in the input layer, and the outputs in the output layer. There could be one or more intermediate hidden layers in between. This type of algorithms uses supervised learning, wherein inputs and outputs are provided, and the error is calculated.

It repeatedly adjusts the weights of the neurons to minimize the error, which is the difference between the actual output and the desired output. The activation function of the artificial neurons in ANN through backpropagation algorithm is computed by the weighted sum of the inputs x_i multiplied by their respective weights:

$$A(\bar{x}, \bar{w}) = \sum_{i=0}^{n} x_t \,, w_{ji} \qquad (1)$$

Where: x_{i} = Inputs

w_{ji} = Weights

The activation depends only on the inputs and the weights, and not on the output. The neuron will be considered linear if the output function is identical to the activation. The most common output function is the sigmoidal function, which allows a smooth transition between the low and high outputs of the neuron (close to zero or close to one). Output depends on the activation, which in turn depends on the inputs and their respective weights.

$$O(\bar{x}, \bar{w}) = 1/(1+e^{A(\bar{x}, \bar{w})}) \qquad (2)$$

Where: x = Inputs

w = Weights

The goal of the training process is to obtain a desired output whenever certain inputs are given. The error (difference between the actual and the desired output), depends on the weights, hence the algorithm needs to adjust the weights in order to minimize the error. The sum of the errors of all the neurons in the output layers is the error of the network (error function):

$$E_j(\bar{x}, \bar{w}, d) = \Sigma_j(O_j(\bar{x}, \bar{w}) - d_j)^2 \qquad (3)$$

Where: O_j = Actual output

d_j = Desired output

The backpropagation algorithm then calculates how the error is dependent on the output, inputs, and weights. The weights can be adjusted afterwards by using the gradient descendent method:

$$\Delta w_{\mathrm{i,j}} = -\eta \, \partial E / \partial \, w_{\mathrm{i,j}} \qquad (4)$$

Where: η = Eta (learning parameter)

∂E = Error

In the equation shown above, the adjustment of the weights depends on the eta (η) and the contribution of the weight to the error function. The adjustment of the weight is greater if the weight contributes significantly to the error. This equation is used until the most appropriate weight (minimal error) is found.

The goal of back propagation algorithm is to find the derivative of E in respect to the actual output. Firstly, one should figure out what percentage of the error depends on the required output, which is the derivative E with respect to O_j.

$$\partial E/\partial O_j = 2(O_j - d_j) \qquad (5)$$

Where: ∂E = Error

O_j = Actual output

d_j = Desired output

Secondly, what percentage of the output depends on the activation, which in turn depends on the weights.

$$\partial O_j/\partial w_{ji} = (\partial O_j/\partial A_j)*(\partial A_j/\partial w_{ji})= O_j(1 - O_j)\, x_i \qquad (6)$$

Where: O_j = Actual output

w_{ji} = Weights

A_j = Activation function

x_i = Inputs

Combining equations 5 and 6 gives the interrelation among the output, error and the activation function.

$$\partial E/\partial wji=(\partial E/\partial O\text{j}).(\partial Oj/\partial wji)= 2(Oj- dj)(1 - Oj)xi \qquad (7)$$

Where: Where: ∂E = Error

Oj = Actual output

wji = Weights

= Desired output

xi = Inputs

Hence, the adjustment to each weight given in equations 4 and 7 is:

$$\Delta_{w_{ji}} = -2\eta(O_j - d_j)O_j(1 - O_j)x_i \quad (8)$$

Where: η = Eta (learning parameter)

O_j = Actual output

d_j = Desired output

x_i = Inputs

This equation is used until the minimum error is found. Equation 8 is used to train ANN with two layers. Hence, it is important to calculate how the error depends on the input from the previous layer and not on the weight. Now I move on to the SVM model.

Training and Testing of the Support Vector Machine (SVM)

According to Kim (2003), Support Vector Machine (SVM) allows nonlinear class boundaries to be implemented in a linear model by plotting the nonlinear input vectors into a high-dimensional space. The nonlinear decision boundary in the original space is represented by the constructed linear model in the new space. Hence, SVM is known to create a special type of linear model which is the maximum margin hyperplane that separates and classifies points in a hyper-dimension. The maximum margin hyperplane limits the separation between the decision classes. Support vectors are the training examples that has the lowest variance or distance from the maximum margin hyperplane. A hyperplane that divides the binary decision classes in the three-attribute cases is as follows:

$$y = \ _0 + w_1x_1 + w_2x_2 + w_3x_3 \quad (9)$$

Where: y = Variable outcome

w = Weights that are needed to be learned by the algorithm

x = Attributes value

In Equation 9, the weights are parameters that will determine the hyperplane. The maximum margin hyperplane is given in the following equation regarding the support vector:

$$y = \text{b}+\Sigma\alpha_i\, y_i\, \text{x}(i)\cdot\text{x} \qquad (10)$$

Where: yi = Class value of training example

xi = Training sample

x = Test examples

b, α = Parameters

This equation gives the support vectors and the parameters b and α_i solving a linearly constrained quadratic program. A higher dimensional version of the previous equation is used for cases that are nonlinearly separable as shown below:

$$y = \text{b}+ \Sigma\ \alpha_i y_i \text{K}(\text{x}(i),\text{x}) \qquad (11)$$

Where: y_i = Class value of training example

x_i = Training sample

x = Test examples

b, α_i = Parameters

There are different kinds of kernels for producing inner products to build machines with various types of nonlinear decision surfaces in the input space. Among the different kernels, the model that minimizes the estimated error would be selected.

4. Empirical Results

The previous section discusses the empirical steps in implementing artificial intelligence systems to predict index returns. This section explains the results from the empirical analysis. To test ANN and SVM model accuracy this study implements the following tests: Paired T- test, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Hit-Miss and Direction Symmetry Test. Additional robustness results for the individual indices along with the Artificial Intelligence model forecasts are available upon request.

4.1 Paired T-Test Results

The aim of the Paired t-test is to obtain a statistical significance higher than 5% which shows that the means of the pairs are insignificant from each other. This implies that there is no statistically significant difference between the means of the actual and the predicted values. Refer Tables 2 to 9 for individual results for each index[10].

Table 10: Summary of Paired T-tests for all indices

Actual - Actual closing price of the index. ANN1- Forecasted closing price of the index using ANN with 1-day windowing. SVM1- Forecasted closing price of the index using SVM with 1-day windowing. ANN5- Forecasted closing price of the index using ANN with 5-day windowing. SVM5- Forecasted closing price of the index using SVM with 5-day windowing. ANN30- Forecasted closing price of the index using ANN with 30-day windowing. SVM30- Forecasted closing price of the index using SVM with 30-day windowing.

		PSEi	All Shares	Financials	Industrial	Holding Firms	Services	Mining and Oil	Property
Pair 1	**Actual – SVM1**	0.50*	0.79*	0.00	0.96*	0.00	0.29*	0.18*	0.00
Pair 2	**Actual – SVM5**	0.50*	0.79*	0.00	0.96*	0.00	0.294*	0.18*	0.00
Pair 3	**Actual – SVM30**	0.50*	0.79*	0.00	0.96*	0.00	0.294*	0.18*	0.00
Pair 4	**Actual – ANN1**	0.00	0.00	0.08*	0.08*	0.00	0.00	0.23*	0.00
Pair 5	**Actual – ANN5**	0.01	0.00	0.08*	0.00	0.00	0.67*	0.00	0.13*
Pair 6	**Actual – ANN30**	0.75*	0.00	0.02	0.06*	0.78*	0.05*	0.00	0.55*

[10]According to Table 2, pairs 1, 2, 3 and 6 are forecasted accurately as they are statistically insignificant. This implies that their forecasted values have little to 0 difference with the actual values. Table 3 shows that pairs 1, 2, and 3 are forecasted accurately as they are statistically insignificant with 0.794, 0.795 and 0.794 significance, respectively. This implies that their forecasted values are very similar to the actual values. Table 4 shows that pairs 4 and 5 are forecasted accurately as they are statistically insignificant with 0.08 significance. Table 5 shows that pairs 1, 2, 3, 4 and 6 are forecasted accurately as they were statistically insignificant with 0.964, 0.964, 0.963, 0.081 and 0.062 significance, respectively. Table 6 shows that only pair 6 is forecasted accurately as it is statistically insignificant with 0.785 significance. Table 7 shows that pairs 1, 2, 3, 5 and 6 are forecasted accurately as they are statistically insignificant with 0.294, 0.294, 0.294, 0.669 and 0.054 significance, respectively. Table 8 shows that pairs 1, 2, 3 and 4 are the most accurate as they are statistically insignificant with 0.179, 0.179, 0.179 and 0.226 significance, respectively. Table 9 shows that pairs 5 and 6 are forecasted accurately as they are statistically insignificant with 0.126 and 0.554 significance, respectively.

Table 10 shows that there are selected pairs with a significance higher than 5%, which indicates statistical insignificance. This shows that statistically insignificant pairs have the possibility of having little to 0 residuals - implying higher accuracy in forecasting actual values. According to Table 10, SVM1, SVM5, and SVM30 demonstrate consistency in its accuracy in forecasting values. PSEi, All Shares, Industrial, Services and Mining and Oil indices are consistently insignificant in pairs 1 to 3. Financials, Holding Firms, and Property indices, on the other hand, consistently show significance which means that these indices are forecasted with low accuracy using SVM. In contrast, ANN forecasts appear to be inconsistent. Pair 4 is statistically insignificant for Financials, Industrial and Mining & Oil indices. This translates to ANN having high accuracy in forecasting the three indices with inputs from the previous trading day. Pair 5 is insignificant in the Financials, Services and Property indices which means that ANN can accurately forecast with inputs from the past 5 trading days. Finally, pair 6, is insignificant for PSEi, Industrial, Holding, Property and Services indices which can be forecasted accurately using ANN with inputs from the past 30 trading days. Consequently, this study deduces that Artificial Neural Networks (ANN) forecasts which use 30-day inputs and Support Vector Machine (SVM) forecasts which use 1, 5 and 30-day inputs prior to the forecasting day have the highest accuracy for 5 out of 8 indices.

While ANN1 and ANN5 can forecast three indices each. All indices of the PSE can be forecasted by at least one model. Out of the 8 indices of the Philippine Stock Exchange, Industrial and Services indices is forecasted accurately by most of the models while the Holding Firms index is forecasted by only one model (ANN30). PSEi and Mining and Oil index is forecasted by four different models and All Shares Index by SVM. Finally, Property and Financials indices are forecasted by two models each.

ANN can accurately forecast 7 out of 8 indices of the PSE. ANN30 is insignificant in predicting PSEi, Industrial, Holding Firms, Services, and Property indices. However, ANN5 is insignificant in the Financials index, while ANN1 is insignificant in Mining and Oil. This shows that All Shares is the only index ANN is unable to forecast with high accuracy while SVM is unable to accurately forecast 3 out of the 8 indices. Thus, this study concludes based on the Paired T-test results, ANN performs better than SVM in forecasting Philippine stock indices.

4.2 RMSE, MAE, MAPE Results

The tables below provide an overview of the mean for each sector of the Philippine Stock Exchange Index based on the error measures, RMSE, MAE and MAPE. The mean is simply the average value of all the predicted errors of the models compared to the actuals. Kumar and Thenmozhi (2011) used the same error measures to check the accuracy of the models. Lowest mean represents higher accuracy of the predicted value to the actual. Refer Tables 11 to 18 for individual results for each index[11].

[11]Table 11 shows that ANN30 is the most accurate among all the tested models for PSEi, having the lowest RMSE, MAE and MAPE of 9428.71, 74. 92 and 1.13% respectively. ANN30 generated the closest predicted values to the actual values. Table 12 shows that SVM5 is the most accurate

Table 19: Summary of RMSE, MAE and MAPE Results for all indices

***- Lowest mean from tests RMSE, MAE & MAPE. **- Lowest mean from tests MAPE and MAE

*- Lowest mean from RMSE.

AI Model	PSEi	All Shares	Financials	Industrial	Holding Firms	Services	Mining and Oil	Property
SVM1								
SVM5		**						
SVM30								
ANN1			***	**			***	
ANN5			***			*		***
ANN30	***	*		*	***	**		

Table 19 shows the summary of the best forecast results for the eight indices in the Philippine Stock Exchange. It is evident that Artificial Neural Network (ANN) performs better than Support Vector Machine in forecasting. Based from the above results, all indices are accurately forecasted by at least one of the two models with different time windows. RMSE, MAE and MAPE gives consistent results for five out of eight indices. Namely: PSEi, Financials, Holding Firms, Mining and Oil, and Property indices. ANN1 generate higher accuracy in Financials and Mining and Oil indices and ANN5 generate higher accuracy in Financials and Property indices. Finally, ANN30 generate higher accuracy in PSEi and the Holding Firms index. Based on the above results, seven out of eight indices are predicted more accurately by ANN compared to SVM. These seven indices are: PSEi, Industrials, Financials, Holding Firms, Services, Mining & Oil and Property. ANN1 has the lowest mean compared to ANN5 and ANN30 which are more accurate. PSEi and All shares are predicted more accurately by SVM30 than SVM1. Table 19 shows that SVM results in higher accuracy performance for the All Shares index only. Financials index is forecasted with least errors by ANN1 and ANN5. The results of the study generally support similar findings from Msiza, Nelwamondo and Marwala (2007) and Das and Padhy (2012) wherein it is stated that ANN performs better than SVM and contradicts Cao and Tay (2001), Chen et al (2006) and Huang, Nakamori and Wang (2005) who conclude that SVM performs better than ANN.

among all the tested models for All Shares Index having the lowest MAE and MAPE of 39.40 and 1.03% respectively, while ANN30 has the lowest mean of 2571.90 for RMSE. Table 13 shows that ANN1 and ANN5 are the most accurate among all the tested models for the Banking and Finance Index having the lowest RMSE, MAE and MAPE of 295.15, 13.60 and 0.90% respectively. ANN1 and ANN5 generate the closest predicted values to the actual values. Table 14 shows that ANN1 is the most accurate among all the tested models for Industrial Index having the lowest MAE and MAPE of 99.03 and 0.92%, respectively. While ANN30 has the lowest mean for RMSE with 15644.56. ANN1 generate the closest predicted values to the actual values. Table 15 shows that ANN30 is the most accurate among all the tested models for Holding Firms Index having the lowest RMSE, MAE and MAPE of 10670.45, 79.47 and 1.25% respectively. ANN30 generate the closest predicted values to the actual values. Table 16 shows that ANN30 is the most accurate among all the tested models for Services Index having the lowest MAE and MAPE of, 24.12 and 1.67% respectively. ANN5 generate the lowest mean of 1187.79 for RMSE. ANN30 generated the closest predicted values to the actual values. Table 17 shows that ANN1 is the most accurate among all the tested models for Mining and Oil Index having the lowest RMSE, MAE and MAPE of 55443.09, 182.24 and 1.82% respectively. ANN1 generate the closest predicted values to the actual values. Table 18 shows that ANN5 is the most accurate among all the tested models for Property Index having the lowest RMSE, MAE and MAPE of 2767.34, 39.36 and 1.47% respectively, while ANN30 has the lowest mean for RMSE. ANN5 generate the closest predicted values to the actual values.

4.3 Hit-Miss Test Results

Hit-miss test measures how many times the residuals hit the 5% error. If the error is less than 5%, it will be counted as 1 and otherwise 0. One indicates an acceptable range of error, showing that the model has a high accuracy in forecasting. The mean, on the other hand, indicates the number of hits of 1 over the number of occurrences. A minimum of 0 means that the model forecasted results with an error of more than 5%. A maximum of 1 indicates that the model forecasted outputs with an error of less than 5%.

Refer Tables 20 to 27 for individual results for each index[12].

Table 28: Summary of Hit-Miss test results for all indices.

* - has a minimum and maximum hit of 1.

	PSEi	All Shares	Financials	Industrial	Holding Firms	Services	Mining and Oil	Property
SVM1	0.97	1.00*	1.00*	0.97	0.17	0.95	0.58	0.97
SVM5	0.97	1.00*	1.00*	0.97	0.17	0.95	0.58	0.97
SVM30	0.97	1.00*	1.00*	0.97	0.17	0.95	0.58	0.97
ANN1	0.98	1.00*	1.00*	1.00*	0.97	0.95	0.95	0.97
ANN5	1.00*	1.00*	1.00*	1.00*	1.00*	0.97	0.92	0.98
ANN30	1.00*	1.00*	1.00*	1.00*	1.00*	0.97	0.85	0.97

[12]Table 20 shows that ANN5 and ANN30 produce highest accuracy in forecasting the PSEi because the forecasted values do not go above 5% error, indicating 1 in both minimum and maximum. Both models have means that is 100%, implying that there is 0% possibility of it going above 5% error. Table 21 shows that all models produced highest accuracy in forecasting the All Shares Index because the forecasted values do not go above 5% error, indicating 1 in both minimum and maximum. All models have means that is 100%, implying that there is 0% possibility of it going above 5% error. Table 22 shows that all models produce highest accuracy in forecasting the Financials Index because the forecasted values do not go above 5% error, indicating 1 in both minimum and maximum. All models have means that is 100%, implying that there is 0% possibility of it going above 5% error. Table 23 shows that all ANN models (ANN1, ANN5, ANN30) have the highest accuracy in forecasting the Industrial Index because the forecasted values do not go above 5% error, indicating 1 in both minimum and maximum. ANN models have means that is 100%, implying that there is 0% possibility of it going above 5% error. Table 24 shows that ANN5 and ANN30 have the highest accuracy in forecasting because the forecasted values do not go above 5% error, indicating 1 in both minimum and maximum. Both models have means that is 100%, implying that there is 0% possibility of it going above 5% error. Table 25 shows that all models have a minimum of 0 and a maximum of 1. This implies that they have the possibility of having a forecasting error that is greater than 5%. 97% of all occurrences, ANN5 and ANN30 hit an error less than 5%. Hence, implying both models have higher accuracy compared to other models. Table 26 shows that all models have a minimum of 0 and a maximum of 1. This implies that they have the possibility of having a forecasting error that is greater than 5%. 95% of all occurrences, ANN1 hits an error less than 5%. Hence, implying a higher accuracy result compared to other models. Table 27 shows that all models have a minimum of 0 and a maximum of 1. This implies that they have the possibility of having a forecasting error that is greater than 5%. 98% of all occurrences, ANN5 hit an error less than 5%. Hence, implying a higher accuracy result compared to other models.

Models with a minimum and maximum of 1 indicate higher accuracy in forecasting as it lies on an acceptable range of errors (0%-5%). While models that have a minimum of 0 and maximum of 1 indicate lesser accuracy since the errors have a possibility of exceeding 5%. Table 28 shows the summary of results gathered from the Hit Miss test. ANN5 and ANN30 can accurately forecast most of the indices. Namely: PSEi, All Shares, Financials, Industrial and Holding Firms indices. ANN1 forecasts All Shares, Financials and Industrial indices. SVM1, SVM5, and SVM30 can forecast All Shares and Financials index. Hence, All Shares and Financials indices are consistently forecasted by all models. Therefore, the above results show that Artificial Neural Network (ANN) produces higher means compared to Support Vector Machines (SVM) regardless of the time window used for forecasting. Hence, ANN again performs better compared to SVM according to the Hit Miss Test.

4.4 Direction Symmetry Test Results

The Direction Symmetry Test is a statistical measure to assess whether the two models, ANN and SVM can accurately forecast the direction of the eight indices of the Philippine Stock Exchange. The values used in the Direction Symmetry test are binary numbers (0, 1). Numerical value of one (1) is used to determine whether the direction of the predicted values is the same as the actual direction and zero (0) otherwise. The mean shows the percentage of times the models accurately predicted the direction of the actual indices. The study considers the models with the highest mean as the better forecasting model. Refer Tables 29 to 36 for individual results for each index[13].

Table 37: Summary of Direction Symmetry test.
* - has the highest produced mean

	PSEi	All Shares	Financials	Industrial	Holding Firms	Services	Mining and Oil	Property
SVM1	0.38	0.41	0.52	0.43*	0.48	0.45*	0.57*	0.47*
SVM5	0.38	0.41	0.52	0.43*	0.48	0.45*	0.57*	0.47*
SVM30	0.38	0.41	0.52	0.43*	0.48	0.45*	0.57*	0.47*
ANN1	0.43	0.43	0.59*	0.4	0.50*	0.43	0.48	0.41
ANN5	0.43	0.45*	0.59*	0.4	0.50*	0.43	0.5	0.41
ANN30	0.45*	0.43	0.57	0.4	0.50*	0.43	0.48	0.43

[13]Table 29 shows that ANN30 produce 0.45, which is the highest mean, indicating a higher possibility of the predicted direction to move the same as the actual direction. Table 30 shows that ANN5 produce 0.45, which is the highest mean, indicating a higher possibility of the predicted direction to move the same as the actual direction. Table 31 shows that ANN1 and ANN30 produce 0.59, which is the highest mean, indicating a higher possibility of the predicted direction to move the same as the actual direction. Table 32 shows that SVM1, SVM5 and SVM30 produce 0.43, which is the highest mean, indicating a higher possibility of the predicted direction to move the same as the actual direction. Table 33 shows that ANN1, ANN5 and ANN30 produce 0.50, which is the highest mean, indicating a higher possibility of the predicted direction to move the same as the actual direction. Table 34 shows that SVM1, SVM5 and SVM30 produce 0.45, which is the highest mean, indicating a higher possibility of the predicted direction to move the same as the actual direction. Table 35 shows that SVM1, SVM5 and SVM30 produce 0.57, which is the highest mean, indicating a higher possibility of the predicted direction to move the same as the actual direction. Table 36 shows that SVM1, SVM5 and SVM30 produce 0.47, which is the highest mean, indicating a higher possibility of the predicted direction to move the same as the actual direction.

The above table shows the summary results from the Direction Symmetry test. Models with a minimum and maximum of 1 indicate higher accuracy in forecasting as it shows less deviations from the actual direction. However, as seen from the above results no model can produce a minimum or maximum of 1. In more detail, a higher mean indicates most of times the model correctly predicts the direction of the index. SVM produce consistent results for all models. However, ANN performs better in forecasting the following indices: PSEi, All Shares, Financials, and Holding Firms indices. While SVM, better forecasts the following indices: Industrial, Services, Mining, Oil and Property with higher accuracy[14]. However, ANN1 and ANN5 can better forecast the direction of the indices with an accuracy of 0.59 for the Financials index. The highest mean generated by all models is 0.59 for various time windows.

Finally, in sum, for the Paired T-test, ANN perform better than SVM for seven out of eight PSE indices. However, SVM is more consistent across different time windows compared to ANN as evident from the Hit-Miss and Direction Symmetry Tests. Subsequently, RMSE, MAE and MAPE test results show that ANN perform better compared to SVM because it provides minimum errors. The Hit-Miss test also supports the accuracy of ANN over SVM. Hence, based on the above results the study concludes that Artificial Neural Network (ANN) is more accurate in forecasting the values of the different indices.

While the first three tests generate fair results, the Direction Symmetry test results in low accuracy. Both ANN and SVM produce low accuracy in forecasting the direction of index movements. However, compared to SVM, ANN generate higher means indicating higher accuracy. Hence, ANN demonstrate better predictability than SVM in forecasting the value and direction of the indices of the Philippine Stock Exchange index. Out of the three ANN models, ANN30 performs better compared to other models with different time windows. The test results show that all indices can be forecasted by at least one Artificial Intelligence model. Industrial, Financials, and Holding Firm indices show consistent predictability using ANN, while All Shares index, shows consistent predictability using SVM. Hence, this study concludes that the Philippine stock market is indeed predictable and inefficient. Some sectors (Industrial and Financials) are more predictable compared to others, implying variation of predictability and subsequent forms of efficiency across sectors.

[14]The reason for having low accuracy in forecasting is that machine learning adjusts to new prices. Hence, if the model predicts an upward price movement and the actual direction is a downward price movement, it will adjust by predicting the next price movement as a downward movement. This will result in heavier weights placed on the new inputs for the model to adjust accurately to the actual value. Hence, based on the Direction Symmetry test, the means produced by all models are relatively low. This indicates that the model predicts the actual direction with lower accuracy.

5. Conclusion

To summarize, this study's main purpose is to investigate whether Artificial Intelligence models such as Artificial Neural Network (ANN) and Support Vector Machines (SVM) can forecast various indices of the Philippine Stock Exchange. The performances of both models are assessed using 1, 5 and 30-day time windows. The following tests are conducted to test the accuracy of the Artificial Intelligence models' forecasting ability. Namely: Paired T-Test, RMSE/MAPE/MAE, Hit-Miss and Direction Symmetry Test. The first three tests are used to assess the ability of the models in forecasting the value of the indices, while the last test is used to assess the ability of the models in forecasting the direction of the index movements.

The conclusions from the empirical tests proposed here is that Artificial Neural Network (ANN) and Support Vector Machine (SVM) are indeed able to forecast the value and direction of the different indices of the Philippine Stock Exchange. However, ANN performs better in forecasting the value and direction of the next day's closing price compared to SVM. This study further concludes that one-day ahead time window is a better forecasting period compared to other time windows. Moreover, ANN and SVM, respectively, have high accuracy of predicting with a forecasting error of less than 5%. Out of the three ANN models implemented, ANN30 performs better compared to other models with different time windows. The test results show that all indices can be forecasted by at least one Artificial Intelligence model. Industrial, Financials, and Holding Firm indices show consistent predictability using ANN, while All Shares index, shows consistent predictability using SVM.

Finally, this study concludes that the Philippine stock market is indeed predictable and inefficient. Some sectors (Industrial and Financials) are more predictable compared to others, implying variation of predictability and subsequent forms of efficiency across sectors.

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Appendix 1

Table 2: Paired T-Test results for PSEi

Actual - Actual closing price of the index. ANN1- Forecasted closing price of the index using ANN with 1-day windowing. SVM1- Forecasted closing price of the index using SVM with 1-day windowing. ANN5- Forecasted closing price of the index using ANN with 5-day windowing. SVM5- Forecasted closing price of the index using SVM with 5-day windowing. ANN30- Forecasted closing price of the index using ANN with 30-day windowing. SVM30- Forecasted closing price of the index using SVM with 30-day windowing.

		Mean	Std. Deviation	t	Sig. (2-tailed)
Pair 1	**Actual – SVM1**	-38.29	147.23	-1.99	0.50
Pair 2	**Actual – SVM5**	-38.29	147.23	-1.99	0.50
Pair 3	**Actual – SVM30**	-38.29	147.23	-1.99	0.50
Pair 4	**Actual – ANN1**	-51.22	98.44	-3.99	0.00
Pair 5	**Actual – ANN5**	33.01	97.33	2.60	0.01
Pair 6	**Actual – ANN30**	4.00	97.88	.31	0.75

*T*able 3: Paired T-Test results on All Shares Index

		Mean	Std. Deviation	t	Sig. (2-tailed)
Pair 1	**Actual – SVM1**	1.82	53.36	.26	.79
Pair 2	**Actual – SVM5**	1.81	53.36	.26	.79
Pair 3	**Actual – SVM30**	1.81	53.36	.26	.79
Pair 4	**Actual – ANN1**	26.35	47.68	4.24	.00
Pair 5	**Actual – ANN5**	41.94	47.73	6.75	.00
Pair 6	**Actual – ANN30**	12.87	47.46	3.05	.00

Table 4: Paired T-Test results on Financials Index

		Mean	Std. Deviation	t	Sig. (2-tailed)
Pair 1	**Actual – SVM1**	9.03	19.10	3.63	.00
Pair 2	**Actual – SVM5**	9.03	19.10	3.63	.00
Pair 3	**Actual – SVM30**	9.03	19.10	3.63	.00
Pair 4	**Actual – ANN1**	3.91	16.89	1.78	.08
Pair 5	**Actual – ANN5**	3.91	16.89	1.78	.08
Pair 6	**Actual – ANN30**	5.33	17.13	2.40	.01

Table 5: Paired T-Test results on Industrial Index

		Mean	Std. Deviation	t	Sig. (2-tailed)
Pair 1	**Actual – SVM1**	1.78	300.13	.04	.96
Pair 2	**Actual – SVM5**	1.78	300.13	.04	.96
Pair 3	**Actual – SVM30**	1.81	300.09	.04	.96
Pair 4	**Actual – ANN1**	28. 57	123.43	1.77	.08
Pair 5	**Actual – ANN5**	145.21	121.69	9.16	.00
Pair 6	**Actual – ANN30**	30.35	122.44	1.90	.06

Table 6: Paired T-Test results on Holding Firms Index

		Mean	Std. Deviation	t	Sig. (2-tailed)
Pair 1	**Actual – SVM1**	517.67	29.35	17.63	.00
Pair 2	**Actual – SVM5**	517.67	29.35	17.63	.00
Pair 3	**Actual – SVM30**	517.67	29.35	17.63	.00
Pair 4	**Actual – ANN1**	-71.39	13.62	-5.24	.00
Pair 5	**Actual – ANN5**	47.69	13.53	3.52	.00
Pair 6	**Actual – ANN30**	3.71	13.54	.27	.78

Table 7: Paired T-Test results on Services Index

		Mean	Std. Deviation	t	Sig. (2-tailed)
Pair 1	**Actual – SVM1**	4.81	34.95	1.05	.29
Pair 2	**Actual – SVM5**	4.81	34.95	1.05	.29
Pair 3	**Actual – SVM30**	4.81	34.95	1.05	.29
Pair 4	**Actual – ANN1**	-24.24	34.75	-5.35	.00
Pair 5	**Actual – ANN5**	-1.94	34.72	-.43	.66
Pair 6	**Actual – ANN30**	-8.73	34.09	-1.96	.05

Table 8: Paired T-Test results on Mining and Oil Index

		Mean	Std. Deviation	t	Sig. (2-tailed)
Pair 1	**Actual – SVM1**	-108.44	612.86	-1.35	.17
Pair 2	**Actual – SVM5**	-108.45	612.84	-1.35	.17
Pair 3	**Actual – SVM30**	-108.44	612.86	-1.35	.17
Pair 4	**Actual – ANN1**	-37.32	234.47	-1.22	.22
Pair 5	**Actual – ANN5**	-151.47	218.85	-5.31	.00
Pair 6	**Actual – ANN30**	329.57	226.25	11.18	.00

Table 9: Paired T-Test results on Property Index

		Mean	Std. Deviation	t	Sig. (2-tailed)
Pair 1	**Actual – SVM1**	30.56	57.00	4.11	.00
Pair 2	**Actual – SVM5**	30.56	57.00	4.11	.00
Pair 3	**Actual – SVM30**	30.56	57.00	4.11	.00
Pair 4	**Actual – ANN1**	-32.71	52.05	-4.82	.00
Pair 5	**Actual – ANN5**	-10.49	51.95	-1.55	.12
Pair 6	**Actual – ANN30**	-4.14	53.48	-.59	.55

Table 10: Summary of Paired T-tests

		PSEi	All Shares	Financials	Industrial	Holding Firms	Services	Mining and Oil	Property
Pair 1	**Actual – SVM1**	0.50*	0.79*	0.00	0.96*	0.00	0.29*	0.18*	0.00
Pair 2	**Actual – SVM5**	0.50*	0.79*	0.00	0.96*	0.00	0.294*	0.18*	0.00
Pair 3	**Actual – SVM30**	0.50*	0.79*	0.00	0.96*	0.00	0.294*	0.18*	0.00
Pair 4	**Actual – ANN1**	0.00	0.00	0.08*	0.08*	0.00	0.00	0.23*	0.00
Pair 5	**Actual – ANN5**	0.01	0.00	0.08*	0.00	0.00	0.67*	0.00	0.13*
Pair 6	**Actual – ANN30**	0.75*	0.00	0.02	0.06*	0.78*	0.05*	0.00	0.55*

Table 11: RMSE, MAE and MAPE results on PSEi

	RMSE	**MAE**	**MAPE**
SVM1	22771.48	117.70	.017
SVM5	22771.48	117.70	.017
SVM30	22771.48	117.70	.017
ANN1	12137.44	85.11	.012
ANN5	10399.76	83.26	.012
ANN30	9428.71	74.94	.011

Table 12: RMSE, MAE and MAPE results on All Shares Index

	RMSE	**MAE**	**MAPE**
SVM1	2801.20	39.40	.010
SVM5	2801.20	39.40	.010
SVM30	2801.20	39.40	.010
ANN1	2931.24	44.67	.011
ANN5	4000.03	55.15	.014
ANN30	2571.90	40.97	.010

Table 13: RMSE, MAE and MAPE results on Financials Index

	RMSE	MAE	MAPE
SVM1	440.28	16.97	.01
SVM5	440.28	16.97	.01
SVM30	440.28	16.97	.01
ANN1	295.15	13.60	.00
ANN5	295.15	13.60	.00
ANN30	315.00	14.23	.00

Table 14: RMSE, MAE and MAPE results on Industrial Index

	RMSE	MAE	MAPE
SVM1	88499.24	257.38	.02
SVM5	88499.25	257.38	.02
SVM30	88499.24	257.38	.02
ANN1	15788.96	99.031	.00
ANN5	35617.21	166.81	.01
ANN30	15644.56	99.48	.00

Table 15: RMSE, MAE and MAPE results on Holding Firms Index

	RMSE	MAE	MAPE
SVM1	317979.90	518.93	.07
SVM5	317979.90	518.93	.07
SVM30	317979.90	518.93	.07
ANN1	15891.62	103.50	.01
ANN5	12898.27	90.57	.01
ANN30	10670.45	79.47	.01

Table 16: RMSE, MAE and MAPE results on Services Index

	RMSE	MAE	MAPE
SVM1	1221.86	25.62	.01
SVM5	1221.86	25.62	.01
SVM30	1221.86	25.62	.01
ANN1	1775.13	30.87	.02
ANN5	1187.79	25.24	.01
ANN30	1218.43	24.11	.01

Table 17: RMSE, MAE and MAPE results on Mining and Oil Index

	RMSE	**MAE**	**MAPE**
SVM1	381019.365907	534.467732	.054645
SVM5	381019.365907	534.467732	.054645
SVM30	381019.365907	534.467732	.054645
ANN1	55443.090380	182.240560	.018163
ANN5	70036.962757	225.267468	.022520
ANN30	158898.180316	342.107461	.033367

Table 18: RMSE, MAE and MAPE results on Property

	RMSE	**MAE**	**MAPE**
SVM1	4131.02	52.66	.01
SVM5	4131.02	52.66	.01
SVM30	4131.02	52.66	.01
ANN1	3738.90	46.79	.01
ANN5	2767.33	39.35	.01
ANN30	2832.90	41.25	.01

Table 19: Summary of RMSE, MAE and MAPE Results

***- Lowest mean from tests RMSE, MAE & MAPE. **- Lowest mean from tests MAPE and MAE

*- Lowest mean from RMSE.

	PSEi	All Shares	Financials	Industrial	Holding Firms	Services	Mining and Oil	Property
SVM1								
SVM5		**						
SVM30								
ANN1			***	**			***	
ANN5			***			*		***
ANN30	***	*		*	***	**		

Table 20: Hit-Miss test results on PSEi

	N	Minimum	Maximum	Mean	Std. Dev
SVM1	59	0	1	.97	.18
SVM5	59	0	1	.97	.18
SVM30	59	0	1	.97	.18
ANN1	59	0	1	.98	.13
ANN5	59	1	1	1.00	0.00
ANN30	59	1	1	1.00	0.00

Table 21: Hit-Miss test results on All Shares Index

	N	Minimum	Maximum	Mean	Std. Dev
SVM1	59	1	1	1.00	0.00
SVM5	59	1	1	1.00	0.00
SVM30	59	1	1	1.00	0.00
ANN1	59	1	1	1.00	0.00
ANN5	59	1	1	1.00	0.00
ANN30	59	1	1	1.00	0.00

Table 22: Hit-Miss test results on Financials Index

	N	Minimum	Maximum	Mean	Std. Dev
SVM1	59	1	1	1.00	0.00
SVM5	59	1	1	1.00	0.00
SVM30	59	1	1	1.00	0.00
ANN1	59	1	1	1.00	0.00
ANN5	59	1	1	1.00	0.00
ANN30	59	1	1	1.00	0.00

Table 23: Hit-Miss test results on Industrial Index

	N	Minimum	Maximum	Mean	Std. Dev
SVM1	58	0	1	0.97	0.18
SVM5	58	0	1	0.97	0.18
SVM30	58	0	1	0.97	0.18
ANN1	58	1	1	1.00	0.00
ANN5	58	1	1	1.00	0.00
ANN30	58	1	1	1.00	0.00

Table 24: Hit-Miss test results on Holding Firms Index

	N	Minimum	Maximum	Mean	Std. Dev
SVM1	58	0	1	0.17	0.37
SVM5	58	0	1	0.17	0.37
SVM30	58	0	1	0.17	0.37
ANN1	58	0	1	0.97	0.18
ANN5	58	1	1	1.00	0.00
ANN30	58	1	1	1.00	0.00

Table 25: Hit-Miss test results on Services Index

	N	Minimum	Maximum	Mean	Std. Dev
SVM1	59	0	1	.95	.22
SVM5	59	0	1	.95	.22
SVM30	59	0	1	.95	.22
ANN1	59	0	1	.95	.22
ANN5	59	0	1	.97	.18
ANN30	59	0	1	.97	.18

Table 26: Hit-Miss test results on Mining and Oil Index

	N	Minimum	Maximum	Mean	Std. Dev
SVM1	59	0	1	.58	.49
SVM5	59	0	1	.58	.49
SVM30	59	0	1	.58	.49
ANN1	59	0	1	.95	.22
ANN5	59	0	1	.92	.28
ANN30	59	0	1	.85	.36

Table 27: Hit-Miss test results on Property

	N	Minimum	Maximum	Mean	Std. Dev
SVM1	59	0	1	.97	.18
SVM5	59	0	1	.97	.18
SVM30	59	0	1	.97	.18
ANN1	59	0	1	.97	.18
ANN5	59	0	1	.98	.13
ANN30	59	0	1	.97	.18

Table 28: Summary of Hit-Miss test results.
* - has a minimum and maximum hit of 1.

	PSEi	All Shares	Financials	Industrial	Holding Firms	Services	Mining and Oil	Property
SVM1	0.97	1.00*	1.00*	0.97	0.17	0.95	0.58	0.97
SVM5	0.97	1.00*	1.00*	0.97	0.17	0.95	0.58	0.97
SVM30	0.97	1.00*	1.00*	0.97	0.17	0.95	0.58	0.97
ANN1	0.98	1.00*	1.00*	1.00*	0.97	0.95	0.95	0.97
ANN5	1.00*	1.00*	1.00*	1.00*	1.00*	0.97	0.92	0.98
ANN30	1.00*	1.00*	1.00*	1.00*	1.00*	0.97	0.85	0.97

Table 29: Direction Symmetry test results on PSEi

	N	Minimum	Maximum	Mean	Std. Dev
SVM1	59	0	1	0.38	0.48
SVM5	59	0	1	0.38	0.48
SVM30	59	0	1	0.38	0.48
ANN1	59	0	1	0.43	0.50
ANN5	59	0	1	0.43	0.50
ANN30	59	0	1	0.45	0.50

Table 30: Direction Symmetry test results on All Shares Index

	N	Minimum	Maximum	Mean	Std.Devn
SVM1	58	0	1	0.41	0.49
SVM5	58	0	1	0.41	0.49
SVM30	58	0	1	0.41	0.50
ANN1	58	0	1	0.43	0.50
ANN5	58	0	1	0.45	0.50
ANN30	58	0	1	0.43	0.50

Table 31: Direction Symmetry test results on Financials Index

	N	Minimum	Maximum	Mean	Std.Dev
SVM1	58	0	1	0.52	0.50
SVM5	58	0	1	0.52	0.50
SVM30	58	0	1	0.52	0.50
ANN1	58	0	1	0.59	0.49
ANN5	58	0	1	0.59	0.49
ANN30	58	0	1	0.57	0.50

Table 32: Direction Symmetry test results on Industrial Index

	N	Minimum	Maximum	Mean	Std.Dev
SVM1	58	0	1	0.43	0.50
SVM5	58	0	1	0.43	0.50
SVM30	58	0	1	0.43	0.50
ANN1	58	0	1	0.40	0.49
ANN5	58	0	1	0.40	0.49
ANN30	58	0	1	0.40	0.49

Table 33: Direction Symmetry test results on Holding Firms Index

	N	Minimum	Maximum	Mean	Std.Dev
SVM1	58	0	1	0.48	0.50
SVM5	58	0	1	0.48	0.50
SVM30	58	0	1	0.48	0.50
ANN1	58	0	1	0.50	0.50
ANN5	58	0	1	0.50	0.50
ANN30	58	0	1	0.50	0.50

Table 34: Direction Symmetry test results on Services Index

	N	Minimum	Maximum	Mean	Std.Dev
SVM1	58	0	1	0.45	0.50
SVM5	58	0	1	0.45	0.50
SVM30	58	0	1	0.45	0.50
ANN1	58	0	1	0.43	0.50
ANN5	58	0	1	0.43	0.50
ANN30	58	0	1	0.43	0.50

Table 35: Direction Symmetry test results on Mining and Oil Index

	N	Minimum	Maximum	Mean	Std.Dev
SVM1	58	0	1	0.57	0.50
SVM5	58	0	1	0.57	0.50
SVM30	58	0	1	0.57	0.50
ANN1	58	0	1	0.48	0.50
ANN5	58	0	1	0.50	0.50
ANN30	58	0	1	0.48	0.50

Table 36: Direction Symmetry test results on Property Index

	N	Minimum	Maximum	Mean	Std.Devn
SVM1	58	0	1	0.47	0.50
SVM5	58	0	1	0.47	0.50
SVM30	58	0	1	0.47	0.50
ANN1	58	0	1	0.41	0.49
ANN5	58	0	1	0.41	0.49
ANN30	58	0	1	0.43	0.50

Table 37: Summary of Direction Symmetry test.
* - has the highest produced mean

	PSEi	All Shares	Financials	Industrial	Holding Firms	Services	Mining and Oil	Property
SVM1	0.38	0.41	0.52	0.43*	0.48	0.45*	0.57*	0.47*
SVM5	0.38	0.41	0.52	0.43*	0.48	0.45*	0.57*	0.47*
SVM30	0.38	0.41	0.52	0.43*	0.48	0.45*	0.57*	0.47*
ANN1	0.43	0.43	0.59*	0.4	0.50*	0.43	0.48	0.41
ANN5	0.43	0.45*	0.59*	0.4	0.50*	0.43	0.5	0.41
ANN30	0.45*	0.43	0.57	0.4	0.50*	0.43	0.48	0.43