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Predicting Stock Market Trends Based on Macroeconomic Indicators through Machine Learning Approach: A Case Study of KSE 100 INDEX

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ABSTRACT

The purpose of our research is to model the monthly price of the KSE 100 index based on Pakistan's macroeconomic indicators using a Machine Learning (ML) approach. The novelty of the study is forecasting the future value of the stock market using ML. Monthly data was collected for the period from Feb 2004 to Dec 2020. The output layer of our study is the closing price of the KSE 100 index, and the input layer consists of 16 macroeconomic variables of the Pakistan economy, which are the industrial production index (IPI), the exchange rate (EX-RATE), money supply (M2), consumer price index (CPI), foreign direct investment (FDI), Treasury bill on 3-months treasury, interest rate as KIBOR – Month Average (1 Month), Foreign Exchange reserves (FXR), Consumer Financing for house building (house financing), Balance of Trade (BOT), crude oil, Gold, Labor force participation rate, GDP growth (annual %), Households and NPISHs Final consumption expenditure (household consumption) (current US$), and Domestic savings. The prediction uses the Artificial Neural Network (ANN) Backpropagation algorithm. The model developed in this research achieved 99% accuracy using macroeconomic indicators. The accuracy level indicates that the model of the KSE 100 index can predict future trends. This study also forecasts the future monthly values of the KSE 100 index from Jan 21 to Jun 23 and daily future values from Oct 1, 2022, to Dec 31, 2020.

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1. Introduction

The stock market is an essential part of the financial sector and plays a significant role in any country (Demir, 2019). The stock market is acknowledged as the source of financial resource redistribution between different entities in the economy. Progress in the stock market is considered progress in the economic growth of a country. The situation of a country's economy is illustrated by the stock market's movement. When the stock market performs positively, it shows economic growth in the country, and vice versa. Economic factors influence the stock market's movement, so it is necessary to find out which factors influence stock market fluctuations (Pilinkus, 2010). Investors have an interest in raising profit and trying to minimize the risk of loss. For that reason, they search for the techniques and tools that would predict the stock market. However, predicting the stock market is not an easy task due to its dynamic, nonlinear, stochastic, and uncertain nature. That's why the use of computational intelligence and machine learning approaches is increasing day by day to create an accurate prediction model of the stock market (Kumbure, Lohrmann, Luukka, & Porras, 2022). This study trains the data of the Pakistan stock exchange and the main macroeconomic variables of Pakistan to develop the model with the ANN backpropagation algorithm.

The stock market is considered the best place to generate capital for business (Zaffar & Hussain, 2022). The stock market is important at both macro and micro levels, at a macro level it generates efficient capital, which helps to promote economic efficiency; at the micro level, it directly affects the wealth of business firms and individuals (Mohammed & Abu Rumman, 2018). Economic factors directly or indirectly affect investors' decisions because their decisions consider the overall economic and market situation. Any uncertainty or crisis in the stock market generally affects the economy. Stock markets are affected by domestic macroeconomic conditions (Demir, 2019). The stock markets have shown rapid growth in emerging economies and created opportunities for investment in the past few years. Domestic and global news affect the stock market in emerging countries and create an uncertain environment (N. Raza, Shahzad, Tiwari, & Shahbaz, 2016).

The stock market's daily fluctuation is because of economic, political, and social factors (Mohammed & Abu Rumman, 2018). Moreover, the stock market cannot work independently because it is affected by internal and external factors. Chen, Roll, and Ross (1986) introduced macroeconomic factors in the model to measure stock market returns and showed that economic indicators have a systematic impact on the stock market. The macroeconomic factors influence the stock market positively as well as negatively (Kumar, 2013). The direction of macroeconomic determinants indicates the economic situation of the country, affects the stock market, and helps investors in making decisions (Pilinkus, 2010). The stock market of Pakistan is affected by economic, political, and legal aspects and is influenced by macroeconomic indicators (Akbar, Butt, & Chaudhry, 2018).

The stock market of Pakistan was established on September 18, 1947. But officially, it was integrated on March 10, 1949, as the Karachi Stock Exchange. There were three stock exchanges operating in Pakistan with separate indices, management, and trading interfaces. In 2016, all exchanges were merged and introduced as PSX by implementing the Demutualization and Integration Act 2012.

Initially, the stock market started with five listed companies with a total capital of $11 million. But now, there are 531 companies listed with a total market capitalization of $44 billion (As of Dec 31, 2021, PSX). The country, with 225.2 million people , has only 252,322 total investors in PSX as of April 30, 2021 (DAWN). Compared to our neighboring countries, this number is quite low. The most common reasons for the general public not investing in PSX are a lack of awareness, concerns about the safety of the stock market, trust issues, and a preference for investing in gold and real estate.

The two main analytical approaches used in studies about stock market prediction are technical analysis and fundamental analysis. Fundamental analysis is an analytical approach that observes the fundamental economic factors that affect stock price changes. In the case of technical analysis, historical data of stock prices and volume data are used to predict the trends of stock prices.

The stock market has a nonlinear pattern, which is difficult to predict. The nonlinear mathematical solution is made feasible by using a large data set and fast processing. Machine learning is a powerful mechanism for examining stock market trends (Wang, 2022). It is used to expose the patterns in data. Complex data is analyzed quickly and generates precise results by machine learning approaches (Rouf et al., 2021). The most commonly used method for nonlinear pattern data is the artificial neural network (Selvamuthu, Kumar, & Mishra, 2019). ANN is capable of approximating the most complex functions and increases the accuracy level of prediction. ANN is a computer-based model that tries to replicate the human brain. More than 90% of business applications use multilayered feedforward neural networks with the backpropagation algorithm. ANN backpropagation is the most common algorithm used for prediction and predicts future data with good accuracy. When talking specifically about the KSE 100 index, only a few researchers have used the machine learning approach. The KSE 100 index prediction with macroeconomic analysis was available in only one or two studies Mehak Usmani, Ebrahim, Adil, and Raza (2018) used a few variables and data for a short period.

In our study, we used ANN backpropagation with a multi-layer perceptron model to predict the stock market movement using historical data of macroeconomic variables. Some past pieces of research Hussainey and Khanh Ngoc (2009); Kwon and Shin (1999); Kyereboah-Coleman and Agyire-Tettey (2008); Pilinkus (2010) proved that selected variables affects the stock market.

2. Literature Review

The prediction of the stock market has become a challenging task nowadays. Machine learning approaches were used for the prediction of the stock market performance. Both internal and external factors influenced the stock market. Literature on the stock market analysis streamed on the macroeconomic indicators, News, historical data, machine learning approaches, and external and internal factors.

The reviewed papers present a comprehensive overview of the complex relationship between macroeconomic indicators and stock market performance, employing diverse methodologies and data analysis techniques. Here's a synthesis of their findings:

Kumar (2013) explored the impact of various macroeconomic factors on the Indian stock market. Identified three factors explaining 79% of the variance in variables, suggesting that the macro environment significantly influences the stock market in India. Kyereboah-Coleman and Agyire-Tettey (2008) focused on inflation, lending rates, treasury bill rates, and AGC dummy. Their error correction model indicated that high lending and inflation rates had a negative effect on the stock market. New company listings improved market performance by 34%. Al-Ameer, Hammad, Ismail, and Hamdan (2018) examined the relationship between Gold and the stock market. Found that this correlation is crisis-dependent and varies over time. No Granger causality was detected between Gold and the stock market. Shabbir, Kousar, and Batool (2020) investigated the influence of oil and gold prices on the stock market using the ARDL model. They discovered that both oil and gold prices significantly affected the stock market.

Arjoon, Botes, Chesang, and Gupta (2012) focused on the inflation rate. They used a structural bivariate vector autoregressive (VAR) approach and found that constant inflation had a positive long-run influence on stock prices. Jebran and Iqbal (2016) analyzed the impact of foreign exchange on stock markets in Asian countries using the EGARCH model. They found asymmetric volatility spillover, with a more pronounced effect in developing countries. Kaneko and Lee (1995) explored the impact of various factors on the U.S. and Japanese stock markets. They found that news about premium risk, term premium, and industrial production growth significantly impacted the U.S. market, while changes in oil prices, exchange rates, and terms of trade were significant in the Japanese market. Feldmann (2011) examined the correlation between unemployment and stock market activity, finding that more stock market activity correlated with low unemployment rates. Gultekin (1983) investigated the relationship between inflation and stock returns, concluding that there was no significant positive relation between nominal stock returns and expected inflation.

Singh (1993) explored the impact of money supply announcements on stock prices, with the linear response model showing no significant change in stock prices with unexpected money supply announcements. Sibande, Gupta, and Wohar (2019) analyzed the relationship between unemployment and stock returns using various models, suggesting a complex relationship with both linear and nonlinear components. Wang (2022) employed macroeconomic and technical indicators for stock market prediction, finding that a combination of these indicators was more effective. Hussainey and Khanh Ngoc (2009) investigated the relationship between macroeconomic indicators and the Vietnamese stock market, finding significant associations. Hondroyiannis and Papapetrou (2001) analyzed the impact of various factors on the Greek stock market, concluding that exchange rates had a positive impact, while other factors had a negative influence. Kwon and Shin (1999) explored the long-run relationships between stock indices and macroeconomic indicators in the Korean stock market. Alamsyah and Zahir (2018) used artificial neural networks to predict the IDX composite trends accurately using economic variables.

Boyacioglu and Avci (2010) predicted ISE national 100 index return with high accuracy using an adaptive network-based fuzzy inference system (ANFIS). Selvamuthu et al. (2019) achieved high accuracy in predicting stock market movements using various learning algorithms. Zaffar and Hussain (2022) compared different models for predicting KSE 100 index, finding variations in performance across market cycles. Akbar et al. (2018) explored the long-run relationship between the stock market and economic growth. Ali, Mubeen, Lal, and Hussain (2018) used a logistic regression model to predict stock market performance with high accuracy. Rasheed, Ishaq, Anwar, and Shahid (2021) analyzed various macroeconomic variables' associations with the KSE 100 index, finding different impacts of inflation, interest rate, and gold price. Khan, Ahmad, Akram, and Ishaq (2021) examined relationships between macroeconomic indicators and stock markets across countries using panel regression models. K. Raza (2017) predicted the KSE 100 index using multiple machine learning methods, with MLP achieving the highest accuracy.

These studies collectively contribute to our understanding of the intricate interplay between macroeconomic variables and stock market performance, offering valuable insights for investors, policymakers, and researchers. Various machine learning approaches have been predominantly employed to predict stock market trends solely based on historical data. However, there has been a limited number of studies that have incorporated macroeconomic variables into the prediction of stock market performance. In the specific context of the Pakistan Stock Exchange, there is only one study that used a limited set of three or four variables and analyzed a short time frame using diverse machine learning techniques.

As a response to this gap in research, our study aims to evaluate the predictive capabilities of the stock market and forecast its future values by integrating a comprehensive set of macroeconomic variables. To achieve this, we have adopted an artificial neural network-based machine learning approach. This research represents an innovative step towards analyzing the stock market, leveraging the insights provided by macroeconomic indicators, particularly in the context of the KSE 100 INDEX.

3. Theoretical Background

The purpose of our study is to develop a model for the stock market and macroeconomic indicators using a machine learning approach. The novelty of our research lies in predicting the stock market with a focus on major economic indicators influencing it. This research is also beneficial for investors.

Fluctuations in the stock market index depend on various factors, with economic activity being a significant contributor. Many expected and unexpected factors affect the stock market, but the relationship between macroeconomic variables and the stock market is critical. Several models provide the basis for this link, rooted in economic theory. The two main models are the one-factor Capital Asset Pricing Model (CAPM) and the multifactor Arbitrage Pricing Theory (APT).

The CAPM is a traditional approach to measuring stock returns, focusing on market risk premium. The APT expands on the CAPM, describing the linear function of various variables, including macroeconomic indicators. APT models can be single-factor or multi-factor, allowing you to choose specific factors to consider.

The APT model suggests that the stock market is influenced by macroeconomic indicators (Aithal, Dinesh, & Geetha, 2019). However, it primarily addresses short-run relations, whereas the long-run relationship is explored through the Dividend Discount Model.

Economic activities are represented by the behavior of macroeconomic indicators, and government policies related to these variables impact the stock index. The government releases data daily, monthly, and yearly, which significantly influences stock market performance. Investors seek to predict the market's future condition for profitable investments, with a focus on macroeconomic indicators.

The literature contains numerous studies that highlight the influence of macroeconomic indicators on the stock market index and how to predict market performance. However, there are few studies globally on predicting the stock market using macroeconomic analysis. In our case study, we predict the KSE 100 index using macroeconomic indicators and historical market data, which is a relatively unexplored area. Only one study on the Pakistan stock market utilized macroeconomic variables, but it used only a limited set of variables and a short data time frame (Mehak Usmani et al., 2018).

4. Methodology

4.1. Data

We collected monthly data from Feb 2004 to Dec 2020. The data sources include the monthly publication of the State Bank of Pakistan, while data related to Households and NPISHs Final consumption expenditure (household consumption) (current US$) was obtained from the Pakistan Bureau of Statistics. In literature, studies have used various macroeconomic indicators to predict the performance of stock markets. The present study has included all those variables which were used in past in various studies to predict the stock market performance. Crude oil prices were collected from Index Mundi. The dependent variable in our study is the closing price of the KSE 100 index, while the independent variables include 16 macroeconomic variables from the Pakistan economy: industrial production index (IPI), exchange rate (EX-RATE), money supply (M2), consumer price index (CPI), foreign direct investment (FDI), Treasury bill on 3 months treasury, interest rate as KIBOR – Month Average (1 Month), Foreign Exchange reserves (FXR), Consumer Financing For house building (house financing), Balance of Trade (BOT), crude oil, Gold price, Labor force participation rate, GDP growth (annual %), Households and NPISHs Final consumption expenditure (household consumption) (current US$), and Domestic savings. The collected data was combined into a single dataset, checked for missing values, and adjusted for consistency in units.

4.2. Artificial Neural Network

The artificial neural network is inspired by biological neural networks and replicate the human brain to perform specific tasks. It combines simple elements to create intelligent behavior. This approach offers several advantages, including adaptive learning, self-organization, and real-time operation.

An artificial neural network typically consists of three layers: the input layer, output layer, and at least one hidden layer. The hidden layer adds complexity to the network.

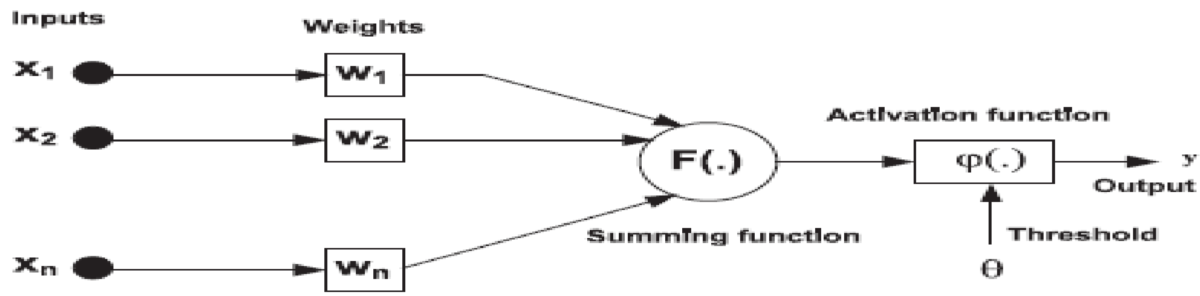

Figure 1: Artificial Neural Network Mechanism

Figure 1 show that inputs $x_1, x_2, x_3, \ldots\ldots\ldots\ldots .. x_n$ are present the neuron in the network. These inputs are multiplied by the weights w_{k1}, w_{k2} , $w_{k3}, \ldots\ldots\ldots w_{kn}$ and then sum them all input after multiplying with weight. The result of that sum is named as linear combiner.

$$v_k = \sum_{j=1}^{n} w_{jk} x_j \quad (1)$$
$$y_k = \varphi(v_k - \theta_k) \quad (2)$$

V_k is presenting the summing function and y_k is present the final output that comes after applying the activation function and threshold. The backpropagation algorithm is used to adjust the network's connection weights based on gradient descent and mean square error. The goal is to minimize the sum of squares of errors. Random weights are chosen at the initial stage, and then the network starts training the dataset.

There are three phases of backpropagation.

Phase 1

In this phase, the input pattern is estimated, and the input layer sends data to the output layer using the activation function to obtain the network's output value.

Phase 2

In the second phase, the error is determined by taking the difference between the desired value and the network's output value.

Phase 3

In the third phase, the weights are adjusted to reduce the network error value. All factor values are obtained, and all weights in the network are changed simultaneously.

This study aims to predict the stock market via macroeconomic indicators' analysis using a machine learning approach. We used monthly data for 16 macroeconomic indicators and applied the Backpropagation algorithm, a common method in Artificial Neural Networks (ANN), using Python software.

Machine learning, a subcategory of artificial intelligence, builds mathematical models based on training data to make predictions and decisions. We employed supervised learning, a machine learning approach that relies on historical data to resolve the research problem. Our specific method of choice is the artificial neural network, a branch of machine learning. In this research, we predict the stock market's movement using ANN Backpropagation, which involves a multi-layer perceptron model with three hidden layers. The three layers Backpropagation network is expressed in mathematics as

Hidden layer

$$y_j = f(\sum_i w_{ji} x_i - \theta_j) = f(net_j) \quad (3)$$
$$net_j = \sum_i w_{ji} x_i - \theta_j \quad (4)$$

Above y_j is present the neuron of hidden layer, x_i is input neurons, and w_{ji} the network weight.

Output layer

$$z_i = f(\sum_i v_{lj} y_i - \theta_i) = f(net_j) \quad (5)$$
$$net_i = \sum_i v_{ij}\, y_i - \theta_i \quad (6)$$

Above z_j is present the neuron of output layer, and v_{li} the value of network weight between hidden and output layers.

Error of output neurons

$$E = \frac{1}{2}\sum_l (t_l - z_l) = \frac{1}{2}\sum_l (t_l - \text{f} (\sum_i v_{ij}\, y_i - \theta_i))^2 \quad (7)$$
$$\text{E} = \frac{1}{2} \sum (t_i - \text{f} (\sum_i w_{ji} x_i - \theta_j) - \theta_l)^2 \quad (8)$$

Modification of Weight Value

Derivation of the node of output by means of error function

$$\frac{\partial E}{\partial v_{lj}} = \sum_{k=1}^{n} \frac{\partial E}{\partial z_k} . \frac{\partial E}{\partial v_{lj}} = \frac{\partial E}{\partial z_l} . \frac{\partial z_l}{\partial v_{lj}} \quad (9)$$

E is a function comprising several z_k but only one z_l is associated with v_{lj} and all the z_k are autonomous from each other, in this formula,

$$\frac{\partial E}{\partial z_l} = \frac{1}{2}\sum_l \left[-2(t_k - z_k) . \frac{\partial z_k}{\partial z_l}\right] = -(t_l - z_l) \quad (10)$$
$$\frac{\partial z_l}{\partial v_{lj}} = \frac{\partial z_l}{\partial net_l} . \frac{\partial net_l}{\partial v_{lj}} = f'(net_l) . y_j \quad (11)$$

In this means,

$$\frac{\partial E}{\partial v_{lj}} = -(t_l - z_l) . f'(net_l) . y_j \quad (12)$$

Assume the error of input node is

$$\delta_l = -(t_l - z_l) . f'(net_l) \quad (13)$$

In this means

$\frac{\partial E}{\partial v_{lj}} = -\delta_l .\ y_j$ (14)

Deviation of hide layer node by error function

$\frac{\partial E}{\partial w_{ji}} = \sum_l \sum_j \frac{\partial E}{\partial z_l} . \frac{\partial z_l}{\partial y_j} . \frac{\partial z_l}{\partial w_{ji}}$ (15)

E is a function comprising several z_l; it is targeted at w_{ji}, corresponding to one y_j, and associated to all z_l, in this formula,

$\frac{\partial E}{\partial z_l}=\frac{1}{2}\sum_k \left[-2(t_k - z_k).\frac{\partial z_k}{\partial z_l}\right] = -(t_l - z_l)$ (16)

In this means,

$\frac{\partial E}{\partial w_{ji}} = \sum_l (t_l - z_l).f'(net_l).\ v_{lj}\ .f'(net_j).x_i$=-$\sum_l \delta_l\, v_{lj} f'(net_j).x_i$ (17)

Assume the error of hide layer node is

$\delta'_j = f'(net_j).\sum_l \delta_l v_{jl}$ (18)

In this means,

$\frac{\partial E}{\partial w_{ji}}$=-$\delta'_j x_i$ (19)

As the modification of weight Δv_{lj} and Δw_{ji} is in proportion to the error functions and descends along the gradient, the weight modification of hide layer and output layer is stated as follows:

Δv_{lj} =-η$\frac{\partial E}{\partial v_{jl}}$= η$\delta_l\, y_j$ (20)

In above formula, η denotes the learning rate. The modification between the input layer and hide layer is stated as follows:

Δw_{ij} =-η$\frac{\partial E}{\partial w_{ji}}$= η′$\delta'_j\, x_i$ (21)

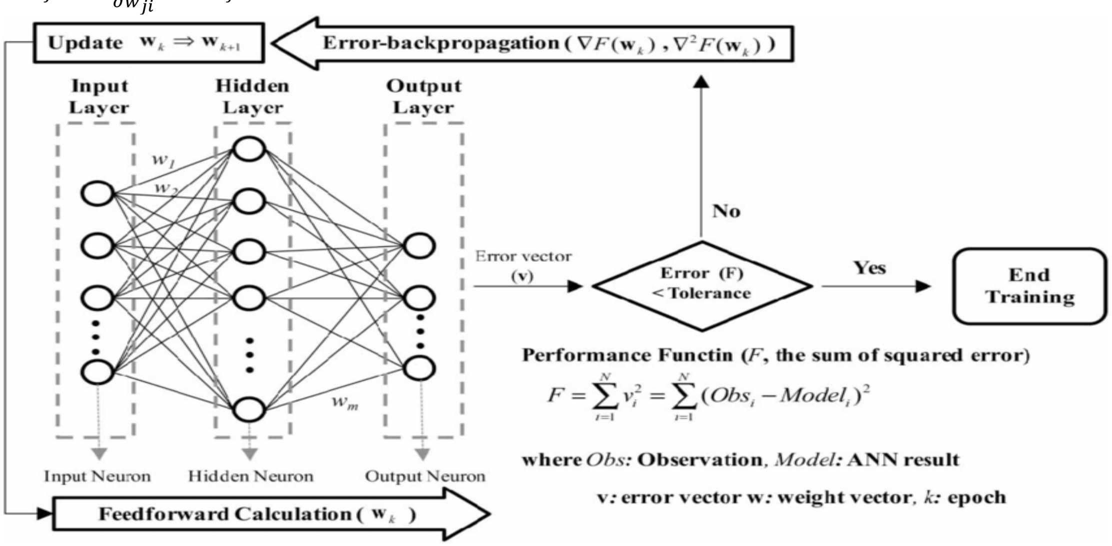

Figure 2: Flow Chart of Backpropagation Algorithm

By subtracting the actual value from the predicted value and taking the square after that multiple it by ½ we get the error. After finding the error adjust the weight between the hidden layer and output layer, and also between the hidden layer and input layer.

Repeat the whole steps of the training set till TSSE < ϵ. Where ϵ. is the tolerance error. When the error rate come in the acceptable range then it means our model was ready to predict the future data. Figure 2 explains the the flow chart of backpropagation algorithm.

5. Results and Discussion

In this study, our main objective is to predict the stock market by employing macroeconomic analysis through the use of the ANN Backpropagation algorithm. We utilized the ANN Backpropagation with a multi-layer perceptron model featuring three hidden layers to investigate the future values of the KSE 100 index based on macroeconomic indicators and past data.

The modeling in our research revolved around the KSE 100 index at the month-end and daily closing prices. We designed the study using the Python programming language with the KERAS library. The backpropagation ANN consists of an input layer, three hidden layers, and an output layer. In the input layer, all independent variables are represented, with each variable assigned to one of the three neurons. These explanatory variables are represented by each node. The output layer in the network represents the dependent variable, which, in our case, is the KSE 100 index, representing the Pakistan stock exchange market. The independent variables encompass the key macroeconomic indicators of the Pakistan economy.

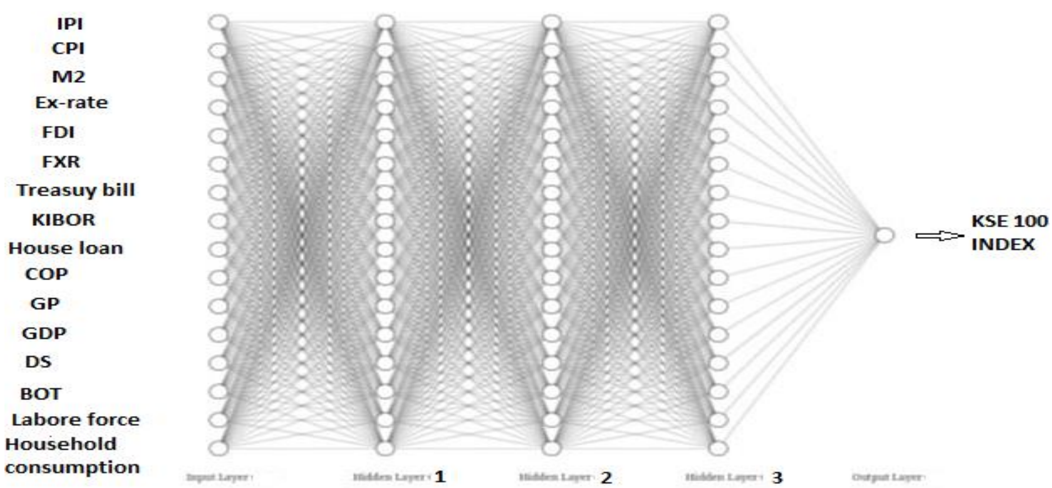

Figure 3: Artificial Neural Network Architecture of KSE 100 Index

Figure 3 illustrates the neural network in our study. The input layer contains the major macroeconomic indicators, while the three hidden layers lead to the output layer, representing our dependent variable—the KSE 100 index. The hidden layers comprise 50 neurons, and the input layer has three neurons. The model's output layer consists of only one neuron. The input layer's neurons are interconnected with the hidden neurons through weights, and the hidden layers' neurons are connected to the output layer's neuron via weights. Initially, weight values are assigned randomly and adjusted during iterations to minimize error. The next step involves the feedforward process, divided into two steps. The first step calculates the values of neurons in the hidden layer, and the second step uses these values to calculate the output. Input neuron values are transmitted through the network to the hidden layer's neurons. The backpropagation training algorithm is employed to train the network. These input neuron values are then multiplied by the weights connecting the neurons, resulting in the estimation of the hidden layer values. The hyperbolic tangent (tanh) activation function $fx = \frac{2}{1+e^{\wedge}(-2x) - 1}$ $fx = \frac{(e^{\wedge}x - e^{\wedge}-x)}{e^{\wedge}x + e^{\wedge}-x)}$ is used for the estimation of hidden layer values.

For calculating the output layer, a linear activation function is used. The subsequent step involves error assessment in the output layer (KSE 100 index). Once the error is identified, it is employed to adjust the weights during backpropagation. The error is first transmitted to the hidden layer from the output layer. Next is the weight update, determined by the rate of change, achieved by multiplying the output neuron's value with the error and learning rate. In our training process, the learning rate is set at 0.0015. The learning rate acts as a scalar parameter controlling the rate of change. Subsequently, the error is transmitted from the output neuron to the input layer, and, as before, error assessment is crucial to updating the weights. The weight plays a pivotal role in the network by reducing error to achieve a well-fitted model that can predict future values. Such a process is unmanageable for large datasets, which we employed in our study, leading us to design a Python program using the Keras library.

Our input data set is 12*16, its mean sixteen years with all 12 months, and 1*11 its mean that 2004 is considered from Feb. So, our data set is consisting on 203 months. And KSE 100 index historic data from Jan, 1, 2001 to September, 30, 2022, for daily prediction. The data set split into two parts:

- Training set
- Validation set

Of the data, 80% is designated for training, and the remaining 20% is used for validation. The training set encompasses 13.5 years, and the validation set covers 3.4 years. We set the learning rate at 0.0015, with a maximum network epoch of 5000. Graph 1 illustrates the training and validation accuracy. The graph demonstrates that the accuracy increased as the error reduced. Our Artificial Neural Network program, equipped with the Backpropagation algorithm, predicts the KSE 100 index with 99% accuracy using the 16 macroeconomic indicators of the Pakistan economy. Our model indicates that the KSE 100 index can be predicted effectively through the use of artificial neural networks. Our study surpasses the accuracy of the study by M. Usmani, Adil, Raza, and & Ali (2016), showcasing a more precise prediction of the KSE 100 index through the utilization of 16 macroeconomic indicators. The value of the parameter involved in the training ANN are shown in Table 1 while the training and validation is presented in Figure 4.

Table 1
Values of Parameters Involved in the Training of the Artificial Neural Network

Parameters	Values
Learning rate	0.0015
Maximum epoch	5000
Input layer	1
Hidden layers	3
Output layers	1
Input Neuron	3
Hidden Neuron	50
Output Neuron	1
Training Function	Backpropagation algorithm

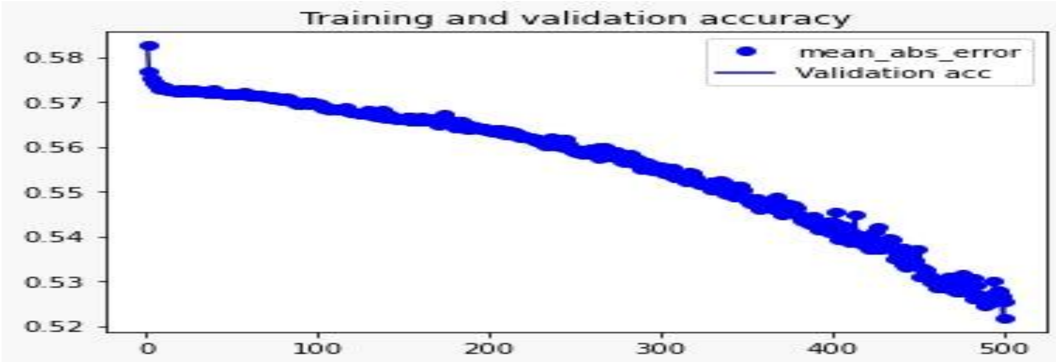

Figure 4: Training and Validation Accuracy

The present study forecasts the future values for the KSE 100 index using an Artificial Neural Network. We aim to forecast month-end and day closing prices by utilizing 16 years and 11 months of data on macroeconomic variables and the KSE 100 index. If the macroeconomic variables perform similarly to previous years, then the stock market performs as shown in the graph. Figure 5 displays the future value trend of the month-end close price from January 2021 to May 2023. Figure 6 shows the actual and forecast values of KSE 100 index.

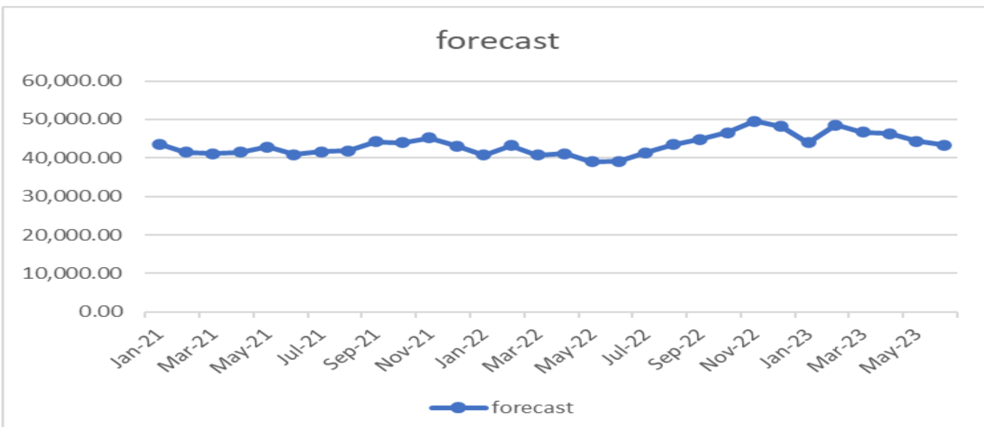

Figure 5: Future Trend of KSE 100 Index

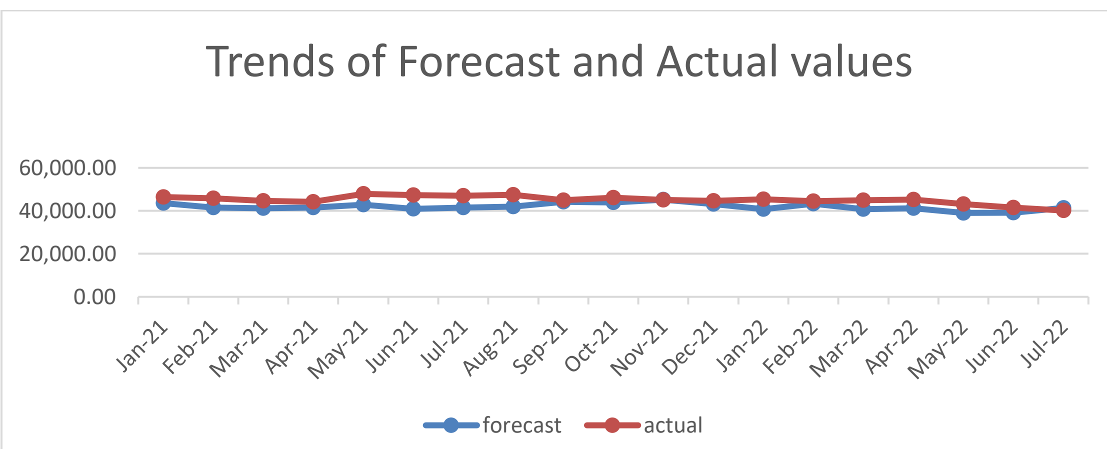

Figure 6: Line Chart of Forecast and Actual Values

Figure 6 illustrates the comparison of future forecasting values and actual values of the KSE 100 index. The blue line represents the forecast values, and the orange line represents the actual values. The closing price is the same on Nov 21. The graph shows that the actual values are either more than or near the forecasting values and are not below the actual values. This implies that the Artificial Neural Network predicts the future value and helps generate maximum profit returns. Predicting the month-end close price is a challenging task with only one factor. We improve the predicted values to be more accurate by introducing other factors of the market and using daily data.

We also predict the values of KSE 100 presented in Figure 7 by using the KSE 100 index daily historic prices from October 2, 2022, to January 1, 2023.

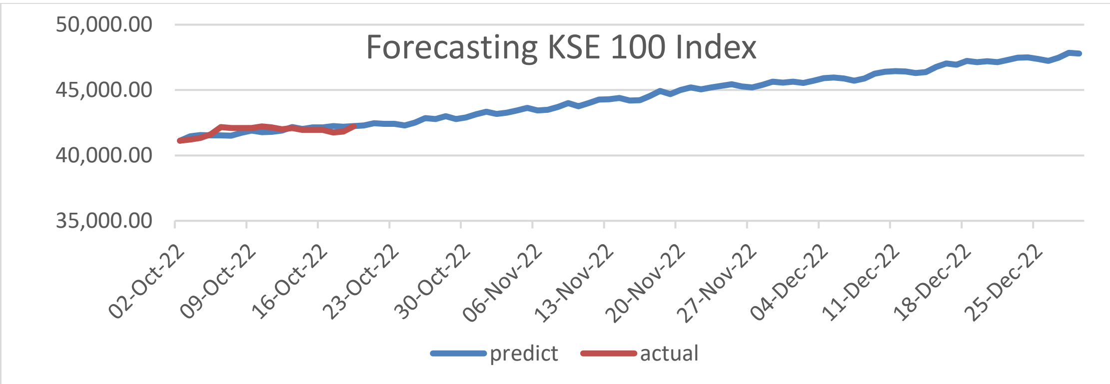

Figure 7: Daily Prediction of KSE 100 Index

Figure 7 shows the daily forecasting of the KSE 100 index for three months (October 2022 to January 2023). It is observed that value of KSE 100 index is increasing and moved from 41000 points to 48000 points. Figure 8 shows that the comparison of actual closing prices and forecast closing prices of the KSE 100 index.

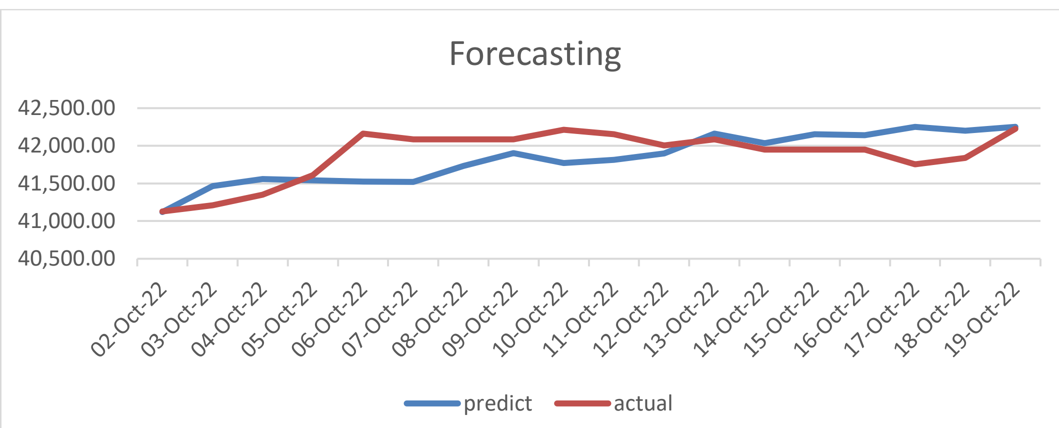

Figure 8: Actual and Predicted Prices of KSE 100 Index

The study suggests that the KSE 100 index can be predicted as the difference between actual and predicted values is minimal. This study is fruitful for investors, banks, mutual funds, and brokerage houses. The machine learning algorithms utilized more and maximum data to obtain accurate results.

6. Conclusion

The stock market plays a vital role in the growth of any economy. The Pakistan Stock Exchange also holds significant importance in the economy. Numerous studies demonstrate that the Pakistan stock market is influenced by macroeconomic indicators. The novelty of our study lies in using machine learning algorithms to predict stock market performance. With these algorithms, more accurate results are typically obtained compared to basic statistical models.

The main purpose of the study is to model the monthly price of the KSE 100 index based on Pakistan's economic indicators, utilizing machine learning methods to predict stock market performance. In this study, we examined the relationship between macroeconomic indicators and the Pakistan stock exchange through a machine-learning approach. The ANN Backpropagation used a multi-layer perceptron model with three hidden layers to investigate the future value of the KSE 100 index based on macroeconomic indicators and previous data. The input layer has 3 neurons, and the hidden layers have 50 neurons. The output layer has only one neuron. Eighty percent of the data are used for training, and the remaining 20 percent of the data are used for validation. The learning rate is 0.0015, and the maximum epoch of the network is 5000. The tanh activation function was used to estimate the hidden layers, and the linear function was used to estimate the output layer.

Our Artificial Neural Network program with a backpropagation algorithm predicts the KSE 100 index with 99% accuracy using the 16 macroeconomic indicators of the Pakistan economy. The results show that only 203 instances of the KSE 100 index can predict the month-end close price using the artificial neural network. KSE 100 index daily data were used to predict the daily close price. The present study demonstrates that the KSE 100 index is more influenced by economic indicators by forecasting the future trends of the index. Our forecasting values are near the actual values, which is helpful for investors to generate maximum profit because the actual price is equal to or more than the forecasting values. The model of the KSE 100 index can predict future trends by providing different and more data. The present study proves that the Artificial Neural Network predicts the future values of the stock market.

The present study has used only macroeconomic indicators to predict the trend of the stock market in Pakistan. Further research can be carried out by incorporating social and political indicators along with macroeconomic indicators to predict stock market trends.

Authors’ Contribution

Kinza Bukhari: Retrieved the data set, conducted data analysis, and write the draft.
Atif Khan Jadoon: Idea of the study is given.
Munawar Iqbal: Idea of the study is given.
Ayesha Arshad: Revise, and approved the final version.

Conflict of Interests/Disclosures

The authors declared no potential conflict of interest w.r.t the research, authorship and/or publication of this article.

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