DOI: https://doi.org/10.71317/kjard.2.6.2026.288

The Kashmir Journal of Academic Research and Development

Journal homepage: https://rjsaonline.org/index.php/KJARD

Assessing the Performance of Prediction Models for the KSE 100 Index: Empirical Evidence based on ARIMA, Artificial Neural Networks, and Hybrid Model

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ARTICLE INFO

Received:
April 24, 2026
Revised:
May 06, 2026
Accepted:
May 20, 2026
Available Online:
June 08, 2026

Keywords:
KSE 100 Index; ARIMA; exponential smoothing; artificial neural networks; hybrid models

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ABSTRACT

The prediction of the stock market has paved the way for minimizing the awareness of risk perception associated with portfolio investment. Previous studies evaluated multiple methods to find the best predictive model for future stock prices but concluded that there is no single model suitable for all stock markets. Consequently, for the investor, there is a great need to find the best predictive model for a rational investment decision. In this context, several models such as autoregressive integrated moving average (ARIMA), exponential smoothing, artificial neural networks (ANN), and hybrid (neural network and ARIMA, ARIMA and exponential smoothing, and neural network and exponential smoothing) are tested for the Pakistan Stock Market for the daily closing, open, high, and low price of the KSE 100 Index from 2000 to 2022 to explore the best predictive model. The results show that ARIMA is the best method for the prediction of stock prices based on the KSE 100 index and suggest that the stakeholder follows the pattern predicted by ARIMA.

Introduction

The stock market has been a prominent investment avenue in latest years because of the poor rates of return on other financial products. Private and financial firms are both interested in share price index forecasting. Therefore, due to the intrinsically chaotic and moving characteristic of stock values, creating accurate projections of this sort is a difficult undertaking (Abu-Mostafa & Atiya, 1996; Li et al., 2002). For rational decision making of investors, stock market is based on the optimal model of prediction. There are so many models studied in the previous literature producing different optimal results for different markets but there is no study that explain the optimal predicting model for Pakistan stock market. The findings revealed that none of the single approach could be implemented evenly across all markets for investors that can allow them to make rational decisions (Mallikarjuna & Rao, 2019). So, we need the most effective predictive modelling for investors. The novelty of this research is that this study is limited to Pakistan because much empirical research published on Bangladesh, India and other emerging and developed markets. The primary objective of this research is to evaluate and predict the volatility of the Pakistan Stock Exchange (PSX) for the foreseeable future. This study motivates the investors who wants to invest in Pakistan stock market can forecast future by evaluating forecasting models.

Forecasts are future projections that consider both the present situation and the past. With properly distributed and diversified financial assets, there is a great likelihood of significant long-term growth. As a result, making predictions about the stock market has gained significance and popularity. Forecasting has, though, been found to be an exciting task because of market volatility and the unreliable property of the stock market. Although it is hard to make perfect forecasts over time, there are several models that are comparatively precise when predicting a time - series data, such as stock prices. Understanding and foreseeing stock yields is essential to asset evaluating models, portfolio determination and VAR predictions, yet there is controversy about whether stock returns are foreseeable by any means. There are two types of predicting approaches utilized in the research: statistical approaches and artificial intelligence models (AI). Instability is forecasted using predictive methods such as ARIMA and GARCH (Franses & Ghijsels, 1999). Campbell and Shiller (1988) observed that certain financial factors may be used to predict stock market results to evaluate the consistency of stock returns both inside and outside of samples (Aiolfi & Favero, 2005; Goyal & Welch, 2003; Lunde & Timmermann, 2005). Investors and scholars have lately become interested in forecasting stock returns in developing economies. Developing stock markets provide potential for high returns with less correlation to those of developed economies for foreign investors. Developing markets carry greater risks. However, that there are several methods for predicting stock market returns, not any methodology can be used consistently for the yields of all stock markets. The best model was determined to be ARIMA (1,0,4), while the best ARIMA model for calculating the occurrence of COVID-2019 was determined to be ARIMA (1,0,3).

In comparison to projections produced by the individual models, Wang and Meng (2012) found that the hybrid version of a combined ANN and ARIMA model provides better estimates of the energy usage of a China province. In a variety of application areas, such as stock market investing, big data analytical approaches created with machine learning algorithms are receiving greater attention. The ability of the Artificial Neural Network (ANN) is to handle non - linear technique, undefined, and high-frequency econometrics without knowing the allocation of the input data is what makes it appropriate for stock market forecasting. ANN is a forecasting method to deal with data utilizing input factors to produce a result variable. This approach has been utilized in clinical analytic, to foresee rate of inflation, to anticipate rate of interest, to foresee the prices of stock and many other applications. Huang and Jane (2009) suggested a hybrid model for stock market forecasting that employs the ARX estimation model and the grey system. Several central banks, including the Bank of Canada Tkacz and Hu (1999), and the Bank of Jamaica Serju (2002) are now adopting ANN-based prediction model to forecast different macroeconomic indices. Linear time-series models cannot capture the pattern of several financial time series, such as trade rates and financial exchange data. Some features in time-series data, such as unpredictability and structural breakdowns, cannot be adequately characterized using linear time-series models. That’s why non-linear time-series models are often developed to account for such nonlinear characteristics.

Research on estimating stock returns has shown that stock returns are foreseeable utilizing linear regression models. Moreover, current findings indicate that non - linear models beat linear models for predicting market returns. A Markov system exchanging model is likewise utilized to evaluate a nonlinear connection between stock costs and profits, as proposed by (Driffill & Sola, 1998). ANN models have gained a lot of consideration as a good tool for predicting monetary measures Swanson and White (1995). Campbell et al. (1993) created a framework that has ramifications for how stock market returns auto correlated as a non - linear function of trading. The traditional approach may be used on both homoscedastic and heteroscedastic time series situations. An ARIMA procedure is equal to a homoscedastic situation. Thus, a heteroscedastic scenario is not identical to any ARIMA process. As a result, exponential smoothing may be used to a broader range of models than the ARIMA category. The financial econometrics in a firm's financial statements are studied to assess the stock's performance. Popular financial author that is Basu (1983) Fama and French (1992) Fama and French (1988) Fama and French (2017) believes that financial and accounting ratios are critical tools for forecasting stock market success. Financial ratios are now commonly employed in crucial assessment to predict future stock performance (Mubeen et al., 2014).

The exponential smoothing model outperforms the ARIMA, LES, and random walk (RW) models in short-term forecasting Dong et al. (2013) Cadenas et al. (2010). Hyndman et al. (2002) developed a quantitative model for ES built on the previous research of Ord et al. (1997). The methodology included stochastic methods that underpin the different kinds of exponential smoothing and allowed for the generation of estimations of maximum likelihood of smoothing variables. The exponential smoothing method is a basic yet efficient technique to time-series projecting Maia and Gonçalves (2008) and was invented by (Box, 1994); Gardner Jr (2006); (Ord et al., 1997; Trigg & Leach, 1967).

The rest of the paper is structured as follows. The second section discusses prior literature and develops the research hypotheses. The empirical methodology is depicted in the third section. The fourth section reports the empirical outcomes. The last section concludes and formulates the policy implications of the study.

Literature Review and Hypotheses Development

A positive relation exists among financial markets and development of the economy according to theories and models (Beck & Levine, 2004; Guptha & Prabhakar, 2018; Levine, 1997; Rajan & Zingales, 1996; Rousseau & Wachtel, 2000). Stock markets are known for their high levels of instability, creativity, and complexities (Cristelli, 2013; Johnson et al., 2003; Wieland, 2015). Several variables affect stock market changes, including macroeconomic factors, global factors, and human behavior. The danger and unpredictability of investing can be reduced if a forecasting method or approach can foresee the market's trajectory. It would assist governments and regulators make better decisions and take corrective action by increasing investment flows into stock markets. When it comes to evaluating changes in price of the stock, the two different views exist fundamental and technical analysis. Fundamentalists forecast stock prices based on financial evaluations of companies or industries. For many years, both concepts interacted as investment decision-making processes. Random walk theory, often called the efficient market hypothesis, presented a challenge to these ideas in the 1960s. In certain experimental experiments, stock prices were shown to have a “random walk” (Erdem & Ulucak, 2016; Konak & Şeker, 2014; Tong et al., 2014). Most of the empirical research, though, have discovered that prices of the stock are foreseeable (Almudhaf, 2018; Darrat & Zhong, 2000; Harrison & Moore, 2012; Lo & MacKinlay, 2011; Owido et al., 2013; Said & Harper, 2015).

When evaluating alternative strategies using SETAR, certain empirical investigations discovered that this strategy outperformed linear models (Boero & Marrocu, 2002; Clements & Smith, 1999; Fırat, 2017). Recurrent neural network models, for example, were presented in 1980 as a category of artificial intelligence (AI) models for predicting. Data driven ANN are irregular, or adaptable to oneself, with very few theoretical hypotheses. As a result, ANNs are useful and appealing for predicting time series data. These models produce more precise predictions than basic and linear models, according to numerous studies (Aras & Kocakoç, 2016; Ghiassi et al., 2005; Mostafa, 2010). There are also several neural network methods for estimating stock returns. Traditional ANN models, and ANN models integrated with linear models, have been proven to give more reliable estimates than other models in most investigations (Asadi et al., 2012; Khandelwal et al., 2015; Mallikarjuna et al., 2018; Wang et al., 2011). Khashei and Bijari (2010) related autoregressive integrated moving average (ARIMA), artificial neural networks (ANNs), and Zhang’s hybrid model and conclude that Hybrid model beats the other models. Singular spectrum analysis is a commonly utilized technique, a strong non - parametric technique that requires no previous premise relating the data (Golyandina et al., 2001; Hassani et al., 2013). It has been proposed to use hybrid methodologies to simulate data structure that is complicated for increased accuracy (Asadi et al., 2012; Khandelwal et al., 2015; Khashei & Bijari, 2012). When comparing linear and non - linear models to hybrid models (HM), it was revealed that hybrid models outperformed individual models Khashei and Hajirahimi (2017). A few research attempted to develop a strategy for estimating a group of markets' stock returns. In G7 countries, the efficiency of models on assets was investigated (Guidolin et al., 2009). Scholars have carried forth a variety of estimation methods over the past few decades that can be divided into linear or straight methods and non-linear techniques. The linear forecast methods primarily rely on conventional statistical and economic methods, such as (ARMA) Arora and Taylor (2018) and (ARIMA) Karemera and Kim (2006). These conventional statistical techniques can yield excellent predictions under linear constraints, but they are unable to capture the intrinsic characteristics of non-linear and complex time-series analysis in reality Wu et al. (2019). Time-series data prediction is among the most well-known and frequently studied subjects in the data analysis sector. Utilizing both linear and nonlinearities may be possible to improve forecasting capabilities over both short and long timeframes among these data sets could be quite significant.

In many fields of research using (potentially nonlinear) time series data, combining an ARIMA model with an ANN model appears to be quite successful. Numerous scholars are investigating the viability of the ARIMA models for predicting macro-economic indicators. An ARIMA (1,1,0) shows higher projecting presentation for joblessness rates in Canada, according to Power and Gasser (2012) research. According to Etuk et al. (2012)an ARIMA (1, 2, 1) can be used to predict Nigeria's rate of unemployment. According to Hendry and Clements (2003) the accuracy of utilizing the mean-squared prediction error matrices or generalized estimates second instant. Numerous academics have found that qualitative aspects like political influences and economic trends may be used to forecast the stock market. A significant role was played by global events. Thus, they suggested developing a stock market forecasting system by combining quantitative and qualitative elements. Lastly, their research revealed that NNs based on both comparing quantitative and qualitative aspects to those that are solely dependent on numerical factors that the current market price imitates the integration of all the existing data (Yoo et al., 2005). Researchers suggested a hybrid model that combines GA-based fuzzy logic with ANN. The model incorporates both quantitative (technological characteristics) and qualitative (political and psychological) aspects. The evaluation findings show that the neural network that considers both quantitative and qualitative criteria outperforms the neural network that just considers quantitative elements in terms of clarity of buying-selling points and buying-selling performance Kuo et al. (2001). Emin (2011) investigated several multivariate classification-based prediction models approaches and compared them to a variety of parametric variables as well as nonparametric models that estimate the path of the return on the index.

Manzan (2007) and Liew et al. (2003) utilized a smooth transition autoregressive (STAR) model, whereas Dufrénot et al. (2005); Jamaleh (2001) used a Self-Exciting Threshold Autoregressive (SETAR) model. Estimating monetary time series, for example, the securities exchange has provoked the attention of applied analysts due to the significant contribution that the financial sector plays in the economy of any country. Right up 'til now, the ARIMA method is the most frequently utilized time series model for estimating share market econometrics. In view of the ramifications for a country’s economy, the topic of choosing the ideal ARIMA model for market projection has attracted a large body of experimental exploration. In this study, we look at the topic of choosing the optimal ARIMA for forecasting in Botswana and Nigeria. We examine the forecasting performance of multiple candidate ARIMA models using conventional model selection criteria such as AIC, BIC, HQC, RMSE, and MAE in order to choose the optimal ARIMA model for estimating market in every nation under consideration (Adebayo et al., 2014).

The following are the hypotheses developed for this study based on the findings.

H1: ARIMA model is suitable for capturing linearly behavior parts. This model is best to estimate the large number of time series.

H2: ES is a basic methodology for smoothing time series information that utilizes the exponential window capability.

H3: ANN is optimal model for stock price prediction. The model suggested as a useful nonlinear alternative for forecasting time series.

H4: Hybrid model is expected to be favorable since it evaluates both linear and nonlinear patterns individually before merging the forecasts to improve overall performance. It's a combination of Hybrid with Neural Network and ARIMA, Hybrid-ARIMA and Exponential Smoothing and Hybrid **-** Neural Network and Exponential Smoothing.

Empirical Methodology

Data and Sample

The daily stock prices of KSE 100 index for the period 2000 to 2022 were obtained from website Yahoo Finance to evaluate the predicting ability of the given models. For the purpose of completing this study, secondary data is utilized and arranged in excel. The variables identified are different types of prices that is opening, closing, high and low prices used for different time period in this. The methodology of the study can be explained as follows. The six models that are combined to complete this research are as follows. Firstly, models are explained thoroughly and then forecasting measures of errors used to evaluate the efficiency of given models. Results are based on these forecasting measures.

Mallikarjuna and Rao (2019) presented the empirical results of various forecasting techniques like ARIMA, SETAR, SSA, ANN and Hybrid for stock returns for developed and emerging markets. For time series prediction, a variety of methodologies are available. Box and Jenkins, 1970 developed autoregressive integrated moving-average (ARIMA) for time-series models and forecasting models. ARIMA model used in a few researches to estimate returns on stock market (Adebiyi et al., 2014; Al-Shiab, 2006; Mondal et al., 2014; Ojo & Olatayo, 2009). Exponential smoothing approaches have grown in popularity among academics because of its resilience Gardner Jr (2006). The adaptive exponential smoothing (AES) model has the benefit of changing its variables when the time series changes its behavior, enabling it to foresee rapid changes. As a result, the AES approach is often utilized to anticipate instability in the market Taylor (2004) of significant stock indices such as Japan's Nikei 225 index (Leung et al., 2000). Wang and Meng (2012) discovered that projections of the power usage of a Chinese province were more accurate when ANN and ARIMA models were combined than when they were used separately. In order to get around the limits of ANN models and produce even more precise findings, Khashei et al. (2009) suggest a new hybrid approach that uses a flexible regression analysis. For modelling financial sector forecasts, he presented a hybrid ARIMA-ANN technique.

Quantitative Techniques

Keeping in view the objective of the study, five methods will observe to find out the most suitable forecasting technique for investors.

- Autoregressive integrated moving average (ARIMA)
- Exponential Smoothing (ES)
- Artificial neural networks (ANN)
- Hybrid Model (Neural Network and ARIMA)
- Hybrid Model (ARIMA and Exponential Smoothing)
- Hybrid Model (Neural Network and Exponential Smoothing)

ARIMA Model

ARIMA model is the famous linear models, having been introduced in 1970 by George Box and Gwilym Jenkins. The worth of a variable in the future in ARIMA models is calculated using a straight line of the variable's historical observations and certain random mistakes. The following is the procedure for generating the time series.

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} \ldots\ldots, + \emptyset_p y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} \ldots.\ \theta_q \epsilon_{t-q} + e_{t,} \tag{1}$$

yt denotes the dependent variable to be explained at t, and c denotes the constant or intercept; ϕi p q are numbers that represents the model's AR MA orders. et stands for error term.

Identification, estimation, and diagnostic checking are all part of a three-step iterative process in this approach. Defining a preliminary method by determining the AR (p) and MA (q) terms order is the first stage in the identification process. Once a tentative model has been defined, the model's variables should be evaluated that the total measure of errors is diminished, which is typically accomplished via optimization technique that is non-linear. After estimating the parameters, diagnostic testing for the model's appropriateness is required, which entails determining whether the model's expectations regarding the errors εt are fulfilled. If the model is good enough, forecasting can be done; If it's not, parameter prediction and model validation should be used to find a new model. Assume that the random error εt is distributed uniformly, the mean with 0 and a constant variance is σ2.

ARIMA, or autoregressive integrated moving average, is a statistical analysis model that uses time series data to better understand the data set or anticipate future trends. Autoregressive statistical models anticipate future values based on previous values. For example, an ARIMA model may attempt to estimate a company's earnings based on previous performance or predict a stock's future pricing based on past performance. Regression analysis in ARIMA shows the dependency of variable as compare to other factors. It forecasts future time series by taking differences between series values. We use ARIMA model when data is non-stationary. To convert data into stationary we apply the differencing step method. Trend and seasonal components are the sources of non-stationary data. By using differencing procedure two or more times trend component can be removed and to remove seasonal components from data we use seasonal differencing. The time series should be not stationary in any case.

Exponential Smoothing

Brown and End each independently made the methodology. During the Second Great War, Brown worked for the US Naval force. His errand was to make a global positioning framework for fire control information to decide the location of submarines. Afterward, he utilized this technique to expect interest for substitution parts (a stock control issue). In his book on stock control from 1959, he talked about those ideas. The Workplace of Maritime Review financed Holt's examination, and he freely made remarkable smoothing models for seasonal information as well as ceaseless cycles with direct patterns. It involves the exponential window capability for smoothing time series data, a guideline strategy. The determining strategy of exponential smoothing has gotten some momentum for a scope of time series econometrics. For univariate econometrics without a pattern or irregularity Single Exponential Smoothing SES is utilized, some of the time known as the smoothing coefficient or smoothing factor.

The formula for the SES is:

$$S_t = \alpha X_t + (1-\alpha) S_{t-1} = S_{t-1} + \alpha (X_t - S_{t-1}), \tag{2}$$

Where 0≤α≤1 is the smoothing parameter. The rate at which the weights decrease is controlled by the parameter α. It just takes alpha (α) as a boundary that direct the dramatic rot of the impact of the perceptions from prior time steps, relegated to a number somewhere in the range of 0 and 1. More smaller numbers show that a greater amount of the past perceptions is thought about while delivering a gauge, though bigger qualities show that the model emphases for the most part on the latest past perceptions. Only the latest information is considered while making forecasts, subsequently a number close to 1 shows speedy learning, while a number near 0 shows slow learning (past perceptions to a great extent effect on estimates).

It is an estimating method that uses a weighted average of previous data as the prediction. As the observations age, the weights decay exponentially. As a result, the weight of the observation in the forecast increases with the date of observation. It is a simple process for defining anything based on earlier conventions made by the user, such as seasonality.

Hybrid Models

Since stock returns are complicated in nature, either merely linear or entirely non-linear models may be not enough for expecting them. In assessing the effectiveness of ANNs in linear regression issues, sample size and noise level are critical. (Markham and Rakes, 1998). As a result, ANNs may not be appropriate for a wide range of data.

A system capable of dealing with both linear and non-linear data, such as a hybrid model, could be a viable prediction option.

$$y_t = L_t + N_{t,} \tag{3}$$

In above equation, Lt denotes the linear element and Nt represents the non-linear. The residuals described as: Let et represents the residual at t time then: $et = yt - yt + \hat{L}t$

$\hat{L}$t,is the estimated value at time t.

The existence of linear association in the residuals implies that the linear model is insufficient. Hence residuals are particularly main in detecting the appropriateness of linear models. Furthermore, any substantial nonlinear behavior in the residuals implies a linear model restriction. ANNs can be used to discover nonlinear relationships by modelling residuals. For residuals with n input nodes, the ANN model will be:

$$e_t = f\,(e_{t-1}, e_{t-2}, \ldots e_{t-n}) + \varepsilon_t, \quad (4)$$

f is a non-linear function described by the neural network, and εt, is the random error. Indicating the prediction as Nt, the total estimation will be:

$$\hat{y}_t = \hat{L}_t + \hat{N}_t, \quad (5)$$

$\hat{y}_t$ is the hybrid model's predicted value, which is a mixture of linear and non-linear models.

The complete h-step prediction is as follows:

$$\hat{y}_{t+h} = \sum_{m=1}^{M} w_{m,h,t}\hat{y}_{t+h}, \quad (6)$$

$$w_{m,h,t} = (1/msfe_{m,h,t})^k / \sum_{j=1}^{M} (1/msfe_{m,h,t})^k, \quad (7)$$

$\hat{y}_{t+h,m}$ is the prediction point for h steps with time.

There are two steps in this hybrid approach. The first stage is to analyze the data's linear part with ARIMA. In second stage is to create a model for the residuals by using ANN, acquired from ARIMA, which contain info about the data's nonlinearity. The findings of the ANN model can used to predict the ARIMA model's error terms. In the same way as the ARIMA and ANN models, the hybrid model incorporates the features of both in modelling time series data. As a result, using hybrid models to enhance prediction performance could be helpful.

Hybrid Model – Neural Network & ARIMA

Over the last 20 years, the ANN model has gotten a lot of attention. Because of its nonlinear and non-parametric adaptive-learning features, it is one of the most powerful techniques for pattern categorization. Many researches have been undertaken in which ANNs were compared to various traditional approaches, among others. When its linking function was nonlinear, the ANN model outperformed the ARIMA model. When the connecting function was linear, however, the ARIMA model outperformed the ANN model. This is hardly unexpected given that the ARIMA model was created particularly for this purpose.

Previous research indicates that the hybrid model outperforms the models. For example, the hybrid models, as well as separate stochastic and ANN models, were used to forecast drought in India using a standardized precipitation index series, and the hybrid model was shown to have the highest accuracy.

Several researches are being undertaken to forecast probable evolution using various models. These models are built on a variety of assumptions, and the assessments that accompany them are likely to be biased. The ARIMA model based using epidemiological data to anticipate epidemiological trends in prevalence 2019 is only valid if the data follows just a linear pattern.

Hybrid Model – ANN & Exponential Smoothing

The ES method has been determined to be one of the most successful projecting approaches among the numerous forecasting models. Because the exponential smoothing approach is merely a type of linear model, it can only capture linear characteristics of financial time series. However, financial time series are frequently nonlinear and erratic. Furthermore, because the smoothing constant drops exponentially, the exponential smoothing approach produces basic models that only employ a few prior values to anticipate the future.

Although ANN models are successful in financial time series forecasting, they have certain disadvantages. Because the actual world is so difficult, there are both linear and nonlinear patterns in financial time series. Using solely a nonlinear model for time series is insufficient since the nonlinear model may ignore some linear properties of time series data. To blend the linear and non-linear models for forecasting financial data. This is due to the fact that the ANN model and the exponential smoothing model are complimentary. On the one hand, the ANN model can detect tiny non-linear characteristics concealed in time series data, but when predicting, it may overlook some linear trends. The ES approach, on the other hand, may provide decent outcomes in linear trends of series data but cannot provide non-linear patterns, which might bring erroneous projections.

Hybrid Model – ARIMA & Exponential Smoothing

The hybrid model satisfies numerous distinct model parameters, allowing for the simple construction of group predictions. The hybrid model is made up of three different models: ARIMA, exponential smoothing, and ANN. These models were created utilizing a hybrid approach. The forecasting Hybrid package includes a model instruction. This program fits several equations and merges them with either equal weights or weights determined by in-sample anomalies.

Artificial Neural Networks

ANN is a versatile mathematical structure for modelling many non-linear data types. ANN models have the advantage of being data-driven universal approximators for estimating a wide variety of roles. Among the most well-known extensively used methods for forecasting time series data is a single hidden layer feed-forward neural network.

Three layers of simple processing units are linked together by acyclic links to form a network. defines the model's structure. The expression of the relation among output yt and the inputs (yt-1, yt-2,…,yt-p) describes as:

$$y_t = w_0 + \sum_{j=1}^{q} w_{j.g}\left(w_{0,j} + \sum_{i=1}^{p} w_{ij}.y_{t-1}\right) + \varepsilon_t, \qquad (8)$$

Here f is a structure of network and weights-based function, and w is a vector containing all attributes. As a result, this NN model resembles a nonlinear autoregressive model. The dimension of the input vector and the number of lagged observations should be chosen carefully, p, is another critical step in ANN modelling. This is likely the most important parameter to estimate in an artificial neural network model, reflects the time series' non-linear autocorrelation structure is determined by this value. There is, still, no general rule that can be used to determine the value of p. As a result, experiments are frequently done to determine the best p and q values. The network structure can now be trained after the parameters p and q have been specified. The sigmoid functions are the most commonly utilized activation functions in ANNs.

One of the sigmoid function's alternatives is the hyperbolic tangent (tanh) function. It can be summed up as given below.

$$\tanh(x) = 1-e^{-2x} / 1+e^{-2x}, \qquad (9)$$

Rectified linear units described as:

$$f(x) = \max(0,x), \qquad (10)$$

The neuron's input is denoted by the letter x. The ReLU has a value range of 0 and ∞.

Continuous bell-shaped curves identify Gaussian activation functions. The node output is evaluated in terms of class membership depending on how close a specific average value's net input (1 or 0). This described as,

$$f(x) = 1/\sqrt{2\pi}\sigma^{e(x\mu)^{2/2}}\sigma^2, \qquad (11)$$

ANN is a prominent and contemporary approach for creating financial market forecasts that also incorporates technical analysis. A group of threshold functions is included with ANN. These functions are trained on previous data and used to forecast the future by coupling them with adaptive weights. It addresses how the human mind capability. To work, it reenacts countless connected handling units that copy dynamic portrayals of neurons. The handling units are comprised of layers of strategy. A brain network is made of three layers: an info layer with units addressing the info fields, at least one secret layers, and a result layer with a unit or units addressing the objective field. The associations between the units have changing qualities. The main layer gets input information, and every neuron in the accompanying layer gets values proliferated from the neuron in the past layer. At long last, the result layer delivers an outcome. The organization can acquire by analyzing individual records, estimate them, and changing the loads if the forecast is wrong. There are some limitations of ANN model. In the first place, many statistical forecasting models are reliable and sophisticated, but artificial neural network approach and modelling techniques are evolving quickly. Secondly, in comparison to statistical models, ANN takes up more computing time. Third, models of artificial neural networks are more difficult to understand.

Forecast performance measures

Forecast accuracy measures how effectively a prediction model estimates the selected variable. To assess a model's applicability for a specific data set, many accuracy metrics are utilized. There are numerous accuracy measurements in the research such as MAPE, ME, MAE, SMAPE, MSE and RMSE. In this study, we used MAD, MAPE and RMSE since it is one of the best approaches for evaluating predicting correctness for econometrics. RMSE is used by different researchers because they considered it to be the best ways to measure data predicting accuracy, and since this parameter has been used in a number of past researches, like (Lu & Wu, 2011; Makridakis et al., 2008).

Following criteria are used to determine the best fitted model.

- MAD (mean absolute deviation).
- RMSE (root-mean square error).
- MAPE (mean absolute % age error)

Mean Absolute Deviation (MAD) is described as follows:

$$\text{MAD} = \frac{1}{N}\Sigma \mid x_i - \mu| \tag{12}$$

where xi = the data element, N = size of the set, μ = mean.

Mean Absolute Percent Error (MAPE) is depicted as below:

$$\text{MAPE} = \frac{1}{n}\Sigma| \frac{A_t - F_t}{a_t} | \tag{13}$$

where A_t = actual value, F_t = forecast value, n = number of fitted points.

Root Mean Squares Error (RMSE) is exchibited below:

$$\text{RMSE} = \sqrt{\frac{1}{N}\Sigma(y_i - \hat{y}_i)^2} \tag{14}$$

where N = number of data points, y_i = observed values, $\hat{y}_i$ = predicted values.

Empirical Results

This section exhibits the empirical findings that include performance metrics for different forecasting techniques used in the Pakistan stock market. Tables 1–5 provides the RMSE, MAD and MAPE values of the predicted series test sets for all approaches. (i.e., ARIMA, ANN, ES, Hybrid NN and Arima, Hybrid Arima and ES and Hybrid NN and ES) for open, low, high and close price respectively. The model with the lowest RMSE, MAD and MAPE picked as the most suited model.

Figure 1 and Table 1 focus on valuation of model accuracy for Opening Price of KSE 100. According to the reported results of the error analysis, the ARIMA has the lowest error values and is extremely accurate.

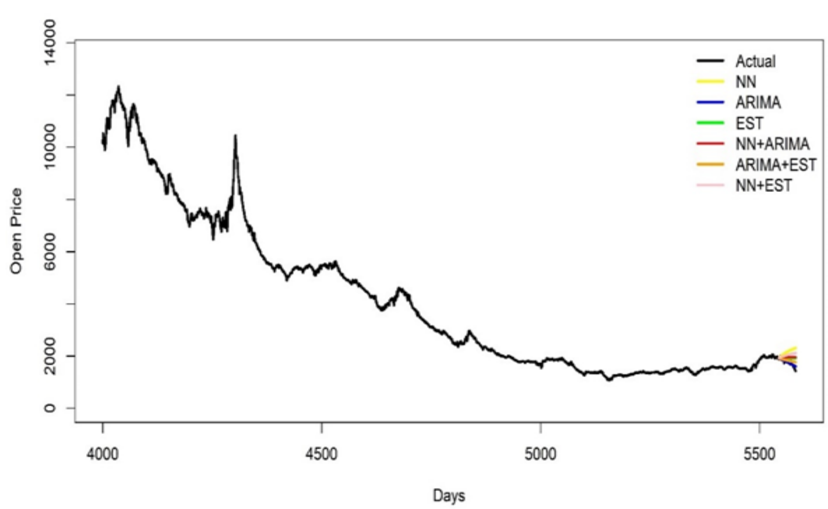

Figure 1. The model selection criterion for ARIMA, NN, EST, ANN+ARIMA, ARIMA+EST and NN+EST: Opening Price

Table 1. Values of model accuracy for Opening Price of KSE 100

Model	MAD	MAPE	RMSE
Neural Network Model	376.224	22.613	451.382
Arima Model	*59.344	*3.416	*78.624
Exponential Smoothing	168.497	10.181	208.636
Hybrid Neural Network and Arima	195.326	11.786	238.520
Hybrid Arima and Exponential Smoothing	97.970	5.897	126.330
Hybrid Neural Network and Exponential Smoothing	268.716	16.207	327.199

Notes: *denotes the model with the minimum error values.

The values of model accuracy (MAD, MAPE, RMSE) for ARIMA are 59.344, 3.416 and 78.624. In Figure1, graph also explains ARIMA is close to actual than other models. Artificial Neural Network is more far away from actual data and has large measures of errors while evaluating forecasting models in opening price of KSE 100. Moreover, Hybrid with combination of ARIM + ES model provides better results after ARIMA model. Likewise, Neural Network with the combination of ARIMA is more appropriate than simple Neural Network. The least model is Neural Network in opening price of KSE 100 and has the highest error values of model accuracy that are 376.224, 22.613 and 451.382.

Figure 2 and Table 2 focus on valuation of model accuracy for High Price of KSE 100. According to the empirical results, the ARIMA has the lowest error values and is extremely accurate. The values of model accuracy (MAD, MAPE, RMSE) for ARIMA are 58.587, 3.362 and 79.015. The above graph shows that Machine Learning model that is Neural Network predicts better results in high price of KSE 100 than in opening price. Moreover, Hybrid with combination of ARIMA + EST model provides better results. The least model is Hybrid with the combination of Neural Network + EST in high price of KSE 100 and has the highest error values of model accuracy that are 789.743, 45.825 and 895.206.

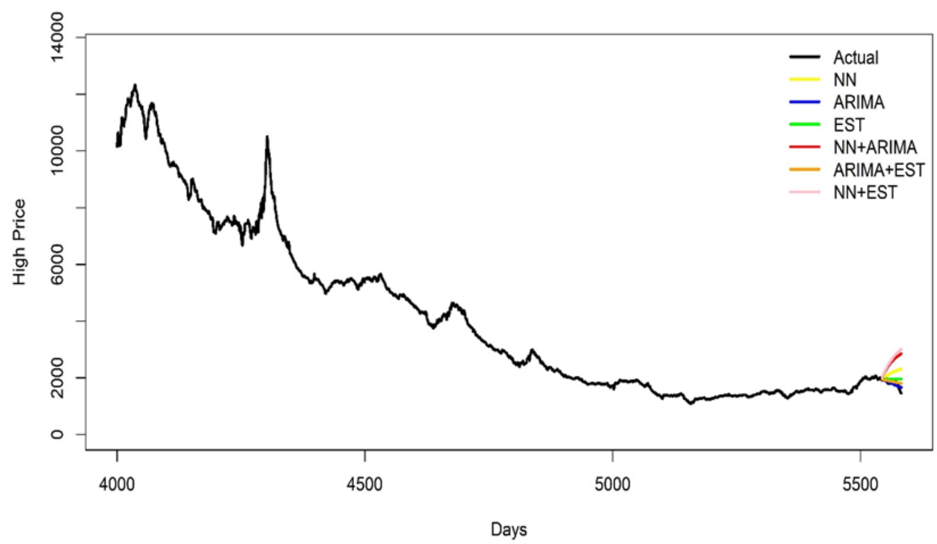

Figure 2. The model selection criterion for ARIMA, NN, EST, ANN+ARIMA, ARIMA+EST and NN+EST: High Price

Table 2. Values of model accuracy for High Price of KSE 100

Model	MAD	MAPE	RMSE
Neural Network Model	359.398	21.091	428.454
Arima Model	*58.587	*3.362	*79.015
Exponential Smoothing	166.813	9.874	208.007
Hybrid Neural Network and Arima	708.864	41.132	802.698
Hybrid Arima and Exponential Smoothing	98.439	5.821	127.765
Hybrid Neural Network and Exponential Smoothing	789.743	45.825	895.206

Notes: *denotes the model with the minimum error values.

Figure 3 and Table 3 emphasis on valuation of model accuracy for Low Price of KSE 100. According to the empirical analysis, the ARIMA has the lowest error values and is extremely accurate. The values of model accuracy (MAD, MAPE, RMSE) for ARIMA are 60.385, 3.606 and 79.348. The above graph shows that Machine Learning model that is Neural Network predicts better results in low price of KSE 100 than in opening price. Moreover, Hybrid with combination of ARIMA + EST model provides better results. The least model is Hybrid with the combination of Neural Network + EST in low price of KSE 100 and has the highest error values of model accuracy that are 287.941, 17.538 and 347.753.

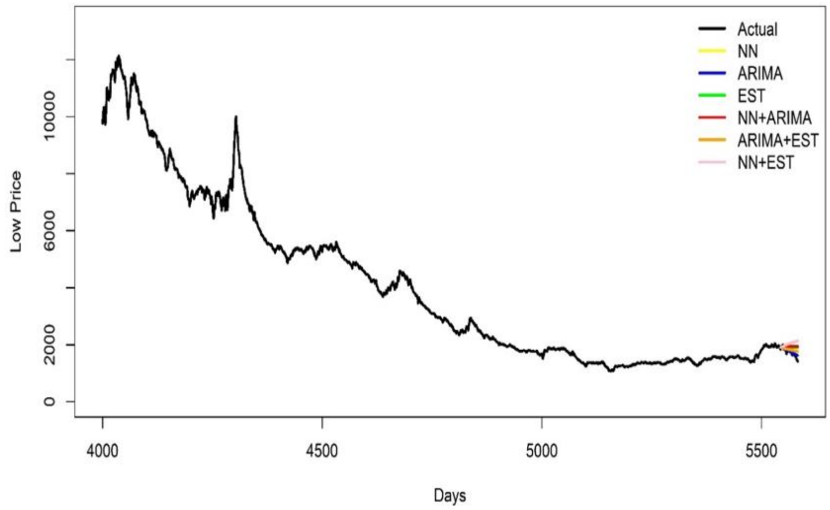

Figure 3. The model selection criterion for ARIMA, NN, EST, ANN+ARIMA, ARIMA+EST and NN+EST: Low Price

Table 3. Values of model accuracy for Low Price of KSE 100

Model	MAD	MAPE	RMSE
Neural Network Model	117.772	7.182	147.359
Arima Model	*60.385	*3.606	*79.348
Exponential Smoothing	176.009	10.737	214.683
Hybrid Neural Network and Arima	200.039	12.183	240.971
Hybrid Arima and Exponential Smoothing	108.082	6.580	135.131
Hybrid Neural Network and Exponential Smoothing	287.941	17.538	347.753

Notes: *denotes the model with the minimum error values.

Figure 4 and Table 4 focus on evaluation of model accuracy for Closing Price of KSE 100. Accordingly, the ARIMA has the lowest error values and is extremely accurate. The values of model accuracy (MAD, MAPE, RMSE) for ARIMA are 61.138, 3.457 and 80.419. The above graph shows that Machine Learning model that is Neural Network predicts better results in low price of KSE 100 than in opening price. Moreover, Hybrid with combination of ARIMA + EST model provides better results. The least model is Hybrid with the combination of Neural Network + EST in closing price of KSE 100 and has the highest error values of model accuracy that are 204.992, 12.265 and 252.109.

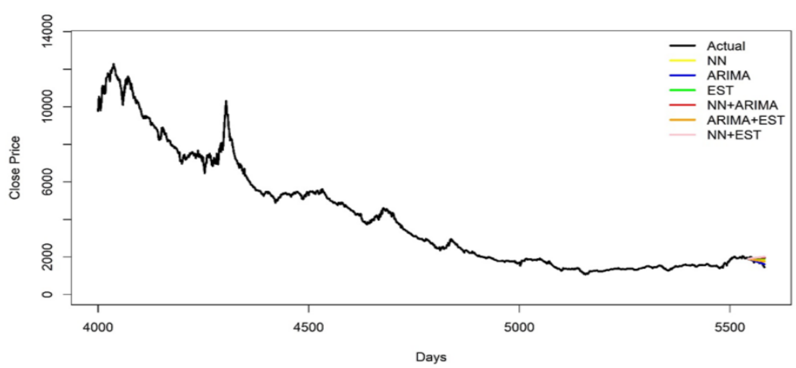

Figure 4. The model selection criterion for ARIMA, NN, EST, ANN+ARIMA, ARIMA+EST and NN+EST: Closing Price

Table 4. Values of model accuracy for Closing Price of KSE 100

Model	MAD	MAPE	RMSE
Neural Network Model	114.431	6.820	144.896
Arima Model	*61.138	*3.457	*80.419
Exponential Smoothing	157.462	9.418	194.599
Hybrid Neural Network and Arima	183.716	10.979	224.533
Hybrid Arima and Exponential Smoothing	89.232	5.284	115.349
Hybrid Neural Network and Exponential Smoothing	204.992	12.265	252.109

Notes: *denotes the model with the minimum error values.

Discussion

Tables 1-4 depicts the various values for different models, with RMSE, MAD and MAPE values and shows that not any method performed consistently in all markets. ARIMA model outperformed the others, providing ideal estimates for open, close, high and low price. The linear forecast methods primarily rely on conventional statistical and economic methods, such as (ARMA) Arora and Taylor (2018) and (ARIMA) Karemera and Kim (2006). These conventional statistical techniques can yield excellent predictions under linear constraints. Based on above results, all models show different results in case of high, low, closing and opening price of KSE 100. Although, machine learning model outperformed statistical models but in case of opening price, statistical model ARIMA beat the Artificial Neural Network. The findings show that the neural network that considers both quantitative and qualitative criteria outperforms the neural network that just considers quantitative elements in terms of clarity of buying-selling points and buying-selling performance Kuo et al. (2001).

ANN when combined with ARIMA model evaluated better results. To forecast, using the ANN model integrated with linear models, have been proven to give more reliable results than other models in most investigations (Asadi et al., 2012; Khandelwal et al., 2015; Mallikarjuna et al., 2018; Wang et al., 2011). Khashei and Bijari (2010). Hence, results also show that the Artificial Neural Network performed better in high, low and closing prices. So, on above basis, H1 is accepted and rejected all other hypotheses. Hybrid model is used with different combination of models like Hybrid (ANN+ARIMA, ARIMA+EST and NN+EST) and Hybrid with ARIMA + EST evaluated better results than other combinations of Hybrid model. Models evaluated based on measures of errors used in this research.

Concluding Remarks and Policy Implications

We utilized the Hybrid model to take advantage of the abilities of the ARIMA, ANN, and ES models in time series estimation of Pakistan Stock Returns. Further, ARIMA, ANN and ES models were used for Pakistan Stock market. The result shows that ARIMA model were best among all models. Hybrid was used with the combination of ARIMA, ANN and ES. KSE 100 Index data collected from 2000 to 2022. Forecast accuracy measures RMSE, MAD, MAPE used to evaluate efficiency of models. These accuracy measures used to evaluate the best model for Pakistan Stock market. It has been observed that MAD, MAPE and RMSE values of ARIMA model in all prices is low than other forecasting models. So, ARIMA model is best fit for Pakistan Stock Market.

As a result of the risk, ambiguity, and volatile characteristics of stock markets, minimizing investor risk can be accomplished by accurately predicting stock returns. Thus, forecasting methods can help for better decision making. Managers, researchers and investors can make well-informed predictions about the future with the support of forecasts that might save their time and money while also allowing them to make better decisions and to select the most suitable forecasting method.

There are some limitations of this study that are time constraints and firm based constraints. This study is particular related to stock index. In addition, further research in this area might be conducted by examining other forecasting models. Also, these models can be executed for calculation stock returns for Pakistan Stock Market. Further research can also be done on models by using different forecasting measures of errors for Covid 19 data as well. I also recommend that along with stock market, commodity market can also use to understand the pattern of different prices.

- **Funding:** No funding has been allocated for this article.

- **Institutional Review Board Statement:** Permission for this manuscript is not required by the Institutional Review Board.

- **Transparency:** We believe in maintaining a high level of transparency throughout our research process to ensure the credibility and reliability of our findings.

- **Data Availability Statement:** The corresponding author is prepared to provide study data upon reasonable request. To promote transparency and reproducibility, we are committed to sharing the data that support our conclusions.

- **Competing Interests:** No competing interests have been declared.

Authors' Contributions

Sayyed Sadaqat Hussain Shah: Conceptualized and designed the experiments; Drafted the paper. reagents, materials, analysis tools, or data.

Ayesha Khalid and Lubna Irrum: Analyzed and interpreted the data; Wrote the paper.

Acknowledgment: We extend our deep appreciation to all individuals who contributed to data collection and review.

Your assistance has been invaluable in ensuring the quality and accuracy of this work.

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