PARAMETER
JURNAL MATEMATIKA, STATISTIKA DAN TERAPANNYA

e-ISSN. 2829-6303
Vol. 04, No. 3, December 2025
Page 537-550

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Forecasting the Inflation Rate Using Long Short-Term Memory Model Based on Consumer Price Index

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Abstract
Human life is constantly exposed to risks such as illness, accidents, and death, which create financial uncertainties for individuals and families. Life insurance serves as an essential financial instrument to mitigate these risks by transferring potential liabilities to insurance companies. This study analyzes premium reserves for whole life and term life insurance using the New Jersey Prospective Method, applying a 6% interest rate and the 2023 Indonesian Mortality Table (TMPI) as the basis of calculation. Actuarial commutation functions are employed to compute annuity values, single net premiums, annual net premiums, and reserve allocations across different ages. The results indicate that reserve values increase with age, reflecting higher mortality risks, with whole life insurance showing a sharper escalation compared to term life insurance. The New Jersey Prospective Method demonstrates accuracy and consistency in reserve estimation, particularly by setting zero reserves in the first policy year, thereby supporting initial liquidity. These findings highlight the method's effectiveness in maintaining financial stability and readiness of insurance companies to meet future claims and long-term obligations to policyholders.

Keywords: *New jersey method, premium reserve, term life insurance, whole life insurance.*

: https://doi.org/10.30598/parameterv4i3pp537-550

Research Article ***Open Acces***
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Submitted: April 2025
Accepted: December 2025

1. INTRODUCTION

Inflation is one of the economic indicators that affect the financial stability of a country. High inflation can cause people's purchasing power to lead, while inflation that is too low can signal economic stagnation. Therefore, inflation prediction is an important aspect of economic policy making. One of the primary methods for analyzing inflation is through the use of the Consumer Price Index (CPI), which captures price fluctuations of goods and services over a given time period. In addition, while inflation forecasts are important for the government when preparing the draft state budget, for the general public, inflation data plays an important role when planning investments [1].

In recent years, the utilization of artificial intelligence and deep learning technologies in economics has been growing. Long Short-Term Memory (LSTM) is a widely used variant of recurrent-based artificial neural networks, known for its superior performance over conventional methods in processing time series data. LSTM's ability to recognize patterns from historical data, this model can be used to predict inflation more accurately. Recent studies have evaluated the performance of SARIMAX and LSTM models in forecasting the import volume of HS-05 commodities in Indonesia. The analysis results indicate that the SARIMAX model outperforms the LSTM model in terms of prediction accuracy. However, this study still confirms that LSTM excels in capturing non-linear patterns in economic data [2]. There are other studies that discuss the application of LSTM in cooking oil price analysis using deep learning methods. Their results show that the LSTM model is able to recognize price patterns well and has more accurate prediction performance than conventional methods [3]. A price prediction model based on LSTM for large red chili peppers and curly red chili peppers has been effectively developed and demonstrates the ability to accurately capture price trends, producing predictions that follow actual trends with a low error rate. These results can be utilized by various parties to anticipate price fluctuations [4].

This study offers a methodological contribution through the development of a forecasting framework that integrates a Long Short-Term Memory Autoencoder (LSTM-AE) for anomaly detection and correction before inflation modeling is conducted using LSTM. Unlike previous studies that generally apply forecasting models directly without an anomaly-cleansing process, this study leverages the capability of LSTM-AE to identify deviations from historical patterns through reconstruction error, including significant anomalies during the 2004–2005 period, which are subsequently addressed using linear interpolation to produce a more stable and representative time series. This two-stage approach has not been identified in prior CPI-based inflation forecasting studies, particularly within regional contexts such as Ambon City, which remains relatively underexplored in the literature. Building upon this framework, the purpose of the present research is to employ the LSTM model to predict the inflation rate in Ambon City using CPI data that have been refined through the anomaly-handling process. This integrated application is expected to serve as an effective analytical approach for understanding regional inflation dynamics and supporting more targeted economic planning and management efforts. Accordingly, the findings of this study are anticipated to not only advance the development of time-series-based prediction methods, but also provide valuable insights for local governments, financial institutions, and policymakers in formulating economic strategies that are responsive to local price fluctuations.

2. RESEARCH METHODOLOGY

2.1. Inflation

A persistent and pervasive increase in the cost of goods and services over a given time period is referred to as inflation. Price increases that are temporary or only cover a few commodities are not categorized as inflation [5]. Inflation is closely related to the monetary aspect, especially when the amount of money circulating in the economy increases beyond the growth of real output, which in turn reduces people's purchasing power [6].

In Indonesia, inflation is measured by the Badan Pusat Statistik (BPS) using the Consumer Price Index (CPI). The CPI reflects the average change in the prices of a representative set of goods and services typically consumed by urban households.. This package includes more than 800 commodities grouped into several expenditure groups such as food, transportation, health, education, and others [7].

$$\text{Inflation} = \left| \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} \times 100\% \right| \tag{1}$$

Where CPI_t is the Consumer Price Index at period t, and CPI_{t-1} is the Consumer Price Index in the previous period.

2.2. Consumer Price Index

The Consumer Price Index (CPI) is an economic indicator that tracks the variation in price levels of a representative selection of consumer goods and services commonly purchased by households over a specific period. The rate of inflation (price increases) or deflation (price decreases) of various commodities and services is reflected in changes in the CPI's value over time [8]. In Indonesia, the Consumer Price Index (CPI) is compiled and released on a monthly basis by Statistics Indonesia (Badan Pusat Statistik or BPS). The Laspeyres formula, which contrasts the price of a fixed set of products and services in the present period with their price in a specified base period, is used to generate the index. The Laspeyres index is calculated using the following formula:

$$\text{CPI} = \frac{\sum(P_t \cdot Q_0)}{\sum(P_0 \cdot Q_0)} \times 100 \tag{2}$$

Where $\boldsymbol{P_t}$ represents the price of each good or service in the current period, $\boldsymbol{P_0}$ refers to the corresponding price in the base period, $\boldsymbol{Q_0}$ is the quantity of each item in the base period, which serves as a fixed weight to reflect its importance in consumer spending.

2.3. Long Short-Term Memory

Long Short-Term Memory (LSTM) is a specialized form of Recurrent Neural Network (RNN) designed to effectively process time series data with long-range dependencies. Unlike standard RNNs, LSTM addresses the vanishing gradient problem, thereby improving its performance in sequence prediction tasks [9]. Conceptually, LSTM can be viewed as an RNN architecture with more sophisticated internal units [10]. LSTM generally outperforms standard RNNs when dealing with time series data characterized by long intervals and delayed dependencies. LSTM applies weights and biases to specific equations at each gate, allowing the model to process and retain information more efficiently. Each unit of the LSTM receives input at a specific time ($\boldsymbol{x_t}$) and combines it with the output of the previous unit ($\boldsymbol{h_{t-1}}$). The first process that occurs is through the forget gate, which functions to determine whether information from the previous memory state ($\boldsymbol{C_{t-1}}$) should be forgotten or retained [11].

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \tag{4}$$

In Equation (3) the sigmoid activation function $\boldsymbol{\sigma}$ maps the concatenated vector $[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}]$ to a value between 0 and 1, producing $\boldsymbol{f_t}$. This value represents the proportion of prior knowledge to forget, where $\boldsymbol{f_t = 1}$ indicates that all previous information is preserved, while $\boldsymbol{f_t = 0}$ means it is completely ignored. The computation is guided by the forget gate's weight matrix $\boldsymbol{W_f}$ and bias vector $\boldsymbol{b_f}$. Equation (4) then combines this filtered memory with new information selected by the input gate, where $\boldsymbol{i_t}$ denotes the input gate activation and $\boldsymbol{\widetilde{C}_t}$ represents the candidate memory content generated at the current time step. Together, these processes determine the final updated cell state, balancing past information with newly relevant inputs.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{5}$$

$$C_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{6}$$

Then the calculation at the Input Gate on Equation (5) and (6) derived from a combination of $\boldsymbol{x_t}$ and $\boldsymbol{h_{t-1}}$ processed through two activation functions, sigmoid and tanh. The sigmoid function is used to generate $\boldsymbol{i_t}$, which determines how much new information will be written to memory, while the tanh function generates new memory candidates $\boldsymbol{C_t}$. Subsequently, the cell state is updated by integrating the retained information from the forget gate with the newly received input from the input gate.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{8}$$

The final step is the output gate in Equation (7) and (8) $\boldsymbol{o_t}$ which regulates the extent of information extracted from the memory cell that will be passed on as output $\boldsymbol{h_t}$. This output is influenced by $\boldsymbol{x_t}$ and $\boldsymbol{h_{t-1}}$ as well as modifications made to the memory cell by the tanh function in the last equation. By utilizing this three-gate mechanism, LSTM is able to remember long-term information and discard irrelevant information, making it highly effective for time series data modeling.

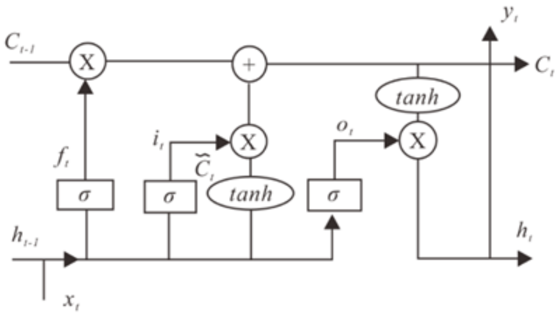

Figure 1. LSTM Architecture

To put it another way, the forget gate regulates the amount of information that can be retained in long-term memory, or the amount that effects the present and future. The forget gate regulates how much of what has been collected may be used as current output, while the input gate is helpful for regulating how much fresh information (input) can be added to long-term memory [12].

2.4. Long Short-Term Memory Autoencoder (LSTM-AE)

An unsupervised neural network called an autoencoder is made to use input data to choose the best encoding and decoding structure. It usually consists of a latent space, an encoder, a decoder, an input layer, and an output layer. The encoder compresses the input into a lower-dimensional latent representation as the data is transmitted via the network, and the decoder uses this encoded information to recreate the final output. The network's weights are adjusted by propagating the mistake that results from comparing the reconstructed output to the original input.

In particular, the encoder compresses an input vector $\boldsymbol{x} \in \mathbb{R}^{\boldsymbol{m}}$, the encoder transforming $\boldsymbol{x}$ into a lower-dimensional representation $\boldsymbol{z} = \boldsymbol{e}(\boldsymbol{x}) \in \mathbb{R}^{\boldsymbol{n}}$. This latent embedding is subsequently fed into the decoder, which reconstructs it to generate an output $\widehat{\boldsymbol{x}} = \boldsymbol{d}(\boldsymbol{z}) \in \mathbb{R}^{\boldsymbol{m}}$. Reconstruction error comparing the original input and the generated output is minimized to optimize the autoencoder during training [13].

$$\mathrm{L} = \frac{1}{2}\sum_{x} \|x - \hat{x}\|^2 \tag{9}$$

The primary objective of an autoencoder is not merely to replicate the input at the output. Instead, by constraining the latent space to a lower dimensionality than the input ($\boldsymbol{n} < \boldsymbol{m}$) the model is compelled to capture the most salient and informative features of the data. In essence, a key characteristic of the autoencoder (particularly in the context of LSTM-based architectures) is its ability to perform dimensionality reduction while preserving the essential structure of the original time series. An LSTM Autoencoder is a type of autoencoder in which both the encoder and decoder components are implemented using Long Short-Term Memory (LSTM) networks. Using LSTM's ability to capture long-range temporal patterns, this architecture is especially well-suited for applications like anomaly detection and time series forecasting. In essence, the LSTM units are employed to model temporal dependencies across multivariate input sequences.

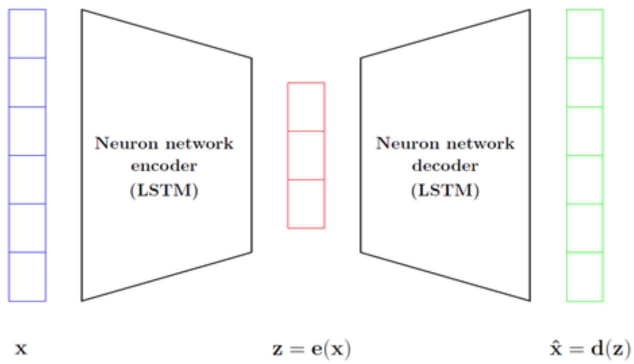

Figure 2. LSTM Autoencoder Architecture

An encoder-decoder model trained exclusively on normal multivariate time series data can be effectively utilized for anomaly detection. Since the model is exposed only to normal patterns during training, it learns to accurately reconstruct them. Consequently, when presented with an anomalous sequence, the reconstruction error tends to increase, serving as a signal for the presence of an anomaly [14].

2.5. Mean Absolute Percentage Error (MAPE)

In evaluating the performance of a prediction model, the use of appropriate evaluation metrics is essential to assess its accuracy and effectiveness, one commonly used metric is the Mean Absolute Percentage Error (MAPE). This evaluation metric provides insight into the model's ability to accurately predict the true values, and serves as a basis for determining which model performs best in generating reliable predictions. Through this evaluation analysis, we can measure the extent to which the model can minimize errors and provide accurate forecasts[15]. The formula for determining the MAPE value is:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|y_i - \hat{y}_i|}{|y_i|}\right) \times 100\% \tag{10}$$

Where $\boldsymbol{y_i}$ is the actual value at $\boldsymbol{i}$ observation, $\boldsymbol{\hat{y}_i}$ is he predicted value for that same observation, and $\boldsymbol{n}$ represents the total number of observations included in the calculation.

2.6. Analytical Methodology

This research involves a series of essential phases, beginning with data acquisition, followed by preprocessing and exploratory analysis, data partitioning into training and testing sets, development of a prediction model using LSTM, anomaly detection through LSTM-based autoencoder, and evaluation of model performance. The initial step in this research is the collection of data on Inflation Rate and Consumer Price Index for the period 1999 to 2024 from the BPS Ambon City website, and the Python programming language is used to build the LSTM model.

Data preprocessing and exploration steps are carried out by checking for missing data values, data normalization, and data exploration to determine data characteristics and identify data patterns through plot visualization. Because LSTM is very sensitive to data scale, data normalization is carried out to prevent data with large values from dominating the data. This research uses the min-max normalization method with a range of values $[0, 1]$ with the equation **[16]**:

$$y_{i,j} = \frac{x_{i,j} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{11}$$

Where $y_{i,j}$ represents the normalized value, $x_{i,j}$ denotes the original data point to be normalized, while $\min(x_j)$ and $\max(x_j)$ refer to the minimum dan maximum data values of the data in feature j, respectively.

The data is separated into two categories: test data and training data. Several combinations of percentages between training and test data are tested in order to complete this data division process. In this study, 20% of the data is test data and 80% is training data. The test results show that the larger the proportion of training data, the higher the model accuracy tends to be. This is because the diversity of data variations enables the model to identify a broad range of pattern structures during the testing phase. Subsequently, the LSTM algorithm was applied to both datasets, with the model being fitted to the training set and evaluated using the test set to measure its performance **[17]**.

The modeling process employs the LSTM algorithm, resulting in a trained model capable of predicting the inflation rate in Ambon. **Equations (3)** to **(8)** are used to calculate the vector at each unit gate in the LSTM algorithm. Initializing parameters, such as the number of neurons in the input, hidden, and output layers, as well as the batch size, number of epochs, and optimizer settings like the learning rate, is the first step in LSTM modeling. One of the key factors in creating a model is the optimizer, which is essential for increasing model accuracy. In this research, the initial parameter determination is done randomly. LSTM has two activation functions, namely tanh which functions to convert input x into a range between -1 to 1, and sigmoid activation function to convert input x into a range between 0 to 1. The formulas of the tanh and sigmoid activation functions are [18]:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{12}$$

$$\tanh(x) = 1 \cdot \sigma(2x) - 1 \tag{13}$$

The LSTM Autoencoder model is applied to detect anomalies in Inflation data. The two primary parts of an autoencoder are a decoder that reconstructs the sequence from the latent representation and an encoder that maps the input sequence into a low-dimensional latent representation. Inflation data that has been normalized using Min-Max Scaling is then managed with LSTM-AE in the form of timesteps. After training, data reconstruction is then performed and the reconstruction error is calculated with the equation [19]:

$$\text{error}_t = \|x_t - \hat{x}_t\| \tag{14}$$

If the error exceeds the threshold, then the point is classified as an anomaly. Handling anomalies and missing data values by applying linear interpolation implemented through the interpolate() function of the pandas library. Linear interpolation is a numerical method that estimates the value between two data points with the assumption that the change between points is linear. Given two points namely (x_0, y_0) and (x_1, y_1), the value of y at point x which is between them can be calculated by the formula [20]:

$$y = y_0 + \frac{(x - x_0)}{(x_1 - x_0)} \cdot (y_1 - y_0) \tag{15}$$

This approach is suitable for economic time series data such as inflation and CPI which have a tendency for gradual changes over time. Missing data values will be filled using linear interpolation to maintain the continuity of the data trend, the anomalous points detected from the Autoencoder LSTM model are emptied filled with linear interpolation. This process allows for data recovery without compromising the stability of the general pattern, as well as avoiding the bias that extreme values can cause.

The last stage is to evaluate the model using MAPE to see which is the best model between LSTM without handling anomalies or LSTM modeling by handling anomalies detected by LSTM Autoencoder.

3. RESULT AND DISCUSSION

3.1. Data Exploration

The data exploration stage was conducted to describe and identify the characteristics of the dataset, which comprises monthly observations spanning the period from 1999 to 2024. The dataset includes 312 observations for the Consumer Price Index (CPI) and 309 observations for the inflation rate, compiled in a time series format.

Descriptive statistical analysis was employed to summarize the key characteristics of each variable, including the mean, standard deviation, median, as well as minimum and maximum values. Furthermore, exploratory data analysis was carried out through time series visualizations of CPI and inflation in Ambon to observe patterns and fluctuations over time.

Table 1. Descriptive Statistics of Inflation and CPI

Dataset	Minimum	Maximum	Average	Standard Deviation
Inflation	−6.07%	8.95%	0.5056%	1.674%
CPI	105.09	292.45	145.8289	51.986

Standard deviation reflects the extent of data variability. A large value indicates wide dispersion from the mean, while a small value shows that data points are closely clustered around the average. **Figure 3** presents a plot illustrating the temporal trend of the Consumer Price Index (CPI) in Ambon City from 1999 to 2024. The graph shows fluctuations in CPI values over time. A sharp increase is observed up to 2004, followed by a sudden drop, likely due to changes in the calculation method or rebasing. In the following years, the CPI gradually increased with occasional spikes, then remained relatively stable after 2020. This pattern is consistent with the high standard deviation (51.99), indicating a wide spread and considerable variability in consumer price levels throughout the observed period.

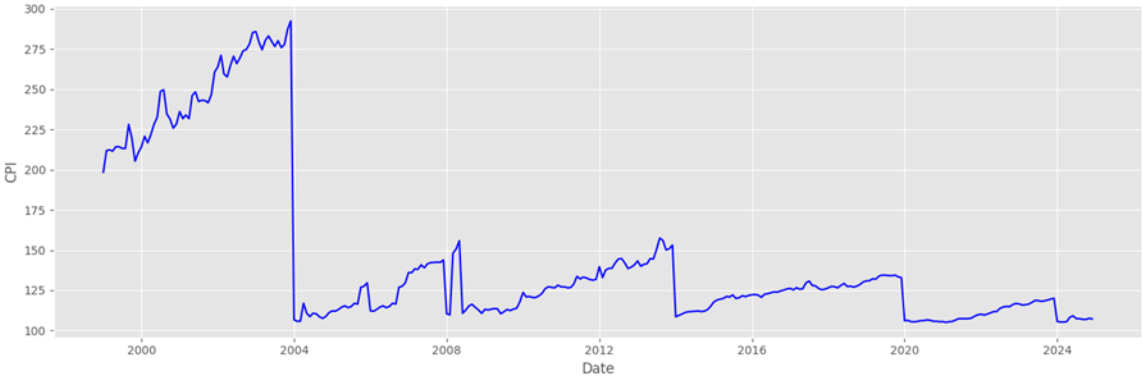

Figure 3. Graph of Inflation Rate in Ambon from 1999 to 2024

In **Figure 4** presents the inflation rate trend in Ambon since 1999 to 2024. The graph shows frequent and sharp fluctuations, particularly in the early 2000s, with values ranging from approximately −**6**% to over 8%. These extreme variations suggest periods of both inflation and deflation, possibly influenced by external economic shocks or local price adjustments. Over time, the inflation rate appears to become more stable, especially after 2015. This fluctuation pattern aligns with the standard deviation value of 1.67, indicating a moderate level of variability in monthly inflation throughout the observed period.

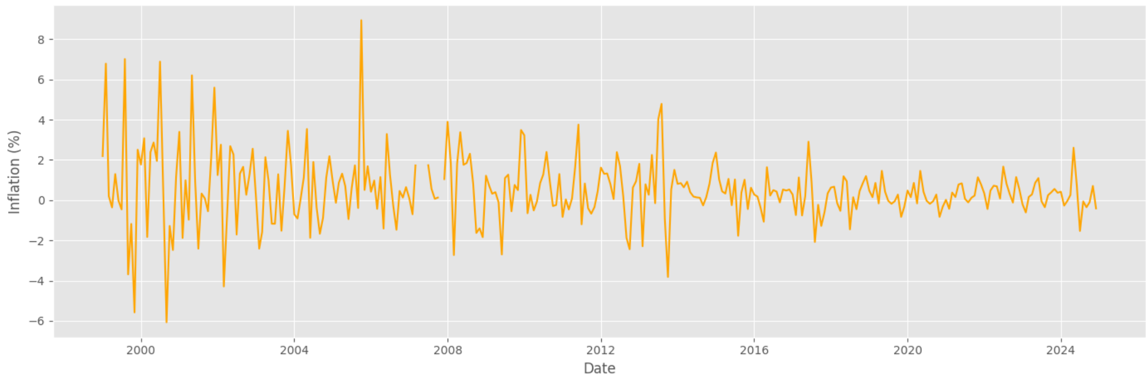

Figure 4. Graph of Consumer Price Index in Ambon from 1999 to 2024

Data preprocessing began with identifying missing values using the isna().sum() function in Python. The dataset consists of monthly Consumer Price Index (CPI) and inflation rate records for Ambon City from 1999 to 2024. Upon inspection, no missing values were found in the CPI data. However, the inflation dataset contained 3 missing values in the inflasi column. To handle this issue, a linear interpolation technique was implemented in a forward direction using the interpolate() method. A subsequent validation confirmed that all missing values had been effectively imputed, resulting in a complete and consistent dataset suitable for further analysis.

3.2. Inflation Rate Prediction with LSTM without Handling Anomalies

In this stage, the dataset used consisted of the original monthly inflation and CPI data from Ambon City, in which missing values were handled by removing any rows containing NaN values, without applying interpolation. No anomaly detection or outlier handling was performed in this experiment, meaning that the model was trained on raw but non-null data that may still contain extreme values. After removing missing entries, the data was normalized using Min-Max scaling, which transformed all values into a range [0, 1]. This normalization was applied separately to the input feature (CPI) and the target variable (inflation) to ensure stable gradient updates throughout the training phase of the LSTM model.

The predictive model was constructed using the Long Short-Term Memory (LSTM) architecture, implemented in Python with the Keras library (TensorFlow backend). The model was initialized with several critical hyperparameters, including the number of neurons per layer, learning rate, batch size, and total training epochs. In this study, the LSTM network architecture comprises two stacked LSTM layers, each containing 64 units of neurons, Dropout layers were added to reduce overfitting, and a Dense output layer with a single neuron was added at the end. The model was trained over 50 epochs with a batch size of 16 using the Adam optimizer with a learning rate of 0.00001. During training, mean squared error (MSE) was employed as the loss function, and a linear activation function was utilized in the output layer.

The purpose of using this architecture is to learn temporal dependencies within the CPI time series and estimate future inflation values. Mean Absolute Percentage Error (MAPE) was adopted as the sole metric for evaluating the predictive accuracy of the model. The result yielded a MAPE value of 69.57%, indicating a relatively high prediction error, which suggests that the model struggled to generalize patterns effectively from the given input data.

3.3. Anomly Detection with LSTM Autoencoder and Its Handling

The LSTM Autoencoder architecture is utilized to identify anomalies in the inflation data of Ambon that has been normalized using the Min-Max Scaler method. The model consists of one LSTM encoder layer with 64 units and one LSTM decoder layer that reconstructs the input sequence. A batch size of 16 and a Mean Squared Error (MSE) loss function were used during the 50 epochs of training. Following training, the model uses the CPI input to produce reconstruction predictions and computes the reconstruction error as the foundation for anomaly identification. Anomaly points are determined based on a threshold at the 95th percentile of the error distribution, where error values exceeding this threshold are classified as anomalies.

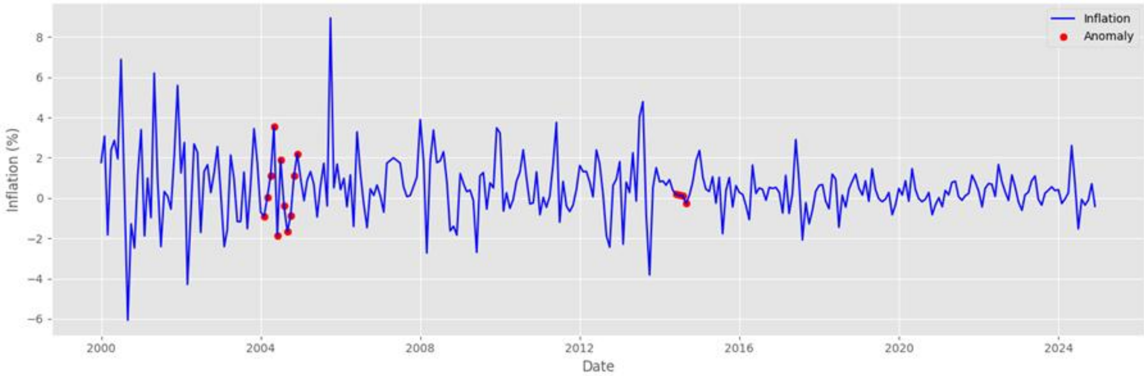

Figure 5. Detecting Inflation Anomalies with LSTM Autoencoder

In **Figure 5**, the red dots indicate observations that the LSTM Autoencoder identified as anomalies, whereas the blue line shows the actual monthly inflation values.. Significant anomalies were observed especially around 2004–2005, where abnormal spikes in inflation were detected, suggesting structural shifts or reporting irregularities during that period. A few minor anomalies were also identified around 2015. The detected anomalies show that the model can identify data that differs significantly from the existing trend. This indicates the presence of data that does not match the studied Inflation pattern. Overall, the LSTM Autoencoder can identify anomalies quite well, especially at points that show significant changes in inflation.

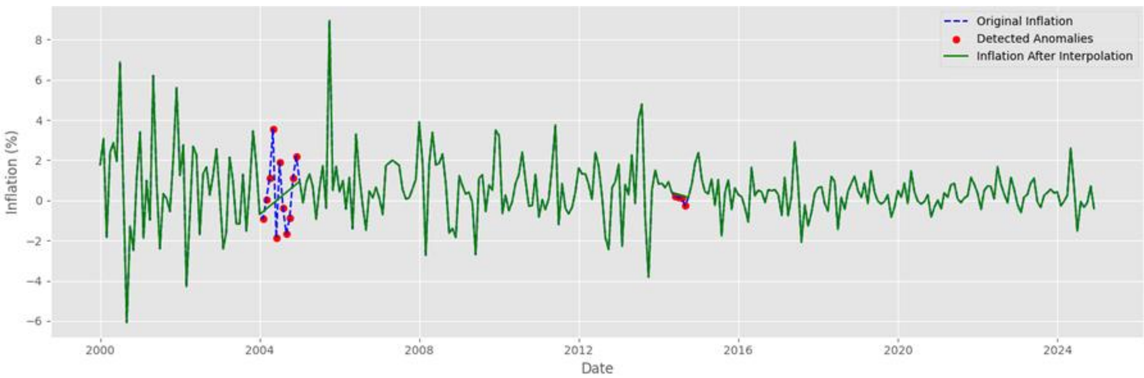

Figure 6. Anomaly Handling with Linear Interpolation

To address the detected anomalies, the values corresponding to those points were set to NaN in both the inflation and CPI. These missing values were then handled using linear interpolation, leveraging surrounding data points to estimate realistic values and maintain continuity.

In **Figure 6,** where the dashed blue line represents the original inflation data, red points show the detected anomalies, and the green line indicates the cleaned series after interpolation. This approach allowed the data to retain its temporal structure while removing extreme fluctuations that could distort the training of subsequent LSTM prediction models. Overall, the LSTM Autoencoder effectively captured irregularities in the CPI-driven inflation series, and the anomaly handling process resulted in a smoother, more reliable dataset for forecasting tasks.

3.4. Inflation Prediction with LSTM after Handling Anomalies

The data used in this stage consists of the Consumer Price Index (CPI) and monthly inflation data for Ambon, which had previously undergone anomaly detection using an LSTM Autoencoder. Values identified as anomalies were removed and subsequently imputed using linear interpolation. In addition, all missing values were also handled using the same interpolation method to ensure the dataset was clean and ready for modeling.

After ensuring the dataset was free from both outliers and missing values, normalization was applied using the Min-Max Scaling technique. This step is essential because LSTM networks are highly sensitive to input scale. Excessive value ranges may cause instability in gradient updates during backpropagation. Therefore, the CPI data (as input) and the inflation data (as target) were normalized separately to a [0, 1] range.

The next step involved the creation of sequential data (windowing), as LSTM models require inputs in the form of time-based sequences to capture temporal patterns effectively. In this study, a timestep value of 2 was used, which means the model utilizes CPI data from the two previous months to predict inflation in the following month. Following sequence formation, the data was divided into two subsets: 20% for testing and 80% for training. The input data was then reshaped into a three-dimensional format (samples, timesteps, features) to match the input structure required by LSTM networks implemented using the TensorFlow/Keras framework.

The Long Short-Term Memory (LSTM) architecture implemented in this study consists of two LSTM layers, each comprising 50 neuron units. The initial LSTM layer was set with *return_sequences=True* to enable the passing of sequential outputs to the next layer. Each LSTM layer was followed by a Dropout layer with a rate of 0.2 to reduce the risk of overfitting. A final Dense layer containing a single neuron serves as the output layer, responsible for producing the predicted inflation value. The default activation function applied in the LSTM layers was tanh, following the standard Keras setup. The model was built using the Adam optimizer with a learning rate of 0.001. The loss function, Mean Squared Error (MSE), aims to minimize the deviation between the actual training values and their corresponding predictions.

To determine the optimal model configuration, several experiments were conducted by varying the input sequence length (timesteps) and the number of hidden layers. The table below presents the results of different model architectures based on their MAPE:

Table 2. Experimental Results of LSTM

Timesteps	Hidden Layers	Output Neuron	MAPE (%)
4	1	1	8.99%
3	1	1	8.81%
12	1	1	8.86%
6	1	1	9.59%
2	2	1	8.67%

From these results, the best configuration was achieved with timesteps = 2, two hidden LSTM layers, and one output neuron, resulting in the lowest MAPE of 8.67%. This configuration was therefore used in the final model training for inflation prediction. The model was optimized using the MSE loss function and the Adam (Adaptive Moment Estimation) algorithm using default settings, such as a learning rate of 0.001. The training process was conducted over 50 epochs with a batch size of 16, and validation was performed on the test data (20% of the total dataset) to evaluate the model's generalization capability.

The final evaluation involved the use of multiple performance indicators, such as the Mean Absolute Percentage Error (MAPE). Based on the best-performing configuration, the resulting MAPE was 8.67%, indicating that the model exhibits a reasonably good predictive capability for monthly inflation trends in Ambon.

Based on the modeling results using a Long Short-Term Memory (LSTM) architecture with two hidden layers, each consisting of 50 units and a dropout rate of 0.2, and an input sequence length (timesteps) of 2, the predicted monthly inflation values for the next six months are as follows: 0.5254, 0.5677, 0.6024, 0.6026, 0.6026, and 0.6026. All prediction outputs were rescaled back to their original units (percent inflation) using the inverse transformation function of the MinMaxScaler, enabling the results to be interpreted directly as estimated monthly inflation rates for Ambon City over the upcoming six-month period.

4. CONCLUSIONS

This study aimed to predict the monthly inflation rate in Ambon City using the Consumer Price Index (CPI) as the main input variable and the Long Short-Term Memory (LSTM) neural network as the predictive model. The data underwent several pre-processing stages, including anomaly detection using LSTM Autoencoder, handling of missing and anomalous values via linear interpolation, and normalization using Min-Max Scaling. Sequential data were generated with a timestep of two months, and the dataset was divided into training (80%) and testing (20%) subsets before being reshaped into the 3D format required by LSTM models.

The final architecture of the LSTM model comprised two stacked LSTM layers, each containing 50 units, followed by dropout layers with a rate of 0.2 to mitigate overfitting. The network concluded with a dense output layer consisting of a single neuron. The model was trained for 50 epochs using the Adam optimizer with a learning rate of 0.001, and the Mean Squared Error (MSE) served as the loss function. The model evaluation demonstrated that the LSTM delivered a satisfactory level of predictive accuracy, achieving a Mean Absolute Percentage Error (MAPE) of 8.67%. This finding highlights the model’s capability to capture historical CPI patterns and effectively map them to monthly inflation fluctuations. The model also demonstrated stability during training and validation processes and avoided overfitting.

To conclude, the LSTM model applied in the present research has demonstrated its effectiveness in forecasting inflation using time series data. These findings can serve as a reference for local governments and economic institutions in formulating anticipatory strategies for price changes in Ambon City. Future research is recommended to explore more complex architectures and incorporate additional macroeconomic indicators to improve predictive accuracy.

Funding Information

There was no external sponsorship for this project. All financial responsibilities associated with the study were undertaken by the authors.

Author Contributions Statement

Author	Contribution Roles
Syella Zignora Limba	Conceptualization, Methodology, Software, Formal Analysis Investigation, Data Curation, Visualization, Writing (original draft), Writing (review and editing), Project Administration, Resources.
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Conflict of Interest Statement

Authors state no conflict of interest

Data Availability

The dataset used in this research is publicly accessible through BPS–Statistics Indonesia at https://www.bps.go.id/

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