



## Original Article

# Comparative Study of Machine Learning (ML) and Conventional Time Series Methodologies in Modelling the Exports Trade of Pakistan

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## ABSTRACT

Export trade is a pivotal driver of economic growth and stability in any nation, including Pakistan. Accurate modelling of export trade holds immense significance as it allows for informed decision-making and strategic planning. By employing advanced techniques like machine learning alongside traditional time series models, we can gain deeper insights into the dynamics of exports, anticipate trends, and adapt policies and strategies accordingly. This study focuses on comparative study of different machine learning and time series models in forecasting the exports trade of Pakistan. The dataset used in this study spans from 1972 to 2021, containing yearly data on exports (% of GDP) for Pakistan. This study focuses on employing various machine learning models, including the MLP model, ELM model, and classical time series models like ARIMA and Exponential smoothing, to model and forecast the exports of Pakistan. The model that best met the KPI criteria was chosen as the optimal candidate for predicting the behaviour of the exports trade data. The outcomes of the study concluded that MLP model outperformed in performance metrics, with  $MSE = 0.49$ ,  $RMSE = 0.70$ ,  $MAE = 0.53$ , and a  $MAPE = 4.27$ . among all alternative models, including the Extreme Learning Machine model, ARIMA model, and Simple Exponential Smoothing. Our study highlights the effectiveness of the Multi-layer Perceptron (MLP) model as a valuable tool for forecasting exports. Its accuracy empowers policymakers to make well-informed decisions, ensuring a more sustainable and prosperous economic future.

## Introduction

Export modelling holds significant importance as it provides important insights and predictions related to international trade activities for nations and companies. For companies engaged in global trade, export modelling plays a vital role in devising effective business strategies. Organisations can make informed decisions regarding production capacity, inventory management, market expansion, and pricing strategies by understanding future export trends. Precise export modelling empowers these companies to anticipate changes in demand and supply patterns, thereby aiding, optimising logistics operations, supply chain management, and reducing inventory costs. Researchers have successfully utilised different modelling techniques, such as multivariate time series analysis, ARIMA, VAR, SVR, and ANN, to examine and forecast various aspects of exports in other regions. It highlighted the critical export role in the economic growth of non-oil developing countries and emphasised the need to increase exports to address the balance of payments issues Bond (1985). Extended demand and supply functions to test the relationship between exports and imports Khan & Knight, (1988). Also, it investigated the long-run convergence of import and export patterns in 50 countries and found stable relationships in 57% of low-income countries Arize (2002). Three categories are employed for each export and import, assuming Pakistan's export demand is exogenous Naqvi et al. (1983).

Various studies were conducted on Pakistan's export performance, estimated elasticities of export demand, and supply for primary and manufactured exports from 1959 to 1980 (Anwar, 1985). In addition, the simultaneous equation model proposes exploring the relationship between economic growth, exports, and other macroeconomic variables Afzal (2004). It is concluded that the economy has driven exports more than exports have driven the economy (Afzal & Ali, 2008). They also examined the impact of the real exchange rate, income, import prices, and foreign exchange reserves on import demand in Pakistan from 1980 to 2008.

The study Ghafoor (2005) analysed the trade pattern in Pakistan from 1971 to 2003 and forecasted imports and exports up to 2010, employing ARIMA modelling and a log-linear model. Moreover, various research focused on forecasting Pakistan's exports to SAARC countries, using the univariate ARIMA model by Box and Jenkins Mehmood & Ahmad, (2012) Besides the evidence of export's positive and significant impact on Pakistan's economy was provided by Javed et al. (2012). Likewise, the imports and exports of Pakistan from 1947 to 2013 were forecasted by using the Box-ARIMA Farooqi (2014). The impact of exports on Pakistan's economic growth, utilizing time series data was examined from 1972 to 2014 (Ahmad et al. 2017). On the other hand, the impact of exports on the economic growth of Pakistan and India from 1990 to 2016 was studied, employing unit root tests Khan & Khan, (2020).

The performance of autoregressive models was compared with seasonal dummies and the Box-Jenkins Approach for the fiscal year 2020 Daniyal, et al. (2024). Also, the forecasting accuracy of ARIMA, regression, and neural network models was compared by focusing on exports, population size, wheat area, and production as factors Ghauri et al. (2020). Numerous alternative approaches were utilized, including exponential smoothing, ARIMA, VAR, Engle-

Granger, and vector error correction models, to forecast agricultural exports and imports in South Africa Abd-Elaal et al. (2013).

This work investigates how Deep Learning (DL) methods can improve prediction accuracy through a systematic analysis of data from the CEIC Information Global Database Yousfani et al. (2024).

This study uses a quantitative research methodology because it allows for a larger sample size, greater objectivity, and accuracy. Utilizing VEC and ARDL, macroeconomic data from 1980 to 2019 was procured from the Tanzania Bureau of Statistics and the World Bank to assess the impact of trade liberalization on export outcomes Ghauri et al. (2020). The goal of this study is to analyze the US exchange rate, imports, and exports' time series features. The existence of a co-integrating link between exports, imports, and the exchange rate is empirically investigated in this work Qureshi et al. (2020). Using 58 international trading partners, this study tests the factors that influence prospective export markets for Pakistan's textile, clothing, and apparel exports. To examine the influence of particular macro and political factors on export flow, the gravity model is evaluated using modern panel econometrics Khan & Khan (2020). This study investigates the fluctuations in macroeconomic factors that impact Pakistani imports (Mehmood & Ahmad, 2012). In this work, time-series data covering the years 1960–2010 are used to apply the ARIMA model to examine trade patterns and predict future trends in the context of Pakistan Mehmood & Ahmad (2012). By utilizing (AR) with seasonal dummies and Box-Jenkins methods, two econometric models will be evaluated in order to anticipate imports and exports for the fiscal year (FY) 2020 Khan et al. (2024).

The primary aim of this study is to employ Machine Learning (ML) models for modelling Pakistan's export trade, with a focus on forecasting future export trends. The main research hypothesis centers around the effectiveness of Multilayer Perceptron (MLP) models in accurately predicting Pakistan's future export trade. The objective can be framed as follows:

1. MLP does not forecast the export trade of Pakistan effectively
2. MLP model forecasts the export trade of Pakistan effectively

The study's structure involves several key sections. Section 2 literature review, section 3 discussed the comprehensive analysis of the data and materials used in the research. In Section 4, the research methodology is elaborated, along with the selection and explanation of different models employed in the study. Section 5 presents an in-depth exploration of data pre-processing techniques and processing procedures. Lastly, Section 6 is devoted to discussing the results obtained from the models and their implications for policy-making decisions.

## Literature review

Machine learning is being used for univariate time series forecasting. However, few research compares their prediction accuracy to established statistical methods. In 1996, Hill et al. compared statistical methods to multi-layer perceptrons. The neural network method much outperformed the latter. Using M3 competition time data, Ahmed et al. (2010) compare multiple machine learning methods for this assignment. Their findings show that multi-layer perceptron

and Gaussian processes predict best. These techniques were not compared to ARIMA or exponential filtering. Cerqueira et al. (2019) studied statistical and machine learning forecasting models in a unique case study. They found that subsequent methods had a higher average rank (predictive performance). Rules-based regression, a Quinlan's model tree variant, has the greatest average rank among 62-time series. Makridakis et al. (2018) use many statistical methods to improve on Ahmed et al. (2010). They found that most statistical techniques beat machine learning for univariate time series forecasting. Both single-step and multi-step forecasts show this effect. The nearest neighbor method, decision trees, support vector regression, Gaussian processes, and neural networks are examined. Statistical methods such as ARIMA, naïve, exponential smoothing, and theta are used. Although Makridakis et al. (2018) increased their comparison study, we argue that their sample size is biased. A huge dataset of 1045 M3 competition time series is used. However, each time series is tiny. The average is 116 observations. Our working hypothesis is that machine learning cannot develop a generalizable regression function under these conditions.

In Pakistan, Iqbal et al. (2010) examined the causal link between economic development, import and export, and foreign direct investment. From 1998 to 2009, they used quarterly time series data. VECM co-integration was employed to test causation. Malik et al. (2010) assessed economic growth and foreign debt. Pakistani 1972–2005 time-series data is utilized. GDP was the output variable, whereas foreign debt and debt servicing were inputs. Traditional OLS modeling confirmed this connection. The study found that foreign debt and debt services hurt GDP growth. Rising foreign loans and debt payments reduce economic growth. Chani et al. (2011) examined inflation and economic growth to support widespread poverty. Annually, time series data were utilized from 1972 to 2008. Destitution was an output variable, with GDP, investment, trade openness, and inflation as inputs. Study participants took the ARDL restricted exam. This study found long-term links between economic progress, trade liberalization, poverty, investment, and inflation. Economic growth hurt poverty, while inflation helped. The impact of commercial liberalization on poverty was limited. Hussain and Malik studied inflation and Pakistan's economy in 2011. They were paid annually to review data from 1960 to 2006. Data was estimated using the threshold model, ECM, and Granger causality test. This investigation found favorable correlations between inflation and economic growth. One-way link: inflation drives economic growth but not economic growth creates inflation. In the short run, ECM results showed inflation is not balanced. The threshold model implied inflation above the threshold, which slowed economic development. Pakistan maintained its inflation rate to avoid an economic development-related spike. Economic progress, trade liberalization, and foreign direct investment in Turkey and Pakistan were examined by Klasra (2011). They were anticipated to utilize 1975–2004 annual time series data. GDP was the outcome variable, whereas FDI, exports, and trade openness were inputs. Research was explored using ARDL modeling. The study found a bidirectional causal association between exports and trade openness in Pakistan and FDI in Turkey. Pakistan's long-term nexus findings support trade openness and growth, whereas Turkey's growth-driven export hypothesis is verified. Abbas (2012) examined

Pakistan's GDP-exports relationship. From 1975 until 2010, they used data. They tested long-term and short-term causation with the Johansen co-integration and Granger causality tests. The study found short- and long-term unidirectional causality. Building local production facilities and encouraging investment are essential. Sultana et al., (2013) predicted Pakistani inflation and growth using time series. Monthly time series data from July 2008 to June 2013 was used. They predicted inflation and economic development using ARIMA and decomposition. MAD and SSE were employed to evaluate their performance. They found that the ARIMA model predicts inflation and economic growth better than decomposition. Ali and Abdullah (2015) examine Pakistan's trade openness and economic progress. They were requested to investigate 1980–2010 using time series data. Real GDP, gross fixed capital formation, financial development, and secondary school enrollment were output variables. The short-term nexus was analyzed using Johanson co-integration, Granger causality, and vector error correction. GDP growth and trade openness exhibited a short-term positive association, but trade liberalization had a 20% negative impact on economic growth. Selling raw materials instead of completed things causes this. Pakistan's economic growth, financial development, and foreign commerce were investigated by Gokmenoglu et al., (2015). Their research employed 1967–2013 annual time series data. Inputs were imports, exports, money supply, domestic lending to private institutions, and private sector credit, and output was economic growth. The co-integration test and Granger Causality approach examined variable relationships. The study found a long-term link between economic growth, financial development, and international trade. The causality test showed that financial development affects economic growth and imports. The results showed that government financial development aid would stabilize economic growth. Jebran et al. (2018) examine how trade terms affect Pakistani economic development. Time series data from 1980 to 2013 was used. GDP per capita was an output metric, including gross capital creation, total labor, income, and net barter terms of trade as inputs. They predicted short- and long-term economic growth using the ARDL bound model. The study found that labor boosts economic growth in the short and long run. Capital had a substantial and positive long-term impact on economic growth, but it had little immediate impact. Trade terms hurt short- and long-term economic growth. Twenties Trade conditions affect economic development, thus economic regulations are important, according to studies. Financial inclusion and Pakistan's economic progress were examined by Ali et al., (2019). This study employed 1985–2017 time-series data. They utilized annual real GDP growth as an output variable and financial inclusion index, investment, inflation, and trade openness as independent factors. They estimated with the ARDL bound test. This study found that financial inclusion boosts economic growth in the short and long run. Rural and female Americans need financial awareness. Talib and Fan., (2019) examined Pakistan's long-term and short-term economic development, industrial production, and energy consumption Qureshi and Ahmed (2022). Time series data from 1981 to 2014 was used. GDP per capita, industrial production, and energy consumption per capita were their output and input variables. They assessed these measures' long- and short-term connections with Granger causality using the autoregressive distributed lag (ARDL) bound approach. According to this study, economic

growth increases industrial production and energy consumption over time. Granger causality results show that economic growth and manufacturing output were unidirectional, whereas manufacturing output and energy consumption were bidirectional. According to Yousfani, K., et al., (2021) GDP, foreign trade industrial production used to explain variations in real economic growth. Awan and Qasim., (2020) examined Pakistan's economic development and external debt. They utilized 1980–2017 time-series data on GDP, foreign debt exports, imports, yearly population growth, gross capital formation, and debt services. They examined variable correlations using ARDL and Error Correction Models. Debt services, import volume, foreign debt, and population growth rate all hurt GDP, the study found. Exports, labor force participation, and gross capital creation boosted GDP. Pakistan must reduce foreign debt and boost production, exports, and taxes. Sabri (2023). Predicting Pakistan's macroeconomic indicators using conventional and artificial network interpolation. Gross domestic output (volume, NGDPD) and total investment were projected from 2013 to 2023. Analytical procedures include moving averages, exponential smoothing, Brown's single-parameter linear, Brown's second-order exponential, Holt's two-parameter linear, and decomposition Ramzan and Qureshi, (2022). The study examines how well the artificial neural network model predicts long-term economic drivers and compares it to time-series data sets (Ahmed & Hussain, 2022). This study proposes a wheat production forecasting model using machine learning. The northern wheat-growing regions of Pakistan are a case study because of their importance to the agricultural industry. The best attribute subset for agricultural production was selected from five years of data. Our findings confirm machine learning algorithms' prediction capacity on a limited crop dataset. This discovery might be applied to different crops and regions. Khan (2022). Pakistan's inflation and exchange rate figures from January 1989 to December 2020 are anticipated in this study. SVM, polynomial regression, ANNs, and k-nearest neighbor were employed in this investigation Qureshi et al., (2022). The training set featured data from January 1989 to December 2018, used to train machine algorithms, while the test set contained data from January 2019 to December 2020, used to assess machine learning. RMSE and MAE were utilized to evaluate the algorithms in this study. ANNs exhibited the lowest RMSE and MAE of all research techniques. The test set demonstrated that polynomial regression (degree 1) and ANN outperformed SVM and KNN for inflation rate analysis and forecasting based on error prediction (Saeem et al., 2021). This article suggests using sentiment analysis on Twitter "tweets" to estimate currency exchange rates using machine learning. Data from a currency website and Pakistani company tweets with finance-related terms was used to construct a dataset of USD-PKR exchange rates. Data preparation was used to send the raw dataset to natural language processing. Response variables in the standardized dataset were labeled as "1" for a rise and "-1" for a decline in the exchange rate. Principal component and linear discriminant analysis were utilized to represent the dataset in three-dimensional vector space. The sampling-based clusters were employed for data optimization. Five machine learning classifiers (random forest, bagging, naïve Bayes, and support vector machine) were used to examine the optimized dataset. The simple logistic classifier estimates USD and PKR exchange rates with the maximum

accuracy of 82.14% (Khan et al. 2021). The transforming patterns of ancient Chinese agricultural development and fruit production are examined using key crop production data from 1980 to 2050 and a range of fruit production data (apples, avocados, citrus fruits, pears, and grapes). This analysis predicted future fruit production using Chinese production statistics. Chinese National Bureau of Statistics data on total fruit growth output for the relevant timeframe is used to predict future fruit production using deep neural networks Qureshi et al. (2023). A variance-based generate output accuracy formula gives the proposed method 95.56% accuracy. The primary aim of this study is to employ Machine Learning (ML) models for modeling Pakistan's export trade, with a focus on forecasting future export trends. The main research hypothesis centers around the effectiveness of Multilayer Perceptron (MLP) models in accurately predicting Pakistan's future export trade Iftikhar et al. (2023). The hypothesis can be framed as follows:

**Ho:** MLP does not forecast the export trade of Pakistan effectively

**Hi:** MLP model forecasts the export trade of Pakistan effectively

## Data and Materials

This section focuses on the methodology and concepts employed in modelling exports as a percentage of GDP in Pakistan. The data was collected from the World Bank website (<https://data.worldbank.org/indicator/NE.EXP.GNFS.ZS?locations=PK>), specifically the yearly data on Pakistan's exports of services and goods as a percentage of GDP from 1972 to 2021. Forecasting equations are statistical functions utilized to predict the unpredictable behaviour of a phenomenon, which aids in decision-making. These equations make use of past information, such as the lagged variable  $y_{t-1}$ , to predict the present value  $Y_t$  and understand this behavior. The objective is to find a mathematical function  $F$  that effectively captures the inputs and produces the desired output. In this study, the conventional Box-Jenkins methodology, ETS (Error, Trend, Seasonality), machine learning models, and extreme learning models were utilized as modeling approaches. These techniques were applied to analyze and forecast the exports as a percentage of GDP in Pakistan.

## Research Methodology

Modelling and contrasting machine learning models with traditional modelling techniques is the primary goal of this research. Data sets for testing and training have been separated from the overall data. Examining the stationarity is the first step in the underlying study. Subsequent analysis will be conducted if the data remains uniform at level 0. The first difference between  $Y_t$  and  $Y(t-1)$  will be used to make our series stationary if it fails to be stationary. To verify if the series is stationary, the dickey-fuller (ADF) test is going to be used. The ACF and PACF analyses, which are graphical representations, are part of the process of identifying the candidate model. The next step is to choose the best candidate models among the different models that satisfy the mentioned model selection criteria. The data has been split into 80% training and 20% testing.

## Box-Jenkins ARIMA model

Generally, auto-regressive models in time series analysis combine with integrated moving average models to create a new type of time series model known as auto-regressive moving average (ARIMA) models. The representation of ARIMA model is represented as ARIMA (p,d,q), where p denotes the AR order, d is the differenced trend, and q is the moving average order. While the resultant variable  $Y_t$  varies in a linear manner on both its past and present stochastic terms, the model MA (q) model indicates that the outcome variable  $Y_t$  relies linearly on its prior values and its most recent residuals  $\varepsilon_t$  (stochastic term) Iftikhar et al. (2024). ARMA (p,q) models, which combine the MA and AR models, are the precursors of the (ARMA) model. The following equation serves as a general representation of the ARMA model.

$$Y_t = \alpha + U_1 Y_{t-1} + U_2 Y_{t-2} + \dots + U_p Y_{t-p} + \varepsilon_t - \phi_1 \varepsilon_{t-1} - \phi_2 \varepsilon_{t-2} - \dots - \phi_q \varepsilon_{t-q} \quad (1)$$

## Simple Exponential Smoothing (SES)

The most basic type of exponential smoothing, known as SES, is appropriate for time series data that lacks seasonality or a trend. It utilizes an optimization parameter (alpha) to regulate the rate of decay and gives historical observations exponentially decreasing weights. The following is the formula for SES Tawiah, Daniyal, and Qureshi (2023).

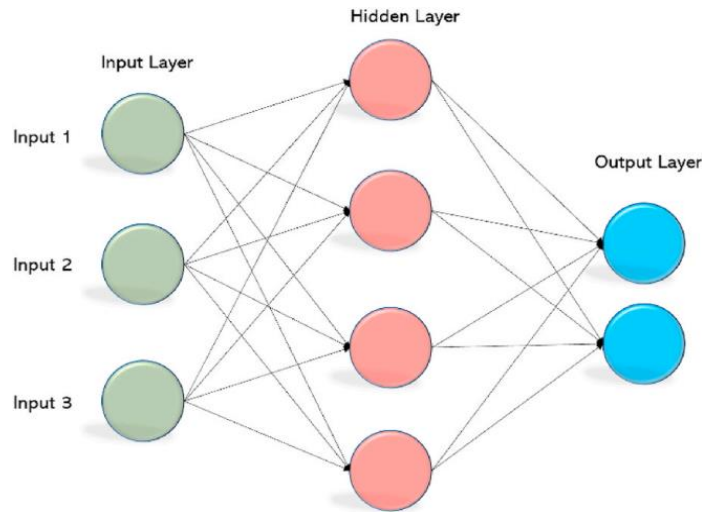
$$Forecast_t = \alpha * Observation \text{ at time } t + (1 - \alpha) * Forecast_{t-1} \quad (2)$$

## Multilayer Perceptron (MLP) approach

A popular kind of ANN for supervised learning tasks like regression and classification is the Multi-Layer Perceptron (MLP). To produce the desired output, MLP transforms the input data using numerous layers of interconnected nodes, or neurons. The network is called a "perceptron" because it is modelled after the structure and function of the biological neurons in the human brain. The network can be expressed mathematically in the following form;

$$y = f_s \left[ \sum_{k=0}^K w_{1k}^0 \left( f \sum_{n=0}^N w_{kn}^i u_n + b_n \right) \right] \quad (3)$$

Given that the activation function of the middle layers is  $f_s$  and the resultant layer activation function is  $f_s$ , the network inputs  $u_n$  represent the bias of the network  $b_n$ . The intermediate layer's weight is denoted by  $w_{kn}^i$  the output signal by  $y$ , and the output neurons' connections by  $w_{1k}^0$ . Figure 2 illustrates the MLP model's diagrammatical structure.



**Figure 2. Structure of Multilayer perceptron (MLP) with a m hidden layer**

### Extreme Learning Machine (ELM)

ELM is a machine learning algorithm that was proposed by Huang et al. in 2006. ELM is one of a kind of feed-forward (NN) model that is characterized by its efficient training process and fast computational speed.

The basic equation of an ELM model is represented as:

$$J = g(Y \cdot W + b) \quad (4)$$

where:  $Y$  represents the input data, which is  $N \times d$ , a matrix of size, The numbers  $N$  and  $D$  stand for the total samples and input characteristics, respectively.

$W$  represents matrix of randomly generated input weights, with size  $d \times L$ , where  $L$  is the number of hidden neurons or nodes.

- $b$  is a bias vector of size  $1 \times L$  added to each hidden neuron.
- $H$  is the hidden layer output matrix of size  $N \times L$ , obtained by applying an activation function  $g(\cdot)$  element-wise to the linear combination of inputs and weights.
- $C$  is the matrix of output weights, with size  $L \times K$ , where  $K$  is the number of output classes or regression targets.
- $Y$  is the output matrix of size  $N \times K$ , representing the predicted outputs.

The main idea behind ELM is that the input weights ( $W$ ) and biases ( $b$ ) are randomly assigned and fixed during the training phase, allowing the network to be trained quickly Qureshi et al. (2023). The only weights that need to be determined are the output weights ( $C$ ), which can be efficiently computed using a least squares method:

$$C = (HT \cdot H) - 1 \cdot HT \cdot Y \quad (5)$$

Once the output weights are calculated, the model can be used to make predictions by applying the equation  $Y = H \cdot C$ .

## Key Performance Indicators (KPIs) for Model Selection

To evaluate the performance of all forecasting models, we employed MAE, RMSE, and MAPE as the criteria for model selection; They have the following expressions.

$$MSE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2 \quad (6)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (8)$$

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{x_t} \right| * 100 \quad (9)$$

## Results and Discussion

The study begins by analysing the time series plot of export data from 1972 to 2021 as in Figure 2. The visual representation of the series shows that the graph is non-stationary. The Dickey fuller test will be applied to check whether the series is stationary at level (0).

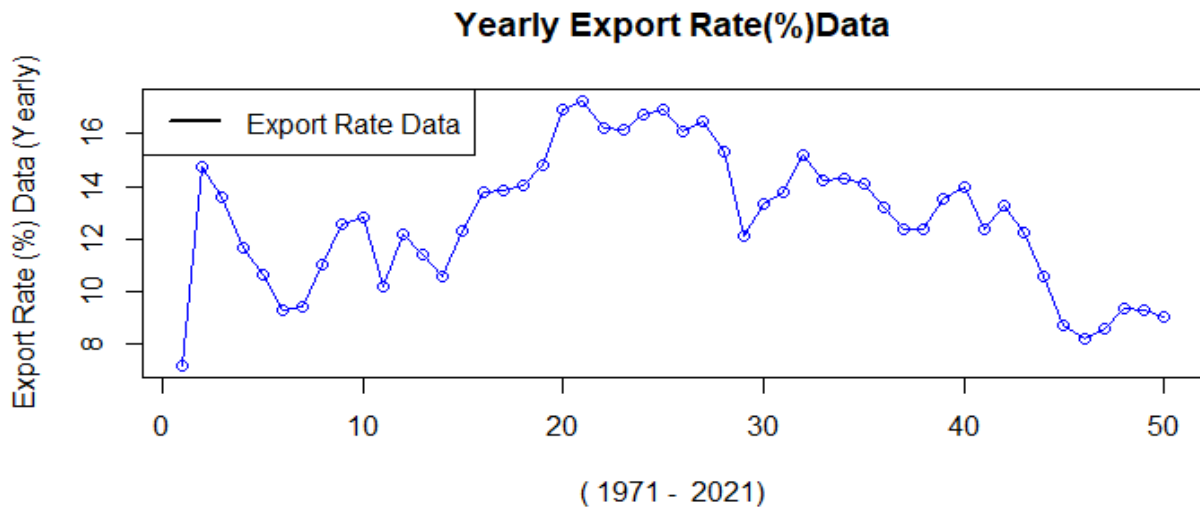


Figure 1: time series plot of Exports of Pakistan from 1972 to 2021

At level (0), the ADF- test statistic of -2.66, coupled with a p-value of 0.0879, establishes that the time series is non-stationary. To make the series stationary, the first difference was applied, and subsequently, retest the series using the ADF test.

### ADF test on differenced Series

The first differenced series displays stationarity, as evidenced by the ADF test statistic = -9.29  
p-value = 0.000\*\*\*.

Next, we construct the ACF and PACF correlogram to identify potential candidate models for the time series. In this study, we explore four different models, two of which are non-linear, while the other two are linear models. The selection process aims to compare and determine the most suitable time series forecasting model. It is essential to note that linear models necessitate the assumption that the data should be stationary, a condition not applicable to non-linear models Daniyal et al. (2024). Thus, the choice of model depends on the stationarity characteristics of the data. The four models discussed in this study are employed for modelling and predicting the data, leveraging the data-splitting technique. Specifically, the dataset is divided into two sets: the training data and the testing data. The training set encompasses 80% of the data, while the remaining 20% constitutes the testing set, facilitating model evaluation and validation.

**Table 1: MSE, RMSE, MAE, and MAPE criterion for MLP, ELM, ARIMA, and SES (Training dataset = 80%)**

Models	MSE	RMSE	MAE	MAPE
MLP	0.49	0.70	0.53	4.27
ELM	0.99	0.98	0.85	6.95
ARIMA	2.10	1.45	1.11	8.88
SES	3.17	1.78	1.27	10.78

**Table 2: MSE, RMSE, MAE and MAPE criterion for MLP, ELM, ARIMA, and SES (Training dataset = 20%)**

Method	MSE	RMSE	MAE	MAPE
MLP	10.41	3.23	3.60	22.33
ELM	11.46	3.39	3.60	22.90
ARIMA	14.90	3.86	3.59	25.92
SES	14.77	3.84	3.45	24.35

In this study, we first employed the Multi-Layer Perceptron (MLP) model on the export dataset, configuring it with five hidden nodes and utilizing the sigmoid function. The model processed the data with three input lags and featured one output layer Yousfani et al. (2024). The

outcomes of the MLP model yielded outperforming performance metrics, with MSE = 0.49, RMSE = of 0.70, MAE = 0.53, and a MAPE = 4.27. Subsequently, we applied alternative models, including the Extreme Learning Machine model, ARIMA model, and Simple Exponential Smoothing, to the export dataset, presenting their respective results in Table 1. However, the comparison revealed that the MLP method consistently outperformed the other models on the training dataset [Figure 2]. To further assess the models' capabilities, we subjected them to evaluation on a separate testing dataset, and the testing errors for each model were documented in Table 2. Once again, the MLP model exhibited remarkable superiority, yielding the lowest MSE, RMSE, MAE, and MAPE values of 10.41, 3.23, 3.60, and 22.33, respectively Iftikhar et al. (2024). Graphical representations of all the methods were also included in Appendix A for comprehensive visualization and comparison. Furthermore, we provide a sample of the test data observations in a table and utilized the models to generate forecasts. Notably, the MLP method showcased random forecast point estimates and demonstrated the least errors when compared to the other methodologies, reaffirming its outstanding forecasting performance Qureshi et al. (2022).

Based on these findings, we can confidently state that the MLP method offers an efficient approach for forecasting export data, as it consistently yields the lowest errors when compared to the alternative models.

**Table 3: Point Forecast for all candidate models for the testing dataset**

Test data	MLP	ELM	ARIMA	SES
13.97	9.052995	9.170806	9.113374	9.121474
12.42	9.135353	9.399501	9.323085	9.423453
8.58	9.125757	9.510248	9.315365	9.924456
12.24	9.143159	9.508642	9.156639	9.825544
10.60	9.270313	9.520442	9.137934	9.823345
8.74	9.386692	9.567244	9.254281	9.921435
8.22	9.470958	9.595878	9.286294	9.425565
13.28	9.499867	9.589131	9.203837	9.620983
9.39	9.544036	9.548106	9.167058	9.221554
9.30	9.550236	9.427951	9.223323	9.321034

## Conclusion and Policy Making in the Future

Since exports play a big part in the country's economy and support the livelihoods of millions, making well-informed decisions based on precise forecasts can open up significant growth opportunities. By understanding how the market works, and anticipating changes in demand, Pakistan can build a strong and sustainable export sector, which in turn contributes to the country's economic stability and development. Keeping in view the importance of export trade and the current economic situation, this study focused on developing the model for export

forecasting, using a comprehensive approach that combines traditional time series analysis techniques with advanced machine learning algorithms.

In the existing literature, several studies [18-26] have explored the modelling of Pakistan's export trades, predominantly relying on conventional methodologies. However, limited research has been conducted to compare machine learning algorithms with these conventional models specifically for export forecasting. Addressing this gap, the present study introduced a machine learning model adapted for forecasting Pakistan's exports from 1972 to 2021.

The study focused on four models, consisting of two classical time series models and two machine learning models, to analyse the data. The results obtained from these models were compared to determine their performance. The dataset was divided into training and testing sets, allowing for the selection of the most suitable model that met the well-known model selection criteria. In the ML models, the feed-forward method was used to predict 80% of the export dataset, while the remaining 20% was reserved for testing purposes. Based on the specified criteria for model selection, the MLP model, a machine learning model, outperformed the other models in both scenarios where the data was split into 80% and 20% for testing purposes.

Policymaking regarding the importance of exports in Pakistan's economy is crucial for sustainable economic growth. To make informed decisions, the application of the Multi-Layer Perceptron (MLP) model proposed in our study for forecasting exports can provide valuable insights. By utilizing the MLP model, policymakers can assess and predict future export trends accurately. This forecasting approach enables the identification of potential challenges and opportunities in the export sector, leading to the formulation of effective policies that promote export growth, enhance competitiveness, and foster economic stability in Pakistan. The MLP model's ability to analyse complex data patterns and provide reliable predictions empowers policymakers to make evidence-based decisions and implement targeted strategies to boost exports, thus driving overall economic development in the country.

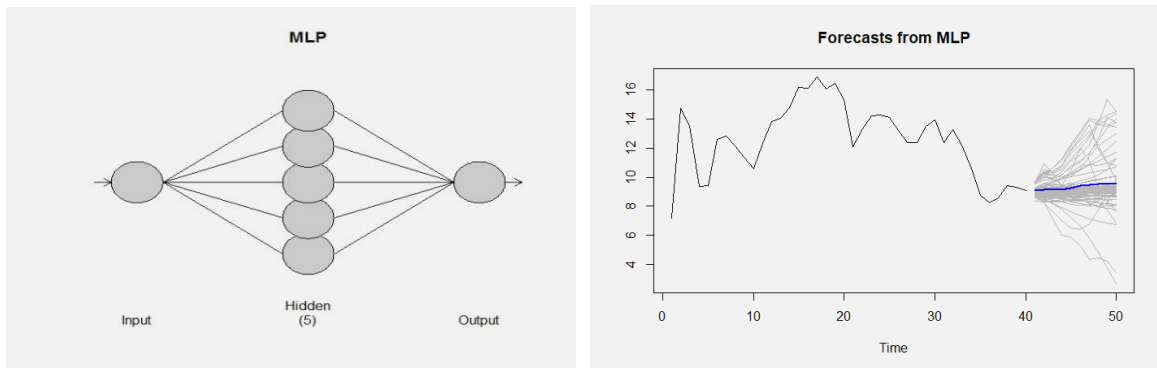
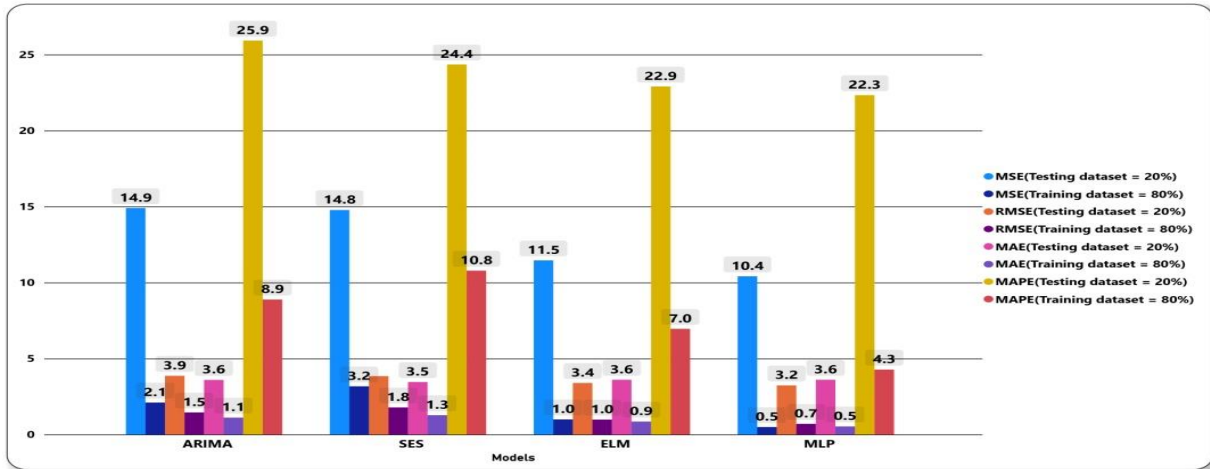
**Limitation of the study:** The study relies on a limited data set from 1972 to 2021. However, the accuracy of the prediction may affect the quality and extensiveness of the data used in the study. The most recent and realistic data can increase the model forecasting competencies. Also, the MLP model did well compared to the other methods, even though it did not simplify well to a diverse set of data or another export scenario of further countries. Therefore, the results are specific to the Pakistan export trade and it may not be applied collectively. Furthermore, this study did not add external indicators such as political instability, economic conditions, or trade strategies which may significantly affect exports. Therefore, including these indicators can provide a more complete forecasting model.

**Theoretical Implication:** The current study value adds to the present literature on export forecasting by signifying the effectiveness of the machine learning model most specifically to the Multilayer Perception in managing the complex and nonlinear relationship of time series data. Further, this study strengthens the perspective of machine learning processes to outclass the traditional statistical methods in export forecasting by boosting the further examination of mixed

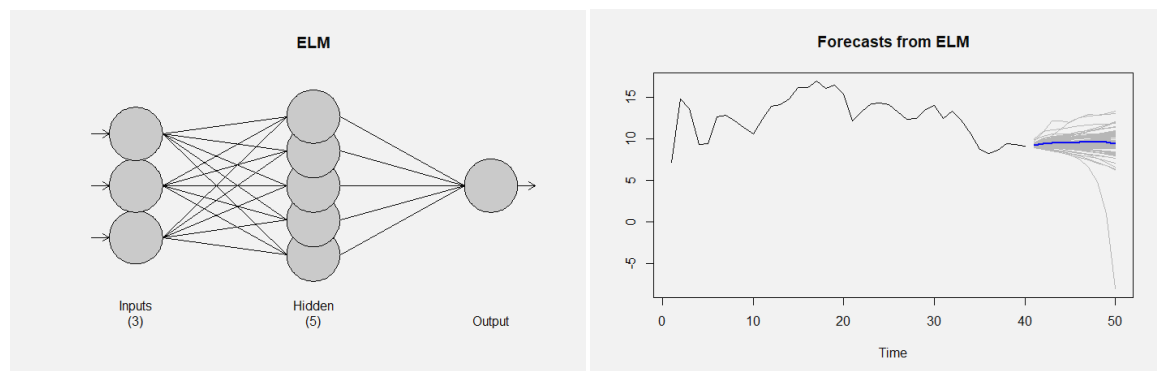
models that syndicate the strengths of both approaches. Also, by effectively employing the MLP model in real-world economic data, this study highlighted the significance of AI in economic development and the formulation of policy. Hence, it covers the way for assimilating AI tools in the research of macroeconomics.

## Appendix A

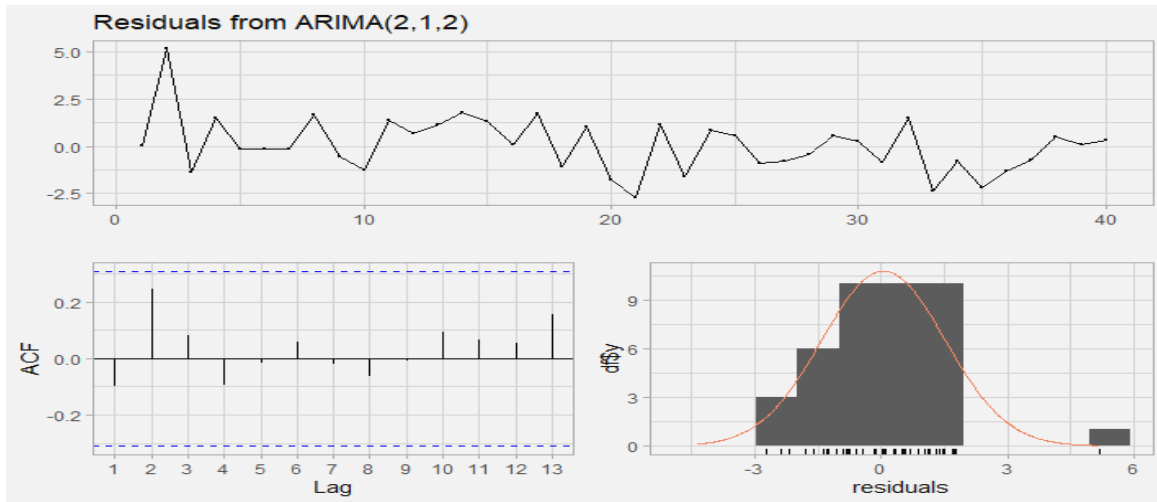
**Figure 2: Key performance indicators of Different Models based on training and testing dataset**



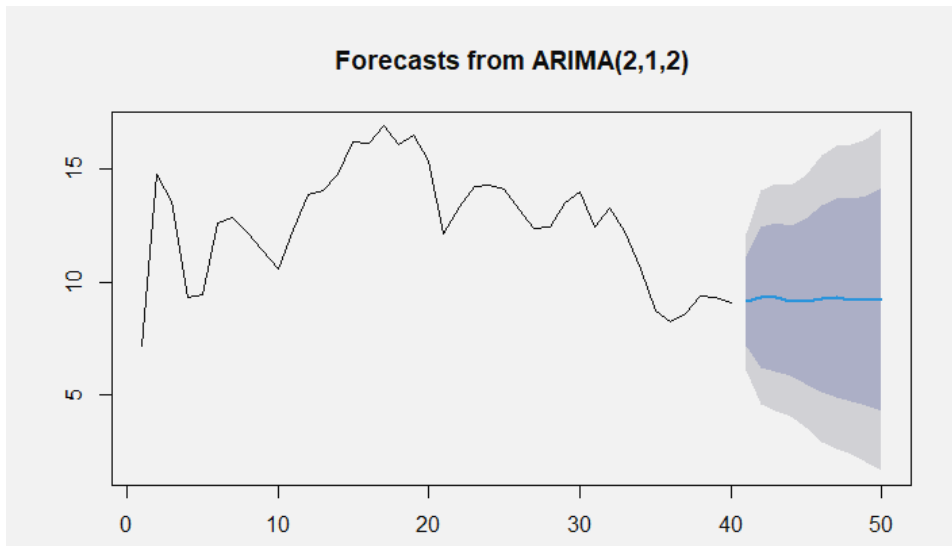
**Fig 3: Forecast from MLP model**



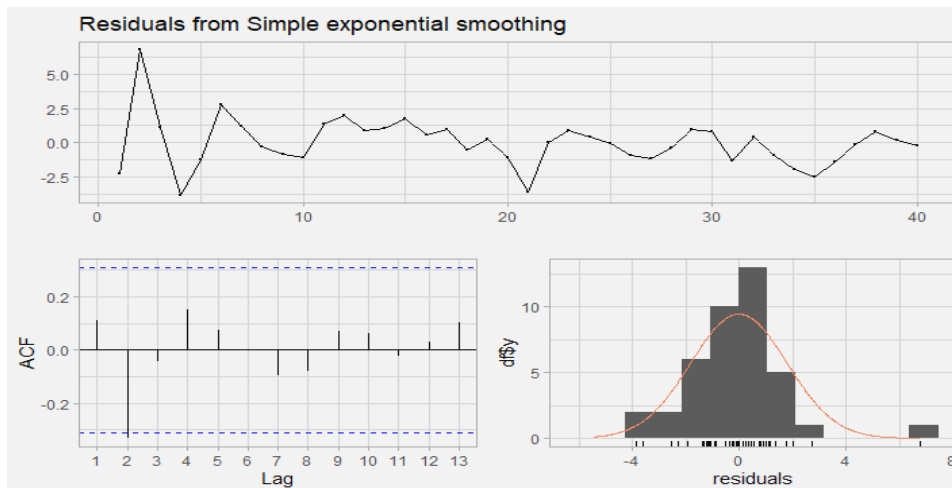
**Fig 4: Forecast from ELM model**



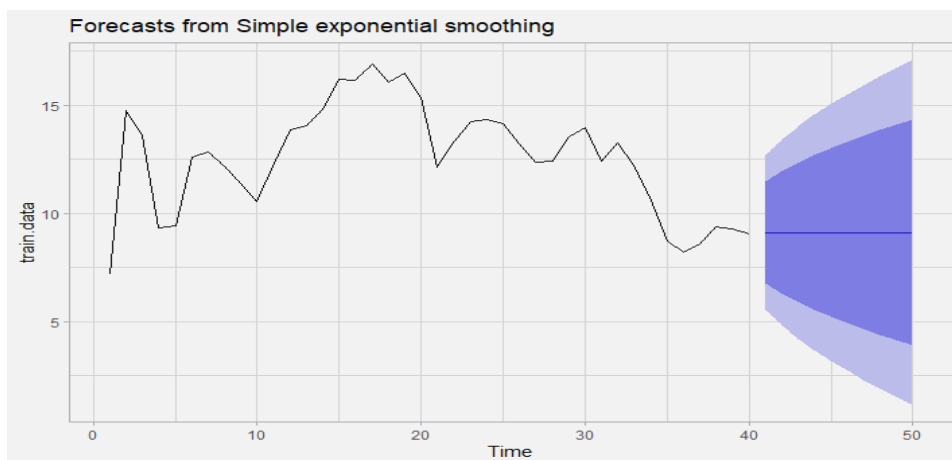
**Fig 5: Diagnostic Checks for ARIMA((2,1,2) Model**



**Fig 6: Forecast from ARIMA model**



**Fig 7: Diagnostic Checks for SES model**



**Fig 8: Forecast from SES model**

**DECLARATIONS:**

1. **Availability of data and materials:** Data will be available as per the reasonable request.
2. **Competing interests:** The authors declare they have no competing interests.
3. **Funding:** No funding is received.

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