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Application of machine learning methods in forecasting economic growth and inflation of Vietnam

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Inflation and economic growth are two crucial indicators for any country in the world. In light of the importance of these two economic indicators, the forecast of economic growth and inflation has become a significant topic that national governments have traditionally prioritized. This study aims to apply popular machine learning algorithms such as KNN and MLP to build models for predicting economic growth and inflation. We also provide a comparison of the predictive accuracy between these machine learning algorithms and traditional forecasting models such as VAR and LASSO. Specifically, we employ techniques such as VAR, LASSO, KNN, and multi-layer perceptron (MLP) to construct forecasting models for Vietnam's economic growth and inflation using data collected from 1996 to 2021. The accuracy of the models is assessed using three indices: RMSE, MAE, and MSE. The empirical results show that according to all three indicators, RMSE, MAE, and MSE, the forecasting models of economic growth and inflation by the MLP model are the most accurate. Based on the results, we have concluded that the MLP model is a valuable tool for future forecasting because it can describe the nonlinear relationships between variables in the model and visually map them.

keywords: VAR, LASSO, KNN, MLP.

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1 Introduction

Economic growth and inflation are two critical indicators of any economy in the world. Economic growth reflects the development of a country, helping to enhance its status and to attract investment into that country. Economic growth has an impact on implementing social policies, changing the structure of economic sectors, forming new industries, and generating a large number of new employment for locals. Contrary to economic growth, high inflation causes macroeconomic instability by affecting consumption, investment, saving, and many other aspects of an economy. Furthermore, high inflation in a country reduces public trust in that country's national currency. Although they are considered two macroeconomic indicators that deeply affect socio-economic life, inflation and economic growth have a connection. This relationship has been indicated in many theories and empirical studies. Specifically, Keynes' theory shows that countries have to accept a certain inflation level to boost the economy in the short term. However, this positive relationship does not exist forever. When inflation exceeds a threshold, economic growth decreases (Stockman, 1981; Ocran and Biekpe, 2007). In the long term, when economic growth has reached the optimal level, inflation will not affect the economic growth, but now inflation is the result of excessively supplying money to the economy.

Forecasting economic growth and inflation has long attracted the attention of national governments due to how crucial these two factors are to the economy.

Sustainable economic growth is the goal that all governments aim for in order to stabilize the macroeconomy and improve labor qualifications. To achieve this, they apply advanced science and technology, enhance organizations and production management, increase the efficiency of labor materials, and effectively utilize associated natural resources while protecting the environment. Besides, high inflation in any situation and any country reveals the government's limited ability to operate and manage the economy. Therefore, forecasting inflation has become a core business that the central bank of any country has to perform. Accurate inflation forecasting will help the central bank implement the monetary policy to ensure economic growth and stabilize the value of the domestic currency.

Many methods of forecasting economic growth and inflation have been developed, such as: Günay (2022); Sbrana et al. (2017); Garcia et al. (2017); Modugno et al. (2016); Altug and Uluceviz (2013). Macroeconomy forecasting is a highly complex business. Over the past decades, by applying increasingly mathematical tools to economic research, economic forecasting methods have developed continuously. Mathematical and econometric models have been thoroughly applied in the forecasting business. Up to now, the forecasting methods of economic growth and inflation can be divided into quantitative methods and qualitative methods. The quantitative methods can be divided into causal methods (multivariate regression, quantile regression, logit regression, probit regression, etc.), and time series methods (Moving average, trend and seasonal analysis, vector autoregressive, ARIMA analysis, etc.). The qualitative methods are divided into the Delphi method, the Exploratory analysis, and the Expert opinion collection.

However, forecasting becomes more challenging during periods of economic crises and pandemics (Foroni et al., 2022). Currently, the COVID-19 outbreak, which originated in Wuhan, China, in late December 2019, has spread worldwide. The pandemic has quickly impacted various economic and social sectors, causing financial markets to fluctuate and the global economy to plunge into recession. Faced with the impact of the pandemic, international organizations continually adjust their forecasts for the global economy and countries worldwide. Short-term economic conditions during the COVID-19 crisis have become a major concern for economic decision-making and policy. Unfortunately, in situations such as economic crises and pandemics, traditional forecasting models may not be effective due to abnormal behavior by economic agents. Additionally, the theoretical foundations for building these models rely on assumptions under normal economic conditions. Therefore, our study aims to contribute a different perspective on forecasting by applying machine learning algorithms such as KNN and MLP. These algorithms do not require a specific model, so they may be a useful solution in special forecasting cases. A comparison of the accuracy of machine learning algorithms and traditional models such as VAR and LASSO will also be conducted in this study.

The remaining part of the paper is designed as follows: Section 2 introduces traditional forecasting methods and machine learning algorithms; Section 3 will present the model used to forecast economic growth and inflation. The forecasting results using the above methods will be presented in Section 4, and Section 5 will provide the conclusion of the paper.

2 Methodology

2.1 Vector Autoregressive Model (VAR)

The Vector Autoregressive Model (VAR) is an econometric technique used to forecast and analyze an economy. The basic assumption of VAR is that the present values of the variables can be explained by the past values of the variables involved (Lütkepohl, 2009). The VAR(p) model has the following form:

$$y_t = v + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t \tag{1}$$

where $y_t = (y_{1t}, ..., y_{Kt})^T$ is a (Kx1) random vector, A_i is fixed (KxK) coefficient matrix, $v = (v_1, ..., v_K)^T$ is a fixed (Kx1) vector of intercept coefficients, $u_t = (u_{1t}, ..., u_{Kt})^T$ is a K-dimensional vector of white noise.

The VAR model is performed in the following order: (i) Testing stationarity of the time series, (ii) determining the optimal lag p for the VAR model, and (iii) estimating the VAR model with the optimal lag p. In this paper, the Augmented Dickey-Fuller test (ADF) is used for testing stationarity. Determining the optimal lag p is based on the criterions such as Likelihood-Ratio statistic (LR), Akaike information criteria (AIC), Hannan-Quinn information criteria (HQ), Schwarz information criteria (SC), Final Prediction Error (FPE) criterion.

The VAR model has some advantages, namely (i) no need to determine endogenous and exogenous variables in the model; (ii) estimating a system of simultaneous equations will give better estimates than estimating each equation separately, (iii) the method to build and estimate the VAR model is simple, and variables in the model can be endogenous variables which are performed through the lagged variables of themselves or other variables in the model. Besides the advantages, the VAR model has some disadvantages as well, such as: (i) the variables in the model must be stationary so that there is no spurious regression occurring when estimating the parameters in the model; (ii) unlike the simultaneous equation models, the VAR model is still based on theories and uses less a priori information, the exclusion or inclusion of new variables plays an important role in determining model.

2.2 Least Absolute Shrinkage and Selection Operator Model (LASSO)

$$y_i = \beta_0 + \sum_{j=1}^{p} x_{ij}\beta_j \tag{2}$$

where y_i is dependent variable and p is the number of explanatory variables $x_i = (x_{i1}, \ldots, x_{ip})$. With xi and yi belonging to the set R^p and set R respectively. $\beta = (\beta_1, \ldots, \beta_p)^T$ is the weight vector belong to the set R^p and intercept coefficient β_0 in the set R.

The pair (β_0, β) is estimated by the OLS model based on minimizing squared error as follows:

$$\underset{\beta_0,\beta}{\text{minimize}} \left\{ \frac{1}{N} \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 \right\} = \frac{1}{N} \|y - \beta_0 1 - X\beta\|^2 \tag{3}$$

where: $y = (y_1, \ldots, y_N)^T$, X is an Nxp matrix and $1 = (1, \ldots, 1)^T$. Equation (3) can be explained as follows: $\beta = (X^T X)^{-1} X^T y$

With the OLS model, the pair (β_0, β) calculated as above will be unbiased estimates. However, the variances of coefficient estimators will be large. Therefore, the efficiency of forecasts based on the OLS model will not be high. To increase the accuracy of the forecast, Hastie et al. (2015) suggest that it is possible to reduce the number of regression coefficients or set certain coefficients to 0. This may lead to bias in estimating regression coefficients but it will reduce variances of expected values and, therefore, increase the forecast's accuracy. This idea allows the modification of the OLS model to the LASSO model, which is implemented as follows:

$$\underset{\beta_0,\beta}{\text{minimize}} \left\{ \frac{1}{N} \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{p} \beta_j \right\} = \frac{1}{N} \|y - \beta_0 1 - X\beta\|^2 + \lambda \|\beta\| \tag{4}$$

The main problem in the LASSO algorithm is to choose the optimal value of lambda. There are many methods to choose the optimal lambda value, such as Cross-validation, Theory-driven, and Information Criteria. In this paper, we use the Cross-validation method to select the optimal lambda value.

The least absolute shrinkage and selection operator model (LASSO) has some advantages, namely (i) determining the independent variables in the model that mainly impact on the dependent variable, and the other independent variables have no significant impact, their regression coefficients will be approximated 0; (ii) this method will minimize the variances of estimators, thus giving more accurate forecasting results than other methods. However, a disadvantage of this method is that the estimators of regression coefficients obtained will be biased. Therefore, this method will be best suited for forecasting purposes.

2.3 K-Nearest Neighbor Model (KNN)

According to Cover and Hart (1967), the K-nearest neighbor (KNN) algorithm is one of the simplest and most effective classification algorithms in Machine Learning. KNN is used to classify a new data sample by comparing it to previously known data samples. Specifically, KNN calculates the distance between the new data point and all the training data points, and then selects the K closest points to the new data point. The majority class among these K closest points is then assigned to the new data point as its predicted class.

The KNN algorithm is based on the assumption that similar data points tend to have similar classes. This assumption is reflected in the algorithm's distance metric, which is used to measure the similarity between data points. The most commonly used distance metric in KNN is the Euclidean distance, which is calculated as follow:

$$D(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \quad (5)$$

where x and y are two data points, and x_i and y_i are their ith feature values.

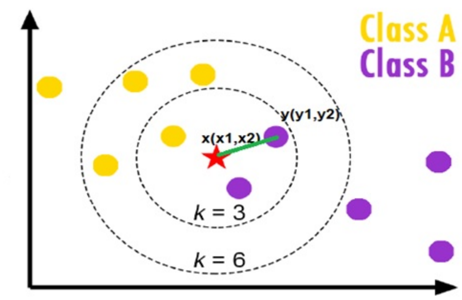

Figure 1: A Typical K-Nearest Neighbor Model

The K parameter in KNN is a hyperparameter that specifies the number of closest neighbors to consider when making predictions. Choosing the optimal value of K is critical for the performance of the algorithm. A small value of K can lead to overfitting, while a large value of K can lead to underfitting.

KNN is a non-parametric algorithm, meaning that it does not make any assumptions about the underlying distribution of the data. This makes KNN a flexible algorithm that can be used with any type of data, regardless of its distribution.

2.4 Multi-layer perceptron model (MLP)

Artificial Neural Networks – ANNs are computational tools that simulate neural networks in the human brain and can map nonlinear relationships between inputs and outputs. The analytical efficiency of ANNs has remarkable results in many different fields, and artificial neural networks are increasingly being used in statistical scientific research (Movagharnejad et al., 2011).

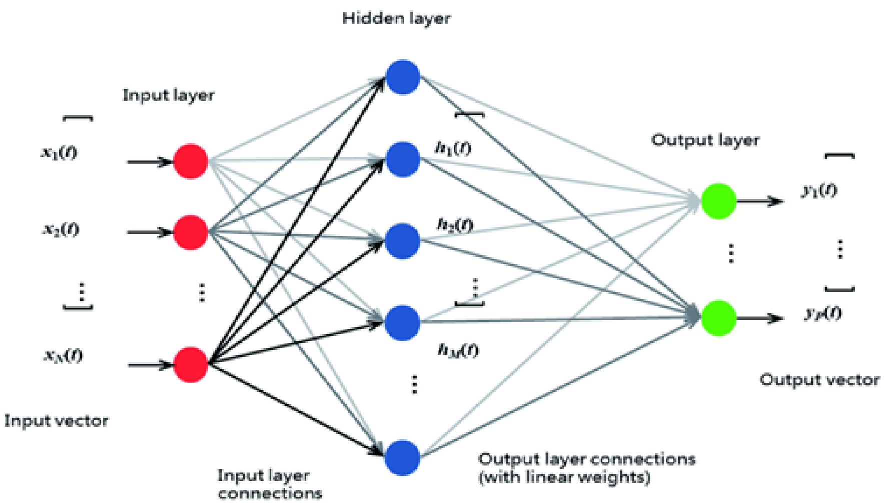

Figure 2: A Typical MLP Neural Network

Figure 2 shows that a typical MLP model has one input layer, one hidden layer, and one output layer. The data stream from the input layer to the output layer through the hidden layer(s), and the weights are then determined by the learning process performed by the back-propagation algorithm. This algorithm optimizes the quadratic cost function. The independent variables determine the number of neurons in the input layer, and the number of neurons in the output layer represents the number of dependent variables (Boroushaki et al., 2003).

The MLP models have some advantages such as: (i) the ability to continuously adapt the model to each research objective based on the given input and output data; (ii) a great advantage of the MLP model is that the building and estimation of the model are not based on economic theories about the relationship between the variables in the model, so when the economy has large fluctuations that change economic theories, the evaluation and analysis based on the MLP model will not be affected; (iii) according to the universal approximation theorem, the MLP model with hidden layers and neurons in each layer can represent any continuous function. Besides the advantages, the MLP model also has an outstanding disadvantage. There is no specific rule and formula for determining the number of hidden layers in the network and the number of neurons in each hidden layer.

This paper develops the MLP model with the input layer, including the explanatory variables for the output layers' fluctuations: economic growth and inflation, respectively. In theory, there could be one or several hidden layers, but the universal approximation theorem suggests that the MLP model with a single hidden layer with a sufficiently large number of neurons can represent any input-output structure (Tambe et al., 1996). Therefore, the proposed MLP model has a single hidden layer.

3 The forecasting model of economic growth and inflation

Many different macroeconomic variables can explain inflation and economic growth. Many domestic and foreign researches have shown that economic growth and inflation can be explained through variables such as industrial output, money supply (Vo et al., 2000; Vinh and Fujita, 2007), labor force (Akinboade et al., 2001; Kim, 2001), foreign investment capital (Kim, 2001), trade value (Camen, 2006; Vinh and Fujita, 2007). In this paper, we use these variables to forecast economic growth and inflation in Vietnam. The data is collected in the period from 1996 to 2021 from sources such as the International Monetary Fund (IMF) and the State Bank of Vietnam. The proposed research model has the following form:

$$y_t = v + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t \tag{6}$$

Where: $y_t = (y_{1t}, ..., y_{Kt})^T$ is a (7x1) vector of the variables namely economic growth year t (GDP_t), inflation year t (INF_t), trade-to-GDP ratio year t ($TRADE_t$), the growth rate of labor force (H_t), industrial output to GDP ratio year t (IND_t), the growth rate of total liquidity year t (M_t), the foreign direct investment capital year t (FDI_t). A_i is the fixed (7x7) coefficient matrix, $v = (v_1, ..., v_K)^T$ is a vectors of intercept coefficients, $u_t = (u_{1t}, ..., u_{Kt})^T$ is a vector of white noise.

Table 1: The Variables in the forecasting model

Notation	**Descriptions**	**Source**
GDP_t	Economic growth year t	Monetary Fund (IMF)
INF_t	Inflation year t	Monetary Fund (IMF)
$TRADE_t$	Trade-to-GDP ratio year t	Monetary Fund (IMF)
H_t	Growth rate of labor force year t	Monetary Fund (IMF),
IND_t	Industrial output to GDP year t	Monetary Fund (IMF)
M_t	Growth rate of total liquidity year t	The State Bank of Vietnam
FDI_t	Foreign direct investment capital year t	Monetary Fund (IMF)

Due to the limitation of research data in Vietnam, in this paper, we use the optimal lag $p = 1$ to estimate the VAR and LASSO models. For models built using KNN and MLP algorithms, to construct a model for economic growth prediction, we identified GDP as the output variable, and the input variables for the model included INF, $TRADE$, H, IND, M, and FDI. To construct a model for inflation prediction, we identified INF as the output variable, and the input variables for the model included GDP, $TRADE$, H, IND, M, and FDI. A specific functional form is not necessary for both KNN and MLP algorithms. In all four model estimation methods, we used 80% of the data for model training (training data) and 20% of the data for model validation (testing data).

The accuracy of the models on the testing data will be calculated using the metrics of Root Mean Square Error (RMSE), Mean Squared Error (MSE) and Mean Absolute Error (MAE) as follow:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N}} \tag{7}$$

$$MAE = \frac{\sum_{i=1}^{N} |y_i - \hat{y}_i|}{N} \tag{8}$$

$$MSE = \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N} \tag{9}$$

where y_i is the real output value, $\hat{y}_i$ is the forecasting values obtained from the VAR model, the LASSO model, the KNN model and the MLP model.

4 Empirical Result

4.1 The Estimated Result of the VAR Model

Before estimating the VAR model, we test the stationarity of the time series in the research model. The result is shown in Table 2.

The result of the stationarity test indicates that, all of the time, the series in the forecasting model is stationary at the first difference. Therefore, we use the first differences to estimate the VAR model with the optimal lag of 1. Table 3 represents the result of the VAR estimation.

We continue to use the equations with the dependent variables of GDP and INF in the VAR system of equations to forecast the testing dataset. The computed metrics of RMSE, MSE, and MAE are presented in Table 4.

4.2 The Estimated Result of the LASSO model

Next, we estimate the LASSO model with the dependent variables being economic growth and inflation, respectively. The lambda coefficients in the models are chosen by the Cross-Validation (CV) method. The estimated result represents in Table 5. We continue to use the equations with the dependent variables of GDP and INF to forecast

Table 2: The Result of the Stationarity Test

Variables	T Statistic (p-value)	Variables	T Statistic (p-value)
FDI	0.7513 (0.9906)	FDI	-3.7315 (0.0109)
GDP	-3.8468 (0.0081)	GDP	-5.3654 (0.0003)
H	-3.1564 (0.0392)		-4.2479 (0.0049)
IND	-2.0729 (0.2564)		-4.2366 (0.0035)
INF	-2.9632 (0.0536)		-5.8548 (0.0001)
M	-4.4188 (0.0022)		-6.5853 (0.0000)
TRADE	-0.1748 (0.9639)		-6.1028 (0.0001)

the testing dataset. The computed metrics of RMSE, MSE, and MAE are presented in Table 6.

4.3 The Estimated Result of the KNN model

We conducted the estimation of KNN models with GDP and INF as the respective output variables for economic growth and inflation. The KNN model estimation results are demonstrated by determining the optimal value of K for each model based on the accuracy of the forecast. The results are presented in Figure 3 below.

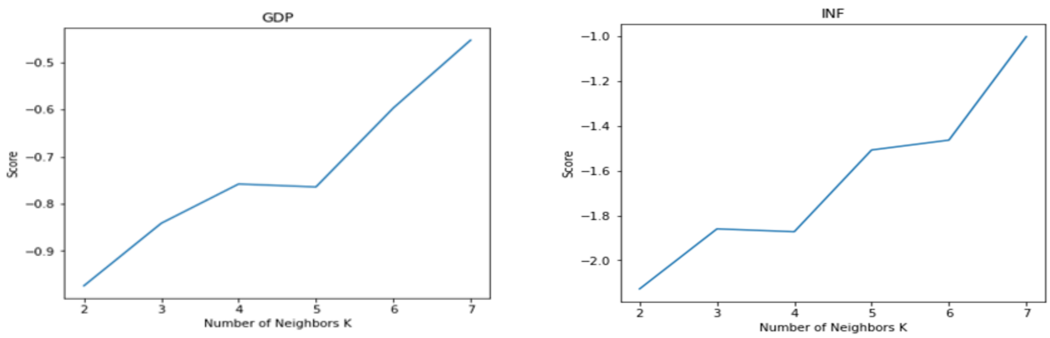

Figure 3: The results of determining the optimal K for the models with output variables GDP and INF

The results of training models with the KNN algorithm show that for the output variables GDP and INF, the optimal value of K chosen is 7. Therefore, we use this value

Table 3: The VAR Estimation Result

	D(FDI)	D(GDP)	D(H)	D(IND)	D(INF)	D(TRADE)	D(M)
D(FDI(-1))	0.052904	-1.74E-10	-7.54E-13	-6.66E-11	1.44E-09	-2.02E-09	-5.20E-09
	(0.25448)	(1.9E-10)	(1.9E-12)	(2.5E-10)	(1.1E-09)	(1.6E-09)	(2.5E-09)
	[0.20789]	[-0.91888]	[-0.39843]	[-0.27090]	[1.31957]	[-1.27420]	[-2.07270]
D(GDP(-1))	-2.75E+08	0.260420	0.001818	-0.087113	0.825830	-0.637420	-4.903124
	(5.0E+08)	(0.36903)	(0.00368)	(0.47910)	(2.12007)	(3.07971)	(4.88490)
	[-0.55395]	[0.70568]	[0.49346]	[-0.18183]	[0.38953]	[-0.20697]	[-1.00373]
D(H(-1))	1.42E+10	5.435762	0.794292	-15.55002	-57.63301	-33.55718	-50.22842
	(7.9E+09)	(5.87484)	(0.05865)	(7.62706)	(33.7505)	(49.0275)	(77.7653)
	[1.79510]	[0.92526]	[13.5432]	[-2.03880]	[-1.70762]	[-0.68446]	[-0.64590]
D(IND(-1))	1.87E+08	0.071538	-0.001056	-0.095331	-1.894747	-2.855632	-4.303367
	(2.3E+08)	(0.16793)	(0.00168)	(0.21802)	(0.96475)	(1.40144)	(2.22290)
	[0.83060]	[0.42600]	[-0.63014]	[-0.43726]	[-1.96398]	[-2.03764]	[-1.93593]
D(INF(-1))	-81081685	0.006983	0.000608	0.081004	-0.762704	-1.080124	0.360751
	(6.9E+07)	(0.05165)	(0.00052)	(0.06706)	(0.29675)	(0.43107)	(0.68375)
	[-1.16890]	[0.13519]	[1.17955]	[1.20792]	[-2.57018]	[-2.50566]	[0.52761]
D(TRADE(-1))	58022562	-0.025592	-0.000291	0.052261	0.194807	0.188160	0.374043
	(5.2E+07)	(0.03838)	(0.00038)	(0.04982)	(0.22047)	(0.32026)	(0.50798)
	[1.12591]	[-0.66687]	[-0.75950]	[1.04896]	[0.88362]	[0.58753]	[0.73634]
D(M(-1))	20072543	0.024188	0.000202	0.026056	-0.021061	0.244767	-0.433664
	(2.0E+07)	(0.01525)	(0.00015)	(0.01980)	(0.08764)	(0.12731)	(0.20193)
	[0.97985]	[1.58562]	[1.32605]	[1.31565]	[-0.24032]	[1.92267]	[-2.14763]
C	5.66E+08	0.354493	0.002669	-0.487675	-2.982052	5.371239	0.468620
	(4.1E+08)	(0.30679)	(0.00306)	(0.39829)	(1.76247)	(2.56024)	(4.06094)
	[1.37506]	[1.15550]	[0.87159]	[-1.22443]	[-1.69197]	[2.09794]	[0.11540]
R-squared	0.409773	0.335334	0.966023	0.600332	0.513326	0.600452	0.562840
Adj. R-squared	0.114660	0.003000	0.949035	0.400497	0.269989	0.400678	0.344260
Sum sq. resids	2.15E+19	11.90765	0.001187	20.07000	393.0021	829.3035	2086.435
S.E. equation	1.24E+09	0.922251	0.009207	1.197319	5.298262	7.696490	12.20783
F-statistic	1.388528	1.009028	56.86402	3.004148	2.109528	3.005657	2.574983
Log likelihood	-486.8621	-24.46417	76.88702	-30.20667	-62.92714	-71.14163	-81.29051
Akaike AIC	44.98746	2.951288	-6.262456	3.473334	6.447922	7.194694	8.117319
Schwarz SC	45.38420	3.348031	-5.865713	3.870076	6.844665	7.591436	8.514062
Mean dependent	6.32E+08	-0.051575	-0.019525	0.109751	-0.018805	5.474394	0.520352
S.D. dependent	1.32E+09	0.923637	0.040783	1.546373	6.201100	9.941745	15.07553

Table 4: The result of RMSE, MAPE and MSE indicators

Indicator	GDP	INF
RMSE	2.0112	3.4075
MSE	4.0448	11.6110
MAE	1.7148	3.0031

Table 5: The estimated result of the LASSO model with economic growth and inflation as the dependent variables

Variable	GDP	INF
GDP		-0.1947
INF	-0.0092	
TRADE	-0.0218	0.0126
H	0	-4.1010
IND	0	0
M	-0.0408	-0.1323
FDI	0	0.5445
The optimal value of lambda	0.9012	0.6485

Table 6: The result of RMSE, MAPE and MSE indicators

Indicator	GDP	INF
RMSE	1.7137	3.2083
MSE	2.9368	10.2934
MAE	1.3438	2.6751

to predict the output variables GDP and INF on the testing dataset. The computed metrics of RMSE, MSE, and MAE are presented in the table below.

Table 7: The result of RMSE, MAPE and MSE indicators

Indicator	GDP	INF
RMSE	1.6201	3.5892
MSE	2.6246	12.8822
MAE	0.9874	3.2809

4.4 The Estimated Result of the MLP Model

We implement the MLP model, with our output variables being economic growth and inflation. The MLP model is structured with three layers: an input layer (consisting of the model's independent variables), a hidden layer, and an output layer (comprising the economic growth and inflation variables). Theoretically, the MLP model includes one input layer, one output layer, and multiple hidden layers. However, according to the Universal Approximation Theorem, an MLP neural network that possesses a single hidden layer with a sufficiently large quantity of neurons can adequately represent any given input-output mapping (Tambe et al., 1996). Thus, in this study, we choose to employ a single hidden layer configuration. The optimal number of neurons within this hidden layer will be identified by examining the predictive accuracy of the models generated with different neuron quantities.

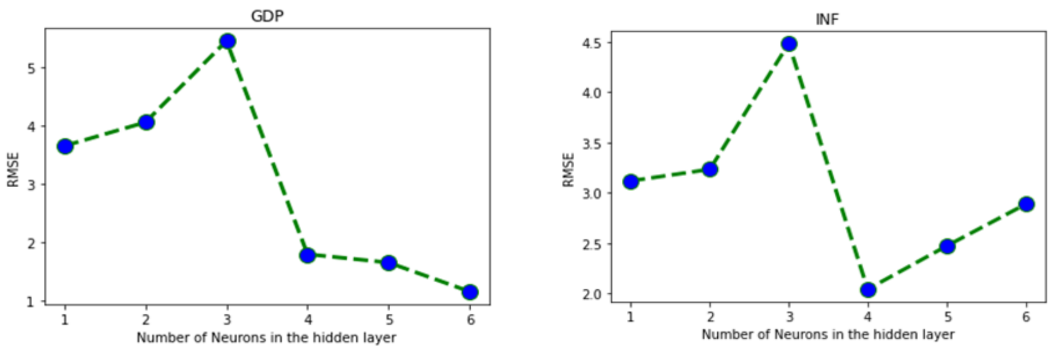

Figure 4: The results of determining the number of neurons for the models with output variables GDP and INF

The optimal number of neurons in the hidden layer for the GDP prediction model is 6, as shown in Figure 4. Meanwhile, the optimal number of neurons in the hidden layer for the INF prediction model is 4. Subsequently, we continued to train these MLP models with the determined number of neurons in the hidden layer as mentioned above. The results are presented in Figures 5.

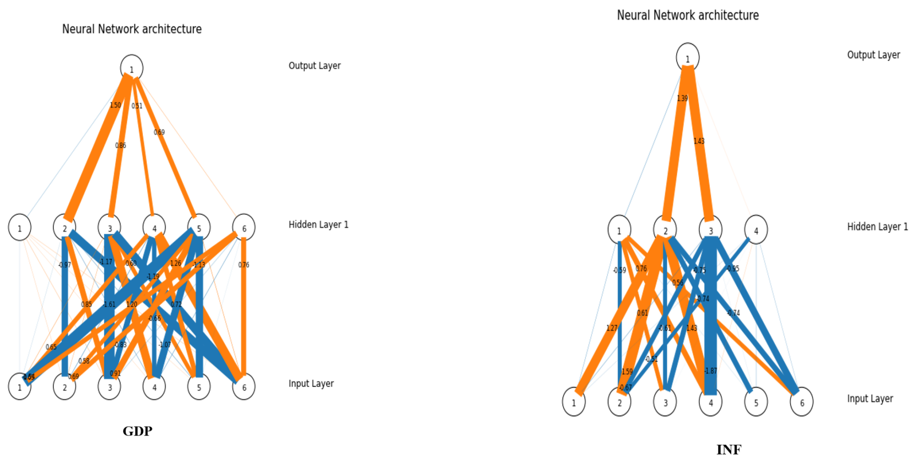

Figure 5: The estimated result of the MLP model with economic growth and inflation as the output variables

Table 8 presents the results of computing the RMSE, MSE, and MAE metrics for the output variables of GDP and INF, respectively.

Table 8: The result of RMSE, MAPE and MSE indicators

Indicator	**GDP**	**INF**
RMSE	1.1523	2.0413
MSE	1.3278	4.1668
MAE	0.8671	1.5112

5 Conclusion

Economic growth and inflation are the basic indicators of the national economies. Therefore, many analysts, policymakers, and government authorities of countries have taken part in analyzing the situations, influencing factors, and forecasting the fluctuations of the two indicators.

With the volatile and nonlinear nature of inflation and economic growth, in this paper, the MLP neural model as an effective tool to describe the nonlinear mapping relationship is developed to forecast the two variables. In addition, we also use other popular forecasting models, such as the VAR model, the LASSO model and the KNN model. The forecasting results of the models are then compared to each other to find the best forecasting model. The results show that according to all three indicators, RMSE, MAPE, and MSE, forecasting economic growth and inflation by the MLP model has the highest accuracy.

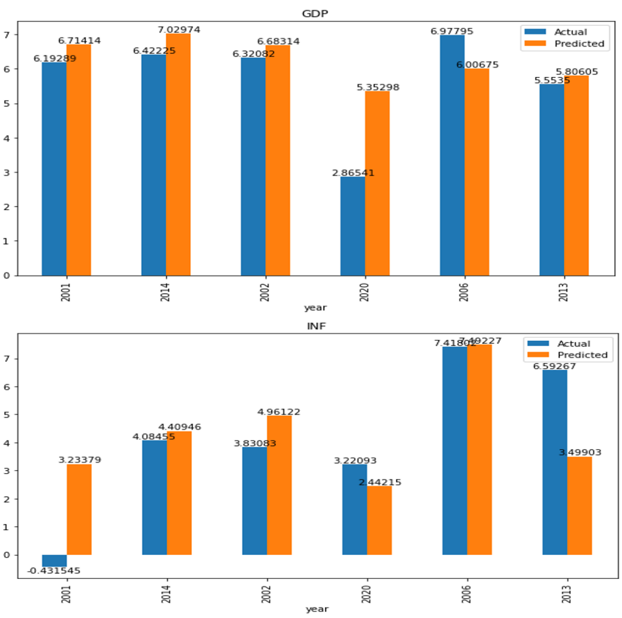

Figure 6: MLP model predictions for GDP and INF on the testing data

Therefore, our results have shown that the MLP model is a valuable tool for future forecasting because it describes the nonlinear relationship between variables in the model and can visually map these nonlinear relationships. Besides, the forecasting results by the MLP model can be improved by the back-propagation algorithm. Artificial Neural Networks – ANNs models, in general, and MLP neural models, in particular, are really effective when used with big data.

Data Availability Statement

The data and python codes for this study can be found on our GitHub page: `https://github.com/anhle32/APPLICATION-OF-MACHINE-LEARNING-METHODS-.git`.

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