TIME SERIES MODELING USING THE HYBRID CONVOLUTIONAL NEURAL NETWORK (CNN)-LONG SHORT TERM MEMORY (LSTM) METHOD FOR INFLATION PREDICTION IN INDONESIA

Thesis

By

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ABSTRACK

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By

Kinasih Sasikarani

Inflation is an important macroeconomic indicator that reflects changes in the general prices of goods and services. In such conditions, conventional forecasting methods based on linear assumptions often have limitations in capturing dynamic patterns in time series data. This study applies a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) deep learning model to model and predict monthly inflation in Indonesia. The CNN-LSTM model combines the ability of CNN to extract short-term patterns from time series data with the ability of LSTM to capture long-term dependencies. Monthly inflation data for Indonesia from 2000 to October 2025 was used in this study. The research stages included data pre-processing, data normalization, time series data formation, CNN-LSTM model development and training, and model performance evaluation. Model performance was evaluated using the Root Mean Squared Error and Mean Absolute Error metrics. This study aims to obtain an accurate inflation forecasting model and understand the ability of the CNN-LSTM hybrid model to capture inflation dynamics in Indonesia, thereby providing empirical support for economic planning and policy-making.

Keywords: Inflation, Time Series, Prediction, Deep Learning, Convolutional Neural Network, Long Short Term Memory, Mean Squared Error, Root Mean Squared Error, Mean Absolute Error.

ABSTRAK

PEMODELAN *TIME SERIES* MENGGUNAKAN METODE *HYBRID CONVOLUTIONAL NEURAL NETWORK* (CNN)-*LONG SHORT TERM MEMORY* (LSTM) UNTUK PREDIKSI INFLASI DI INDONESIA

Oleh

Kinasih Sasikarani

Inflasi merupakan indikator makroekonomi penting yang mencerminkan perubahan harga barang dan jasa secara umum. Dalam kondisi tersebut, metode peramalan konvensional berbasis asumsi linear sering kali memiliki keterbatasan dalam menangkap pola dinamis pada data deret waktu. Penelitian ini menerapkan model *deep learning hybrid Convolutional Neural Network–Long Short-Term Memory* (CNN-LSTM) untuk memodelkan dan memprediksi inflasi bulanan di Indonesia. Model CNN-LSTM mengombinasikan kemampuan CNN dalam mengekstraksi pola jangka pendek dari data deret waktu dengan kemampuan LSTM dalam menangkap ketergantungan jangka panjang. Data inflasi bulanan Indonesia periode 2000 hingga Oktober 2025 digunakan dalam penelitian ini. Tahapan penelitian meliputi pra-pemrosesan data, normalisasi data, pembentukan data deret waktu, pembangunan dan pelatihan model CNN-LSTM, serta evaluasi kinerja model. Kinerja model dievaluasi menggunakan metrik *Root Mean Squared Erro*r dan *Mean Absolute Error*. Penelitian ini bertujuan untuk memperoleh model peramalan inflasi yang akurat serta memahami kemampuan model hybrid CNN-LSTM dalam menangkap dinamika inflasi di Indonesia, sehingga dapat memberikan dukungan empiris bagi perencanaan dan pengambilan kebijakan ekonomi.

Kata-kata kunci: Inflasi, Deret Waktu, Prediksi, *Deep Learning, Convolutional Neural Network, Long Short Term Memory, Mean Squared Error, Root Mean Squared Error, Mean Absolute Error*.

TIME SERIES MODELING USING THE HYBRID CONVOLUTIONAL NEURAL NETWORK (CNN)-LONG SHORT TERM MEMORY (LSTM) METHOD FOR INFLATION PREDICTION IN INDONESIA

KINASIH SASIKARANI

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Hereby declare that this thesis is the result of my own work and all writings contained in this thesis have followed the rules of scientific writing at the Lampung University.

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BIOGRAPHY

Kinasih Sasikarani was born in Gadingrejo Village, Lampung Province on April 06, 2004. She is the second of two children of Mr. Puspito Kurniawan and Mrs. Helma. She has an older brother named Arief Fadly Kurniawan.

She began her early education at Darussalam Kindergarten in the academic year 2009-2010. She continued her elementary school at SDN 02 Gadingrejo in 2010-2016. Then took junior high school education at SMPN 01 Gadingrejo in 2017-2019 and continued her high school education at SMAN 01 Gadingrejo in 2019-2022.

In 2022, Kinasih Sasikarani continued her undergraduate education at the Department of Mathematics, Faculty of Mathematics and Natural Sciences, Lampung University through the National Selection for State University Admission (SNMPTN).

During her university years, she participated as member of the Anniversary of the Mathematics Department (DINAMIKA) in 2023 and 2024. From 23 December 2024 to 31 January 2025, she completed a professional internship at the Badan Perencanaan Pembangunan, Riset dan Inovasi Daerah Kota Bandar Lampung (BAPPERIDA) in Bandar Lampung city. Furthermore, from July to August 2025 she conducted a Real Work Lecture (KKN) in Kupang Raya, Bandar Lampung. She also completed an internship at Badan Pusat Statistik (BPS) in Pesawaran Regency from August 25 to October 24, 2025.

WORD OF INSPIRATION

“All your ups and downs are normal, dreams and questions that time will answer, give yourself time to grieve, celebrate your feelings as a human being.”
-Baskara Putra

“And be patient, for the promise of God is true.”
(Q.S Ar-Rum: 60)

“Life can be heavy, especially if you try to carry it all at once. Part of growing up and moving into new chapters of your life is about catch and release.”
-Taylor Swift

DEDICATION

With deep gratitude to Allah SWT for all His blessings, guidance, and grace, which have enabled me to complete this thesis, I dedicate this work to:

My beloved parents, Puspito Kurniawan and Helma, for their love, unceasing prayers, and immeasurable sacrifices in every step of my life and education. My three beloved siblings, Arief Fadly Kurniawan, Ayu Andina Lestari, and Tiara Puspa Prameswari, as well as my entire extended family, who have always provided support, attention, motivation, and prayers so that I could persevere and continue to strive to reach this stage.

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and for the courage to come this far. I humbly present this work as a sign of life's journey and as proof that everything has meaning. Congratulations on your victory.

The author acknowledges that this thesis is far from perfect and may still contain shortcomings, both in presentation and writing technique. Therefore, constructive criticism and suggestions are highly welcomed to improve the quality of this work. The author hopes that it will be useful for the readers.

Bandar Lampung, 29 January 2026

Kinasih Sasikarani

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I. INTRODUCTION

1.1 Background and Issues

Forecasting is an important process in decision making, which is used to estimate future events or values based on available historical data (Tuncar et al., 2024). According to (Hyndman et al., 2021), there are two main approaches to forecasting, namely quantitative and qualitative methods. Quantitative methods are used when past data is available and can be analyzed statistically, while qualitative methods are used when historical data is not available and rely more on intuition or expert opinion. Quantitative methods have been proven to provide more objective and measurable prediction results, particularly within the areas of economics and finance.

One of the main approaches in quantitative methods is time series analysis, which is data collected periodically and sequentially based on time. Time series are used to capture patterns in data, such as trends, seasonality, and cycles that can help in predicting future values.

With the development of technology and the increasing need for more accurate predictions, conventional forecasting methods are being abandoned and replaced by machine learning and deep learning approaches (Lim et al., 2021). One of the most popular deep learning methods for handling time series data is Long Short-Term Memory (LSTM), which is capable of capturing long-term dependencies in data. However, LSTM has limitations in extracting short-term patterns from data. To address this issue, a hybrid method combining Convolutional Neural Network (CNN) and LSTM was introduced. CNN functions to extract short-term features or patterns from the data, while LSTM plays a role in modeling long-term relationships.

Previous studies has demonstrated the advantages of the CNN-LSTM hybrid model. According to (Bai et al., 2018), the combination of CNN-LSTM can improve prediction performance on time series data with complex patterns. Research by (Zhang et al., 2023), also shows that CNN-LSTM model demonstrates more accurate predictive performance compared to other approaches. In addition, research by (Nguyen-Da et al., 2023), proves that the hybrid method is more effective than single methods such as Gated Recurrent Unit (GRU) and Recurrent Neural Networks (RNN).

In macroeconomic terms, inflation serves as a crucial indicator that shows the overall rate at which the prices of goods and services change within a particular area. Inflation signifivantly influences the purchasing power of the population and the stability of the economy, making it a key consideration in the formulation of fiscal and mmonetary polices (Bank Indonesia, 2023). As a developing country, Indonesia has inflation dynamics that are influenced by various factors, such as food prices, exchange rates, energy prices, and global external factors. High inflation fluctuations can cause economic uncertainty, so accurate inflation predictions are needed to support economic policy formulation (BPS, 2023).

Based on the background of forecasting and the potential of the CNN-LSTM hybrid method in analyzing complex time series data, Therefore, researchers are interested in conducting this study with the aim of predicting inflation in Indonesia using the hybrid CNN-LSTM method. It is hoped that the results of this study can provide useful information in supporting economic planning and policy-making in Indonesia.

1.2 Problem Statement

The research questions for this study are as follows:

1. How to build a hybrid CNN-LSTM model to predict inflation in Indonesia.
2. How accurate is the hybrid CNN-LSTM model in predicting inflation in Indonesia.

1.3 Research Objectives

Based on the above problem formulation, the objectives of this research are as follows:

1. To build an inflation forecasting model in Indonesia using the hybrid CNN-LSTM method.
2. Evaluate the performance of the hybrid CNN-LSTM model in predicting inflation in Indonesia based on evaluation metrics.

1.4 Research Benefits

The benefits of this research are as follows:

1. Contributing to the literature in the field of time series forecasting with a deep learning approach, specifically the hybrid CNN-LSTM method on macroeconomic data.
2. Providing information on inflation predictions that can be used by the government in formulating economic policies.

II. LITERATURE REVIEW

2.1 Forecasting

According to (Robial, 2018), forecasting involves predicting the future value of a variable by analyzing historical data and identifying past trends. In general, forecasting is based on past data which is then analyzed using certain methods or techniques. Furthermore, past data is collected, studied, analyzed, and linked over time.

According to (Groß et al., 2021), forecasting can be divided into three types based on its time frame, namely:

a. Short-term forecasting, which is forecasting conducted to compile forecasts on a daily or hourly basis.

b. Mid-term forecasting, which is forecasting conducted to compile forecasts within a weekly to monthly time frame.

c. Long-term forecasting, which is forecasting conducted to compile forecasts within a monthly to yearly time frame.

2.2 Time Series

A time series is a collection of data that is recorded and observed sequentially at equal time intervals. Time series aim to analyze historical data patterns and make forecasts for the future (Hyndman et al., 2021).

According to (Wei, 2019), time series data consists of four primary components:

1. Trend, which is a long-term tendency,

2. Seasonality, which is a recurring pattern over a specific period,
3. Cycle, which is long-term fluctuations,
4. Irregular/noise, which is variation that cannot be explained by trends, seasonality, and cycles.

Traditional models that are often used in time series analysis are Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Exponential Smoothing (ETS), and Vector Autoregression (VAR). Traditional models such as ARIMA and ETS are effective for linear and stationary data, but have limitations in capturing non-linear relationships and long-term dependencies in complex data (Makridakis et al., 2018). To address these shortcomings, numerous studies have started ultilizing machine learning and deep learning methods to analyze time series data.

2.3 Machine Learning

Machine Learning (ML) is a branch of artificial intelligence (AI) that focuses on developing algorithms capable of learning from data to make predictions or decisions without explicit instructions (Jordan et al., 2015).

According to (Sarker, 2021), ML is divided into four main paradigms:

1. Supervised Learning, where models are trained using labeled data (input- output), such as linear regression, Support Vector Machine (SVM), and Random Forest.
2. Unsupervised Learning, where models are trained without labels with the aim of discovering hidden structures or patterns, such as K-Means Clustering (K-NN) and Principal Component Analysis (PCA).
3. Semi-supervised Learning, combines elements of both supervised and unsupervised learning. In this approach, models are trained on a mix of labeled and unlabeled data to achieve more accurate predictions than what supervised learning alone can offer.
4. Reinforcement Learning, where models are trained using trial-and-error with reward-based feedback.

ML is commonly applied in time series forecasting because it can effectively model non-linear relationship that traditional statistical techniques often fail to capture (Goodfellow et al., 2016).

2.4 Deep Learning

Deep Learning (DL) is a subset of machine learning that ultilizes neural networks with multiple layers to identify and extract intricate patterns and representations from data (LeCun et al., 2015).

According to (Schmidhuber, 2015), DL has several advantages:

1. Automatic Feature Learning, which is the ability to extract features automatically without manual feature engineering,
2. Non-linear Modeling, which is modeling to capture complex non-linear relationships in data,
3. Transfer Learning, which is modeling that can be reused in different domains after being trained on large datasets,
4. Skalabilitas, which is the flexibility to be applied to images, text, sound, and even time series data.

In time series forecasting, DL architectures such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) are widely used. These models can identify both short-term patterns more effectively that traditional methods and conventional machine learning approaches (Lim et al., 2021).

2.4.1 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning architecture specifically developed to handle data structured in a grid format, such as images, one-dimensional signals, and time series data. Its core mechanism involves the convolution operation, which is the use of a kernel (filter) that is useful for extracting short-term features at various levels of abstraction, followed by an activation function and a dimension reduction stage (pooling). The main characteristics of CNN are weight sharing, which reduces the number of parameters, and translation invariance, making it more efficient than conventional neural networks (fully connected neural networks) in capturing complex patterns (Kiranyaz et al., 2020).

According to (Krichen, 2023), CNN have several main components, includding:

1. Convolutional layer (filter/kernel, stride, padding), which functions to detect local features. One-dimensional convolution operations can be formulated as follows:

$$S(t) = \sum_{k=0}^{K-1} x(t+k)\, w(k) \tag{2.1}$$

   Where:

   $S(t)$ = Short term trend

   $x(t)$ = Data value at time t

   $w(k)$ = Kernel/filter along K

2. Activation function (ReLu, LeakyReLu, ELU), which adds non-linearity, such as the Rectified Linear Unit (ReLU), which is formulated as:

$$f(x) = \max(0, x) \tag{2.2}$$

3. Pooling layer (max/average pooling), which is useful for reducing spatial dimensions and making features more robust, like max-pooling, it is formulated as follows:

$$p_i = \max_{k=(i-1)r+1,\ldots,ir} (s_k) \tag{2.3}$$

   Where:

   p_i = Output pooling

   s_k = Output Conv1D

   r = Pooling size

   i = $1, 2, \ldots, \left[\frac{N}{r}\right]$

4. Batch normalization, which serves to accelerate and stabilize training,

5. Fully connected layers, are typically ultilized at the final stage of the network for tasks such as classification or regression. Commonly used regulation techniques are dropout, L2 weight decay, data augmentation, and early stopping. It is formulated as follows:

$$y = f(Wx + b) \tag{2.4}$$

Where:

f = Activation function

W = Weight matrix

x = Input vector

b = Bias

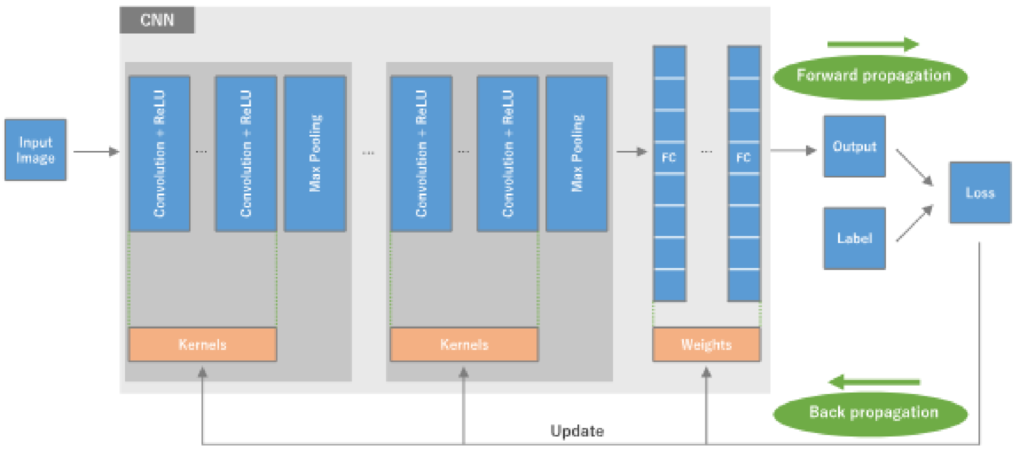

Figure 1. Convolutional Neural Network Architecture (Yamashita et al., 2018)

CNN architecture continues to undergo innovation, such as ResNet with residual connections that serve to overcome the vanishing gradient problem, and DenseNet that serves to strengthen the flow of information between layers. In addition, there are other innovations, namely Squeeze- and-Excitation Networks (SENet) that serve to add an attention mechanism to feature channels, which is useful for improving the quality of CNN representation (Hu et al., 2018).

2.4.2 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is an advanced from of RNN created to address the challenges RNNs face in capturing long-term dependencies, particularly those caused by vanishing and exploding gradient issues (Greff et al., 2017). A Recurrent Neural Network (RNN) is a type of artificial naural network architecture created to handle sequential data by preserving information from earlier steps using a hidden state mechanism. RNNs are highly relevant for time series, text, and audio signal data because they are capable of capturing temporal dependencies in data sequencces (Lipton et al., 2015).

RNNs face vanishing gradient and exploding gradient problems when handling long sequences, which hinders the ability to capture long-term dependencies. To address these challenges, RNNs were developed into Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU), which use gate mechanisms to control the flow of information in the network (Sherstinsky, 2023).

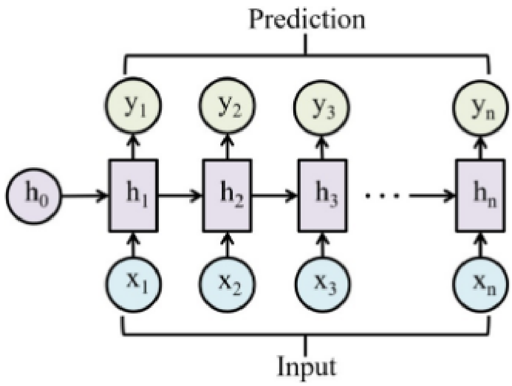

Figure 2. Recurrent Neural Network Architecture (Mienye et al., 2024)

LSTM is widely used in speech recognition, natural language processing, and time series forecasting in the fields of finance, economics, and energy due to its ability to handle non-linear patterns and long-term relationships (Fawaz et al., 2019).

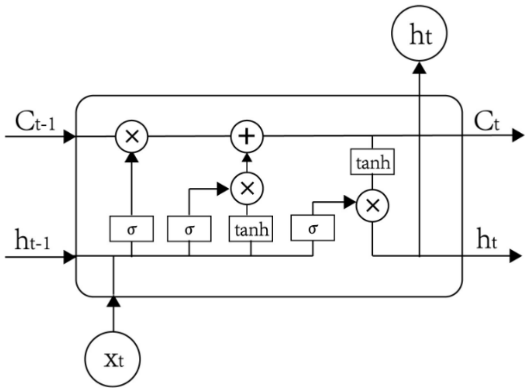

Figure 3. Long Short Term Memory Architecture (Qiu et al., 2020)

Activation functions are an important component in artificial neural networks because they determine whether a neuron will be activated or not, thereby affecting the network's ability to learn non-linear representations (Nwankpa et al., 2018). Two commonly used activation functions are sigmoid and hyperbolic tangent (tanh), where sigmoid limits the output between 0 and 1, while tanh ranges from 1 to 1, thus providing data centered at zero.

LSTM has three main gates to regulate the flow of information, consisting of an input gate, a forget gate, and an output gate. The forget gate functions to determine which information needs to be ignored from the cell state, the input gate functions to regulate new information that needs to be stored, while the output gate functions to control the information output to the hidden state at the next time step (Siami-Namini et al., 2019).

The following are the steps used to regulate the flow of information entering and leaving the LSTM network:

1. The Forget Gate serves to identify which information from the previous cell state is less relevant or unnecessary, so it can be discarded. This process utilizes the sigmoid function, which produces output values between 0 and 1, where 0 indicates complete removal of information and 1 indicates full retention. The operation of the forget gate can be represented by the following equation:

$$f_t = \sigma\left(W_f \times [h_{t-1}, x_t]\right) + b_f \tag{2.5}$$

   Where:

   f_t = Forget gate at time t

   σ = Sigmoid function

   W_f = Weight of forget gate

   h_{t-1} = Output value at time $(t-1)$

   x_t = Input value at time t

   b_f = Bias of forget gate

   The weight value can be expressed as follows:

$$W = \left(-\frac{1}{\sqrt{d}}, \frac{1}{\sqrt{d}}\right) \tag{2.6}$$

Where:

W = Weight

d = Amount of data

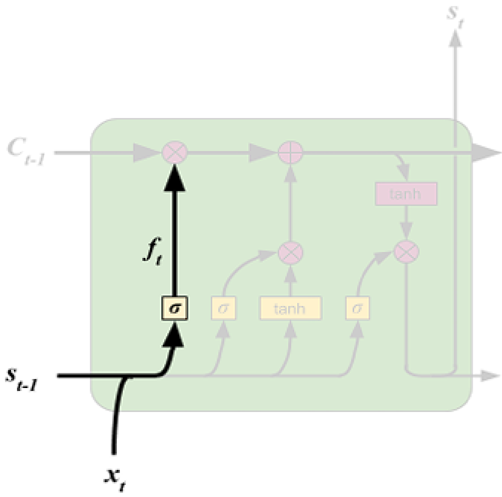

Figure 4. Structure of Forget Gate (Salman et al., 2021)

2. Input Gate, functions to filter and identify which information should be incorporated or updated within the cell state. It utilizes the sigmoid activation function to decide which values will be modified, while the tanh function generates a new candidate vector containing possible information to be stored. The mechanism can be expressed through the following equations:

$$i_t = \sigma\left(W_i \times [h_{t-1}, x_t]\right) + b_i \tag{2.7}$$

Where:

i_t = Input gate at time t

σ = Sigmoid function

W_i = Weight of input gate

h_{t-1} = Output value at time $(t-1)$

x_t = Input value at time t

b_i = Bias of input gate

The new candidate has the following equation:

$$\bar{C}_t = \tanh\left(W_c \times [h_{t-1}, x_t] + b_c\right) \tag{2.8}$$

Where:

$\bar{C}_t$ = New value added to the cell state at time t

$\tanh$ = Hyperbolic tangent function

W_c = Weight of cell state

h_{t-1} = Output value at time $(t-1)$

x_t = Input value at time t

b_c = Bias of cell state

After that, the previous cell state is modified and updated to form the new cell state according to the following equation:

$$C_t = f_t \times C_{t-1} + i_t \times \bar{C}_t \tag{2.9}$$

Where:

C_t = Cell state at time t

f_t = Forget gate at time t

C_{t-1} = Cell state at time $(t-1)$

i_t = Input gate at time t

$\bar{C}_t$ = New value added to the cell state at time t

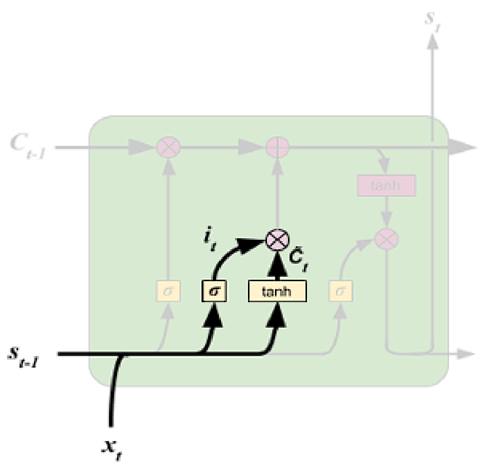

Figure 5. Structure of Input Gate (Salman et al., 2021)

3. Output Gate, determines the final output value of the hidden state. It integrates information from the current input and the cell state, applying the tanh function

to the cell state to control the information flow. After the sigmoid output and tanh output are generated, the two results are then combined through element-wise multiplication to produce the final hidden state. The operation of the output gate is expressed by the following equations:

$$o_t = \sigma \left(W_o \times [h_{t-1}, x_t] + b_o \right) \tag{2.10}$$

Where:

o_t = Output gate at time t

σ = Sigmoid function

W_o = Weight of output gate

h_{t-1} = Output value at time $(t-1)$

x_t = Input value at time t

b_o = Bias of output gate

Then, the cell state is passed through the tanh layer and multiplied by the output obtained from the sigmoid layer to produce the final output in accordance with the previous decision, as follows:

$$h_t = o_t \times \tanh(C_t) \tag{2.11}$$

Where:

h_t = Output value at time t

o_t = Output gate at time t

$\tanh$ = Hyperbolic tangent function

C_t = Cell state at time t

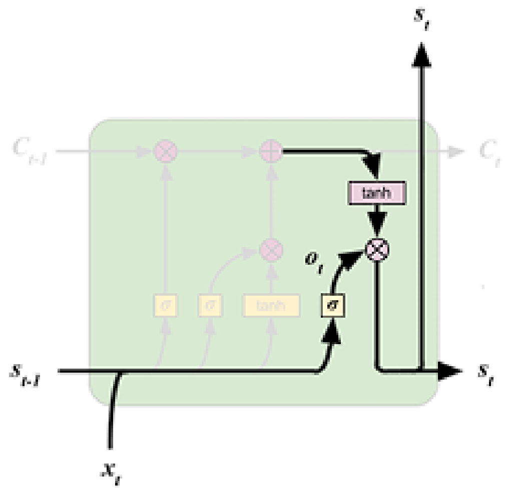

Figure 6. Structure of Output Gate (Salman et al., 2021)

2.5 Hyperparameter Tuning

According to (Yang, 2020), is the process of finding the best parameters in an ML model to improve model performance. These parameters are determined before the training process is carried out. Hyperparameters are settings whose values are set prior to the training process and are not derived from the data itself. Examples include the number of layers, learning rate, number of neurons, batch size, and number of training epochs. The main objective of the tuning process is to find the most optimal combination of hyperparameter values for the model to achieve high accuracy while avoiding overfitting or underfitting (Franceschi et al., 2017)

Hyperparameters commonly used in the training process include the number of neuron units in the hidden layer, the dropout rate, the batch size, and the number of epochs. The batch size determines how many samples are processed before the weight update is performed, which affects the stability and speed of training (Li et al., 2018). Dropout is used to prevent overfitting by randomly deactivating neurons during training, while the number of epochs determines how many times the entire dataset is processed in model training (Feurer et al., 2019).

The optimal combination of hyperparameters will produce a model with better predictive performance, but searching for this combination often requires a long computation time, especially in large-scale DL models (Wang et al., 2018). Therefore, hyperparameters have been developed, one method being grid search, in which all hyperparameter combinations are tested thoroughly. Although systematic, the disadvantage of grid search is that it requires a large amount of computing time, especially when the hyperparameter search space is large. To overcome this limitation, random search is used as a more efficient method.

According to (Bergstra et al., 2012), random search randomly selects hyperparameter combinations from a predetermined search space and has been empirically proven to find near-optimal combinations with fewer trials than grid search. With the same number of trials, random search tends to be more effective because not all hyperparameters have the same significant influence on model performance. Therefore, random search actually allows for broader hyperparameter testing.

2.6 Model Validation

According to (Cerqueira et al., 2019), model validation in time series forecasting requires a special approach that prioritizes the time sequence of data to prevent data leakage, which is a condition where future information is accidentally used in model training. Traditional cross-validation methods such as random k-fold are not suitable for sequential data because they violate the assumption of independence between observations and can produce biased performance estimates. Therefore, validation methods that preserve temporal order are needed, such as time-based holdout, walk-forward validation, and time series split. With time series split, data is divided sequentially, where each fold uses older data as training data and newer data as test data.

The selection of the number of folds (k) in the time series split method is also an important factor in model validation. A value of k that is too small can produce biased performance estimates, while a value of k that is too large can increase the variance of the estimates and the computational load. Therefore, a value of k = 5 is often used because it provides a balance between the stability of the model performance estimates and computational efficiency (Hastie et al., 2019).

In the model validation process, evaluation metrics are needed to measure prediction errors. One of the most commonly used evaluation metrics as a validation loss value is Mean Squared Error (MSE). MSE calculates the average square difference between the actual value and the predicted value, thereby giving a greater penalty to errors with large values (Hyndman et al., 2021). MSE can be formulated as follows:

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \tag{2.12}$$

Where:

y_t = Actual value at time t

$\hat{y}_t$ = Predicted value at time t

n = Number of data points

2.7 Model Evaluation

Model evaluation is an important stage in forecasting research that is used to assess the extent to which the model used is capable of providing prediction results that are close to the actual data. The evaluation process is usually carried out by using error metrics that compare the prediction results with the actual observation values (Makridakis et al., 2018).

2.7.1 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is one of the most commonly used evaluation metrics in measuring the performance of prediction models. RMSE measures the average magnitude of the error between the actual value and the predicted value by giving a greater penalty to high errors because it involves the square of the difference (Hyndman et al., 2021). RMSE can be formulated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{2.13}$$

Where:

y_t = Actual value at time t

$\hat{y}_t$ = Predicted value at time t

n = Number of data points

A smaller RMSE value indicates that the model has low prediction error, making it more accurate. However, because RMSE is sensitive to outliers, its use is often combined with other metrics such as Mean Absolute Percentage Error (MAPE) (Botchkarev, 2019).

2.7.2 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is an evaluation metric used to measure the average difference between actual values and predicted values, thereby providing ana easily interpretable measure of prediction error in original data units (Botchkarev, 2018). The MAE value can be formulated as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} |y_t - \hat{y}_t| \tag{2.14}$$

Where:

y_t = Actual value at time t

$\hat{y}_t$ = Predicted value at time t

n = Number of data tested

MAE is often used in several forecasting methods because of its direct interpretation using original data and its stability against abnormal error distributions, so that in general MAE is compared with other evaluation metrics such as RMSE and Mean Absolute Percentage Error (MAPE) to obtain more in-depth evaluation results (Naser, 2020).

2.8 Inflation

According to (Farandy, 2020), inflation is a macroeconomic event characterized by a persistent rise in the prices of goods and services during a specific time frame. Therefore, inflation affects the purchasing power of the people and the economic stability of a country. Inflation in Indonesia is divided into several components, namely core inflation, which is relatively stable and reflects medium-term domestic pressures; volatile food inflation; and administered prices, which often cause short-term fluctuations.

According to (Santosa, 2017), the definition of inflation covers several aspects, including:

1. Tendency, this refers to the general direction of prices, which usually trend upward over time. Although prices may decrease at certain moments, overall there is an upward movement.
2. Sustained, this indicates that the increase in prices occurs continuously and persists over an extended period.
3. General level of price, which refers to prices in inflation as the prices of goods in general, not just one or two types of goods.

There are several factors that cause inflation in Indonesia, namely supply, demand, and external factors. Supply factors, namely the surge in food prices due to changes in supply, extreme weather, or distribution disruptions, are the main triggers of inflation volatility, as well as government policies on energy price adjustments that affect transportation and production costs (Farandy, 2020). Demand factors, such as an increase in the money supply and production growth exceeding capacity, can lead to high price pressures. External factors, such as a decline in the rupiah exchange rate and an increase in global commodity prices, contribute significantly to inflation in Indonesia (Ahlis, 2021).

III. RESEARCH METHODS

3.1 Time and Place of Research

This research was conducted in the odd semester of the 2025/2026 academic year at the Department of Mathematics, Faculty of Mathematics and Natural Sciences, University of Lampung.

3.2 Research Data

The data used in this study is secondary data, namely Indonesian inflation data obtained from the Central Statistics Agency (BPS) website and accessible at the following link: https://www.bps.go.id/id/statistics-table/2/MSMy/inflasi-bulanan-m-to-m-.html.

3.3 Research Methods

The steps taken in this research are as follows:

1. Descriptive analysis,
2. Performing data pre-processing:
   - Handling missing values if found,
   - Normalizing data using Standard Scaler.
3. Classifying variables into inputs and outputs:
   - Input: inflation data for the previous period (lag),
   - Output: inflation predic.tion for the following month.

4. Divide the data into training data (train set) and test data (test set) based on time sequence.

5. Hyperparameter optimization (Random Search). The following parameters are optimized:

   - Number of CNN filters,
   - CNN kernel size,
   - Number of LSTM units,
   - Learning rate

   The tuning process is carried out using Random Search, which involves randomly selecting parameter combinations to find the best results based on validation error values.

6. Model validation (Time Series Split). To divide the training data sequentially, time series split is used (K=5). Model performance is calculated as the average of all folds.

7. Building a hybrid CNN-LSTM model:

   - CNN layer: extracts short-term patterns and short-term features,
   - LSTM layer: models long-term intertemporal patterns,
   - Dense layer: generating prediction values.

8. Model evaluation uses RMSE and MAE values.

9. Analysis of results and interpretation by comparing error metric values between models, as well as displaying graphs of prediction results with actual values.

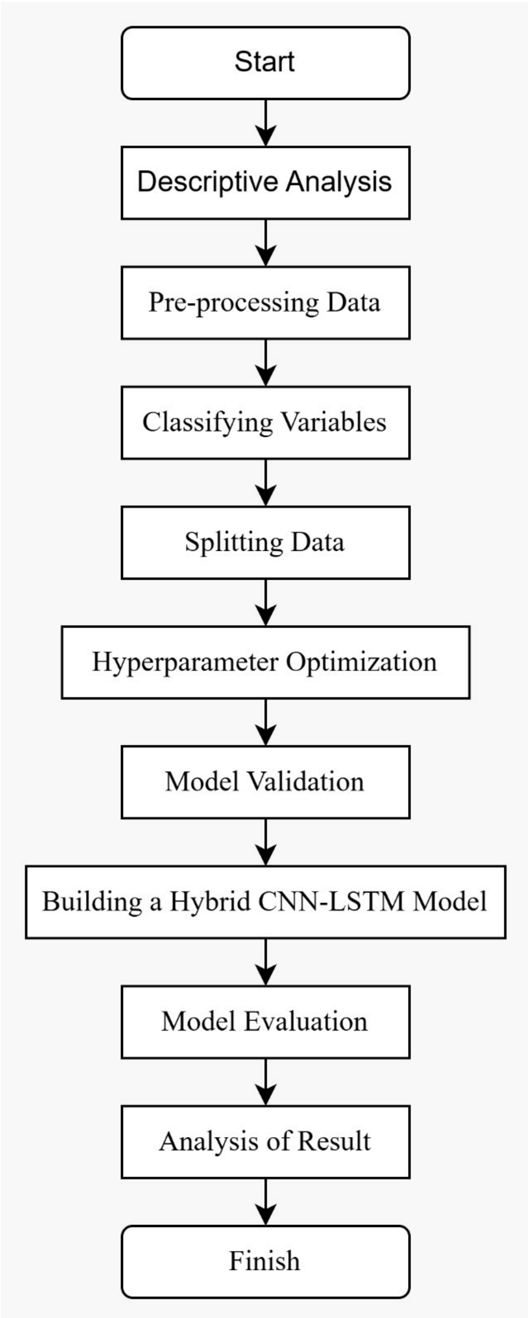

Figure 7. Research Methods Flowchart

V. CONCLUSION

Based on the results of research conducted on time series modeling using the hybrid CNN-LSTM method to predict inflation in Indonesia, the following conclusions were obtained:

1. The hybrid model was built through several stages, namely data preprocessing, lag formation, split data, and hyperparameter tuning. Based on the tuning results, the best parameter combination was obtained, namely 64 filters, kernel size 3, 64 LSTM units, dropout 0.1, and learning rate 0.001, so that the model was able to capture short-term and long-term patterns from the data simultaneously and maximally.
2. The CNN-LSTM hybrid model provided the best accuracy compared to the single CNN and LSTM models. Based on the evaluation results, the CNN-LSTM hybrid model had the lowest values with RMSE = 0.41 and MAE = 0.32 compared to the CNN model (RMSE = 0.46 and MAE = 0.33) and LSTM (RMSE = 0.45 and MAE = 0.35). This indicates that the hybrid model is superior in predicting inflation in Indonesia.

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