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EVALUATION OF MACHINE LEARNING TECHNIQUES FOR FORECASTING MALAYSIA'S CONSUMER PRICE INDEX: A COMPARATIVE STUDY

(Penilaian Kaedah Pembelajaran Mesin untuk Meramalkan Indeks Harga Pengguna Malaysia: Satu Kajian Perbandingan)

YING CHYI CHAM, MUHAMMED HAZIQ MUHAMMED NOR &
BERNARD KOK BANG LEE*

ABSTRACT

Ensuring price stability through accurate measurement and management of the Consumer Price Index (CPI) fosters a stable economic environment conducive to sustainable growth, investment, and employment. As a key economic indicator, the CPI provides a comprehensive assessment of inflation, purchasing power, and the cost of living, serving as an essential tool for policymakers, businesses, and consumers. In Malaysia, the CPI has steadily increased, reflecting a stable inflation rate. Recognizing the need for low and stable inflation, governments prioritize this goal to enhance economic prosperity and societal well-being. Accurate CPI forecasting is crucial for economic stability and informed financial decisions. Machine learning (ML) models have demonstrated significant potential for improving CPI forecasting accuracy over traditional methods. However, research specifically targeting CPI and inflation rate forecasting in Malaysia remains limited. This study evaluates the performance of five ML techniques: Autoregressive Integrated Moving Average (ARIMA), Geometric Brownian Motion (GBM), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Adaptive Neuro-Fuzzy Inference System (ANFIS), in predicting Malaysia's CPI. The models are assessed by comparing their prediction to actual CPI data from October 2022 to September 2023. Results indicate that GRU model performs best, exhibiting the lowest RMSE, MSE, and MAPE scores, thereby highlighting a consistent upward trend in inflation. This study encourages further exploration of Malaysia's inflation using advanced ML models or hybrid approaches to enhance forecasting accuracy.

Keywords: consumer price index forecasting; machine learning models; Malaysia inflation; economic prediction; GRU accuracy

ABSTRAK

Memastikan kestabilan harga melalui pengukuran dan pengurusan yang tepat terhadap Indeks Harga Pengguna (IHP) memupuk persekitaran ekonomi yang stabil dan sesuai untuk pertumbuhan, pelaburan, dan pekerjaan yang mampan. Sebagai penunjuk ekonomi utama, IHP memberikan penilaian menyeluruh mengenai inflasi, kuasa beli, dan kos sara hidup, menjadikannya alat penting untuk penggubal dasar, perniagaan, dan pengguna. Di Malaysia, IHP telah meningkat secara berterusan, mencerminkan kadar inflasi yang stabil. Menyedari keperluan untuk inflasi yang rendah dan stabil, kerajaan mengutamakan matlamat ini bagi meningkatkan kemakmuran ekonomi dan kesejahteraan masyarakat. Ramalan IHP yang tepat adalah penting untuk kestabilan ekonomi dan keputusan kewangan termaklum. Model pembelajaran mesin telah menunjukkan potensi yang ketara untuk meningkatkan ketepatan ramalan IHP berbanding kaedah tradisional. Namun, penyelidikan yang menumpukan khusus kepada ramalan IHP dan kadar inflasi di Malaysia masih terhad. Kajian ini menilai prestasi lima kaedah pembelajaran mesin: Purata Pergerakan Bersepadu Autoregresif (ARIMA), Pergerakan Brownian Geometri (GBM), Unit Berulang Berpagar (GRU), Memori Jangka Pendek Panjang (LSTM), dan Sistem Inferens Neuro-Kabur Adaptif (ANFIS), dalam meramalkan IHP di Malaysia. Model-model ini dinilai dengan membandingkan ramalan mereka dengan data IHP sebenar dari Oktober 2022 hingga September 2023. Hasil kajian menunjukkan bahawa Model

GRU menunjukkan prestasi terbaik, mempamerkan nilai RMSE, MSE, dan MAPE terendah, sekali gus menonjolkan trend menaik yang konsisten dalam inflasi. Kajian ini menggalakkan penerokaan selanjutnya terhadap inflasi Malaysia menggunakan model pembelajaran mesin lanjutan atau pendekatan hibrid untuk meningkatkan ketepatan ramalan.

Kata kunci: ramalan indeks harga pengguna; model pembelajaran mesin; inflasi Malaysia; ramalan ekonomi; ketepatan GRU

1. Introduction

An essential determinant of a nation's long-term economic activity and development is the stability of the price level. Price stability occurs when goods and services' prices remain relatively constant over time. Recognizing price stability as a cornerstone of long-term economic growth ensures not only consumers' purchasing power, but also their cost of living and the advancement of commercial activities. Consumers benefit from price stability because it keeps their purchasing power roughly unchanged. This consistency removes the uncertainty associated with long-term savings goals like retirement or education costs, allowing consumers to put money aside with confidence. As a result, encouraging consumers to spend more efficiently in response to price stability is a fundamental catalyst for healthier economic growth.

Inflation and deflation management is inherently linked to price stability. At its core, inflation represents the gradual depreciation of a currency, driven by rising prices for goods and services. If this decline in purchasing power persists over time, consumers will find their standard of living diminished, as they can buy fewer goods and services with the same amount of money. In extreme cases, such as hyperinflation, the economy may face catastrophic consequences. Inflation can have mixed effects on a nation's economy, yielding both positive and negative outcomes. Dergunov *et al.* (2023) note that low consumption growth often coincides with either very high or very low inflation levels. This indicates that a positive inflation shock can be interpreted as either a positive or negative signal for expected real growth, depending on the broader economic context. High inflation rates may hinder development, leading to increased poverty, unmet daily needs, and economic slowdown. Conversely, stable and low inflation rates can promote economic growth (Sitanggang 2022). For instance, low inflation enables central banks to adjust nominal interest rates, encouraging investment in non-monetary capital projects that drive healthy economic growth. The balance between price stability and inflation rates is a fundamental component of the modern economy, although it can become increasingly complex. Dergunov *et al.* (2023) further elucidate this intricate relationship by highlighting how inflation subtly influences the valuation of tangible assets, such as stocks. Achieving price stability does not necessarily mean a country has zero inflation; in fact, this scenario is highly unlikely, given the influence of global economic factors on the domestic economy. Therefore, it is imperative for all stakeholders to work diligently to avoid high or uncontrolled inflation rates. Keeping inflation below a certain threshold is essential for fostering economic growth, as excessive inflation can negatively impact expansion and employment, similar to the detrimental effects of hyperinflation on economic development (Srivastava *et al.* 2023).

The Consumer Price Index (CPI) serves as a key tool for measuring price stability. It tracks the price changes of a basket of commonly purchased goods and services, including food, housing, transportation, and medical care. By collecting price data from retailers, the CPI reflects price fluctuations affecting the average urban household. Policymakers, central banks, and economists rely on the CPI to make informed economic decisions, adjust interest rates, guide wage policies, and measure the overall economic value. It is also used to calculate purchasing power, adjust government benefits, and set eligibility levels for assistance programs. When the CPI rises, it signals inflation, which affects the purchasing power of consumers, their cost of living, and overall economic decisions (Graf 2020; Castañeda & Chang 2023).

According to the Department of Statistics Malaysia (2024), the CPI in Malaysia was 132.2 in March 2024, slightly higher than 132.1 in February. This reflects an inflation rate of 1.8% in March, with the CPI surpassing 129.9 in March 2023. The main contributors to inflation in March 2024 were increases in housing, utilities, and fuels (3.0%), restaurants and lodging services (3.0%), personal care and other goods and services (2.6%), and transportation (1.3%). Sectors such as health (2.1%), food and beverages (1.7%) and recreation (1.5%) saw more modest increases. At the state level, inflation was lower than the national average of 1.8% in most states, except for Pulau Pinang, Sarawak, Pahang, Selangor, and Perlis, where it exceeded the national rate. Compared to other countries, Malaysia's inflation rate was lower than Vietnam (4.0%), the Philippines (3.7%), the United States of America (3.5%), Korea (3.1%), and Indonesia (3.1%) but higher than China (0.1%) and Thailand (-0.5%).

Although the CPI in Malaysia remains stable, potential disruptors to inflation should be closely monitored. Del Rosario and Koh (2024) identified five such disruptors: the depreciation of the ringgit, increased consumer demand due to economic recovery, fiscal deficit reduction measures such as subsidy cuts, wage hikes, and continued geopolitical tensions like the Russia-Ukraine war. In particular, the Russia-Ukraine war has already affected global supply chain, including raw materials and crude oil, potentially increasing Malaysia's electricity tariffs and power plant operating costs (Ismail 2022; Ming 2022). Despites these risks, experts predict a gradual rise in inflation, with the World Bank forecasting a 2.5% average annual inflation rate (Bernama 2024).

Studying the CPI and inflation in Malaysia is important for several reasons. Accurate inflation forecasts are essential for economic policy, business strategy, and financial planning (Samsudin *et al.* 2016). Understanding inflation drivers, such as money supply and cost-push factors, allows policymakers to implement effective measures to manage inflation and maintain stability (Islam *et al.* 2017). Furthermore, CPI forecasts provide valuable insights for production planning, investment decisions, and cost-of-living adjustments (Konarasinghe 2022). Although forecasting inflation is challenging, Machine Learning (ML) techniques offer promising improvements in prediction accuracy by handling multiple variables and capturing non-linear relationships (Medeiros *et al.* 2019). This study aims to develop effective ML models to predict Malaysia's CPI and inflation rates, thereby contributing to sound economic policies, business strategies, and individual financial planning.

2. Literature Review

Recent years have seen growing interest in the use of ML techniques to forecast inflation and the CPI. Various ML algorithms, such as LASSO Regression, Support Vector Regression, Neural Networks, Random Forest, XGBoost, and LightGBM, have been applied in different contexts to predict inflation (Medeiros *et al.* 2019; Barkan *et al.* 2023; Ivașcu 2023). For instance, Moshiri and Cameron (2000) found that Neural Networks outperformed traditional econometric models in forecasting inflation, particularly during periods of structural change and uncertainty. Additionally, research by Barkan *et al.* (2023) and Almosova and Andresen (2023) showed that using Recurrent Neural Network (RNN) to predict CPI inflation components in the United States led to more accurate results than traditional methods. Barkan *et al.* (2023) applied Hierarchical Recurrent Neural Network (HRNN), which outperformed numerous established inflation prediction baselines. In contrast, Almosova and Andresen

(2023) employed Long Short-Term Memory (LSTM) RNN to forecast monthly United States CPI inflation, revealing that LSTM slightly outperformed autoregressive models, other Neural Networks, and Markov-switching models. Similarly, Yang and Guo (2021) showed that RNNs with Gated Recurrent Units (GRUs) improved inflation rate forecasting in China compared to traditional linear models. These findings underscore the potential of HRNNs, built with GRU and LSTM architectures, to enhance the accuracy of CPI inflation component forecasts.

However, some studies have shown that heuristic methods may not perform well when data is limited. Research by Ivaşcu (2023) and Theoharidis *et al.* (2023) indicated that heuristic methods were not always more effective than simple autoregressive models, especially the Autoregressive Integrated Moving Average (ARIMA) model. Factors contributing to this include insufficient data for proper ML model training, the complexity of tuning models with many parameters, and challenges in capturing non-linear relationships in smaller datasets. Medeiros *et al.* (2019) and Ivașcu (2023) highlighted that these issues can result in overfitting, underfitting, or poor generalization, making simpler models like ARIMA more effective in certain cases. Singh *et al.* (2023) also found that LSTM models could improve CPI prediction in India, even with smaller datasets. Therefore, ARIMA remains a viable option for CPI and inflation rate forecasting, where data limitations can pose challenges for more complex ML models.

Geometric Brownian Motion (GBM) is widely regarded as an effective method for stock price forecasting, as supported by research from Reddy and Clinton (2016) and Kumar *et al.* (2024). While GBM is commonly used for asset price simulations and stock market predictions, its application to CPI and inflation forecasting has been limited. Ibrahim *et al.* (2021) examined the use of GBM and Geometric Fractional Brownian Motion (GFBM) in simulating Malaysia's crude palm oil price, suggesting that GBM, due to its robustness against multiplicative noise, could be useful for CPI and inflation forecasting. Further research could explore the potential of GBM to enhance CPI and inflation rate forecasts in Malaysia.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) has also demonstrated promise in inflation forecasting. For example, Kuzu and Alp (2022) applied ANFIS and ARIMA to forecast inflation using three variables: the Central Bank of the Republic of Turkey’s Policy Interest Rate, the Dollar-Turkish Lira index and the M1 money supply. Their results indicated that ANFIS outperformed ARIMA in predicting. Similarly, Sari *et al.* (2017) found that ANFIS yielded more accurate inflation forecasts in Indonesia compared to traditional methods. ANFIS combines Artificial Neural Networks and fuzzy logic, offering flexibility in modelling input variables and rule bases, which leads to more precise predictions (Vesović & Jovanović 2022). Its adaptability in parameter adjustment and output prediction makes ANFIS a valuable tool for inflation forecasting and maintaining price stability.

Based on this body of research, five distinct ML models were selected for this study: ARIMA, GBM, GRU, LSTM, and ANFIS. The inclusion of these models, each with both linear and non-linear capabilities, aims to enhance the accuracy and depth of CPI forecasts, tailored specifically to Malaysia’s economic context. Each model has unique strengths, enabling a more robust assessment of CPI trends and potential inflation rates.

3. Methodology

3.1. *Operational framework and data preparation procedure*

Figure 1 provides an overview of the entire investigation process, which includes data processing, model construction, cross-validation, and prediction. This study used monthly data on Malaysia's CPI, sourced from Bank Negara Malaysia's official website (https://www.bnm.gov.my/-/monthly-highlights-statistics-in-december-2022). The dataset spans the period from January 1968 to September 2022. Data cleansing was carried out to ensure the dataset was ready for analysis. The final dataset retained two columns and 657 rows: the first column represented the month and year, and the second column contained the corresponding CPI values.

The dataset was divided into training and testing subsets in an 80:20 ratio. The training set consisted of the first 525 rows (January 1968 to September 2011), while the testing set comprised the remaining 132 rows (October 2011 to September 2022). The goal of this comparison was to assess the predictive performance of five ML models in forecasting Malaysia's inflation rate. These model were trained using the training data and the prediction were validated against the testing dataset, enabling a comparison of each model's accuracy.

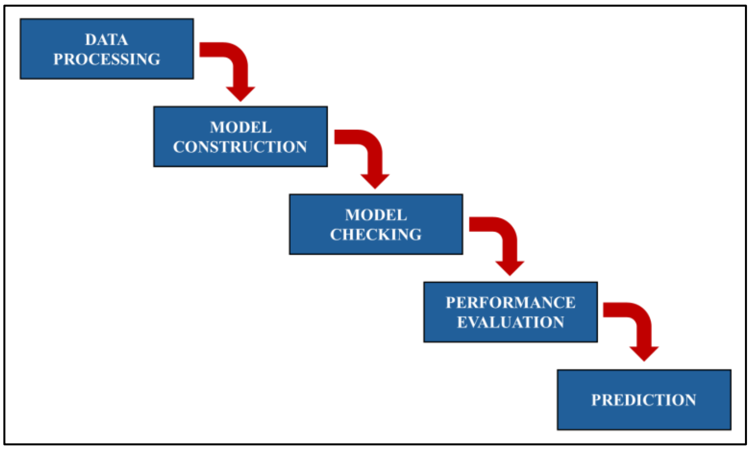

Figure 1: The operational framework used for this study.

3.2. *Model construction*

Data analysis was performed using Python (version 3.11.1), with the code written and executed in Jupyter Notebook. Both the dataset and the Python code used in this research are publicly available on GitHub at the following repository: https://tinyurl.com/3pnh6aur. Each ML model uses Malaysia's CPI as the time series variable.

3.2.1. *ARIMA model*

For the ARIMA models to function correctly, the dataset needed to be stationary. To assess this, the autocorrelation function (ACF) plot was examined. If the data was stationary, no further differentiation was necessary. However, if the data was non-stationary, differentiation was performed before training the ARIMA model. The Kwiatkowski-Philips-Schmidt-Shin (KPSS) test was used to determine the degree of differentiation required to make the data stationary.

After differentiation, ACF plots and partial autocorrelation function (PACF) estimators were used to identify the values of parameters p and q, representing the autoregressive (AR) order and moving average (MA) order, respectively. The parameter d represented the number of differentiations applied. If no differentiation was needed, d was set to zero. Subsequently, the ARIMA (p, d, q) model was used to calculate the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and corrected AIC (AICc) values. Multiple combinations of p and q values were tested to ensure a comprehensive search for optimal parameter values, rather than relying solely on those derived from the ACF and PACF plots.

The best model was selected based on the BIC criterion (Neath & Cavanaugh 2012). AIC and AICc were not used as primary performance criteria due to potential biases when models are overfit, which could reduce accuracy by fitting too closely to the training data trends. The ARIMA model with the lowest BIC value was selected for comparison with other models.

3.2.2. *GBM model*

In the GBM model, the time series variable $S(t_i)$ at time t_i, where $i = 1,2,3, \ldots, n$, is generated using Eq. (1) for any time $t > 0$:

$$S(t_{i+1}) = S(t_i)e^{\left(\mu-\frac{1}{2}\sigma^2\right)(t_{i+1}-t_i)+\sigma\sqrt{t_{i+1}-t_i}\,Z_{i+1}} \tag{1}$$

where Z_1, Z_2,..., Z_n are independent standard normal variables. In this study, $S(t_i)$ represents the CPI value for Malaysia at time t. The parameters μ, σ, and Z_i for the GBM model were estimated based on the training data. The parameters μ, σ, and Z_i are defined as follows: μ represents the drift term, or the average rate of change, indicating the overall trend of the time series over time. σ denotes the volatility term, reflecting the extent of fluctuation around this trend and capturing inherent variability in the data. Finally, Z_i represents the stochastic component, with each Z_i is an independent standard normal variable, introducing randomness to simulate unpredictable influences on CPI values.

3.2.3. *GRU and LSTM model*

The GRU and LSTM models were developed using the *statsmodel* and *TensorFlow* libraries in Python, with the *Keras* framework, following the optimal parameters suggested by Zahara *et al.* (2020) and Sujatna *et al.* (2023). Both GRU and LSTM models were structured with one input layer, three hidden inner layers, and one output layer. Each layer, excluding the output layer, contained 50 units. To balance model training, a batch size of 64 and 100 epochs were used, the latter chosen to prevent overfitting and ensure a fair comparison. The models were optimised using Stochastic Gradient Descent (SGD) with a learning rate of 0.01, a decay rate of 0.7, and a momentum of 0.9. These parameters were selected to ensure optimal model convergence, as supported by previous studies (Zahara *et al.* 2020; Sujatna *et al.* 2023). After constructing the model architecture, the training data was fed into the models for training.

3.2.4. *ANFIS model*

The ANFIS model was constructed using the *anfis* package in Python, following the guidelines set forth by Jang (1993). The training data was imported, and the model was trained by defining the membership function $O_i^1(x)$ for A_i, which represents the degree to which x satisfies the quantifier A_i. This is shown in Eq. (2):

$$O_i^1(x) = \mu_{A_i}(x) \tag{2}$$

The model then identified the parameters a_i, b_i, and c_i, which were used in the membership function, defined as follows in Eq. (3):

$$\mu_{A_i}(x) = \frac{1}{1+\left(\left(\frac{x-c_i}{a_i}\right)^2\right)^{b_i}} \tag{3}$$

These parameters formed the basis for generating predictions of the time series variables.

3.3. *Model diagnostics*

After constructing the models, their efficiency was evaluated through a process known as model diagnostics. This step assessed the model's stability in predicting Malaysia's CPI values. During diagnostics, it was important to examine the error patterns and verify whether the error distribution exhibited normal characteristics, such as a mean of zero and constant variance. To evaluate these characteristics, standard error plots and Q-Q plots were generated using the *statsmodel* package in Python for the ARIMA, GBM, GRU, LSTM, and ANFIS models. The resulting plots were then analysed to assess the model's performance.

3.4. *Evaluation of model performance*

A performance comparison was conducted on the five constructed models, each generating 133 consecutive predictions. The prediction results from each model were represented as vector $\{V_t\}$, while the testing dataset was transformed into vector $\{U_t\}$. These vectors were then compared to assess the prediction accuracy of all five models. A line graph was plotted to visually compare the predicted data $\{V_t\}$ from each model with the actual testing data $\{U_t\}$.

The performance evaluation of the inflation rate forecast for the five ML models was based on three key metrics: Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The following are the equations:

$$RMSE = \sqrt{\frac{1}{T}\left(\sum_{t=1}^{T}(U_t - V_t)^2\right)} \tag{4}$$

$$MSE = \frac{1}{T}\left(\sum_{t=1}^{T}(U_t - V_t)^2\right) \tag{5}$$

$$MAPE = \frac{100\%}{T}\left(\sum_{t=1}^{T}\left(\frac{U_t - V_t}{V_t}\right)^2\right) \tag{6}$$

where T represents the number of testing data points.

The results of the RMSE, MSE, and MAPE calculations for each model were displayed using a bar graph and a table. The model with the lowest RMSE, MSE, and MAPE values was identified as the best-performing model for predicting CPI values in Malaysia.

3.5. *Prediction*

A forecast for the 12 months following September 2022 was conducted using the model selected based on the previous performance evaluation. The model was retrained using the complete dataset, which included CPI values for Malaysia from January 1968 to September 2022. After retraining, a series of graphs were plotted to visualise the predicted trends, which were then analysed and discussed.

4. Results and Discussions

4.1. *Implementation of ARIMA model construction*

Figure 2 presents the ACF plot for Malaysia's CPI training data, covering the period from January 1968 to August 2011. In this plot, the x-axis represents the lag k (where $k = 1, 2, \ldots, \infty$), while the y-axis shows the autocorrelation values. The ACF for this dataset decreases gradually, indicating that the training data is non-stationary. Consequently, the KPSS test was employed to determine the optimal number of differentiation needed to achieve stationarity, with the differentiation process repeated as necessary.

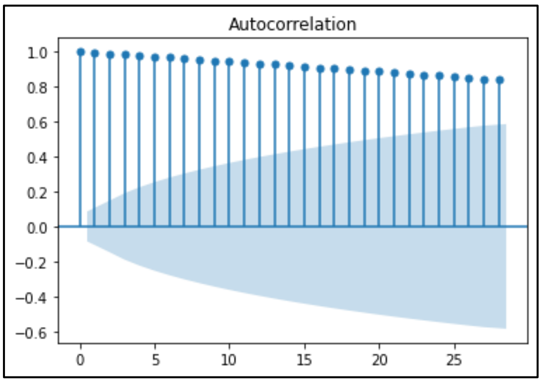

Figure 2: ACF plot of Malaysia's CPI values from January 1968 to August 2011. The gradual decrease in autocorrelation suggests non-stationarity, leading to the application of the KPSS test to determine the required level of differencing for stationarity.

Table 1 summarises the p-values from the KPSS test conducted on three datasets: undifferentiated data, first-order differencing data, and second-order differencing data. The p-value for the training data without differentiation was 0.997. In contrast, the p-values for the first-order and second-order differencing datasets were 1.911×10^{-29} and 3.639×10^{-17}, respectively. Since the p-value from first-order differencing was lower than the commonly used significance level of 0.05, the number of differentiations in this study was set to one. Second-order differencing was avoided to prevent overfitting, despite its p-value also being less than 0.05. Typically, the first-order of differencing with a p-value below the significance threshold is preferred. Additionally, the number of data differentiations corresponds to the d value in the ARIMA (p, d, q) model. Based on the training data, a d value of one was determined to be appropriate for the ARIMA (p, d, q) model.

Table 1: The KPSS test with p-values for training data without differentiation and with first-order and second-order differencing data

Training data	p-value
Without differentiation	0.997
First-order differencing	1.911×10^{-29}
Second-order differencing	3.639×10^{-17}

Figure 3 presents the first-order differencing data plot, along with the ACF and PACF plots for Malaysia's CPI data from January 1968 to August 2011, following one differentiation. In the first-order differencing plot, the x-axis represents the number of months, while the y-axis indicates the autocorrelation value for each month. The ACF and PACF plots display a sinusoidal decline, with the ACF plot levelling off after the second lag. Based on this observation, the parameter values p and q for the ARIMA (p, d, q) model were determined to be 0 and 2, respectively.

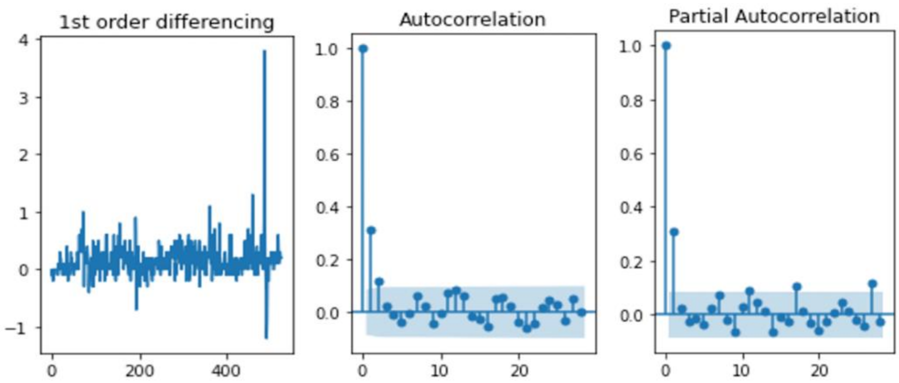

Figure 3: ACF and PACF plots, each differentiated once, accompanied the first-order differencing plot for Malaysia's CPI data from January 1968 to August 2011.

After reviewing the presented plots, it became clear that ARIMA (0, 1, 2) was the initial best fit for predicting Malaysia's CPI values. However, to determine if there were other ARIMA models that could provide more accurate predictions, we evaluated the appropriateness of various models using AIC, BIC, and AICc values. Different combinations of p and q were tested to align with Malaysia's CPI data. Table 2 summarises the AIC, BIC, and AICc values for each potential ARIMA (p, d, q) model. As shown in Table 2, the ARIMA (1, 1, 0) model yielded the lowest AIC, BIC, and AICc values compared to ARIMA (0, 1, 2) and other models. Consequently, ARIMA (1, 1, 0) was selected as the representative ARIMA model for comparison with other ML models.

Table 2: AIC, BIC and AICc values for ARIMA (p, d, q)

ARIMA(p,d,q)	AIC	BIC	AICc
(0, 1, 0)	177.027	185.551	180.365
(0, 1, 1)	132.439	145.223	137.445
(0, 1, 2)	127.683	144.730	134.360
(0, 1, 3)	129.278	150.585	137.622
(1, 1, 0)	**125.731**	**138.515**	**130.737**
(1, 1, 1)	127.500	144.546	134.175
(1, 1, 2)	129.251	150.558	137.595
(1, 1, 3)	130.957	156.526	140.970
(2, 1, 0)	127.464	144.510	134.139
(2, 1, 1)	129.291	150.599	137.635
(2, 1, 2)	130.549	156.118	140.563
(2, 1, 3)	132.359	162.189	144.041
(3, 1, 0)	129.201	150.509	137.546
(3, 1, 1)	131.388	156.957	141.401
(3, 1, 2)	132.031	161.862	143.713
(3, 1, 3)	133.443	167.535	146.794

4.2. *Model diagnostics for ARIMA, GBM, GRU, LTSM and ANFIS*

Figure 4 presents the standardized residuals plot and Q-Q plot for the ARIMA (1, 1, 0), GBM, GRU, LSTM, and ANFIS models. A non-linear pattern in the standardized residuals plot indicates that the errors do not exhibit consistent variance. Conversely, if the errors in the Q-Q plot closely align with the red reference line, it suggests that the error distribution approximates a normal distribution. According to the diagnostic results in Figure 4, only the ARIMA (1, 1, 0) model's errors satisfied the assumption of normality. While the GRU, LSTM and ANFIS models displayed a linear pattern with a zero mean, their variance remained unstable. In contrast, the errors of the ARIMA (1, 1, 0), GBM, and ANFIS models exhibited non-linear behaviour. Although the model efficiency results indicate areas for improvement regarding error distribution and stability, they also provide valuable insights that can guide future model refinements and enhance overall forecasting performance.

4.3. *Evaluation of model performance for ARIMA, GBM, GRU, LTSM and ANFIS*

Figure 5 compares Malaysia's CPI values predicted by the five ML models with the actual CPI values over time. The results show that from September 2011 to September 2022, all models consistently captured the upward trend of Malaysia’s CPI. However, none of the models were able to predict the sharp decline in the 100th month, corresponding to December 2020, when the actual CPI dropped significantly.

The performance of the five ML models, i.e. ARIMA (1, 1, 0), GBM, GRU, LSTM, and ANFIS was evaluated using RMSE, MSE, and MAPE as accuracy indicators. The predicted CPI values from September 2011 to September 2022, along with the corresponding RMSE, MSE, and MAPE values, are shown in Table 3 and Figure 6. Based on the results, the LSTM model performed the worst, with the highest RMSE (4.7050), MSE (4.2724), and MAPE (3.7777%) values, indicating a significant discrepancy between the actual and predicted CPI values. Thus, the LSTM model was deemed unsuitable for predicting Malaysia's CPI. The GBM model also underperformed, with RMSE, MSE, and MAPE values of 2.9013, 2.5131, and 2.2504%, respectively, making it the second worst model.

In contrast, the ARIMA (1, 1, 0) and ANFIS models performed relatively well. The ARIMA model recorded RMSE, MSE, and MAPE values of 2.7664, 2.2329, and 1.9324%, respectively, while the ANFIS model showed RMSE, MSE, and MAPE values of 2.5989, 2.3707, and 2.0646%, respectively. Although the ARIMA model had lower MSE and MAPE values than ANFIS, the ANFIS model had a slightly better RMSE. However, according to Willmott et al. (2005), MSE is considered a more critical criterion than RMSE when evaluating model performance. Therefore, the ARIMA (1, 1, 0) model was considered superior to the ANFIS model.

The GRU model outperformed all others, achieving the lowest RMSE (1.6581), MSE (1.4440), and MAPE (1.2413%) values. These results indicate minimal error between the GRU model’s predicted CPI values and the actual values. Consequently, the GRU model was selected to forecast Malaysia's CPI for the 12 months following September 2022.

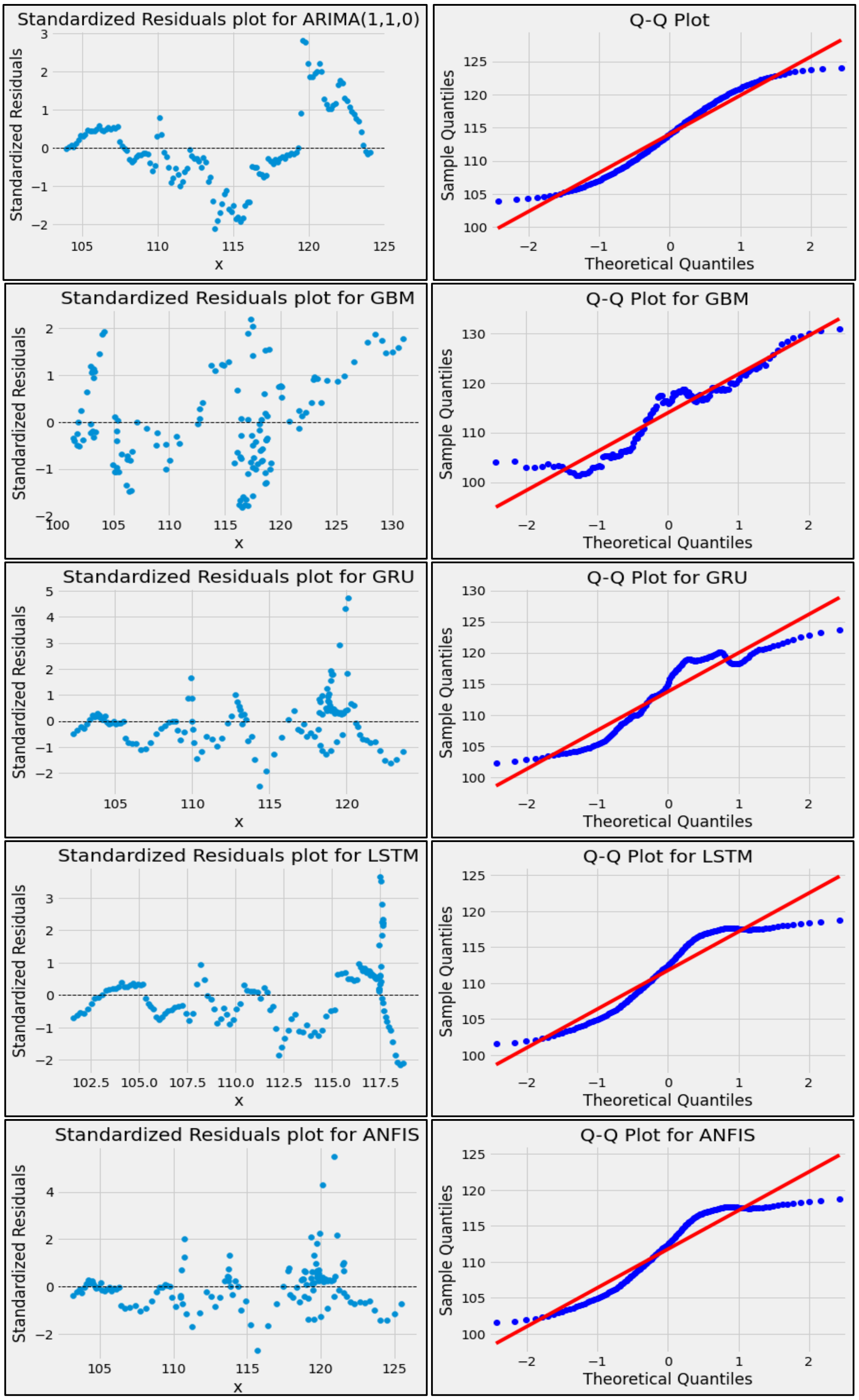

Figure 4: The standardized residuals and Q-Q plot for the ARIMA (1, 1, 0), GBM, GRU, LSTM and ANFIS models.

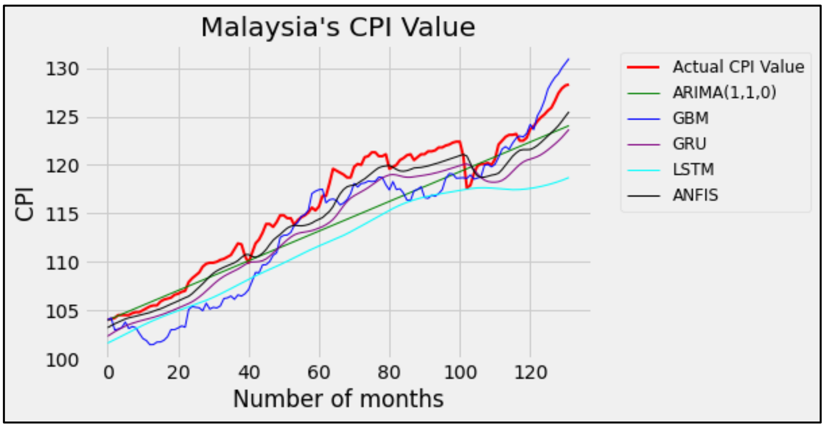

Figure 5: Predicted CPI values for Malaysia, generated by the ARIMA (1, 1, 0), GBM, GRU, LSTM, and ANFIS models, are compared with the actual values over a 132-month period from October 2011 to September 2022.

Table 3: The performance evaluation of the five ML models with RMSE, MSE, and MAPE values

Model	RMSE	MSE	MAPE(%)
ARIMA (1, 1, 0)	2.7664	2.2329	1.9324
GBM	2.9013	2.5131	2.2504
GRU	1.6581	1.4440	1.2413
LSTM	4.7050	4.2724	3.7777
ANFIS	2.5989	2.3707	2.0646

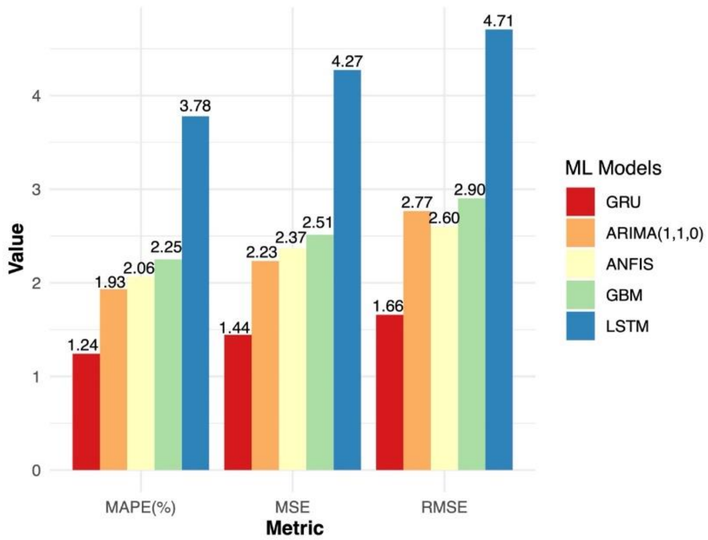

Figure 6: The performance of five ML models in predicting Malaysia's CPI values from August 2011 to September 2022 in bar plot.

4.4. *Results of the forecasting CPI values*

Figure 7 and Table 4 present the forecasted CPI values generated by the GRU model for the 12 months following September 2022. The forecast in Figure 7 shows a steady upward trend in CPI, closely mirroring the actual values with a correlation of 0.99, highlighting the model's strong predictive accuracy. As shown in Table 4, no extreme fluctuations were observed in the forecasted values, indicating a stable inflation rate trajectory from October 2022 to September 2023. This consistency underscores a relatively stable inflation outlook over the forecasted period.

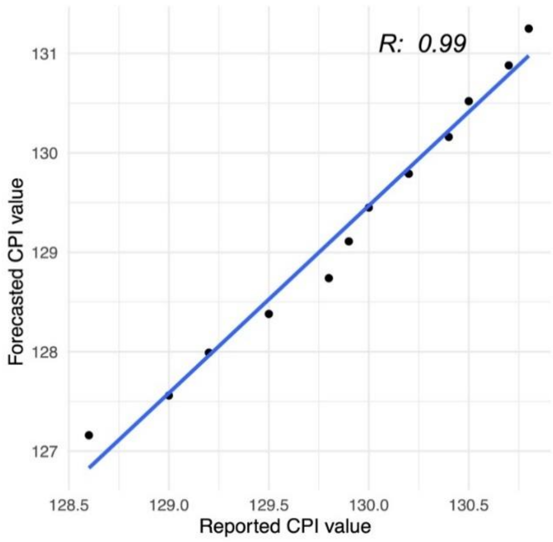

Figure 7: The line graph illustrates Malaysia's forecasted CPI value versus the actual reported CPI value for the 12 months following September 2022, as predicted by the GRU model. The forecast indicates a steady upward trend with a correlation of 0.99, demonstrating the GRU model's strong performance in closely aligning predicted CPI values with the actual reported values.

Table 4: The forecasted values of Malaysia's CPI values after October 2022 using the GRU model

Date	Forecasted CPI value	Reported CPI value
October 2022	127.16	128.6
November 2022	127.56	129.0
December 2022	127.99	129.2
January 2023	128.38	129.5
February 2023	128.74	129.8
March 2023	129.11	129.9
April 2023	129.45	130.0
May 2023	129.79	130.2
June 2023	130.16	130.4
July 2023	130.52	130.5
August 2023	130.88	130.7
September 2023	131.25	130.8

5. Conclusion

This study evaluated five ML models, including ARIMA, GBM, GRU, LSTM, and ANFIS for their effectiveness in predicting Malaysia's CPI. Each model demonstrated a capacity to capture the rising trend in Malaysia's CPI values, projecting an increase that aligns with the actual CPI trajectory from October 2022 to September 2023. However, performance varied when compared to the training dataset, which spanned Malaysia's CPI data from January 1968 to August 2011, with some models falling short in predictive accuracy.

Among the five models, the GRU model stood out, yielding the lowest RMSE, MSE, and MAPE values, making it the most accurate for CPI forecasting in Malaysia. The GRU model's forecast for the following 12 months, starting in October 2022, shows a stable upward trend, reflecting a consistent CPI increase.

This study has some limitations. The training data comprised only 80% of the original dataset, which may impact model accuracy. Additionally, while the GRU and LSTM models used SGD as the optimizers, alternative optimizers and adjustable parameters (e.g., units, epochs, or layers) could potentially improve performance. Lastly, due to limited sector-specific CPI data for Malaysia, the study focuses on overall CPI, without assessing specific economic sectors.

Future research on ML model selection for CPI forecasting in Malaysia would benefit from several refinements. First, comprehensive cross-validation should be conducted to capture the overall data pattern and minimise bias. Second, using higher-frequency data (e.g., daily or weekly) could further enhance prediction precision. Finally, this study recommends exploring advanced ML techniques, hybrid architectures, ensemble methods, or forecast combinations, to improve CPI and inflation rate forecasting accuracy in Malaysia, especially through sector-specific analyses where data availability permits.

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Department of Mathematical Sciences
Faculty of Science and Technology
Universiti Kebangsaan Malaysia
43600 UKM Bangi
Selangor DE, MALAYSIA
E-mail: cychyi126@gmail.com, p120181@siswa.ukm.edu.my, bernardlkb@ukm.edu.my[*]

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[*]Corresponding author