CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This section explains the methodology and applications that will be used in the research. Before getting to the data gathering, this chapter will examine the data description. The data must first be examined in order to accomplish the research's goal. The procedure would begin with gathering and evaluating raw data from many websites, such Trading Economics', index Mundi and Malaysia Informative Bullion Rate. The information must then be calculated using a particular formula. First, the data will be checked for cointegration between all variables and the price of gold using Johansen Cointegration model and Autoregressive Distributed Lag (ARDL). Long Short-Term Memory (LSTM) model and Vector Autoregression (VAR) are used in this study to predict the price of gold in Malaysia. Throughout discussion of the research findings and methodology will be covered in this chapter.

3.2 The Framework

I. Problem Formulation
II. Data Collection
III. Data Pre-processing
IV. Modelling
V. Performance Validation and Evaluation

The details of the research framework for this study are shown in the Figure below

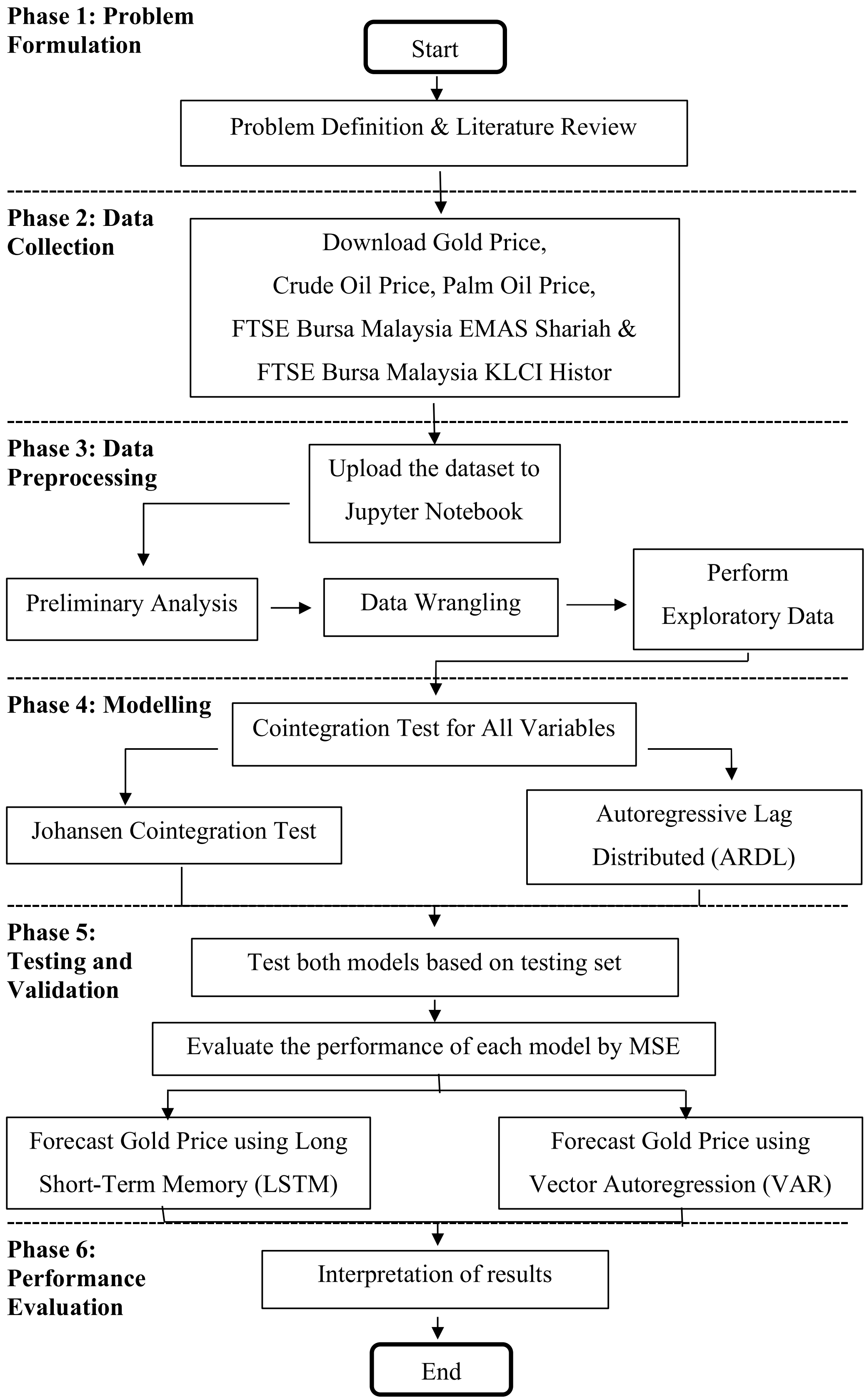

Figure 3.1 Research Framework of Gold Price Prediction

3.3 Problem Formulation

The principal objective of this research is to employ modern econometric approaches to model the influence of oil and stock market prices on gold prices, thereby offering valuable information to Malaysian policymakers and investors. However, in order to guarantee accurate and trustworthy analysis, a number of issues need to be resolved.

I. Ensuring data quality and consistency is a major issue, as the analysis is based on monthly data from January 2013 to December 2023 for gold, crude oil, palm oil, Islamic stock market, and conventional stock market prices. Addressing potential problems with data gaps, outliers, and various data formats falls under this category.

II. It is essential to choose and use the proper econometric models, such as the Granger Causality test, the Autoregressive Distributed Lag (ARDL) model, the Johansen Cointegration test, and the Long Short-Term Memory (LSTM) and Vector Autoregression (VAR) model. In order to handle the complexity of time series data, these models need to be able to capture the causality and long-term relationships between the variables.

It is critical to account for the dynamic character of the variables involved, as gold, oil, and stock market indices are all influenced by a variety of external factors such as geopolitical events, economic policy, and market mood. In order to keep the models accurate and relevant throughout time, they must be updated and improved on a regular basis while taking these dynamic factors into account.

3.4 Data Collection

The following datasets are carefully selected to assist in achieving our objectives. The data is obtained from official website of The World Bank Group and TradingEconomics consist of Inflation Rates, Interest Rates, and commodity prices including monthly crude oil and palm oil prices. The data includes different number of observations respectively for all datasets. Some missing data are interpolated to provide a consistent result. Furthermore, this study focuses on analysing and study the trend of commodity prices movement, relationships of different macroeconomic variables, forecasting the future inflation rate and interest rate. Each data is measured in percentage (%) for inflation and interest rates while crude oil and palm oil are measured in MYR (Malaysian Ringgit) per barrel and metric tonne.

Table **3.1** Data of Each Variables

Data	**Crude Oil Price**	**Palm Oil Price**	**Islamic Stock Market Price**	**Conventional Stock Market Price**
Year Period	Jan 2013 – Dec 2023	Jan 2013 – Dec 2023	Jan 2013 – Dec 2023	Jan 2013 – Dec 2023
Frequency	Monthly	Monthly	Monthly	Monthly
Dataset Size	12 KB	12 KB	9 KB	10 KB

From the table 3.1, the data that represents the Islamic stock market is represented by FTSE Bursa Malaysia EMAS Shariah. While the data from the FTSE Bursa Malaysia KLCI History index provides more conventional stock market information. This research chose this website and this stock market because all Malaysian businesses listed on the Bursa Malaysia Main Market and ACE Market are eligible for inclusion, subject to achieving FTSE's worldwide standards of free float, liquidity, and invest ability. Investors can conduct international analysis and comparison using the FTSE Bursa Malaysia index methodology, and the management of the index series is transparent thanks to a set of Ground Rules. Therefore, it can be said that this data is particularly suitable for usage as one of the variables, aids in achieving the study's main goal.

Every item of data used in this study is secondary data. To be more specific, the data we collected did not match because the data on crude oil prices and palm oil prices is collected monthly rather than daily like other data. In order to synchronize the data with one another and get an accurate result, all data were evaluated and converted into monthly. It is expressed in monetary terms, specifically as Malaysian Ringgit (RM). In order to forecast the gold prices, this study chose to use 10 years period of data, from January 2013 to December 2023. This is because prior study has found that 10 years of data is sufficient to produce accurate forecasts.

Table 3.2 Gold Price, Crude Oil Price, Palm Oil Price, FTSE Bursa Malaysia EMAS Shariah and FTSE Bursa Malaysia KLCI Histor

Datasets	**Attributes**
Gold Price csv	• Date: Date of collected price • Gold Price (MYR): Gold Price in Malaysia Ringgit.
Crude Oil Price csv	• Date: Date of collected price • Crude Oil Price (MYR): Crude Oil Price in Malaysia Ringgit per Barrel.
Palm Oil Price csv	• Date: Date of collected price • Palm Oil Price (MYR): Palm Oil Price in Malaysia Ringgit per Metric Ton.
Islamic Stock Market Price csv (FTSE Bursa Malaysia EMAS Shariah)	• Date: Date of collected price • Price: The current trading value of the stock. • Open: The price at which the stock begins trading when the market opens. • High: The highest price at which the stock traded during a given period. • Low: The lowest price at which the stock traded during a given period. • Change %: The percentage change in the stock's price compared to the previous trading period.

Conventional Stock Market Price csv (FTSE Bursa Malaysia KLCI Histor)	• Date: Date of collected price • Open: The price at which the stock begins trading at the start of the trading day. • High: The highest price at which the stock traded during the trading day. • Low: The lowest price at which the stock traded during the trading day. • Close: The price at which the stock last traded when the market closed. • Adj Close: The closing price adjusted for corporate actions like dividends, stock splits, and new stock offerings. • Volume: The total number of shares traded during the trading day.

3.5 Data Pre-processing

It is necessary to complete preliminary analysis prior to moving on to further pre-processing. A data merging procedure is necessary to bring all of the raw data into one data frame once we have a firm grasp of the features provided in the dataset. Several data wrangling and data transformation procedures will be used on the dataset in an effort to further unify the disorganised raw data. Table 3.3 below lists every detail of the data pre-processing that was used.

Table 3.3 Data Pre-processing Methods

Data Pre-processing	**Purpose**
Preliminary analysis	To evaluate the provided dataset and obtain insightful knowledge for the modelling phase that follows.
Data Cleaning	Find the missing value and eliminate the rows that do not have it.

Data Concatenation	Compile every CSV file from January 2013 to December 2023.
Data Visualization	Plotted a chart illustrating the trend of each variable over ten years of Malaysian data.

3.5.1 Preliminary Analysis

Preliminary analysis is an important step in any data analysis since it helps you become acquainted with the data collection, understand its structure, format, and the sorts of variables it contains. Early investigation can identify problems that must be fixed for reliable analysis, such as missing values, outliers, or contradictions. The function ".info()" is used to retrieve the data information and gives a brief description of the dataframe. It displays every attribute information from the exported dataset, including the datatype, count of rows, and count of null counts. Figure 3.2 displays the gold price dataset information. The command "gold.info()" searches the dataframe "gold" for missing (NaN) values. The result indicates that all values are present. The dataset comprises 132 entries, suggesting that it is a medium-sized dataset. The dataframe comprises two columns: date and price, with datetime64[ns] and float64 as their respective datatypes.

```
gold.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 132 entries, 0 to 131
Data columns (total 2 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Date              132 non-null    datetime64[ns]
 1   Gold Price (MYR)  132 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 2.2 KB
```

Figure 3.2 Data Information of Gold Price Dataset

Figure 3.3 displays the palm oil price dataset information. The command "palm_oil.info()" searches the dataframe "palm oil" for missing (NaN) values. The result indicates that all values are present. The dataset comprises 132 entries, suggesting that it is a medium-sized dataset. The dataframe comprises two columns: date and price, with datetime64[ns] and int64 as their respective datatypes.

```
palm_oil.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 132 entries, 0 to 131
Data columns (total 2 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   DATE                   132 non-null    datetime64[ns]
 1   Palm Oil Price (MYR)   132 non-null    int64
dtypes: datetime64[ns](1), int64(1)
memory usage: 2.2 KB
```

Figure 3.3 Data Information of Palm Oil Price Dataset

The dataset information for crude oil prices is shown in Figure 3.4 The dataframe "crude oil" is searched for missing (NaN) values using the command "crude_oil.info()". According to the outcome, every value is present. Given that there are 132 entries in the dataset, it appears to be of medium size. The date and price columns in the dataframe have the datatypes datetime64[ns] and int64, respectively.

```
crude_oil.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 132 entries, 0 to 131
Data columns (total 2 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   DATE                    132 non-null    datetime64[ns]
 1   Crude Oil Price (MYR)   132 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 2.2 KB
```

Figure 3.4 Data Information of Crude Oil Price Dataset

The information on the Islamic stock market price dataset is shown in Figure 3.5 The dataframe "Islamic Stock Market" is searched for missing (NaN) values using the command "islamic_stock.info()". According to the outcome, every value is present. Given that there are 132 entries in the dataset, it appears to be of medium size. Six columns make up the dataframe: date, price, open, high, low, and change percentage. Each column contains the datatype for each item.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 132 entries, 0 to 131
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Date      132 non-null    object
 1   Price     0 non-null      float64
 2   Open      0 non-null      float64
 3   High      0 non-null      float64
 4   Low       0 non-null      float64
 5   Change %  0 non-null      float64
dtypes: float64(5), object(1)
memory usage: 6.3+ KB
```

Figure 3.5 Data Information of Islamic Stock Market Price Dataset

The traditional stock market price dataset information is shown in Figure 3.6. The dataframe "conventional stock market" is searched for missing (NaN) values using the command "conventional_stock.info()". According to the outcome, every value is present. Given that there are 132 entries in the dataset, it appears to be of medium size. The dataframe has six columns: date, open, high, low, close, adj close, and volume. The datatypes for each column are objects and float64.

```
conventional_stock.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 132 entries, 0 to 131
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       132 non-null    object
 1   Open       132 non-null    float64
 2   High       132 non-null    float64
 3   Low        132 non-null    float64
 4   Close      132 non-null    float64
 5   Adj Close  132 non-null    float64
 6   Volume     132 non-null    int64
dtypes: float64(5), int64(1), object(1)
memory usage: 7.3+ KB
```

Figure 3.6 Data Information of Conventional Stock Market Price Dataset

3.5.2 Data Cleaning

In order to identify missing values and eliminate rows and columns with no values, data cleaning is done in this part. Figure 3.7 shows that while all datasets are free of missing values, some of the columns are not relevant to our research. It is therefore necessary to eliminate the following columns: 'Open', 'High', 'Low', 'Change %' from the Islamic stock market price dataset; and 'Open', 'High', 'Low', 'Close', 'Volume' from the conventional stock market price dataset. The process of removing these columns is depicted in Figure 3.8. The Islamic stock market price dataset now consists solely of date and price columns, whereas the traditional stock market price dataset only includes date and adj close columns.

```
# Check duplicate data for each datasets
gold_dup = gold.duplicated().sum()
print("Number of Duplicate Rows of gold price dataset:", gold_dup)

palm_oil_dup = palm_oil.duplicated().sum()
print("Number of Duplicate Rows of palm oil price dataset:", palm_oil_dup)

crude_oil_dup = crude_oil.duplicated().sum()
print("Number of Duplicate Rows of palm oil price dataset:", crude_oil_dup)

islamic_stock_dup = islamic_stock.duplicated().sum()
print("Number of Duplicate Rows of palm oil price dataset:", islamic_stock_dup)

conventional_stock_dup = conventional_stock.duplicated().sum()
print("Number of Duplicate Rows of palm oil price dataset:", conventional_stock_dup)
```

```
Number of Duplicate Rows of gold price dataset: 0
Number of Duplicate Rows of palm oil price dataset: 0
Number of Duplicate Rows of palm oil price dataset: 0
Number of Duplicate Rows of palm oil price dataset: 0
Number of Duplicate Rows of palm oil price dataset: 0
```

Figure 3.7 Data Cleaning for All Datasets

```python
columns_drop_islamic_stock = ['Open', 'High', 'Low', 'Change %']
islamic_stock.drop(columns=columns_drop_islamic_stock, inplace=True)
islamic_stock
```

	Date	Price
0	Jan-13	11,112.97
1	Feb-13	11,105.74
2	Mar-13	11,357.06
3	Apr-13	11,663.19
4	May-13	12,403.80
...	...	...
127	Aug-23	10,920.64
128	Sep-23	10,874.52
129	Oct-23	10,841.59
130	Nov-23	10,929.36
131	Dec-23	10,988.71

132 rows × 2 columns

```python
columns_drop_conventional_stock = ['Open', 'High', 'Low', 'Close', 'Volume']
conventional_stock.drop(columns=col[illegible] conventional_stock, inplace=True)
conventional_stock
```

	Date	Adj Close
0	Jan-13	1627.550049
1	Feb-13	1637.630005
2	Mar-13	1671.630005
3	Apr-13	1717.650024
4	May-13	1769.219971
...	...	...
127	Aug-23	1451.939941
128	Sep-23	1424.170044
129	Oct-23	1442.140015
130	Nov-23	1452.739990
131	Dec-23	1454.660034

132 rows × 2 columns

Figure 3.8 Drop Unnecessary Column

3.5.3 Data Concatenation

A method for combining data from related datasets into a single, cohesive dataset in data analysis is called data concatenation. Since our data is gathered gradually in batches, it is crucial to this research that we combine all datasets from January 2013 to December 2023. This enables us to combine all of the datasets into one for analysis. An example of how we concatenate data across all datasets is shown in Figure 3.9.

```python
# Merge all dataset in one dataframe
merged_df = pd.concat([palm_oil, crude_oil, islamic_stock, conventional_stock, gold], axis=1)

merged_df.drop(columns=['Date'], inplace=True)
merged_df
```

	DATE	Palm Oil Price (MYR)	Crude Oil Price (MYR)	Islamic Stock Market Price	Conventional Stock Market Price	Gold Price (MYR)
0	2013-01-01	2557	319.49	11,112.97	1627.550049	5082.220000
1	2013-02-01	2397	333.47	11,105.74	1637.630005	5042.270000
2	2013-03-01	2378	318.73	11,357.06	1671.630005	4952.770000
3	2013-04-01	2286	301.46	11,663.19	1717.650024	4537.530000
4	2013-05-01	2397	299.80	12,403.80	1769.219971	4266.100000
...	...	...	...	...	...	...
127	2023-08-01	4010	396.13	10,920.64	1451.939941	8834.737500
128	2023-09-01	3767	431.20	10,874.52	1424.170044	8875.566667
129	2023-10-01	3679	416.52	10,841.59	1442.140015	9061.206667
130	2023-11-01	3895	380.37	10,929.36	1452.739990	9368.556667
131	2023-12-01	3721	353.61	10,988.71	1454.660034	9494.305000

132 rows × 6 columns

Figure 3.9 Data Concatenation on Merge Dataset

3.6 Data Modelling

The primary aim of this research is to model the impact of oil price and stock market price on gold price using advanced econometric techniques. The process begins with the collection of time series data, encompassing historical records of gold price, crude oil price, palm oil price, Islamic stock market price, and conventional stock market price, measured over monthly intervals from January 2013 to December 2021. This data must then undergo a series of pre-processing steps to ensure its suitability for modeling. Pre-processing includes handling missing values, converting data types, and ensuring the data is stationary—a requirement for many time series models. Stationarity is achieved through techniques like differencing to remove trends and seasonal structures. Figure 3.10 will show the framework of how LSTM and VAR model methodology for forecasting gold price.

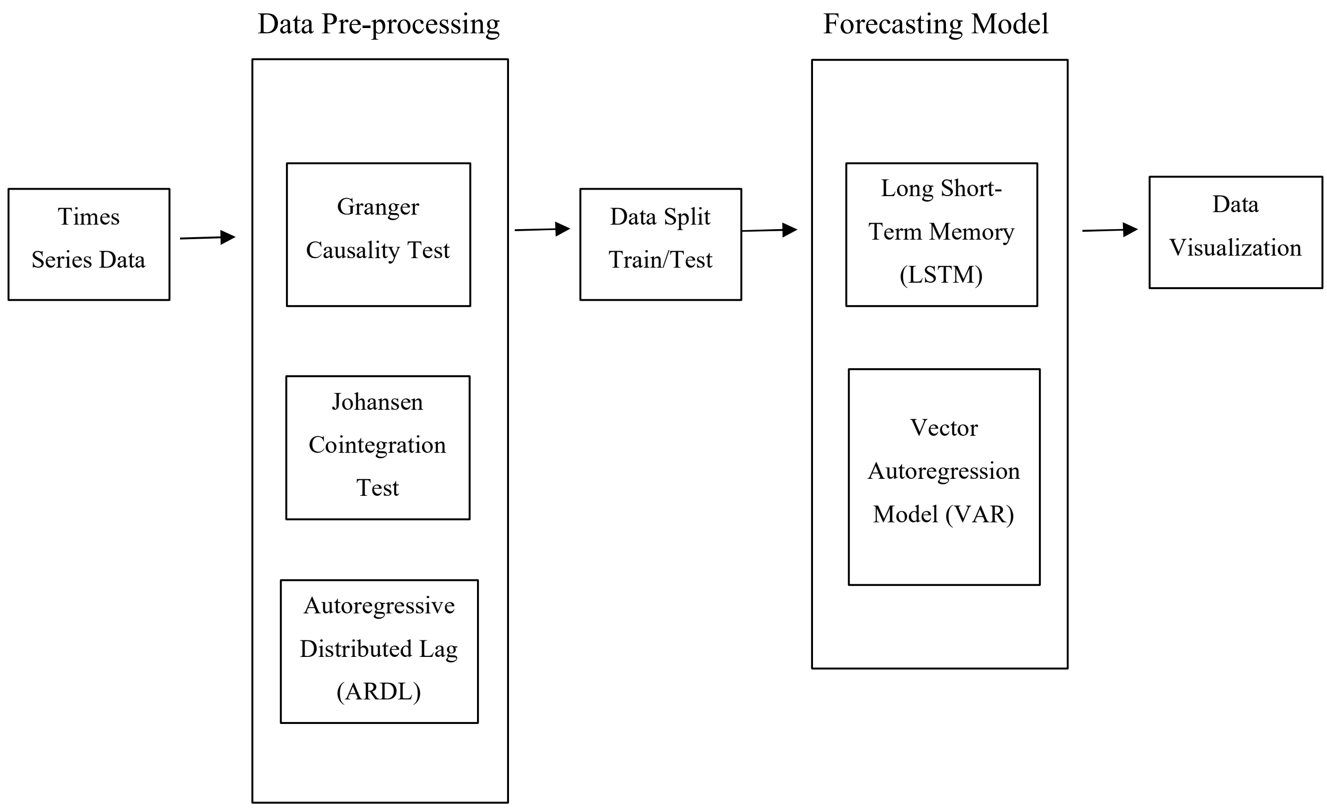

Figure 3.10 LSTM and VAR Model for Gold Price Forecasting Methodology

Once the data is prepared, it is divided into training and testing datasets. This division is essential for validating the model's effectiveness at making forecasts. For this research, the Johansen Cointegration test is employed to determine the long-term equilibrium relationships between the variables. Additionally, the Granger Causality test is used to identify the directional influences between the time series.

The Autoregressive Distributed Lag (ARDL) model is then applied, which is suitable for analyzing the dynamic relationships between the variables over both the short and long term. The ARDL model parameters—lag orders of autoregressive (AR) and moving average (MA) components—are meticulously selected using criteria like the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). This step is crucial as it lays the foundation for how well the model will understand and predict the time series data's behavior.

The model fitting is the next phase, where the ARDL model, armed with the optimal parameters, is trained on the historical data. Upon training, the model's accuracy is evaluated using metrics such as the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE), which provide quantitative measures of the model's predictive performance. Additionally, the Long Short-Term memory (LSTM) model and Vector Autoregression Model (VAR) model are employed for forecasting future values of the time series. These forecasts can be particularly valuable for planning and decision-making processes in the financial sector.

Lastly, the model's predictions are visualized against actual data for a comparative analysis, providing an intuitive and clear assessment of its forecasting capabilities. The visualizations include time series plots and scatter plots that compare predicted and actual values, helping to identify the model's strengths and areas for improvement.

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