PROJECT PROPOSAL

INFLATION FORECASTING USING MULTIVARIATE LONG SHORT-TERM MEMORY (LSTM) RECURRENT NEURAL NETS (RNNs)

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IMRAN Y. A. ABU LIBDA

D121211105

BACHELOR DEGREE PROGRAM

INFORMATICS ENGINEERING DEPARTMENT

FACULTY OF ENGINEERING

HASANUDDIN UNIVERSITY

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I. Title

Inflation Forecasting Using Multivariate Long Short-Term Memory (LSTM) Recurrent Neural Nets (RNNs)

II. Background

Inflation forecasting is a crucial task for policymakers, central banks, investors, and businesses as it can provide valuable insights into the economic environment and help inform financial decisions. Accurate inflation forecasts can aid central banks in setting interest rates, implementing monetary policies, and maintaining price stability. Investors and businesses can use these forecasts to make informed decisions about investments and risk management. However, forecasting inflation is challenging due to the complex and dynamic nature of economic systems, and the wide range of factors that can influence inflation. (Warjiyo, 2019)

Traditionally, inflation forecasting has relied on statistical models and expert opinions to analyze the relationships between inflation and other economic variables, such as GDP, unemployment, and monetary policy (Bashiri, 2021). While these methods can provide valuable insights, they can also be limited in their ability to capture the complexity and dynamics of economic systems. Moreover, the uncertainties and unpredictability of economic developments can make it challenging to accurately forecast inflation even with the most advanced models.

In recent years, machine learning techniques have shown promising results in the field of time series forecasting, particularly in the use of recurrent neural networks (RNNs) such as Long Short-Term Memory (LSTM) networks. These networks are well-suited for sequential data analysis, such as time series forecasting, and have been shown to outperform traditional statistical methods in various applications. (Roser, 2021)

In this project, I propose to use machine learning techniques, specifically a combination of RNN and LSTM with multivariate features, to forecast inflation rates in Indonesia. The LSTM is a type of RNN that is well-suited for tasks that involve sequential data, such as time series forecasting and has been shown to achieve good performance in a range of applications. By using both RNN and LSTM, I aim to capture both short-term and long-term dependencies in the data, leading to more accurate predictions of inflation (Lee, 2020).

To accomplish this, I have collected a relatively small dataset spanning 22 years of monthly data of 15 economic indicators from various sources, including the World Bank database for World Development Indicators.[1], the Central Bank of Indonesia[2], and Trading Economics[3], The dataset contains 15 economic indicators that are known to have an impact on inflation, such as GDP, unemployment, money supply, exchange rates, and commodity prices.

One of the main challenges of working with time series data is the issue of temporal dependencies. Economic indicators can influence inflation rates in complex ways, and their effects can change over time. This is where the combination of RNN and LSTM can be particularly effective. RNNs can capture the temporal dependencies in the data and extract important features, which can then be fed into the LSTM for more accurate prediction. In this research, I plan to use an RNN for the initial processing of the data and then use an LSTM for the final prediction. (Bontempi, 2019)

The dataset will be preprocessed and cleaned to remove any missing or erroneous data, and the relevant features will be selected based on their impact on inflation rates. The model will be trained using a combination of supervised and unsupervised learning techniques, and performance metrics such as mean absolute error (MAE) and root mean

[1] https://databank.worldbank.org/reports.aspx?source=2&country=IDN#
[2] https://www.bi.go.id/en/statistik/
[3] https://tradingeconomics.com/indonesia

square error (RMSE) will be used to evaluate the accuracy of the model (James, 2013).

Once the model is trained, it will be available online through the web app that will be developed using Plotly (Inc, 2021), which is a popular open-source data visualization library that provides a variety of interactive charting tools and graphs. The app will be designed with user-friendliness in mind and will provide users with easy access to the most important information. It will be used to make predictions about future inflation rates in Indonesia for the next 5 years. Overall, the web app will serve as a useful tool for policymakers, investors, and other stakeholders to access the inflation forecasting model and make informed decisions based on the predicted inflation rates.

Overall, this research aims to develop a reliable and accurate method for forecasting inflation rates in Indonesia using multivariate features and LSTM RNNs. The results of this research can have significant implications for policymakers, businesses, and investors in Indonesia and other developing countries facing similar economic challenges.

Keywords: Inflation, Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Forecasting.

III. Problem Statement

Based on the background that has been described, the formulation of the problem to be solved in this study is:

1. How can multivariate economic indicators be used with the Long Short-Term Memory (LSTM) algorithm to accurately predict inflation rates in the short term for Indonesia?
2. How does the combination of LSTM and RNN impact the accuracy of inflation rate predictions compared to using only one of the algorithms?
3. How can the model be validated and applied to the market database to support decision-making in monetary policy and investment strategies?
4. How can the inflation forecasting model be integrated into an online platform to provide accessible and real-time predictions for stakeholders?

IV. Research Objectives

The aim of this research is:

1. Can develop a model that accurately predicts inflation rates in Indonesia over a 5-year horizon using a combination of LSTM RNNs and multivariate economic indicators.
2. Can evaluate the performance of the LSTM RNN model compared to other forecasting methods, such as statistical or econometric models.
3. Can identify the key economic indicators that are most closely associated with inflation in Indonesia to evaluate their relative importance in predicting future inflation rates.
4. evaluate the effectiveness of the system in predicting inflation rates and compare its performance to other forecasting methods.

5. Can implement a system that utilizes market data to make inflation forecasts using the LSTM RNNs model

V. Research Benefits

The benefits of this research are:

1. For policymakers can informed decisions about monetary policy, such as setting interest rates or adjusting the money supply, in order to maintain price stability.
2. For financial market participants can informed decisions about their investments and trading strategies can help them anticipate changes in the value of financial assets.
3. For businesses and consumers can informed decisions about their financial planning and budgeting can help them prepare for potential changes in the cost of goods and services.
4. For the general public to help them understand the economic conditions that may impact their personal finances and the broader economy, and can help them make informed decisions about their spending and saving habits.
5. For academic researchers to contribute the existing knowledge base on inflation forecasting and machine learning techniques, and could provide insights that could inform future research in this area.

VI. Research Limitations

Limitations of the problem of this study are:

1. Targeted market: The study targets the Indonesian market only.

2. Data limitations: The offered data is from 2000 until 2022 on a monthly frequency.
3. Forecast horizon: The short-term nature of the forecast horizon may limit the usefulness of the findings for longer-term planning and decision-making.

VII. Related research

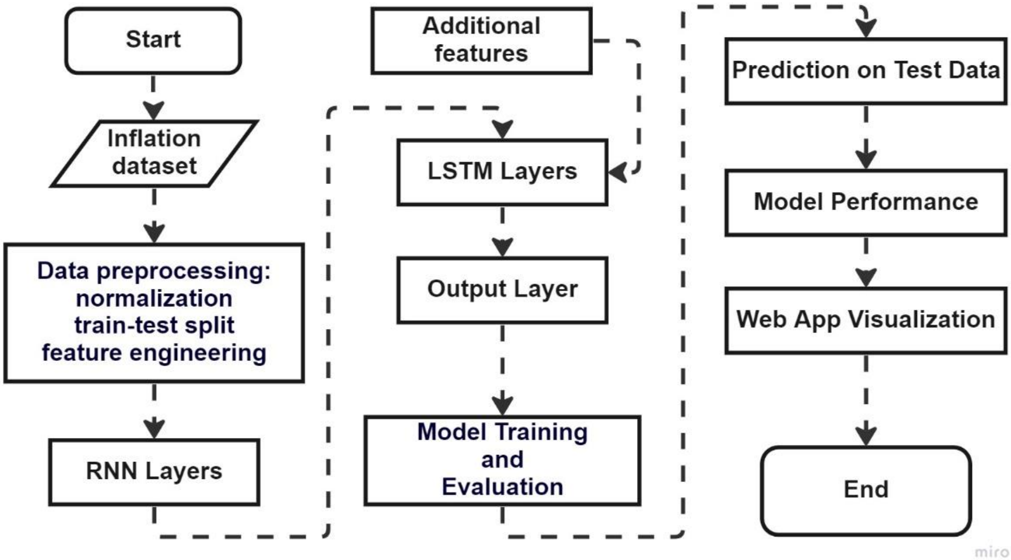
NO	Title	Author	Publisher	Method	Results
1.	Prediksi Nilai Tukar Cryptocurrency Jangka Pendek Dengan Menggunakan Long Short-Term Memory (LSTM)	Muhammad Fandly Fadlurachman	Teknik Informatil Fakultas Teknik Universitas Hasanuddin	Long Short-Term Memory (LSTM)	The LSTM mod is able to predict increases and decreases in cryptocurrency values. Binance Coin (BNB) is gaining value Mean Absolute Percentage (The best MAPE) is 0.083 and Root Mean Square Error (RMSE) is 0.27 attimeframes1 m
2.	Pemodelan Menggunakan Pendekatan Recurrent Neural Network Long Short-Term Memory (RNN-LSTM) Pada Harg Emas Dunia	Alawiyah, Silvi Noor	Muhammadiyah University, Semarang	Recurrent Neural Network Long Short-Term Memory (RNN-LSTM	indicate that the best prediction model using the RNN-LSTM wit an MAE error gets an error val of 14.5923 and a scenario of 30 neurons and an epoch of 500.
3.	Aplikasi Model Recurrent Neural Network Dan Recurrent Neuro Fuzzy Untuk Peramalan Banyaknya Penumpang Keret Api Jabodetabek	Hermawan, Nanang	Universitas Nege Yogyakarta	Model Recurrent Neural Network	The best model for forecasting th number of passengers on th Jabodetabek trai is the recurrent neural network model. MAPE and MSE for training were 1.26% and 29500000 respectively and MAPE and MSE testing were 3.79% and 2610000000 respectively.

4.	Consumer price index prediction using Long Short-Term Memory (LSTM) based cloud computing	S Zahara1, Sugianto1 and I B Ilmiddaviq1	IOP Publishing Ltd	Long Short-Term Memory (LSTM) based cloud computing	The result indicates that Nesterov Adam has a 4.088 RMSE's value, less than other algorithms whic indicates the mo accurate optimization algorithm to predict CPI valu
5.	Oil price forecasting using gene expression programming and artificial neural networks	El-Masry, AA Mostafa, M	Elsevier B.V.	artificial neural networks (ANN)	The results reve that the GEP technique outperforms traditional statistical techniques in predicting oil prices.
6.	Stock Market Prediction Using LSTM Recurrent Neural Network	Adil Moghar, Mhamed Hamiche	University Abdelmalek Essaadi, Morocco	LSTM Recurrent Neural Network	build a model using Recurrent Neural Network (RNN) and especially the Long-Short Terr Memory model (LSTM) to predi future stock market values.
7.	Implementation of Long Short-Term Memory and Gate Recurrent Units on grouped time-series data to predict stock prices accurately	Armin Lawi, Hendra Mesra and Supri Amir	Lawi et al. Journal of Big Data	Long Short-Term Memory (LSTM)	proposes eight new architectura models for stock price forecasting by identifying joint movement patterns in the stock market. Th technique is to combine the LSTM and GRU models with fou neural network block architectures

VIII. System Proposal

The proposed methodology will involve several steps, including data collection and preprocessing, model architecture design, training and validation, and performance evaluation.

A. Flowchart:



Provide a diagram for each process:

1. **Preprocessing**
2. **RNN Layers**
3. **LSTM Layers**
4. **Output Layers**
5. **Model Training**

B. Implementation

1. Data Collection:

In this research, I aim to develop a model for inflation prediction. To accomplish this, I have collected a comprehensive dataset that encompasses various economic indicators known to have an impact on inflation. I have obtained this data from multiple sources such as the World Bank database for World Development Indicators.[4], the Central Bank of Indonesia[5], and Trading Economics[6].

Before using the data, I have conducted a thorough evaluation of its quality and reliability to ensure the validity of my results. This includes checking for any missing or incomplete data points, verifying the consistency of the data with other sources, and considering the sample size and representativeness of the data. Additionally, I have considered any potential biases or errors that may affect the accuracy of the results.

In total, I have collected 15 economic indicators with monthly frequency data ranging from the year 2000 to 2022 (264 months). This large number of indicators will allow me to capture a wide range of factors that may impact inflation, thereby increasing the robustness of my model. By using the latest state-of-the-art techniques in machine learning, I hope to gain new insights into the dynamics of inflation prediction and contribute to the field of economic forecasting.

There is no definitive list of the top 15 economic indicators that affect inflation, as different indicators may have varying impacts in different countries and at different times. However, some commonly cited indicators in Indonesia include:

1. *Consumer Price Index (CPI):* This indicator measures the changes in the prices of goods and services consumed by households. The CPI is widely used as an indicator of inflation, as it reflects the impact of inflation on the cost of living. Higher CPI values indicate that inflation is rising, while lower values suggest deflation or low inflation.

[4] https://databank.worldbank.org/reports.aspx?source=2&country=IDN#
[5] https://www.bi.go.id/en/statistik/
[6] https://tradingeconomics.com/indonesia

2. *Producer Price Index (PPI):* This indicator measures the changes in the prices received by producers for their goods and services. The PPI is considered a leading indicator of inflation, as changes in producer prices are often reflected in consumer prices over time. An increase in the PPI often signals that inflation is on the horizon.

3. *Import Price Index (IPI):* This indicator measures the changes in the prices of imported goods and services. The IPI reflects the impact of changes in global commodity prices, exchange rates, and tariffs on the domestic economy. An increase in the IPI suggests that inflationary pressures are building, while a decrease may indicate disinflationary pressures.

4. *Export Price Index (EPI):* This indicator measures the changes in the prices of exported goods and services. The EPI reflects the competitiveness of the domestic economy in international markets, as well as changes in global commodity prices, exchange rates, and tariffs. An increase in the EPI suggests that the domestic economy is becoming more competitive, while a decrease may indicate a loss of competitiveness.

5. *Employment Cost Index (ECI):* This indicator measures the changes in the total compensation costs of employees, including wages, salaries, and benefits. The ECI reflects the impact of labor costs on inflation, as higher labor costs can lead to higher prices for goods and services. An increase in the ECI suggests that inflationary pressures are building, while a decrease may indicate disinflationary pressures.

6. *Gross Domestic Product (GDP) Deflator:* This indicator measures the changes in the general price level of the economy, considering the prices of all goods and services produced domestically. The GDP deflator reflects the overall inflationary trend in the economy and is considered a comprehensive measure of inflation. An increase in the GDP deflator suggests that inflation is rising, while a decrease may indicate deflation or low inflation.

7. *USD_IDR Exchange Rate:* This indicator measures the exchange rate between the US dollar and the Indonesian rupiah. Exchange rates can have a significant impact on inflation, as changes in the exchange rate can affect the price of imported goods and services, and can also impact the competitiveness of the domestic economy in international markets. A weaker domestic currency

relative to the US dollar generally leads to higher inflation, while a stronger domestic currency can help to control inflation.

8. *Wholesale Price Index (WPI):* This indicator measures the changes in the prices of goods traded between wholesalers and retailers. The WPI is considered a leading indicator of inflation, as changes in wholesale prices are often reflected in consumer prices over time. An increase in the WPI suggests that inflationary pressures are building, while a decrease may indicate disinflationary pressures.

9. *Interest Rate:* This indicator measures the cost of borrowing money, and is set by the central bank. Interest rates play a key role in controlling inflation, as higher interest rates can help to reduce demand for goods and services and slow the pace of economic growth, while lower interest rates can stimulate demand and boost economic growth. Changes in interest rates can also impact the exchange rate and the cost of borrowing for households and businesses.

10. *Ratio of Exports to Imports:* The ratio of exports to imports can be a significant factor in determining inflation, as it can reflect the level of demand for a country's goods both domestically and internationally. If exports are growing faster than imports, it can signal a growing demand for the country's goods, which can lead to higher inflation. On the other hand, if imports are growing faster than exports, it may signal a weaker demand for the country's goods, which could lead to lower inflation.

11. *Manufacturing:* The level of manufacturing activity can also be an important indicator of inflation. When manufacturing is strong, it can lead to increased demand for goods, which can push prices higher. Conversely, when manufacturing is weak, it can lead to lower demand for goods and lower prices.

12. *Balance of Trade:* The balance of trade, or the difference between a country's exports and imports, can also impact inflation. A trade deficit, when a country is importing more than it is exporting, can lead to higher inflation, as it can signal a high demand for goods. A trade surplus, on the other hand, can signal a weaker demand for goods and lower inflation.

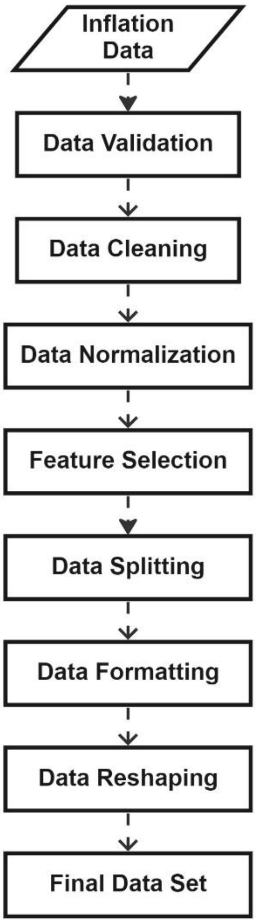
13. *Consumer Confidence Index (CCI):* The consumer confidence index measures the level of confidence that consumers have in the economy. When consumers are confident, they are more likely to spend money, which can drive up demand for goods and lead to higher inflation. Conversely, when consumers are less confident, they are less likely to spend money, which can lead to lower inflation.

14. *Money Supply M2:* The money supply, or the amount of money in circulation in an economy, can also have an impact on inflation. When the money supply is growing rapidly, it can lead to higher inflation, as there is more money available to buy goods and services. Conversely, when the money supply is growing slowly, it can lead to lower inflation.

15. *Foreign Exchange Reserves:* The level of foreign exchange reserves, or the amount of foreign currency held by a country, can also impact inflation. When a country has high levels of foreign exchange reserves, it can help stabilize its currency, reducing the risk of inflation. Conversely, when a country has low levels of foreign exchange reserves, it can increase the risk of inflation.

2. *Data Pre-processing:*

In the data preprocessing stage, several key steps were taken to prepare the data for analysis. These steps included:



Data cleaning and correction: Missing or inconsistent data was identified and corrected, to ensure the data was accurate and reliable.

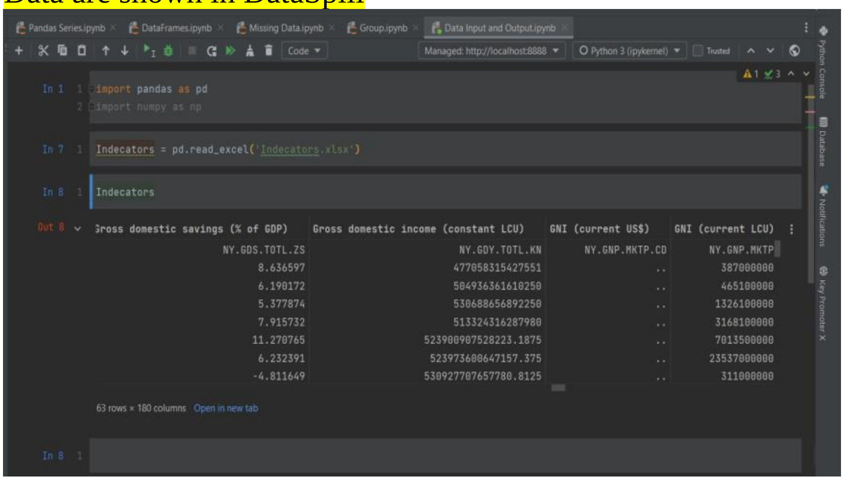
Data normalization: To ensure the data was in a comparable form, all indicators were normalized using appropriate techniques, such as min-max normalization or z-score normalization.

Feature extraction: To capture the most relevant information in the data, relevant features were extracted from the raw data, such as trends, patterns, and seasonality.

Data transformation: To facilitate the analysis and modeling process, the data was transformed into a suitable form for analysis, such as converting time-series data into a supervised learning format.

By implementing these preprocessing steps, the data was transformed into a form that was well-suited for analysis and modeling, which was a critical step in ensuring that the results of the study were accurate and meaningful.

Data are shown in DataSpill



3. ***Select the model:***

The Combination of RNN And LSTM Approach:

Having a relatively small dataset of 22 years of monthly data. This presents a challenge in effectively capturing the complex temporal dependencies in the data and accurately predicting future inflation rates.

Using a combination of RNN and LSTM in my model architecture. One approach is to use an RNN for the initial processing of the data and then use an LSTM for the final prediction. (Advances in Electrical and Computer Technologies, 2021).

RNNs are a popular choice for time series forecasting as they are able to capture the temporal dependencies in sequential data. However, they can suffer from the vanishing gradient problem when dealing with long-term dependencies, which can lead to difficulty in accurately capturing important features in the data.

To address this issue, LSTMs was introduced as an extension of RNNs. LSTMs are designed to avoid the vanishing gradient problem by introducing a memory cell and several gating mechanisms that allow the network to selectively retain and forget information over long periods of time. This makes LSTMs particularly effective in capturing long-term dependencies in the data and making accurate predictions. (Intelligent Algorithms in Software Engineering, 2020)

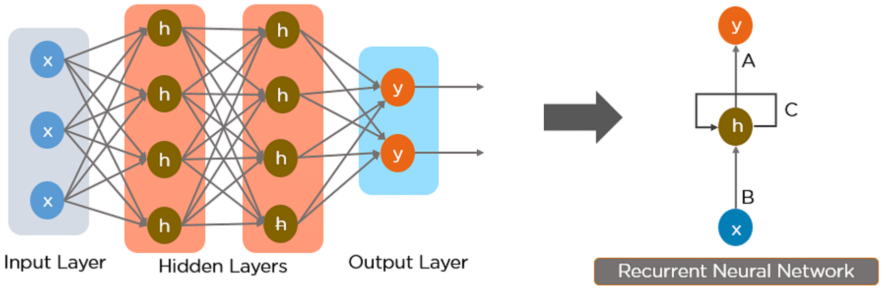
However, in this case, the small size of the dataset may limit the effectiveness of using a standalone LSTM model. Therefore, a combination of RNN and LSTM can be used to effectively capture the temporal dependencies in the data and extract important features for more accurate prediction (Zhang, 2019). In this approach, the RNN can first capture the temporal dependencies in the data and extract important features, which can then be fed into the LSTM for more accurate prediction. (Proceedings of International Conference on Data Science and Applications, 2022)

This combination of RNN and LSTM can be particularly effective when dealing with long-term dependencies in the data, such as those that may be present in the inflation data. Additionally, it can help mitigate the potential issues that may arise from using a standalone LSTM model on a small dataset. Overall, this approach can help to improve the accuracy of inflation predictions and provide more reliable insights for future decision-making.

A. RNN Layer:

The RNN layer is responsible for capturing the temporal dependencies in the input data, which is crucial for time series forecasting. The process of the RNN layer can be described as follows:

The input data is fed into the RNN layer in a sequential manner, one-time step at a time. Each time step corresponds to a single point in time and consists of the input features at that time step.



At each time step, the RNN layer performs a set of operations that transform the input features into a hidden state vector. This hidden state vector contains information about the current input as well as information from previous time steps (Goodfellow, 2016).

The hidden state vector is then passed to the next time step, where it is updated based on the new input features. This process continues until all time steps have been processed.

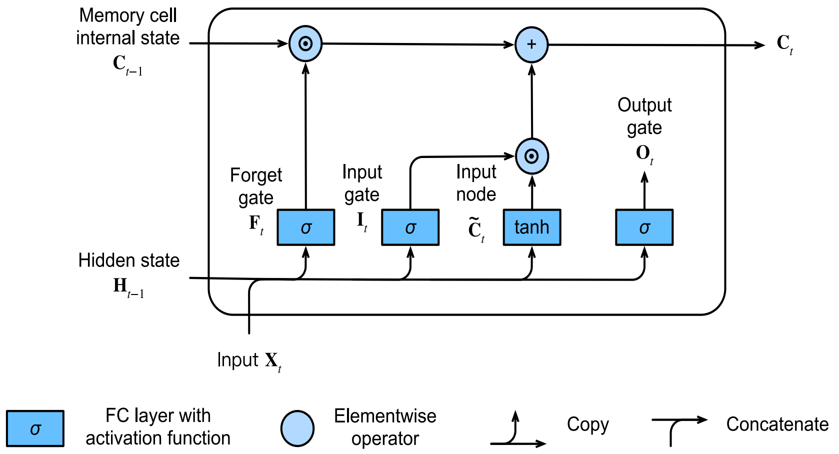
Once all time steps have been processed, the final hidden state vector is output from the RNN layer. This hidden state vector contains important features that capture the temporal dependencies in the input data.

The output from the RNN layer is then passed to the additional LSTM layer. (Machine Learning Algorithms, 2018)

Overall, the combination of RNN and LSTM allows for more effective modeling of the temporal dependencies in the input data, leading to more accurate predictions in time series forecasting tasks.

B. LSTM Layers:

The LSTM layer serves as a way to improve the accuracy of the model by allowing for better capturing of long-term dependencies in the time series data. The full process of using LSTM involves feeding the preprocessed time series data into the RNN layer, which captures the temporal dependencies in the data and extracts important features. Then, the output of the RNN layer is fed into the LSTM layer for more accurate prediction (Lipton, 2015).



Including additional features that are relevant for predicting inflation, which will be preprocessed and concatenated with the time series data before feeding them into the RNN layer. By including these additional features, the model may be able to better capture the complex relationships between different economic variables and provide more accurate predictions.

Concatenating the additional features with the time series data needs to ensure that the dimensions of the additional features match those of the time series data. Once the features have been concatenated, the combined input would be passed through the RNN layer and LSTM layer as before. The LSTM layer would then generate predictions for the inflation rate based on both the time series data and the additional features.

C. Output Layer:

The output layer is responsible for producing the final prediction of the inflation rate for the next 5 years. It takes the output of the previous LSTM layer as input and produces a vector of 60 values, representing the predicted inflation rate for each month over the next 5 years.

The exact function of the output layer is determined by the specific model architecture. Typically, a fully connected (dense) layer with a linear activation function is used for regression tasks such as predicting inflation. The weights and biases of this layer are optimized during training to minimize the difference between the predicted and actual inflation rates, as measured by a chosen loss function (Brownlee, 2018).

Once the additional features have been concatenated with the LSTM output, they can be fed into the final output layer, which will generate predictions for the target variable (inflation rate). The output layer can consist of one or more fully connected layers, with the number of nodes in the final layer corresponding to the number of output variables (60 nodes for the 60-month inflation rate prediction).

Choosing the RNN model that is appropriate for the data and forecasting goals (Martin T. Hagan, 2014). I also consider factors such as the complexity of the model, the size of the training dataset, and the computational resources available. And finally decided to take the Long Short-Term Memory (LSTM) network as an RNN model, and here are several reasons why I've chosen an LSTM network for my project:

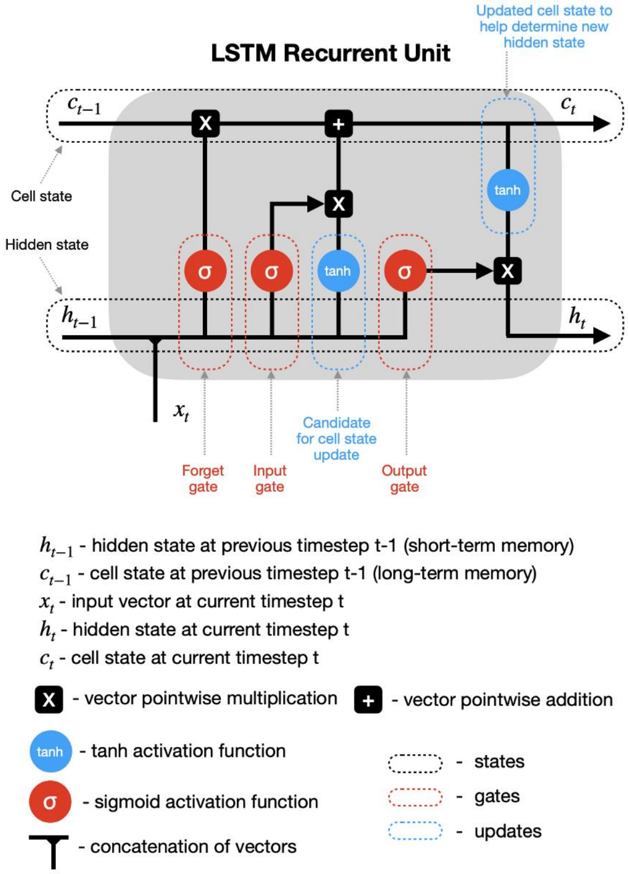
- **a.** *Ability to capture long-term dependencies:* As mentioned, LSTM networks can capture long-term dependencies in sequential data, which will be useful for forecasting tasks that require consideration of past trends and patterns.
- **b.** *Robustness to noise and missing data:* LSTM networks are generally robust to noise and missing data, which can be common issues in time series data. This can make them well-suited for forecasting tasks where data quality is a concern.
- **c.** *Good performance:* LSTM networks have been shown to achieve good performance in a range of time series forecasting tasks, and have been used successfully in many real-world applications (Nakamura, 2005).
- **d.** *Widely used and well-understood:* LSTM networks are widely used and well-understood, and there is a wealth of research and resources available on their use and implementation.

4. ***Design the LSTM network:*** Next, design the LSTM network by specifying the number and size of the layers, as well as the activation functions and any other hyperparameters. It is often helpful toexperiment with different architectures and parameters

to find the best model for a given problem.

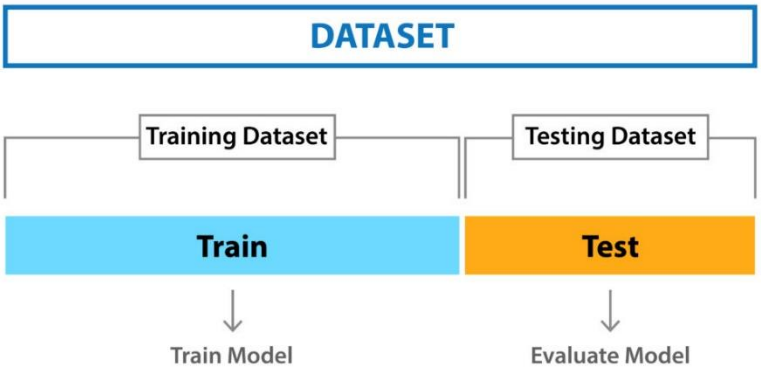
The rule of thumb that helps with supervised learning problems. And we can usually prevent over-fitting if we keep the number of neurons below: $N_h = \frac{N_s}{(\alpha*(N_i+N_o))}$

I number of input neurons.
N_o= number of output neurons.
N_s= number of samples in training data set.
α = an arbitrary scaling factor usually 2-10.



How many hidden units and layers should I use?
How should I initialize the weights of my model?

5. ***Split the data into training and test sets:*** It is important to split the data into a training set and a test set to evaluate the performance of the model.The training set is used to fit the model to the data, while the test set is used to assess the model's performance on out-of-sample data (Ames, 2013).



6. ***Train the LSTM:*** Once the LSTM network is designed, you can train it using the training set. This typically involves using an optimization algorithm, such as stochastic gradient descent, to adjust the weights and biases of the network in order to minimize the error between the predicted values and the true values.

C. Testing & Problems Encountered

1. ***Evaluate the LSTM:*** After training the LSTM, you can evaluate its performance on the test set. This will give you an idea of how well themodel can make predictions on out-of-sample data. You can alsouse other performance metrics, such as mean squared error or mean absolute error, to assess the model's accuracy.

2. ***Fine-tune the LSTM:*** If the LSTM's performance is not satisfactory, youmay need to fine-tune the model by adjusting the hyperparameters or thearchitecture of the network. This may involve going back to step 3 and repeating the design and training process with different settings.

D. Results

It is important to keep in mind that training an LSTM can be a time-consuming process, and it may take several iterations to find the best model for a given problem. It is also a good idea to monitor the model'sperformance over time to ensure that it continues to produce accurate predictions.

E. Data Visualization Web App

Data visualization is an essential aspect of data analysis and communication, as it allows for the representation of complex data in a visual form that is easier to understand and interpret. With the increasing availability of data and the need to make informed decisions based on it, there is a growing demand for interactive and user-friendly web-based applications that enable users to explore and visualize data in real time. Plotly is a powerful open-source library that allows for the creation of interactive and dynamic visualizations in a web browser. In this research, we aim to develop a data visualization web application using Plotly that allows users to easily visualize and interact with various types of data.

The application will provide a user-friendly interface for manipulating data, as well as a range of customizable visualization options. I will also explore the use of machine learning techniques to generate insights and predictions from the data, and how these can be incorporated into the web application for more advanced data analysis. The ultimate goal of this research is to create a user-friendly and interactive web-based tool that enables users to gain insights and make informed decisions based on their data.

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