TIME SERIES FORECASTING ON MONTHLY AVERAGE FOOD PER CAPITA EXPENDITURE IN INDONESIA

NAME : METTA CARANA

PROGRAMME : MASTER OF DATA SCIENCE AND BUSINESS ANALYTICS

YEAR : 2024

[Public Published Version]

This project was done as part of CAPSTONE PROJECT for Data Science Master's Degree completion in Asia Pacific University, Malaysia.

ABSTRACT

Food consumption is an integral part of human lives. In the absence of food, individuals would not get sufficient nutrients to function. The UN placed the importance of food as one of the Sustainable Development Goals in goal no.2 - Zero Hunger. Despite the importance of food consumption, Indonesia still ranked poorly amongst other countries in the Global Hunger Index (GHI). With a score of 17.9, Indonesia is ranked at the 77th placed among 121 countries, and second worst among ASEAN countries, despite being the country with the highest population and area in the region. Studies have also proven that factors such as food prices & expenditures are the most important factors that impact amount of food spending and consumption.

Thus, to address the hunger issue in Indonesia as well as the importance of expenditure, this study aims to develop an optimal model to forecast the average monthly food per capita expenditure in Indonesia, by making use of data provided by the Indonesian Department of Statistics (BPS). With CRISP-DM methodology, time series forecasting methods of univariate and multivariate nature including exponential smoothing, Holt's method, ARIMA, and VAR are implemented to the dataset. The outcome of the study shows that ARIMA (2,1,0) and VAR method with *Vegetables, Fruits,* and *Prepared Food* categories as supporting variables are superior in performance compared to the other models; with the ARIMA having an MAE of 1.33% and the VAR method MAE of <1%. The forecasted result shows the overall food expenditure in Indonesia will continue to rise in the next 5 years, up to IDR 1 million by the year 2027.

Keywords: Time series forecasting, Food expenditure, ARIMA, VAR

TABLE OF CONTENTS

LISTS OF FIGURES

LISTS OF TABLES

CHAPTER I
INTRODUCTION

1.1 INTRODUCTION

Food consumption is a crucial part of human lives. Every individual needs food to gain energy and be able to function in day-to-day activities. In the Sustainable Development Goals constructed by the United Nations (UN), food is represented on goal No. 2 – Zero Hunger. The UN stated the aim of the goal is to “end hunger, achieve food security and improved nutrition, and promote sustainable agriculture” (UN Statistics Division, 2016). In multiple countries, governmental policies also put highlight on national food consumption management, such as in the form of agricultural policies and pricing, providing subsidies, or regulations pertaining basic human rights.

The importance of food is undeniable in order to achieve a better and more sustainable life. However, to this day, the Zero Hunger target is still in progress, with plenty of people still suffer from hunger due to lack of access to adequate food. South-East Asian data record in 2016 showed that 61 million people (± 10%) of the region’s population is still malnourished, although the number has dropped from 118 million (22%) in the year 2002 (UN Statistics Division, 2016). In Indonesia, the undernourishment number itself was 7.9% in 2015, and dropped only to 6.5% in 2022 (GHI, 2022).

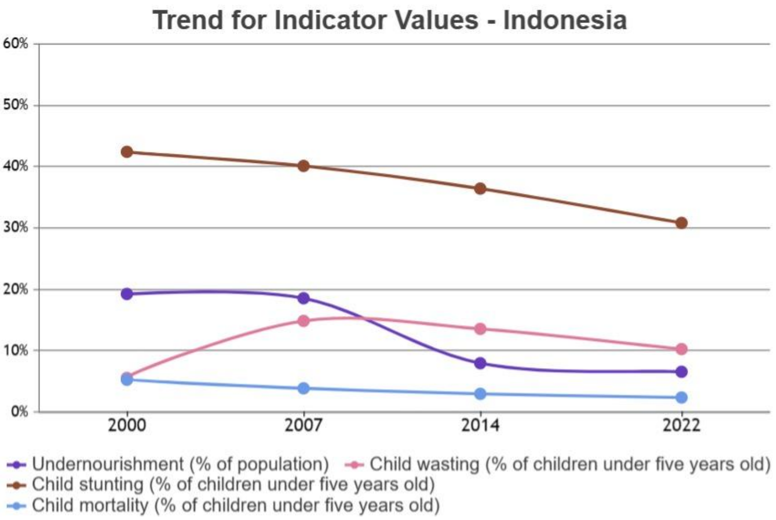


Figure 1. GHI Indicator Values – Indonesia (GHI, 2022)

The number above has only presented results on undernourishment. The Global Hunger Index, a means designed by the UN to monitor how countries are achieving hunger related goals, have four index scores of evaluations as stated in Table 1. Among 121 countries ranked on the Index, Indonesia still ranked on the 77th with an overall index score of 17.9 or moderate in 2022. This ranking is also the second worst amongst the other Southeast Asian countries of rankings at the same period. The indicator which contributed to the highest value is *child stunting*, at 30.8% in 2022. The *child wasting* index value follows at 10.2% and child mortality at 2.3% (GHI, 2022).

Table 1. GHI Indicators

No.	**Indicator**	**Explanation**
1	Undernourishment	Percentage of population that has insufficient calorie intake.
2	Child Stunting	Share of children under five with low height – Chronic undernutrition
3	Child Wasting	Share of children under five with low weight – Acute undernutrition
4	Child Mortality	Share of children that died before reaching 5 years old – inadequate nutrition & unhealthy environment

Studies have identified that higher hunger index are impacted by factors of low income and poverty, presence of global issues such as war or conflicts, as well as poorly structured health and nutrition programs (WHO, 2022). As income and poverty correlates with financial resources, food prices are also an important aspect in obtaining national / regional, or international level of food security, as rising food prices meant citizens expenditure on food also increases. With the world just adapting back through the post pandemic situation and the conflict in Ukraine, level of poverty and inequality in income have made a setback on access of healthy diets from 3 billion people worldwide (IFPRI, 2022). A study by Arndt et al. (2023) on commodity prices in developing countries confirmed that household consumption and poverty are affected the most by rising fuel and food prices due to the Ukraine war, with the increased food prices leading to a decline in nourishment and diet quality. (Beglaryan & Pipoyan, 2023) stated that people that live under the poverty line tend to be the most food insecure as they are most sensitive to food prices. A study done by (Mone & Utami, 2021) on factors determining hunger in Indonesia also proved that variables of food expenditure and rice prices had a significant effect on hunger levels in the country.

In the face of rising food prices, it is important for relevant stakeholders such as food producers, distributors, and policy makers to be able to make relevant and constructive strategies to maintain current levels or slow down the pace of rising food expenditure in the future. To make these decisions, an accurate prediction of food spending is needed. Thus, this study aims to provide a forecast model that can provide accurate estimates on food expenditures in Indonesia on a yearly basis. Utilizing the secondary data of Average per Capita Expenditure (Food and non-food) data provided by the Indonesian Department of Statistics (BPS), the study will evaluate Food Consumption per Capita Expenditure on the national level on historical data coming from the year 2000 – 2022 with time series modelling. The study will then provide a final model which provides predictions with highest accuracy.

1.2 PROJECT BACKGROUND

To this day, there is still few research done on food consumption per capita spending or expenditure forecast in Indonesia, especially those utilizing the national level data. In 2019, a study was conducted by Desiyanti et al. on estimations of average per capita expenditure. However, the study did not specifically target the food spending, was conducted at district level, and was only specific to the West Sumatra province. In the study, the Small Area Estimation (SAE) specific Empirical best linear unbiased prediction - Fay Herriot (EBLUP-FH) model was utilized, with the EBLUP-FH model demonstrating more precise estimation than the direct estimataion method (Desiyanti et al., 2022). A study done using similar time series model was done by Ginanjar et al., (2022) for sub-district level estimation of Jambi region. With Relative Root Mean Square Error (RRMSE) as the error measure evaluator, the study concludes that the EBLUP model can improve the estimation results compared to the direct estimation method. However, although these two studies utilize time series data, the aim of these studies are not to forecast, but to estimate expenditure amount at the lower level from data given at the higher (national / provincial) level.

On research done specifically for time series forecasting, one was done by Suriani & Noviar (2022). Utilizing the average per capita expenditure data for food, the study conducted time series forecast specific for the Aceh province. The study uses the linear least squares trend analysis method to project the expenditure forecast for the year 2022-2023, utilizing yearly historical data from 2018-2021. The result of the study predicted rising food expenditures in the year 2022 and 2023, along with recommendations for relevant stakeholders. Another study on the food domain that incorporates time series forecasting was done on the production and consumption of rice in the South Sumatra region (Indri et al., 2022). Rather than using the expenditure as the estimators, the study estimates the production and consumption in terms of tonnes, with considerations of harvest area, grain prices, fertilizer prices, and rainfall as contributing factors. In presenting the forecast itself, Holt's multiple exponential smoothing method is used to predict yearly rice production and consumption of year 2020-2029 with historical data of year 1987 to 2019.

In 2019, another study was conducted by Wardani et al. (2019) on predicting per capita food and non-food expenditure on province level. The study makes use of the Neural Network (NN) Backpropagation modelling in forecasting the data. Utilizing MSE as a measure of error, the model was tuned on hidden layer, epochs, and learning rate parameters achieving an overall accuracy of 97% (Wardani et al., 2019).

From the five works referenced above, none of the study has done the forecasting process on national level data. Desiyanti et al. (2022) and Ginanjar et al. (2022) utilizes similar data sources, however, is an estimation study rather than a forecasting one. The forecast research done by Suriani & Noviar conducted forecast solely for city level in the Aceh province. In a similar way, Wardani et al. (2019) predicted expenditure only on the province level, and does not target specifically the food expenditure. Indri et al (2022), although the study revolves on the consumption domain, it did not incorporate expenditure data as an input, and was also done only on the South Sumatra province level. And among those, a variety of time series methods are utilized; from the simpler least squares trend method, to the more complex such as Holt's exponential smoothing and NN backpropagation. These shows that there are not enough research done on the national level to predict the average food consumption per capita expenditure on the national level.

Only after a thorough search, that a study that incorporates a similar aim is found. Saragih (2018) utilizes exponential smoothing - double linear one-parameter forecasting method from Brown (Brown's method) to forecast monthly average food consumption per capita spending. Although the research is done only at regency level - Simalungun, North Sumatra, the research specifically calculates expenditures on the Food category at monthly average per capita. In the study, historical data provided by the BPS from 2002 – 2015 is used to predict expenditure at year 2018-2019 (Saragih, 2018).

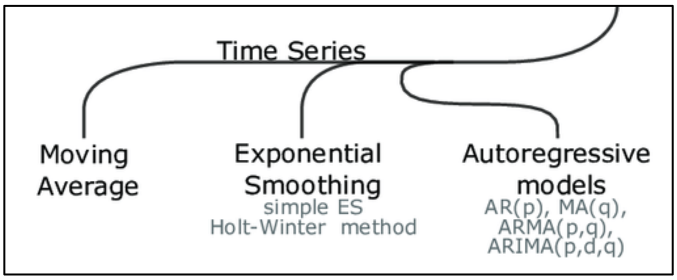


Figure 2. Time Series Forecasting Models

From the works discussed above, it can be said that studies done on the theme of food consumption per capita expenditure is still minimal, with lots of room to grow. The works done on the domain have adopted several time series forecasting models such as least squares, Holt's exponential smoothing, NN backpropagation, and Brown's method. However, there are still variations of time series forecasting methods that have not been experimented in the domain.

The target of the studies was also on the smaller scale, such as regency or city level. Whereas with a national level study, the results can contribute more for a larger scale strategy planning.

Thus, to address the lack of research issue, this study will focus on designing the most suitable forecast model for monthly average food consumption per capita expenditure on the national level in Indonesia. The most suitable model is to be chosen by comparing the accuracy and performance of multiple time series models. The models evaluated will include those of univariate nature, including the traditional moving averages, exponential smoothing and Holt Winters method utilized as utilized in previous works, as well as the autoregressive models such as the Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR) and Vector Error Correction Model (VECM). Examples of time series models utilized for forecasting is displayed in Figure 2.

1.3 PROBLEM STATEMENT

Food consumption and expenditure is an integral part of human life across the globe. However, currently there is still no robust model that can help relevant stakeholders in evaluating the food expenditure data in Indonesia. The availability of food with reasonable prices are important to sustain healthy living with adequate amount of nutrients, especially in urban regions where population are more dense and prices are generally higher. Accurate forecasts on per capita food expenditures allows relevant stakeholders to make more accurate policies and economic planning to ensure food security on a national level. There are currently also minimal number of studies addressing the issue on the national level in the country. Methodologies used on previous works also has not been explored thoroughly, utilizing only few methods such as least squares and exponential smoothing. Thus, it is critical to develop a more sophisticated forecasting model that can account for more seasonality and trend in the food expenditure data in Indonesia. This will allow for more dependable predictions to accommodate national level strategy and planning.

1.4 AIM AND OBJECTIVES

The main aim of this project is to generate an accurate forecast model on monthly average food consumption per capita expenditure in Indonesia within the next 2-3 years, with objective on generating reliable predictions that can assist relevant stakeholders in monitoring and predicting future food consumption patterns in the country.

From the project aim stated above, the objectives of this project are as follows:

1. To analyse the pattern of historical data on food consumption spending per capita in Indonesia from the past 22 years.
2. To identify the best performing model on average per capita expenditure in Indonesia from the univariate and multivariate time series models.
3. To predict average monthly food consumption per capita expenditure in Indonesia for the year 2023-2025 with the most optimal model.

1.5 SCOPE OF THE STUDY

The scope of this study covers the analysis and forecasting of food consumption per capita spending in Indonesia, focusing on the spending in the cities region. The study will provide a forecast model from the existing historical data over the next 3 years, utilizing existing historical data provided in the Indonesian Department of Statistics website. Any existing trends and or seasonality that exists in food consumption spending are to be identified. Various univariate and multivariate approaches of time series models will be implemented to observe their effectiveness and accuracy in generating accurate results.

As a time-series analysis, the study takes into consideration factors that may influence food consumption spending patterns, such as economic fluctuations, geopolitical events and crop yield. However, these factors are not to be examined in a detailed manner, rather focusing on their possible impacts toward the forecasting model.

In evaluating the performance of the model, accuracy will be determined through performance metrics such as MAPE, RMSE, and Tracking Signal. This is to make sure the model generated provides a high degree of reliability and robustness. It should be highlighted that this study is not providing policy recommendations, rather to serve as a tool to support relevant stakeholders in understanding and estimating the average monthly food consumption per capita spending in Indonesia.

1.6 SIGNIFICANCE OF THE STUDY

The significance of this study encompasses 4 distinct categories which are related to socio-economic development in Indonesia. These include significance in governmental policy planning and implementation, consumer behavior, achievement of sustainable development goals, as well as insight provided for further economic studies or development on the national level. The details of each significance are discussed as follows:

1. Governmental Policy and Planning: Accurate projections of food expenditures can help government organisations and policymakers create efficient strategies and policies for

food security, economic planning, and social welfare initiatives. It can aid in resource allocation, the creation of focused interventions, and the promotion of sustainable growth in agriculture and food industries.

2. Consumer Behaviour: The projection of future spending on food would contribute to map the national trend of consumer behaviour in the city areas related to food consumption patterns. This would provide help to multiple market players such as corporations operating in the food and nutrition domain, e-commerce platforms that sell grocery and food products, as well as market investors,
3. Sustainable Development: In this decade, the world has put stressed more importance on building a sustainable environment in the society that humans live in. The United Nations has declared the SDGs as a worldwide commitment where countries worldwide, including Indonesia, should contribute to achieve. Priority on nutrition and food security is listed as one of those goals. This study would help in providing information regarding food expenditure on different categories, thus may help in improving agricultural practices and resource allocation.
4. Economic Insights: This study can give insights on Indonesia's economic dynamics by analysing and projecting trends of food consumption in urban region. Economic Making knowledgeable choices about production, marketing, and investment prospects can aid the food industry, investors, and market analysts. The results may help the nation's economy remain stable and expand overall.

CHAPTER II
LITERATURE REVIEW

2.1 Importance of Food on the Country Level

Food is one of the basic necessities of human life. People need food to survive, do activities, as well as function well in society throughout their lifetime. On the country level, good nutrition consumption by its citizens determines the quality of life and health indicators of a nation (Burlyaeva et al., 2020). A study on diet quality by Luan et al. (2018) found strong negative correlation between adequate dietary intakes with the prevalence of undernutrition on the national level. Fan & Brzeska (2014) on their research regarding China's food and nutrition security emphasizes how the country has designed a comprehensive agenda involving agricultural investments and social safety nets to ensure food security for its enormous population.

Narrowing on the topic of food security itself, a study stated that adequate nutrients and food security is a major challenge due to rising food prices, changing demand patterns, climate change, as well as changing dynamic of the agricultural sector (Grote, 2014). In Nigeria, rice price volatility, notably price of imported rice is the highlighted issue to be addressed in order to improve the national level food security, especially among poor households (Amolegbe et al., 2021). A study by Korir et al (2020) in Kenya also showed similar results, with their results suggesting how rising food costs have led to a decline in food security in the country (Korir et al., 2020). From these studies, it can be deduced that food prices or expenditure is one of the factors that greatly impact the nutrients and food security on the national level.

2.2 Retaled Works on Food Expenditure in Indonesia

Studies on the topic of food expenditure forecasting in Indonesia has not been explored a lot. Despite the importance of food security for national economic development, existing studies have been limited to research done on a district or province level, providing only a narrow view on the food expenditure forecasts specific to certain regions. In chronological order, studies related to food expenditure and forecasting on Indonesian national level will be described.

In 2018, a study is done to forecast the average food expenditure per month for the year 2018 and 2019 in Simalungun District in Sumatra Island. Utilizing the yearly data provided by the Indonesian Department of Statistics from year 2002 to 2015, Saragih (2018) conducted the forecasting with Brown's method of exponential double linear one parameter method. The study declared that the monthly average per capita expenditure for food at Simalungun District level is predicted to be at Rp.462.457.50 in 2018 and then increase to Rp.482.296,30 in 2019. The study does not provide any information regarding measure of error or accuracy of the obtained forecast result.

Wardani (2019) conducted research on prediction of the overall per capita expenditure dataset on the province level. The study yielded result of prediction for each of the provinces. The dataset utilized on the study is taken from the open access data available on the Statistics Department website. Prior to the forecasting process, the author utilizes Excel and Matlab in order to transform the data into a standardized format. The study utlizies the more advanced method of neural network backpropagation modelling to forecast the available data. The architecture is constructed with 4 variations of number of hidden layer, as well as specified value on goal, maximum number of epochs, and learning rate. The accuracy level of the prediction gained is up to 97% with a Mean Squared Error (MSE) value of 0.07.

A study published the recently by Desiyanti et al. (2022) also conducted prediction on average per capita expenditure. Same as study done by Wardani (2019), the study implemented does not focus on food expenditure, rather utilizing data of the overall per capita expenditure of both food and non-food. The scope of the study was on the province level of West Sumatra, and models used include the Small Area Estimation (SAE) and Empirical best linear unbiased prediction - Fay Herriot (EBLUP- FH). The result of the study yielded proves that the EBLUP-FH model gives a more accurate estimation versus the direct estimation method. On the same year, another research was also done by Ginanjar et al., (2022). Utilizing the EBLUP model for estimation in Jambi region. The study uses Relative Root Mean Square Error (RRMSE) as the performance measure. The author concludes that the EBLUP model is able to improve estimation results better versus direct estimation method.

The previous two research focus more on estimation on a higher level utilizing a lower level available data (e.g. district from sub district). Focusing back on studies done on time series forecasting topic, Suriani & Noviar (2022) executes research on forecasting for the Aceh province for year 2022 and 2023. Utilizing the linear least squares method, the study takes data from yearly historical data of 2018- 2021 and creates forecast on the district level such as eastern, southern, and south-western. The results of the study elaborate on the potential increase of food and beverage expenditures in each district and how they compare. The study also provided SMAPE and RMSE measures that indicate theforecast errors as well as analyses regarding factors that affect the rising expenditure trend.

Another study by Indri et al (2022) was also done related to the food domain and utilizing time series forecasting in the research. However, the forecasting done on the study relates to the number of production and consumption of rice, in measures of tonnes. In the study, factors that relate to the rice production and consumption such as grain and fertilizer prices, harvest gains, as well as weather and rainfall are taken into account. With Holt's multiple exponential smoothing method utilized, the study predicted yearly production and consumption of rice for 10 years (2020-2029), basing the forecast on historical data throughout 1987 to 2019. The study also gives insight on which factors affect rice production and consumption positively and negatively.

2.3 Existing Studies on Expenditures, ARIMA, and VAR Modelling

Apart from studies on the national scope, studies on the scope outside of the country gives a better glimpse on the implementation of other approaches that are used in time series forecasting. Alhtough these studies are not in the food domain, the studies referred in this section focus on forecasting expenditures data, which aligns with the target variable of this study.

A study by Zheng et al. (2020) was done in China to predict the total health expenditure in the country for the year 2018-2022. The time series data utilized is from the year 1978-2017, taken from China Statistical Yearbook. Utilizing the R language, various ARIMA model variation are constructed for each of the related time series data that includes total health expenditure, government health expenditure, and social health expenditure. Utilization of ARIMA is due to it being considered as the most appropriate model for time series data which provides stability and simplicity in its design. Stationarity of the data is calculated with Augmented Dickey-Fuller (ADF) test, and AR and MA were calculated utilizing the autocorrelation (ACF) and partial autocorrelation (PACF) functions. The most suitable model is decided based on Akaike information criteria (AIC). The study test the validity of predictions with mean average error and MAPE.

The usage of ARIMA was also done in a study by Jakovljevic et al. (2022) in predicting future health per capita spending forecast in BRICS countries from 2018-2030, with existing data from 1995 -2017. Also executing the forecast with R, the study utilizes *auto.arima* function to find the best fit model to forecast the health spending data. The output of the study is presented in the form of time series line graph for each country. Due to the limited data utilized in the study, the study also discussed the limitation of the model in predicting the next 12 years interval utilizing only 22-year data points.

The above two studies have also elaborated the significance of ARIMA method in time series forecasting, showing the favorability of using it for future predictions of large-scale time series data. Other researchers in the domain of economic growth and GDP also have multiple studies done utilizing the method. Sharma et al. (2022) forecasted India's GDP per capita utilizing ARIMA for the year 2021-2030. ARIMA was used by Voumik & Smrity (2020) in forecasting GDP per capita in Bangladesh. Utilizing historical data from 1972-2019, the study forecasted GDP in the country for the next decade, showing how the GDP and living standards will improve in the coming years (Voumik & Smrity, 2020).

Apart from the implementation of ARIMA, multiple implementations of Vector Autoregression (VAR) method have also been done in forecasting and analyzing time series data related to expenditures or economics such as GDP and expenditures. As VAR is a multivariate forecasting model, the method is utilized when there are more than 1 variable involved in the time series analysis or forecasting process. A study by Zhang & Nguyen (2020) forecasted Australian macroeconomy metrics including GDP growth, CPI inflation, and unemployment rate using the VAR method variations; comparing the standard with flexible Bayesian model. Gershon et al., (2019) examines the how oil price development impact GDP per capita and energy consumption based on data from several African countries utilizing an unrestricted VAR model.

A study by Zeng et al. (2021) also analysed the impact of fiscal expenditures and agricultural output with poverty in China. Based on data from 1990-2019, the study found out how fiscal expenditures give a more significant impact to poverty than the agricultural development factor. Another study by Das (2020) researched on how factors such as R&D spending, patent, and per capita income growth in different countries is related with each other. As VAR method has been widely used in forecasting and analysing time series data in a wide range of topics, this study will incorporate the VAR method to see how well the model can perform in analyzing food expenditure data.

2.4 Time Series Forecasting Methods

The previous sections discussed existing research papers done on the topic of time series forecasting, food expenditure, per capita expenditure, as well as ARIMA and VAR method have been discussed. This section describes the details of the time series forecasting methods that will be utilized in this study, including those present in existing works (MA and exponential smoothing), as well as the ARIMA and VAR models that are to be implemented.

2.4.1 Moving Averages

Moving averages are one of the fundamental and most used time series models in smoothing out fluctuations in data over time. The mechanism of MA involves average the value of the data at certain points with the average of itself over a certain predetermined period which involves its predecessor and successor. The simplest MA is the MA (3) involves three data point; 1 predecessor, 1 current, and 1 successor (Mills, 2019, p.24).

$$MA(3) = \frac{1}{3}(x_{t-1} + x_t + x_{t+1})$$

Simple MA models give equal weight to all observations, while exponential and weighted MA assign different weights to different points, for example to give more importance to recent data. The weights decided on the MA models depend on choosing the smoothing parameter value; with larger value leading to a smoother model trend. Figure x shows an example of the application of an MA in plotting monthly global temperature rise (Mills, 2019, p.26-7).

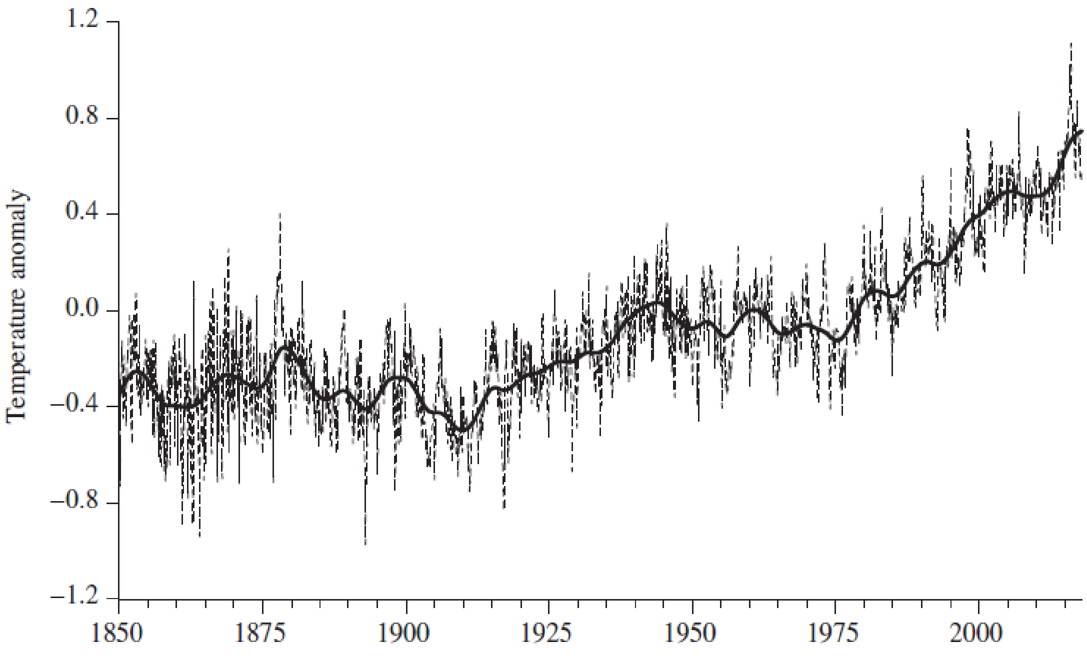


Figure 3. Moving Average on Global Temperature Anomaly

2.4.2 Holt Winter's Exponential Smoothing

Holt Winter's method which is also known as the triple exponential smoothing method is an extension of the original exponential smoothing method that takes into consideration the trend and seasonality that exists in a time series data. The method consists of the forecast equation and three equation components; the level, trend, and seasonality. The method also utilizes weighted averages in calculating the three equation components. In its application, the

Holt Winter's exponential smoothing can also be done with an additive or multiplicative method, where additive assumes that seasonality is more constant, and multiplicative determines seasonality as proportionate to the level and is multiplied with the other equation component (Hyndman & Athanasopoulos, 2018).

Below is the equation for the Additive method:

$$s_t = \gamma^*(1-\alpha)(y_t - \ell_{t-1} - b_{t-1}) + [1-\gamma^*(1-\alpha)]s_{t-m},$$

And for the Multiplicative method:

$$\begin{aligned}
\hat{y}_{t+h|t} &= (\ell_t + hb_t)s_{t+h-m(k+1)} \\
\ell_t &= \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\
b_t &= \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \\
s_t &= \gamma \frac{y_t}{(\ell_{t-1} + b_{t-1})} + (1-\gamma)s_{t-m}
\end{aligned}$$

As the model considers trend and seasonality, the method is suitable to forecast data with long term trends and seasonal patterns. The method is more complex compared to the moving averages as they allow the evaluation of linear trends and seasonality pattern (Hyndman & Athanasopoulos, 2018).

2.4.3 ARIMA

The Auto Regressive Integrated Moving Average (ARIMA) is a powerful time series model that is utilized to model and forecast stationary time series data. The method combines the autoregreesive (AR) and MA method with differencing to achieve data stationarity. When the exponential smoothing is based on the trend and seasonality of the data, ARIMA model aim to give an overview regarding autocorrelations that exist in the data (Hyndman & Athanasopoulos, 2018).

The ARIMA model is defined by three key parameters; the p, d, and q which represents the autoregressive, differencing, and moving average value respectively. The behaviour of long-term forecast would depend upon the order of differencing (d) while the AR and MA components give impact on short term forecast (Mills, 2019). The three parameters of the ARIMA model allow users to modify their forecast by adjusting the AR, MA, and differencing values according to the nature of the data. In finding the optimal ARIMA model, function such as auto.arima() in R is commonly used, where the function will determine the best model that have the lowest Akaike Information Criterion (AIC) or Schwarz Criterion (SC) value, indicating the fit and complexity of the model towards the data (Hyndman & Athanasopoulos, 2018). In a multivariate context, the usage of ARIMA is done utilizing variations such as the Mixed ARIMA or MARIMA, which allows insertion of other variables into the model and makes it more flexible, especially when external variables may impact behaviour of the data (Hyndman & Athanasopoulos, 2018).

.

2.4.4 VAR

The Vector Autoregression (VAR) statistical model is utilized to analyze and forecast multiple time series data simultaneously. It is useful for multivariate forecasting of interrelated variables and is able to capture the relationship and dependencies between them. In its application, the VAR calculate each variable as a linear combination of its past values and the past values of all the other variables. The model is based on the assumption that every model variable depends on each other, and thus allows understanding of how the change in one variable may impact the other variables in the system (Kilian & Lütkepohl, 2017).

Apart from its ability to give forecast results, the VAR method allow users to gain insights regarding interactions between the multiple variables and time series data. The Granger Causality concept can also be applied in VAR models to analyze the direction of dynamic relationship between the variables (Hills, 2019).

2.5 Summary of Literature Review

To summarize all of the relevant works and existing studies in regard to this project, Table 2 shows the literature matrix of the stated works in previous sections. The existing studies discussed has described the relevant time series forecasting methods that have been utilized with datasets in the same domain. Incorporating the methods done on previous works, this project will utilize the Moving average and Holt Winter's exponential smoothing to forecast the Indonesian food per capita spending data. Apart from the existing methods, this project will also utilize more complex model of the ARIMA, MARIMA, and VAR methods which may allow better projection on the food spending forecasts. The utilization of MARIMA and VAR would also allow comparison on how multivariate models generate forecasts compared to the univariate counterparts.

Table 2. Literature Matrix

No.	Author	Aim	Data Source	Methodology	Result and Conclusions	Implication for Future Research
Related Works in Indonesia						
1	Saragih (2018)	Predict average expenditure for consumption on food in 2018-2019 for Simalungun District	Secondary data BPS on spending and consumption 2002-2015	Brown's method	The average food consumption expenditure is predicted to increase.	Implementation of performance measures to indicate how accurate the forecasts are
2	Wardani 2019	To predict and help government institution in forecasting average spending per capita for food and nonfood based on provinces.	BPS data on food and non-food spending.	Backpropagation Neural Network	NN model with 9-81 layer is the best fit model	Show results on the category level, as this study give projection results on the province level
3	Desiyanti 2022	Estimate per capita expenditure at district level of West Sumatra Province in 2019	BPS data on West Sumatra Province, food and non-food	SAE EBLUP-FH estimation	The RRMSE value for EBLUP-FH estimator is smaller, therefore is better in providing more precise estimations	Research can be implemented on a larger level. (Study not specific on TSF)
4	Ginanjar 2022	Compare and evaluate direct vs EBLUP estimation metod to estimate sub-district level per capita expenditure. Scope in Jambi Province	Per capita expenditure data on sub-district level	EBLUP	EBLUP estimation produces more accurate estimation	
5	Suriani & Noviar 2022	Analyze trend of food and beverage consumption expenditure in Aceh	BPS data 2018-2021	Least Square trend analysis method. Measured on SMAPE and RMSE	Projection on year 2022-2023, there is increasing trend on food and beverages consumption spending in Aceh, with noticeable increase in certain region.	Utilization of error measures to measure the accuracy of the forecast.
6	Indri 2022	To analyze rate of rice production and consumption as well as the	Time series data of 33 years 1987-2019	Holt Winter's Exponential Smoothing	projection on 2020-2029. There will be a steady increase in growth of riece production and	Utilization of the exponential smoothing method can be adapted.

		factors that affect the price developments.			consumption in the next decade.	
Works on Expenditures, ARIMA, and VAR						
7	Zheng et al. (2020)	Forecasting China's health expenditure from 2018 to 2022	Time series data from 1978-2017	ARIMA variations	Projected results on total, government, social and out of pocket health expenditure, showing rapid increase in the years to come.	ARIMA models are utilized in expenditure forecasting studies
8	Jakovljevic et al. (2022)	Examine the historical trends of BRICS countries health spending and forecast	BRICS nation health spending data 1995-2017 from HIME	ARIMA Variations	Projected health spending on each of the BRICS countries up to 2030.	
9	Voumik & Smirty 2020	Forecasting GDP per capita in Bangladesh	Yearly GDP per capita data 1972-2019	ARIMA Measures on variation based on ADF, PP, KPSS test	The appropriate model to forecast the Bangladeshi GDP per capita is ARIMA (0,2,1), which is used to forecast the next decade	ARIMA application on GDP data
10	Zhang & Nguyen 2020	Forecasting Australian macroeconomy metrics with Bayesian VAR	20 variables from 1982 Q3 to 2020 Q1.	BVAR variations - Standard - CSV (Common Stochastic volaltiltiy) - MA	Large VAR model with 20 variables tend to outperform small VAR model with less variables. Different VAR variations such as standard or those with flexible error covariance structures may perform better on different variables.	VAR utilization in forecasting macroeconomic measures such as spending and GDP.
11	Gehrson et al 2019	To examine implication of oil price shocks on GDP per capita in selected African countries	- Oil benchmark prices data - GDP per Capita and Energy Consumption data from World Bank	VAR method -stationarity analysis -cointegration analysis - lag selection criteria basedon the AIC and SC	VAR model and impulse response show oil prices will temporarily increase GDP per capita in the short run. Recommends policies that can mitigate the effect of oil price increase	The application of VAR in GDP, with relation to other price indicators.

12	Zeng et al 2021	To analyze the impact o agricultural expenditures and agricultural output with poverty reduction in China	Agricultural fiscal data 1990-2019	VAR model ADF, cointegration, granger causality test, impulse response analysis, Variance decomposition	Fiscal spending plays a much more significant role in reducing poverty than agricultural development.	Application of VAR to find the contribution of each variable to the forecast error
13	Das 2020	To anlayze long run and short run dynamics between R&D spending, patent, and income growth in countries and groups	Time series data of R&D spending, number of patents, and per capita income growth 1996-2017	VAR model Cointegrataion test, granger causality tests, Impulse response function, variance decomposition	There is no long run association among R&D share, patents, and per capita income growth, however short run relationship show positive and negative affect between variables.	VAR can be applied with per capita financial (income) data, in relation to variables related to patents and spending amount.

CHAPTER III
METHODOLOGY

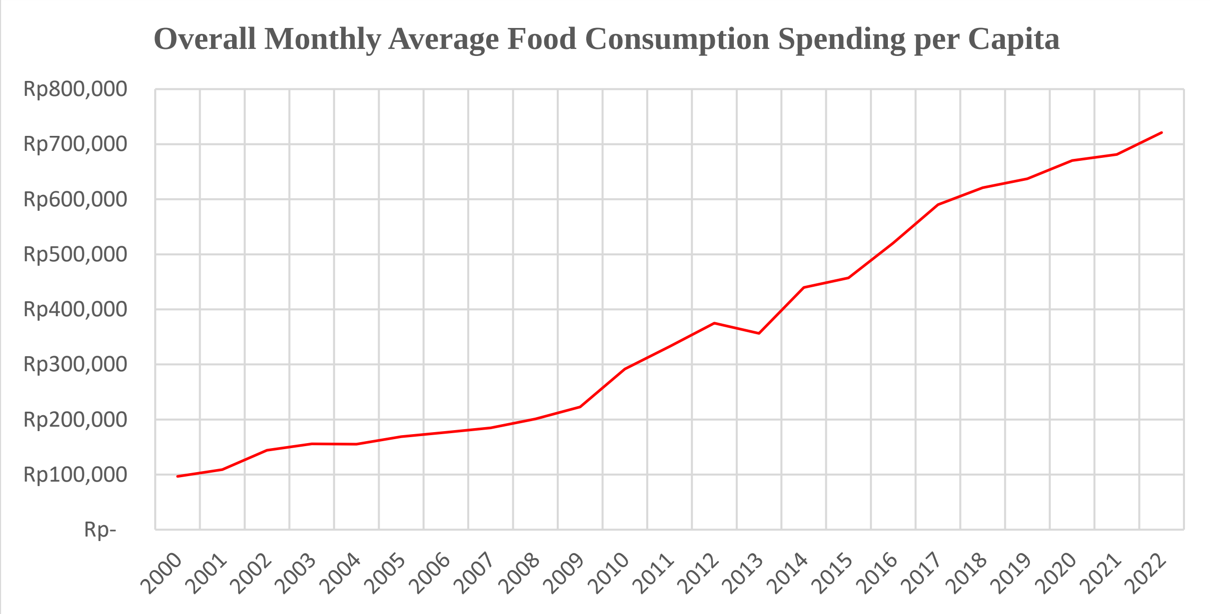
3.1 Methodology Overview

In this project, the dataset of Indonesia's food consumption spending per capita in the city region is to be modelled and forecasting using several univariate and multivariate time series modelling techniques to find out the best model that can represent the data. The models to be utilized include the traditional univariate Moving Average and Exponential Smoothing, Holt's method, ARIMA modeling, and the multivariate VAR method. The dataset itself consists of 23 yearly observations throughout the year 2000 – 2022, each year spending split into 14 food categories and 1 aggregate value. The details of the food categories can be seen in Table 3.

Table 3. Food Categories in the Dataset

Indonesian	English
Padi-padian	Rice and grains
Umbi-umbian	Tubers
Ikan	Fish
Daging	Meat
Telur dan susu	Eggs and Dairy
Sayur-sayuran	Vegetables
Kacang-kacangan	Legumes
Buah-buahan	Fruits
Minyak dan lemak	Oils and Fats
Bahan minuman	Beverages
Bumbu-bumbuan	Spices
Konsumsi lainnya	Other consumables
Makanan dan minuman jadi	Prepared Food and Drinks
Tembakau dan sirih	Tobacco

In Figure 4, the time series data utilized in this project. On the first graph, the aggregate Monthly Average Food Consumption Spending per Capita in the City Region of Indonesia is shown. From the graph, it can be seen that throughout 2000 – 2008, the average food spending in city region of Indonesia shows a stable increase, however a steeper incline starts to happen in 2009, which continues onwards to the current decade. The second graph then shows the exploded version of food spending across 14 categories of food, with categories of prepared food and drinks, tobacco, and rice and grains being the 3 categories that have risen the most in price over the years.



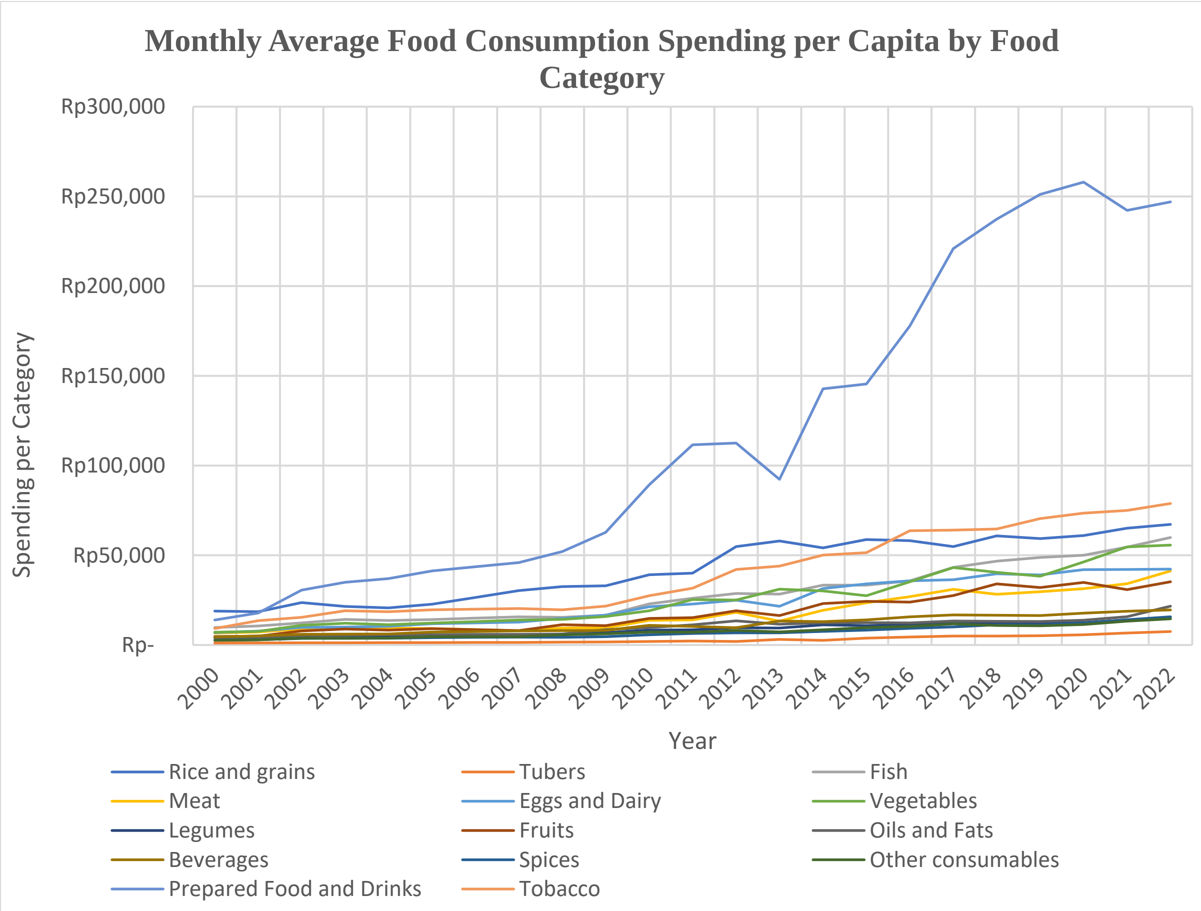


Figure 4. Time Series Data of Monthly Food Consumption Spending per Capita – City Region

In this project, the Cross-Industry Process for Data Mining (CRISP-DM) methodology is adopted. First released in 2000, CRISP-DM is still the standard method that are adopted for studies done on the field of data mining; or utilizing the more popular term today, the data science field. Differing from other project management or process methodologies, the CRISP-

DM methodology is designed to accommodate the data centric processes that data science studies usually need (Schröer et al., 2021). Thus, the CRISP-DM methodology is deemed the most suitable for this study.

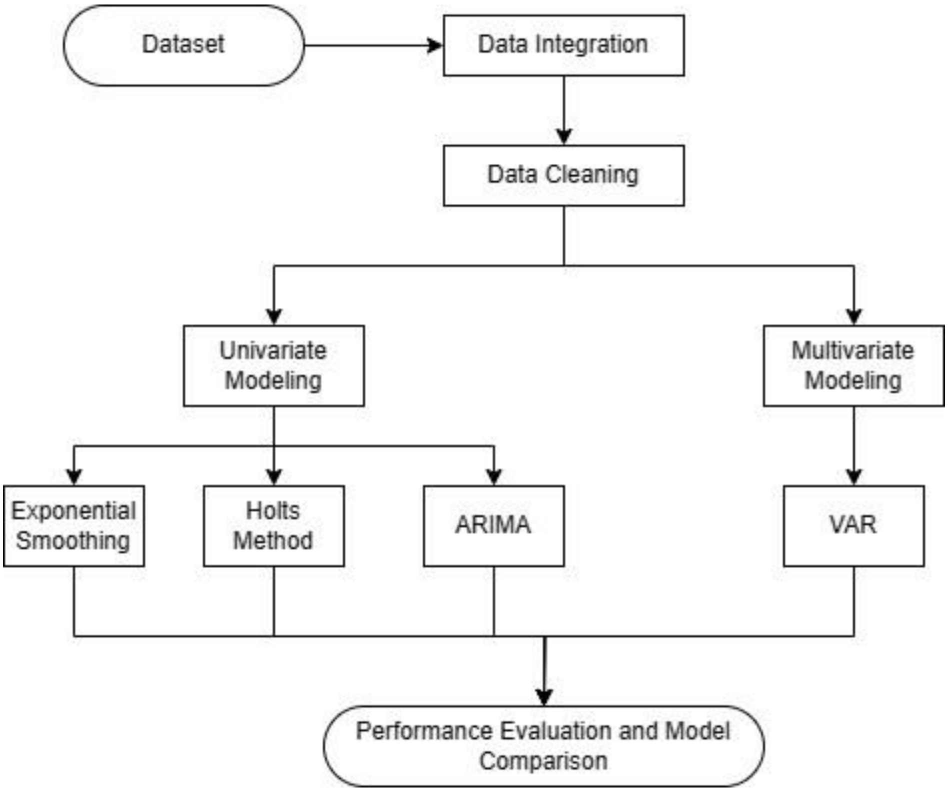


Figure 5. Project Workflow

The methodology itself is divided into 6 sections, including Business Understanding, Data understanding, Data preparation, Modelling, Evaluation, and Deployment. The methodology flowchart is shown in Figure 3. The business understanding of the project was elaborated on the introduction and literature review section. The overview of the dataset utilized describes the data understanding phase. The workflow of the project then continues with data preparation prior to the forecasting process, the execution of multiple models, tuning and comparison of all models, and lastly selection of the best time series model. The workflow of the project is as shown in Figure 5.

3.2 Data Preparation

As the data comes in two separate timeframe records of 2000 – 2012 and 2013-2022, the preparation begins by integration process to align the two period categories. The data then goes through cleaning and transformation process to ensure no missing data exist. The imputation process is specifically done for year 2006 period, where the dataset does not provide any data for that year period. Data is then split into a training period and a testing period data.

The training data is utilized to train the model and develop the forecasts, whilst the test period model is to be used as performance evaluation data points. As the study aims to forecast 2-3 years ahead, the training data encompass data of year 2000-2020 to forecast the data on year 2021 and 2022. The performance of the forecast is measured by comparing results of the forecast with the actual data of the period.

3.3 Univariate and Multivariate Modelling

This phase includes the implementation of various univariate and multivariate models to forecasts the monthly average food per capita expenditure. As described on the previous section, forecasts are initially generated for the year 2021 and 2022, where actual data actually exists. This is to calculate the model performances by comparing the forecasted results with the actual spending data. The models include time series models such as moving average, exponential smoothing, Holt’s method, ARIMA model and the multivariate VAR method.

With the univariate models of Exponential Smoothing and Holt’s method, the forecasting are to be done without extensive preparation. After the generation of the initial forecast, tuning variations may be done to generate the best model out of each method; this may include MA averaging period and smoothing parameter. With the univariate ARIMA model, the best fit model are to be found by fitting the dataset with the auto.arima function, which will help in determining the optimal autoregressive (AR), integration (I), and moving average (MA) value for the data (Mills, 2019). These parameters are defined with the (p,d,q) format, as described below:

p = the lag order, determines the number of lag observations that will be observed.

d = the differencing value, determines how data will be differenced (log) in the modelling process.

q = the moving average value, determines the size of the moving average indicator of the model.

In the multivariate modelling process, the VAR method is to be utilized. As the VAR model is more complex in nature, the monthly per capita food spending data on the category level are to be inserted into the modelling data. Results of the multivariate model will give both the aggregate and category level spending data.

The autoregressive time series models such as ARIMA and VAR may give more robust and accurate representations of the forecast as they have a parametric nature; which means they make assumptions on the underlying distribution of data in the modelling process and are more sensitive to parameter tunings. The stated models are trained and tuned with the training period data, by incorporating the suitable variables and parameters for each model. The results are presented in line chart formats, in comparison with the existing data points.

3.4 Performance Evaluation and Model Comparison

As the project concentrates on modelling time bound data, thus the model performances are evaluated utilizing linear model performance measures with the test period data. The measures provided in the results will include MAE, RMSE, MPE, MAPE, SMAPE, and tracking signal. This is to provide a thorough evaluation on the model performance. Analysis will be focused on the MAE, RMSE, and tracking signal. Table 4 describes the usage and importance of each performance measure (Baggio & Klobas, 2011).

Table 4. Performance Measures

No.	Measure	Description
1	MAE	Mean Absolute Error, shows the absolute difference value between the actual and predicted value.
2	RMSE	Root Mean Squared Error. Determines the error score based on the severity or significance of the errors. This ensures less bias in measure of the forecast results.
3	Tracking Signal	Tracking signal is the ratio of cumulative error to MAE, used to measure how a forecast results are generating constantly higher or lower calculated values.

In this stage, the strengths and weaknesses of each model are listed down along with its error measure in forecasting the average monthly food per capita expenditure in Indonesia. Evaluation results are presented in table format, while each forecast results are displayed in line charts format. The performance of each model will then be the benchmark to determine which model is the best fit to the data and are to be used to forecast expenditure for the year 2023-2025.

3.5 Deployment

From comparisons and analysis done on the evaluation phase, a single model is selected as the most optimal model to forecast the average monthly food per capita expenditure. Utilizing the whole data period (training and test period), forecasts for the specified time frame of 2023-2025 is to be generated and presented as the final model outcome of the project. At this stage the final report for the project is also generated and presented, alongside reviews and recommendations for future studies.

CHAPTER IV
IMPLEMENTATION, DISCUSSION, AND RESULTS

In this chapter, the implementation of analysis and forecasting regarding food consumption spending in Indonesia is conducted. The chapter will begin with visualization of the time series, statistics test done for trend analysis, then the implementation of univariate and multivariate models.

4.1 Visualization and Trend Analysis

Indonesia's monthly average per capita food consumption spending can be seen in Figure 6, has a clear upward trend, with slight deviations in certain years. There is no clear seasonality that can be seen from the data, although there is a distinct difference in upward trend from the year 2000-2010 and from 2010 onwards.

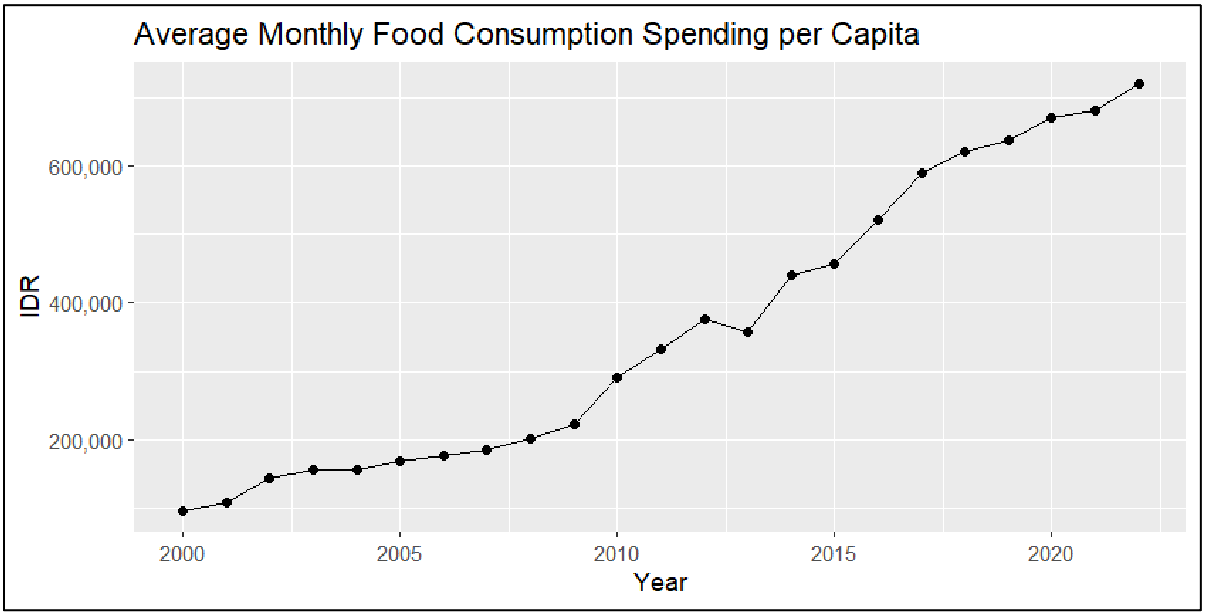


Figure 6. Average Monthly Food Consumption Spending per Capita 2000–2022

To support the visual claims, several tests are conducted to analyse the trend and seasonality in the data. To analyse for stationarity, the Mann Kendall test is conducted. Figure 7 shows the Mann Kendall test results shows a p-value ≈ 0 (<0.05), which is much lower than the significance level of 0.05. Therefore, the Null hypothesis of stationarity is rejected, and the time series data has a trend component. The Tau value of 0.984 further indicates that the time series shows a strong upward trend.

```
> library(Kendall)
> MannKendall(all_food) # strong upward trend
tau = 0.984, 2-sided pvalue =< 2.22e-16
> ndiffs(all_food) # difference lag-1
[1] 1
> nsdiffs(all_food) # no seasonality detected
Error in nsdiffs(all_food) : Non seasonal data
> adf.test(all_food)

        Augmented Dickey-Fuller Test

data:  all_food
Dickey-Fuller = -2.4121, Lag order = 2, p-value = 0.4154
alternative hypothesis: stationary
```

Figure 7. Trend and Seasonality Testing

In Figure 7, the ADF test, ndiffs and nsdiffs functions are also utilized to analyse stationarity, as well as how much differencing is suitable to make the data stationary. The ADF test p-value of 0.41 is > 0.05, therefore the Null hypothesis is not rejected. Data is not stationary and differencing is needed for stationarity. The normal differencing shows lag-1 is a suitable differencing value for the data, while the nsdiffs shows that the data does not have a seasonality component and therefore no seasonal differencing is necessary.

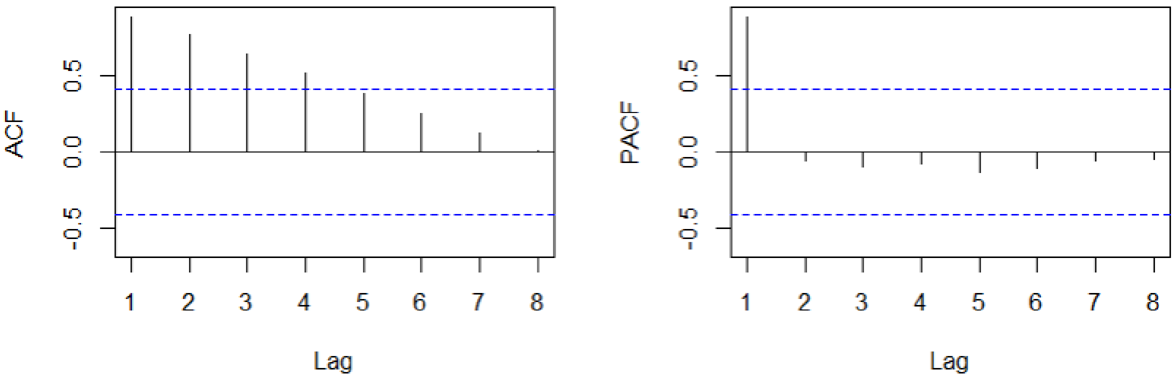


Figure 8. ACF and PACF Plot for Original Data

The ACF plot in Figure 8 is utilized to observe the correlation between observations at different time lags. The ACF plot shows a gradually dying down pattern, which indicate a slow decay that indicates non stationarity. As all the ACF values are all on the positive side, this shows how the time series data tend to move in the same direction. The steady dies down pattern with no oscillation indicates that the data does not have a seasonality component. Meanwhile, the PACF plot that cuts off at lag 1 shows that most of the observations can be directly explained by its direct predecessors, which indicate the data is on a first order AR.

As the test conducted shows the time series data needs a first order non seasonal differencing, Figure 9 shows the ACF and PACF model of the differenced data. Both the ACF and PACF plot now indicate no spike surpassing the threshold line, which indicates no further differencing is needed.

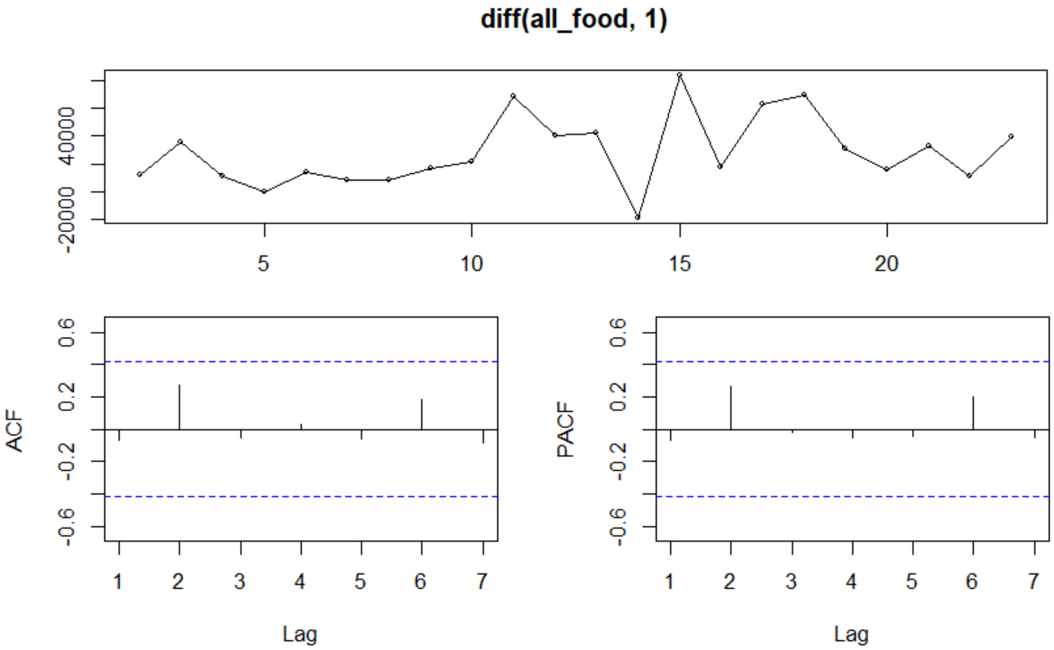


Figure 9. ACF and PACF on First Order Differencing Data

However, despite the ACF and PACF plot, the ADF test conducted on the first order differencing data (Figure 10) shows a p-value of >0.05, which indicates the data is not yet stationary. This indicates the data needs to be forecasted by methods that take into account trend component in the data.

```
> adf.test(diff(all_food,1))

        Augmented Dickey-Fuller Test

data:  diff(all_food, 1)
Dickey-Fuller = -2.2739, Lag order = 2, p-value = 0.468
alternative hypothesis: stationary
```

Figure 10. ADF Test on First Order Differencing Data

4.2 Time Series Forecasting Model Implementation

Prior to implementing the forecasting methods on the time series data, the data is split into training and testing period in a 90:10 ratio. The training data consists of the 2000-2020 timeframe, with the 2021 and 2022 timeframe used as the testing period. To measure the performance of each model, the time series will be forecasted on year 2021-2022 with the training set period. Then, the actual values are compared with the projected values of 2021 and

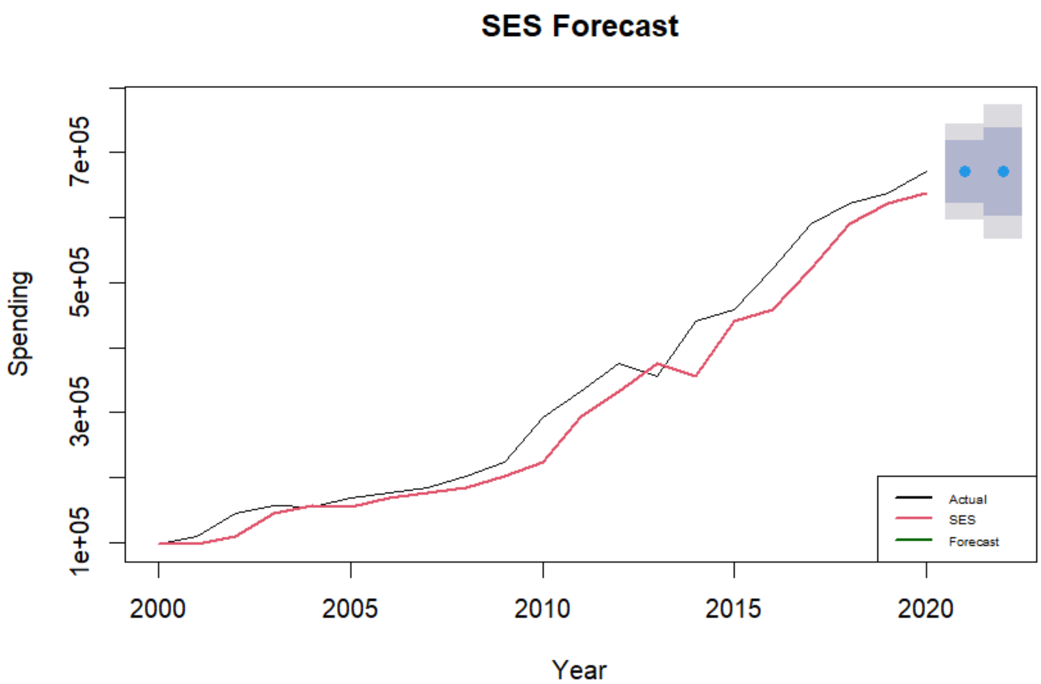
2022. Then the actual forecasting to be generated for the year 2023-2025 will be conducted with the best performing model.

4.2.1 Univariate Model Implementation

In the univariate model implementation, the Simple Exponential Smoothing (SES), Holt's Method, as well as ARIMA is conducted to forecast the model. Initially, the Moving Average method is listed as one of the forecasting methods. However, as MA models are simplistic and is not capable of generating forecast for an extended period, the more complex Holt's model is utilized. The Holt's model is able to take into account the trend and pattern component of the data better due to its consideration of the level and trend component, which is an extension from the SES model itself.

Simple Exponential Smoothing - SES Method

SES method is an extension from the Exponential Moving Average, where forecasting is done by exponentially decreasing the weight of past observations in comparison to more recent ones. As the SES does not consider the trend component of the series, the SES forecast generated has a centre point that is similar to the last forecasted value available, with a diverging lower and upper bound for the forecast (Figure 11).




```
> all_food_ses
   Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
22         670304 622245.3 718362.7 596804.6 743803.4
23         670304 602338.7 738269.3 566360.1 774247.9
```

Figure 11. SES Model Training Set Forecast

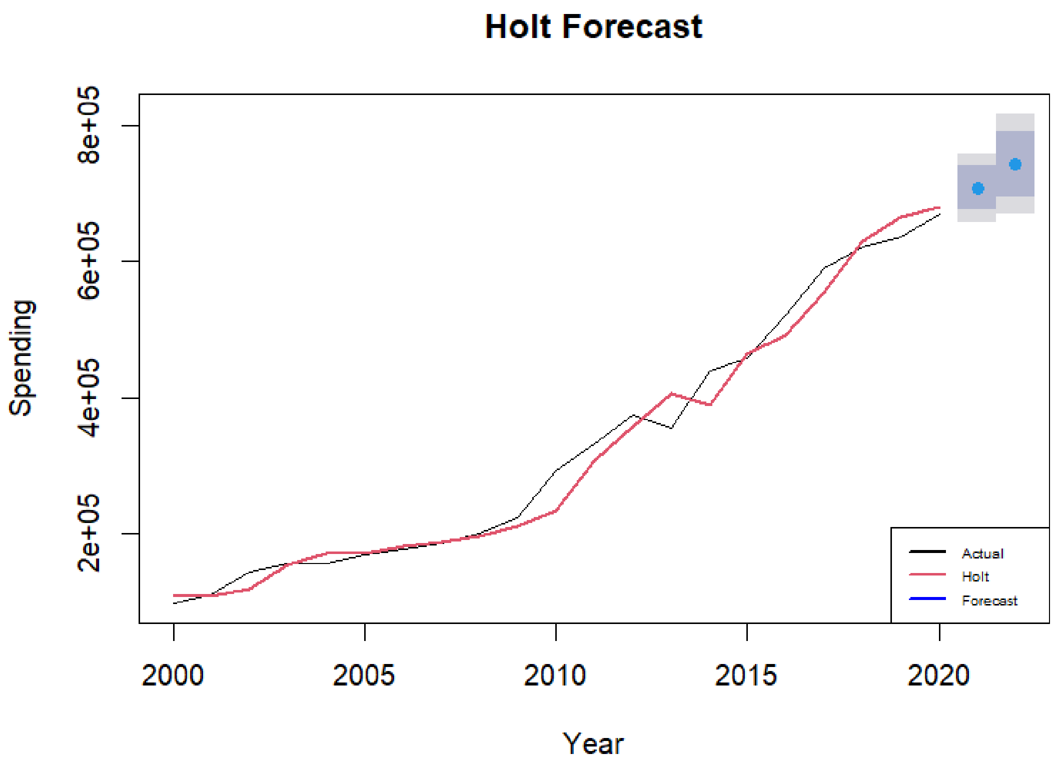
The accuracy of the SES model in Figure 12 shows a 4.3% error for the MPE and MAPE values, with the actual forecast itself diverging around Rp30,000 from the actual spending values according to the ME, MAE, and RMSE values. MASE value of 1.009 on the test set shows that the SES forecast is still not better than the naïve forecast.

```
> accuracy(all_food_ses,all_food_test)
                   ME     RMSE      MAE      MPE     MAPE     MASE
Training set 27312.95 37500.40 29140.76 8.508610 9.039331 0.952381
Test set     30877.00 36735.79 30877.00 4.326486 4.326486 1.009125
                    ACF1
Training set -0.01314679
Test set              NA
```

Figure 12. SES Model Training Set Forecast Accuracy

Holt's Method

With the Holt's method, the forecast is generated with consideration of the data's non-stationary nature or trend, as well as the level of the data. Figure 13 shows how Holt's forecast performs better compared to the SES, with the forecast values closer to the actual spending values. The 2 years forecast generated by Holt's method follow the current upward trend of the data, increasing up to Rp 744,114 in 2022.




```
> holt2122
   Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
22       708058.7 675287.6 740829.8 657939.6 758177.8
23       744114.1 696070.3 792157.9 670637.5 817590.7
```

Figure 13. Holt's Model Training Set Forecast

From the performance evaluation metrics (Figure 14), the Holt's method error measures area also lower compared to the SES, with percentage error around 3.5% and nominal values deviating around Rp 24,900 from actual average spending. With a MASE of 0.81 on the test set, the Holt's method successfully contributes a better forecast versus the naïve forecast.

```
> accuracy(all_food_holt,all_food_test)
                    ME     RMSE      MAE       MPE     MAPE
Training set   5584.714 25571.44 19092.89  1.445063 6.287505
Test set     -24905.389 24975.89 24905.39 -3.562382 3.562382
                  MASE        ACF1
Training set 0.6239956 -0.06733116
Test set     0.8139601          NA
```

Figure 14. Holt's Model Training Set Forecast Accuracy

Autoregressive Integrated Moving Average - ARIMA Method

The initial time series component analysis indicate that the data needs first order differencing to be stationary, and AR1 for the autoregressive component based on the ACF and PACF graph. However, based on the ADF test for the data on first order differencing, the data is still not stationary. To find out the most suitable ARIMA model for the data, the auto.arima function is utilized. 2 models taken into consideration; ARIMA (0,1,0) with drift, and the regular ARIMA (2,1,0) as both has the lowest AIC values.

```
> auto.arima(all_food_train, trace = TRUE)

 ARIMA(2,1,2) with drift         : Inf
 ARIMA(0,1,0) with drift         : 467.4398
 ARIMA(1,1,0) with drift         : 470.1871
 ARIMA(0,1,1) with drift         : 470.2027
 ARIMA(0,1,0)                    : 481.2398
 ARIMA(1,1,1) with drift         : Inf

 Best model: ARIMA(0,1,0) with drift

Series: all_food_train
ARIMA(0,1,0) with drift
```

```
> auto.arima(all_food_train, trace = TRUE, allowdrift = FALSE)

 ARIMA(2,1,2)                    : 479.1076
 ARIMA(0,1,0)                    : 481.2398
 ARIMA(1,1,0)                    : 477.4481
 ARIMA(0,1,1)                    : 480.7225
 ARIMA(2,1,0)                    : 474.1322
 ARIMA(3,1,0)                    : 476.8316
 ARIMA(2,1,1)                    : Inf
 ARIMA(1,1,1)                    : Inf
 ARIMA(3,1,1)                    : 479.2125

 Best model: ARIMA(2,1,0)

Series: all_food_train
ARIMA(2,1,0)
```

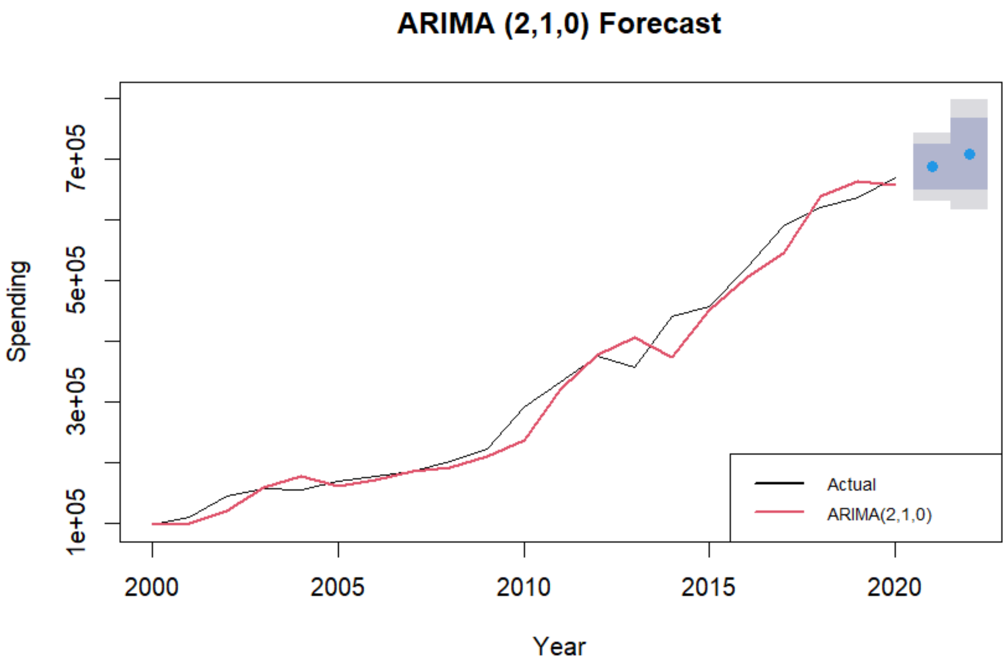
Figure 15. Auto.arima Model Determination

Upon building the 2 model, the regular ARIMA (2,1,0) shows a better performance versus the ARIMA (0,1,0) with drift (Figure 16). The ARIMA (0,1,0) Drift shows better performance in RMSE and MPE, while ARIMA (2,1,0) shows lower error in MAE, MAPE, as well as MASE. Absolute measures of error such as MAE and MAPE give a clear indicator on how the model is performing while weighing a negative and positive value equally. As the food consumption spending forecast is done on a national level which relates to economic measures of the country, MAE can clearly state how much the forecast deviates from the actual value, while MAPE express the percentage value. Therefore, the ARIMA (2,1,0) is chosen as the most optimal ARIMA model in this study.

```
> summary(arima_010drift)
Series: all_food_train
ARIMA(0,1,0) with drift

Coefficients:
         drift
      28678.60
s.e.   5718.99

sigma^2 = 688560256:  log likelihood = -231.37
AIC=466.73   AICc=467.44   BIC=468.73

Training set error measures:
                   ME     RMSE     MAE       MPE     MAPE      MASE
Training set 3.240636 24959.63 19947.3 -2.422128 7.442515 0.6519193
                    ACF1
Training set -0.04911894
> summary(arima_210)
Series: all_food_train
ARIMA(2,1,0)

Coefficients:
         ar1     ar2
      0.2479  0.5069
s.e.  0.1794  0.1830

sigma^2 = 8.45e+08:  log likelihood = -233.32
AIC=472.63   AICc=474.13   BIC=475.62

Training set error measures:
                  ME    RMSE      MAE      MPE     MAPE      MASE
Training set 7791.84 26912.2 19521.75 2.779464 6.426247 0.6380115
                  ACF1
Training set -0.1584119
```

Figure 16. ARIMA Models Accuracy Comparison

The forecast for year 2021 and 2022 is then generated with ARIMA(2,1,0). The forecast result of the training set is shown in Figure 17. The Fitted ARIMA forecast values can be seen to be more accurate compared to the other two previous models.




```
> all_food_arima
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2021       686724.8 649472.0 723977.6 629751.6 743698.0
2022       707611.8 648039.2 767184.5 616503.3 798720.3
```

Figure 17. ARIMA Model Training Set Forecast

To ensure the ARIMA model is sufficient, statistical tests done on the generated model. The Ljung Box test on the model residuals shows a p-value of 0.5, which is larger than the significance value 0.05. Therefore, the ARIMA(2,1,0) model is **Adequate**. The coefficient significance testing then suggested that the ARIMA model might be better represented for the data by including the AR(2) lag value versus the AR(1), indicated by the p-value <0.05 for ar2, but >0.05 for ar1 at the 0.05 significance level.

```
> checkresiduals(arima_210)

        Ljung-Box test

data:  Residuals from ARIMA(2,1,0)
Q* = 2.2501, df = 3, p-value = 0.5221

Model df: 2.   Total lags used: 5

> coeftest(arima_210)

z test of coefficients:

    Estimate Std. Error z value Pr(>|z|)
ar1  0.24791    0.17945  1.3815 0.167126
ar2  0.50694    0.18298  2.7704 0.005598 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 18. ARIMA (2,1,0) Adequacy and Coefficient Test

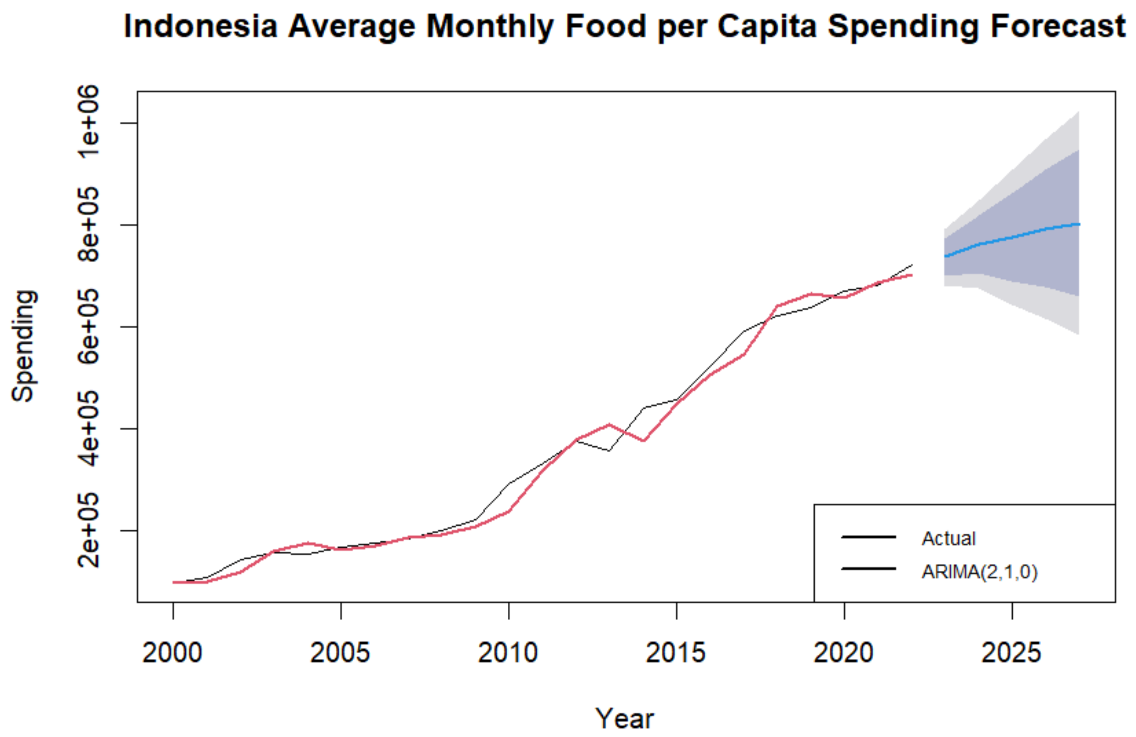
As the ARIMA model is adequate and significant, the performance of the model is compared with the SES and Holt's model to consider which model has the best performance. With ARIMA (2,1,0) accuracy on Figure 19, SES accuracy on Figure 12, and Holt's accuracy on Figure 14, it is concluded that the ARIMA model presented the best results with lowest error values across all measures, as well as the lowest MASE value. Therefore, among the univariate models, the ARIMA model is chosen to generate the forecast for the next 3 years (2023-2025).

```
> accuracy(all_food_arima, all_food_test)
                   ME     RMSE       MAE       MPE     MAPE
Training set 7791.840 26912.20 19521.747 2.7794642 6.426247
Test set     4012.701 10275.38  9459.473 0.5344146 1.333908
                  MASE       ACF1
Training set 0.6380115 -0.1584119
Test set     0.3091553         NA
```

Figure 19. ARIMA Model Training Set Forecast Accuracy

4.2.2 Forecast 2023 – 2025 Period with Best Univariate Model - ARIMA (2,1,0)

ARIMA (2,1,0) is deemed the best forecast model among the Univariate models. The forecast for Average Monthly per Capita Food Consumption Spending in Indonesia for the year 2023-2025 is generated with ARIMA (2,1,0) as shown in Figure 20.




```
> arima_2327_forecast
     Point Forecast    Lo 80    Hi 80    Lo 95     Hi 95
2023       736324.3 700559.7 772088.8 681627.1  791021.5
2024       761160.7 704306.9 818014.4 674210.4  848111.0
2025       775149.0 688589.7 861708.2 642768.0  907529.9
2026       791701.2 677341.4 906061.0 616803.0  966599.5
2027       803068.4 658637.7 947499.2 582180.6 1023956.3
```

Figure 20. ARIMA (2,1,0) Next 5 Years Forecast Nominal Details

The Forecast generated shows that the average food consumption spending in Indonesia will continue its upward trend in the next 5 years. The model has a MASE of 0.63 based on the training set, which is much better compared to the naïve forecast. The forecast model has the probability of 6% by the MAPE or around Rp 19,000 difference between the actual and projected values.

```
> summary(arima_210_whole)
Series: all_food
ARIMA(2,1,0)

Coefficients:
         ar1     ar2
      0.2357  0.5337
s.e.  0.1705  0.1734

sigma^2 = 778814109:  log likelihood = -255.86
AIC=517.71   AICc=519.05   BIC=520.99

Training set error measures:
                  ME     RMSE      MAE      MPE     MAPE      MASE
Training set 7364.55 26023.64 19004.13 2.509706 6.038564 0.6308557
                   ACF1
Training set -0.1544762
```

Figure 21. ARIMA (2,1,0) Next 5 Years Forecast Summary

The Ljung Box test in Figure 22 shows a p-value > 0.05, therefore the Null hypothesis of adequacy is not rejected, and the model is Adequate. Coefficients significance tests shows similar results as what the model give on the forecast with the training set, where the AR(2) value is the significant coefficient, while the AR(1) p-value > 0.05.

```
> checkresiduals(arima_210_whole)

        Ljung-Box test

data:  Residuals from ARIMA(2,1,0)
Q* = 2.517, df = 3, p-value = 0.4722

Model df: 2.   Total lags used: 5

> coeftest(arima_210_whole)

z test of coefficients:

    Estimate Std. Error z value Pr(>|z|)
ar1  0.23573    0.17048  1.3827 0.166743
ar2  0.53368    0.17344  3.0770 0.002091 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 22. ARIMA (2,1,0) Next 5 Years Forecast Adequacy and Coefficients Test

4.2.3 Multivariate Model Implementation and Forecast

The implementation of multivariate forecasting method is executed with Vector Autoregressive (VAR) method. The model is implemented to generate forecast on the overall average monthly per capita food spending by taking into account the spending on food category level. In constructing the VAR forecast, prior analysis including the Granger Causality Test, Cointegration Test, as well as ADF test is done on each variable (food categories).

Granger’s Causality Test

The Granger’s Causality Test aims to test whether there is a causality between values of each variable based on every other existing variable. The tests calculates whether the coefficient of past values in the regression is equal to zero. Table 5 shows the p-value results of each Granger’s Causality Test done on variables of the dataset. A value of <0.05 indicates that the coefficient of past values in the regression equation does not equal zero, therefore the Null hypothesis is rejected and there is *causality* between the two variables.

Focusing on the AllSpend (Overall spending) variable, the Granger’s test show that spendings of Vegetables, Fruits, and Prepared Food are those with p-value <0.05 and therefore indicate causality or influence toward the AllSpend figures.

Table 5. Granger's Causality Tests

Granger's Causality Tests															
Predictors \ Response	AllSpend	Rice_ Grains	Tubers	Fish	Meat	Eggs_ Dairy	Vegetables	Legumes	Fruits	Oils_ Fats	Beverages	Spices	Other_ Consumables	Prepared_ Food	Tobacco
AllSpend		0.013	0.005	0.085	0.712	0.012	0.405	0.026	0.104	0.215	0.006	0.241	0.057	0.051	0.838
Rice_Grains	0.436		0.555	0.418	0.772	0.526	0.656	0.266	0.932	0.002	0.125	0.784	0.511	0.427	0.995
Tubers	0.320	0.154		0.315	0.009	0.042	0.521	0.088	0.309	0.135	0.677	0.115	0.032	0.745	0.100
Fish	0.091	0.433	0.011		0.447	0.059	0.008	0.403	0.107	0.677	0.014	0.132	0.051	0.921	0.486
Meat	0.255	0.043	0.006	0.242		0.163	0.130	0.126	0.056	0.523	0.065	0.062	0.360	0.865	0.191
Eggs_Dairy	0.886	0.000	0.296	0.868	0.065		0.839	0.037	0.661	0.086	0.030	0.321	0.471	0.316	0.746
Vegetables	0.001	0.261	0.201	0.001	0.075	0.001		0.111	0.001	0.465	0.240	0.009	0.094	0.016	0.009
Legumes	0.301	0.432	0.074	0.143	0.169	0.439	0.041		0.169	0.476	0.220	0.921	0.749	0.240	0.717
Fruits	0.004	0.005	0.378	0.037	0.499	0.058	0.049	0.018		0.249	0.003	0.745	0.027	0.032	0.071
Oils_Fats	0.181	0.555	0.011	0.262	0.427	0.294	0.015	0.302	0.047		0.046	0.067	0.248	0.170	0.353
Beverages	0.206	0.069	0.963	0.405	0.400	0.007	0.612	0.052	0.256	0.089		0.640	0.093	0.602	0.050
Spices	0.977	0.150	0.149	0.915	0.530	0.967	0.171	0.885	0.269	0.703	0.317		0.164	0.940	0.944
Other_consumables	0.395	0.102	0.239	0.091	0.846	0.278	0.364	0.468	0.097	0.800	0.088	0.386		0.676	0.450
Prepared_Food	0.010	0.015	0.002	0.626	0.110	0.002	0.543	0.014	0.032	0.023	0.001	0.623	0.009		0.106
Tobacco	0.162	0.037	0.120	0.408	0.967	0.003	0.563	0.000	0.182	0.014	0.219	0.756	0.087	0.805	

Table 6. Cointegration Matrix

Cointegration Matrix															
Predictors \ Response	AllSpend	Rice_ Grains	Tubers	Fish	Meat	Eggs_ Dairy	Vegetables	Legumes	Fruits	Oils_ Fats	Beverages	Spices	Other_ consumables	Prepared_ Food	Tobacco
AllSpend		No	No	No	No	No	Yes	No	No	No	Yes	No	No	Yes	No
Rice_Grains	No		No	No	No	No	No	No	No	No	No	No	No	No	No
Tubers	No	No		No	Yes	No	No	No	No	No	No	Yes	No	No	No
Fish	No	No	No		No	No	No	No	No	Yes	No	No	No	No	No
Meat	No	No	Yes	Yes		No	Yes	No	No	No	Yes	Yes	No	Yes	No
Eggs_Dairy	No	No	No	No	Yes		No	No	No	No	Yes	No	Yes	No	No
Vegetables	Yes	Yes	No	Yes	Yes	No		No	No	No	No	Yes	Yes	Yes	No
Legumes	Yes	No	No	No	No	No	No		No	No	Yes	No	No	No	No
Fruits	No	No	Yes	No	No	No	No	No		No	Yes	No	No	No	Yes
Oils_Fats	No	No	No	No	No	No	No	No	No		No	No	No	No	No
Beverages	Yes	No	No	Yes	Yes	Yes	No	Yes	Yes	No		No	Yes	Yes	Yes
Spices	No	No	Yes	No	Yes	No	Yes	No	No	Yes	No		No	Yes	No
Other_consumables	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No		No	No
Prepared_Food	Yes	No	No	No	Yes	No	No	No	No	Yes	Yes	Yes	No		No
Tobacco	No	No	No	No	No	No	No	No	Yes	No	Yes	No	No	Yes	

Cointegration Test

Next, all the variable combinations are tested on the cointegration component, which is used to establish whether there is a correlation between two time series in the long term. The results shown in Table 6 show results on the cointegration test, in a similar format as the Granger's Causality; the left side are the predictors that contribute to the responses of each column variable. From the cointegration test, it is concluded that not all individual food category expenditures influence the overall expenditures pattern. This indicates that variables that does not show any cointegration is not necessary to be put as input variables in the VAR model, From the table, variables that influence overall AllSpend spending include Vegetables, Legumes, Beverages, and Prepared Food.

Augmented-Dickey Fuller (ADF) Test

The last test implemented prior to implementation of the VAR method is the ADF test, which is done to evaluate stationarity of the time series data. As VAR models works best when the time series is stationary, differencing of the time series need to be considered to gain more accurate forecast results. Details of the ADF test result is attached in Appendix B. Summary of the ADF Test result is as stated in Table 7.

Table 7. ADF Test Result Summary

Variables	ADF on Original Data	ADF on 1st Order Differenced	ADF on 2nd Order Differenced
AllSpend	Not Stationary	Stationary	Stationary
Rice_Grains	Not Stationary	Stationary	Stationary
Tubers	Not Stationary	Stationary	Not Stationary
Fish	Not Stationary	Not Stationary	Stationary
Meat	Not Stationary	Not Stationary	Stationary
Eggs_Dairy	Not Stationary	Stationary	Stationary
Vegetables	Not Stationary	Not Stationary	Stationary
Legumes	Not Stationary	Stationary	Stationary
Fruits	Not Stationary	Stationary	Stationary
Oils_Fats	Not Stationary	Stationary	Stationary
Beverages	Not Stationary	Stationary	Stationary
Spices	Not Stationary	Not Stationary	Stationary
Other_consumables	Not Stationary	Not Stationary	Not Stationary
Prepared_Food	Not Stationary	Not Stationary	Stationary
Tobacco	Not Stationary	Stationary	Stationary

The previous 2 tests indicated that the variables that contribute or correlate with the AllSpend values include the Vegetables, Fruits, and Prepared Food from their Granger's Causality p-values, as well as Vegetables, Legumes, and Beverages, and Prepared Fruit from their Cointegration test. From the result of these 2 tests, the variables chosen to be put as input for VAR forecasting include *Vegetables, Fruits,* and *Prepared Food* as well as the target forecast variable of *AllSpend*. The dataset is differenced twice as the input variables that are being considered are still not stationary after 1st differencing.

VAR Forecast on Training Set

Similar with the procedure done with the univariate forecasting method, the dataset consisting of *AllSpend*, *Vegetables*, *Fruits,* and *Prepared Food* values are split into training period (2000-2020) and testing period (2021-2022). Forecasts are generated for the 2021-2022 period, with forecasted values to be compared with the actual values. In this study, the forecasting with VAR was run on two variations. The initial forecasting was done on the 2nd order differenced data.

As stated in in Figure 23, results of the forecast on 2nd order differencing data does not fit into the original time series data, with inverse differenced forecast values of *AllSpend* only reaching up to IDR 72.985 in 2022, which is 90% MAPE from the original value of IDR 721,084. Forecasted values of other variables are also much lower than what they are expected to be. Although the Durbin-Watson correlation test of residuals stated that the model is sufficient in explaining the relationships that exist in the data (All values close to 2), the forecast result from this model cannot be accepted.

	2021	2022
AllSpend_2d	-8103.07	8765.57
Vegetables_2d	-5092.66	-7629.33
Fruits_2d	-694.46	2685.65
Prepared_Food_2d	21690.49	-15029.38
AllSpend_1d	23608.93	32374.50
AllSpend_forecast	40610.93	72985.43
Vegetables_1d	4599.34	-3029.98
Vegetables_forecast	14741.34	11711.36
Fruits_1d	12799.54	15485.19
Fruits_forecast	17767.54	33252.74
Prepared_Food_1d	17344.49	2315.11
Prepared_Food_forecast	10357.49	12672.60

	Durbin-Watson
AllSpend	1.52
Vegetables	2.28
Fruits	2.75
Prepared_Food	1.86

Figure 23. VAR Train Set Forecast on 2nd Order Differenced Data

Thus, the VAR forecasting attempt is then attempted on the original time series data, where no differencing was implemented. Result of VAR Forecast on the non-differenced data is shown in Figure 24. Details of the regression results can be seen in Appendix C. The forecast results show very aligned numbers with the time series pattern, a steady climb of upward trend. The Durbin Watson's test also indicates the model is sufficient in explaining the relationships within variables of the dataset.

	AllSpend	Vegetables	Fruits	Prepared_Food
0	690643.04	42192.74	36729.83	268458.23
1	709048.09	45813.99	35659.37	274907.31

	Durbin-Watson
AllSpend	2.36
Vegetables	1.86
Fruits	2.08
Prepared_Food	2.19

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sat, 09, Mar, 2024
Time:                     15:47:52
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                    68.1937
Nobs:                     20.0000    HQIC:                   67.3923
Log likelihood:          -765.495    FPE:                1.59405e+29
AIC:                      67.1979    Det(Omega_mle):     6.52924e+28
--------------------------------------------------------------------
Results for equation AllSpend
===================================================================================
                      coefficient       std. error           t-stat            prob
-----------------------------------------------------------------------------------
const               -13650.783632     21986.568160           -0.621           0.535
L1.AllSpend              1.960761         0.529630            3.702           0.000
L1.Vegetables           -1.155165         3.055659           -0.378           0.705
L1.Fruits               -8.718006         5.013367           -1.739           0.082
L1.Prepared_Food        -0.977941         0.647348           -1.511           0.131
===================================================================================
```

Figure 24. VAR Train Set Forecast on No Differencing Data

The performance evaluation measure values in Figure 25 also indicate that the model also exceed the ARIMA (2,1,0) model performance in forecasting the values of the 2021 and 2022 period values, with percentage error only spanning 1.5% and absolute error by ±IDR 10,000 from the original values.

```
Metrics for 2021-2022 VAR Model:
MAE: 10700.47
RMSE: 10783.48
MAPE: 1.52%
SMAPE: 0.76%
MPE: -0.15%
Tracking Signal: [ 0.8684614  -0.24768143]
```

Figure 25. VAR Train Set Forecast Performance Measures

As the VAR multivariate model presented better results compared to the chosen univariate model of ARIMA (2,1,0), the forecast for the next 5 years is thereby also generated with the VAR method.

VAR Forecast on 2023-2027 Food Expenditure

With input values of *AllSpend, Vegetables, Fruits, and Prepared Food* from the year 2000-2022, the forecast of food per capita expenditure in Indonesia is generated with the VAR model for the year 2023-2027. The results of the forecast are shown in a line graph format in Figure 26, with each line color depicting a different food category. All food category expenditure as well as the overall expenditure are projected to continue their upward trend, with the *Prepared Food* category leading on the highest amount of expenditure change. The details of the forecast numbers are attached in Appendix D.

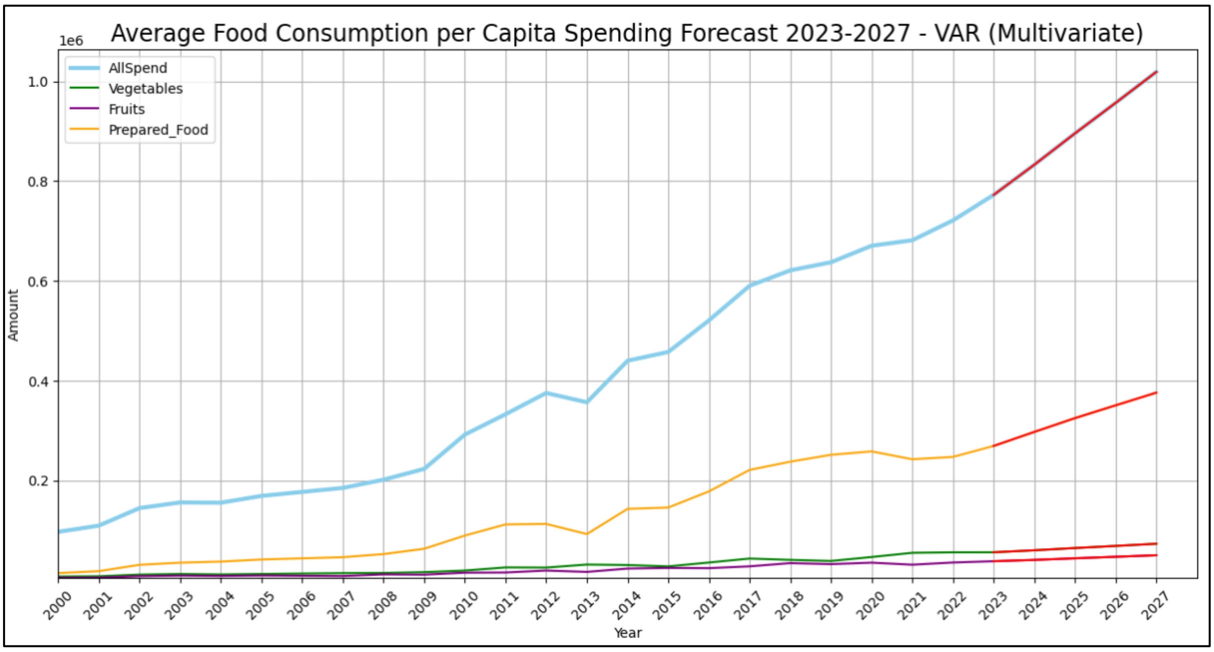


Figure 26. VAR Forecast Line Graph 2023 – 2027

Details of the forecasted values as well as the VAR model regression results are attached in Figure 27. Numbers of the overall food per capita expenditure is predicted to rise by around IDR 50,000 - 60,000 per year from 2023 onwards, ending on a value of IDR 974,643 by 2027. The Durbin Watson's test values of around 1.5-2.5 indicates that the model is sufficient in depicting relationships within the existing variables with minimal indication of autocorrelation problem. The *Vegetable* variable with DW score value of 1.66 indicates a slight positive autocorrelation, while the *Prepared Food* and *AllSpend* values indicate a slight negative autocorrelation. However, as the values of DW score are still close to 2, the model is deemed sufficient as the assumption of independence between observations is not violated.

	AllSpend	Vegetables	Fruits	Prepared_Food
2023	772210.14	55738.94	37805.03	268885.69
2024	832739.51	59702.34	40410.19	297000.03
2025	895607.59	64217.37	43659.66	324690.90
2026	956752.51	68456.11	46719.46	350306.34
2027	1018889.94	72822.03	49764.15	375750.47

	Durbin-Watson
AllSpend	2.48
Vegetables	1.66
Fruits	2.05
Prepared_Food	2.15

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sun, 10, Mar, 2024
Time:                     00:02:44
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                    69.2251
Nobs:                     22.0000    HQIC:                   68.4669
Log likelihood:          -855.432    FPE:                4.43952e+29
AIC:                      68.2332    Det(Omega_mle):     1.95691e+29
--------------------------------------------------------------------
Results for equation AllSpend
==================================================================================
                      coefficient       std. error           t-stat            prob
----------------------------------------------------------------------------------
const               -11222.204493     20890.702359           -0.537           0.591
L1.AllSpend              2.076243         0.455011            4.563           0.000
L1.Vegetables           -2.659446         2.406299           -1.105           0.269
L1.Fruits               -8.630075         4.497050           -1.919           0.055
L1.Prepared_Food        -1.059333         0.591840           -1.790           0.073
==================================================================================
```

Figure 27. VAR 2023 – 2027 Forecast Model Details

The regression equation probability for the AllSpend variable in Figure 27 shows true alignment with real context; as the AllSpend coefficient is the most significant in determining the AllSpend trend, whilst the other variables are less significant, with the Fruits variable being the 2nd most significant at 0.055 probability. Although the other probability p-values are >0.05, the t-stat values of -1 which is larger than the significance value of 0.05 indicate that each of the included supporting variables do have a significant effect towards the dependent variable *AllSpend*.

4.3 ARIMA and VAR Model Comparison and Discussion

Amongst the models applied toward the time series dataset in this study, the ARIMA model comes out as the best univariate forecasting method. And compared with the sole multivariate model utilized – the VAR method, the VAR method presented an even better performance versus the ARIMA model.

In comparing the outcomes of both models, firstly the approach used by each of the two model need to be highlighted. **The ARIMA** model is able to generate accurate results to the forecast due to its consideration of three different components on a time series data; the **level, trend, and seasonality**. Although is univariate in nature, the analysis on multiple component of the time series allows the ARIMA model to give an accurate forecast towards the data; given that the current trend of the data is representative of what is going to happen in the future.

Meanwhile, the multivariate **VAR** method in itself considers only the AR component. However, due to its multivariate nature, VAR considers **the AR component of every variable** that are included in the dataset, and create a forecast equation from relationships between the variables. In the context of this study, the variables include the *vegetables*, *fruits* and *prepared food* expenditures category which shows causality and cointegration with the target variable *AllSpend* that represents the overall average monthly food expenditure.

As one of the **VAR** model **assumptions** is that the time series model is **stationary**, in this study the stationarity component of the data is executed by performing a manual differencing process prior to the VAR forecast execution. This step however does not produce good results as the forecast result yielded from the 2nd order differenced data actually is not applicable to the time series. The VAR forecast result that shows the best performance among all models are taken from the original dataset values where the values are not differenced and the data is not stationary. This may be due to VAR model picking up on the trend in a data and produce forecasts that follow the trend. However, as the VAR model is supposed to be executed on stationary data, it needs to be highlighted that the results gained from this non-stationary series may not be reliable in the long run, especially if the long-term trend that exist in the food expenditure data is not sustainable anymore.

Addressing the ARIMA model forecast variations, initially when the auto.arima function was run in its default settings, the recommended model is the ARIMA (0,1,0) with drift. An ARIMA model with a drift component means the ARIMA model is incorporated with an additional constant that represent a systematic linear trend; which is useful when the time series data exhibit such pattern. The recommendation of this model variation indicate that the AllSpend time series shows a constant upward trend that allows an **ARIMA** model with Drift to perform best. The **drift component** shows that with the constant variable there, the time series data does not need to have any autoregressive characteristic anymore, and thus only need to go through 1st order differencing to ensure stationarity.

Then, to have another ARIMA model implementation apart from the one with Drift, the auto.arima is run once again with a **No Drift** criteria, with the ARIMA(2,1,0) chosen. With this regular ARIMA model, the AR lag 2 component and differencing lag 1 component is able to **depict** the **characteristics** of the time series with **better clarity**, as all pattern and trend of the data is defined by the ARIMA components themselves. The ARIMA (2,1,0) model criteria also align with the initial ACF, PACF, and stationarity analysis that define the data need a 1st order stationarity differencing and an AR (2) component from the ADF test result.

4.4 Conclusion on Implementations

The existing studies on time series forecasting in the similar domain of food expenditure in Indonesia has not implemented to more complex models of ARIMA and VAR. In this study, both the novel methods and previous methods that have been used previously are experimented and tested upon the time series data of monthly food per capita expenditure. The benchmark models implemented include the SES and Holt's method, while the novel methos includes the ARIMA and VAR. Prior to the forecast implementation, analysis on the pattern and component of the time series data indicates that the data has a trend component, with a need of 1st order differencing for stationarity, 2nd lag order for Autoregression, and does not exhibit seasonality.

As the data has not seasonality component, the Holt Winter's proposed method is converted to the Holt's method, which is the simpler model version that accommodate data with no seasonality component. Results of the forecast implementation on training set indicate the ARIMA model to be superior compared to other univariate models.

The chosen ARIMA (2,1,0) model predicted that the overall average monthly food per capita expenditure in the cities region of Indonesia will rise to IDR 803,068 in 2027, with IDR 150,000 lower and upper bound value on either side. This forecast has an MAE value of Rp 9,500, RMSE of Rp 10,275, and MAPE of 1.33%, which is the lowest error measures value compared to the other univariate models.

Application of the multivariate VAR method gives a better understanding about the relationship between the overall spending pattern with the pattern that exist within each food category. Due to its multivariate nature, the VAR model is able to capture the pattern of the model better and comes out with a better performance measures metrics. Although improvements and modifications are necessary to be done in future studies regarding the stationarity and non-stationarity issue of the time series prior to the forecast execution.

CHAPTER V
CONCLUSION AND RECOMMENDATIONS

The execution of time series forecasting with multiple time series method of univariate and multivariate natures have yielded results contributing to the prediction of Average Monthly per Capita Food Expenditure in Indonesia's cities region. This chapter consists of the conclusions taken and recommendations given for future study improvement and development.

5.1 Conclusion

Referring to the objectives of the study, this project focuses on three areas; analysis on the pattern and component of the time series, implementation of multiple time series models from the univariate and multivariate nature, as well as the forecast generation for Monthly Average per Capita Food Expenditure for Indonesia Cities region for at least the next 3 years. According to the implementation and results gained from the study, the conclusion of this project are as follows:

1. The time series data of Monthly Average per Capita Food Expenditure in Indonesia Cities region exhibit a constant upward trend, which indicates non-stationarity and trend component. The ADF test, ACF, and PACF plot shows the time series model has an AR (2) component, with no seasonality.
2. The ARIMA model outperforms the other univariate models that are implemented in the dataset, with less than 3% percentage error compared to -3% error exhibited by the Holt's model. The ARIMA (2,1,0) has a Rp 9,500 MAE, Rp 10,275 RMSE, 1.33% MAPE when tested with the train-test set, with a MASE of 0.3, indicating the ARIMA forecast is much better compared to the naïve forecast.
3. Execution of the sole multivariate model of VAR produces even better results compared to the ARIMA model, with percentage error of < 1% when tested against the test set. This conclude that multivariate time series model can exhibit better results compared to the univariate models as it takes into account the relationship that exists between the input variables (*Vegetables, Fruit,* and *Prepared Food*) with the target variable *AllSpend*.

4. Forecasts are generated for the Monthly Average per Capita Food Expenditure in Indonesia cities region for the year 2023-2027 with the univariate ARIMA and multivariate VAR method. Results of the ARIMA forecast can be seen in Appendix D.

5.2 Recommendations

The implementation of time series models and forecasting of the food expenditure data in this study has generated contribution towards predictions of food expenditure that can be utilized for up to the next 5 years. However, there are still a lot of room for improvement that can be done to improve on the robustness and performance of the model. Below are a list of recommendations that may be implemented in future studies:

1. Further evaluate the input variables chosen for VAR model building. Consideration of additional variables at the food category level may be able to enhance forecast accuracy.
2. Prior to executing the VAR model forecast, conduct further analysis and suitable amount of stationarity differencing to ensure the data is not excessively adjusted from its original values.
3. The ARIMA model implementation may be improved by considering additional parameters such as the Drift models. Combining the VAR and ARIMA model is also a way forward to improve forecast accuracy by creating a multivariate ARIMA model.

REFERENCES

Amolegbe, K. B., Upton, J., Bageant, E., & Blom, S. (2021). Food price volatility and household food security: Evidence from Nigeria. *Food Policy*, *102*, 102061. https://doi.org/10.1016/J.FOODPOL.2021.102061

Arndt, C., Diao, X., Dorosh, P., Pauw, K., & Thurlow, J. (2023). The Ukraine war and rising commodity prices: Implications for developing countries. *Global Food Security*, *36*, 100680. https://doi.org/10.1016/J.GFS.2023.100680

Baggio, R., & Klobas, J. (2011). *Quantitative Methods in Tourism*. Channel View Publications.

Beglaryan, M., & Pipoyan, D. (2023). Review of agrifood systems and malnutrition in Armenia. *Sustainable and Nutrition-Sensitive Food Systems for Healthy Diets and Prevention of Malnutrition in Europe and Central Asia - FAO*, 175–208.

Burlyaeva, E. A., Александровна, Б. Е., Kambarov, A. O., O., K. A., Nikityuk, D. B., & Б., Н. Д. (2020). Changes in the nutritional structure of the population of Russia for 100 years. *Clinical Nutrition and Metabolism*, *1*(1), 17–26. https://doi.org/10.17816/clinutr21188

Das, R. C. (2020). Interplays among R&D spending, patent and income growth: new empirical evidence from the panel of countries and groups. *Journal of Innovation and Entrepreneurship*, *9*(1), 1–22. https://doi.org/10.1186/S13731-020-00130-8/TABLES/9

Desiyanti, A., Toharudin, T., & Suparman, Y. (2022). The implementation of empirical best linear unbiased prediction-Fay Herriot (EBLUP-FH) on the estimation of average per capita expenditure at district level in West Sumatra Province in 2019. *J. Math. Comput. Sci.*, *12*(0), Article ID 129. https://doi.org/10.28919/10.28919/JMCS/7233

Fan, S., & Brzeska, J. (2014). Feeding More People on an Increasingly Fragile Planet: China's Food and Nutrition Security in a National and Global Context. *Journal of Integrative Agriculture*, *13*(6), 1193–1205. https://doi.org/10.1016/S2095-3119(14)60753-X

Gershon, O., Ezenwa, N. E., & Osabohien, R. (2019). Implications of oil price shocks on net oil-importing African countries. *Heliyon*, *5*(8), e02208. https://doi.org/10.1016/j.heliyon.2019.e02208

GHI. (2022). *Indonesia - Global Hunger Index (GHI)* . https://www.globalhungerindex.org/indonesia.html

Ginanjar, I., Wulandary, S., & Toharudin, T. (2022). (PDF) Empirical Best Linear Unbiased Prediction Method with K-Medoids Cluster for Estimate Per Capita Expenditure of Sub-District Level. *IAENG International Journal of Applied Mathematics*, *52*(3). https://www.researchgate.net/publication/363087875_Empirical_Best_Linear_Unbiased_Prediction_Method_with_K-Medoids_Cluster_for_Estimate_Per_Capita_Expenditure_of_Sub-District_Level

Grote, U. (2014). Can we improve global food security? A socio-economic and political perspective. *Food Security*, *6*(2), 187–200. https://doi.org/10.1007/S12571-013-0321-5/METRICS

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting Principles and Practice*. OTexts.

IFPRI. (2022). *Food Prices | IFPRI*. https://www.ifpri.org/topic/food-prices

Indri, J., Yulian, J., & Erni, P. (2022). FORECASTING PRODUCTION AND CONSUMPTION OF RICE AND INFLUENCE OF DETERMINANTS TO INCREASE FOOD SECURITY IN THE SOUTH SUMATRA REGION, INDONESIA. *Russian Journal of Agricultural and Socio-Economic Sciences*, *121*(1), 144–156. https://doi.org/10.18551/rjoas.2022-01.17

Jakovljevic, M., Lamnisos, D., Westerman, R., Chattu, V. K., & Cerda, A. (2022). Future health spending forecast in leading emerging BRICS markets in 2030: health policy implications. *Health Research Policy and Systems*, *20*(1), 1–14. https://doi.org/10.1186/S12961-022-00822-5/TABLES/9

Kilian, L., & Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press. https://doi.org/10.1017/9781108164818

Korir, L., Rizov, M., & Ruto, E. (2020). Food security in Kenya: Insights from a household food demand model. *Economic Modelling*, *92*, 99–108. https://doi.org/10.1016/J.ECONMOD.2020.07.015

Luan, Y., Fischer, G., Wada, Y., Sun, L., & Shi, P. (2018). Quantifying the impact of diet quality on hunger and undernutrition. *Journal of Cleaner Production*, *205*, 432–446. https://doi.org/10.1016/J.JCLEPRO.2018.09.064

Mills, T. C. (2019). *Applied Time Series Analysis*. Elsevier.

Mone, D. M. V, & Utami, E. D. (2021). Determinan Kelaparan di Indonesia Tahun 2015-2019. *Seminar Nasional Official Statistics*, *2021*(1), 547–556. https://doi.org/10.34123/semnasoffstat.v2021i1.962

Saragih, B. F. F. (2018). *Peramalan Rata-Rata Pengeluaran untuk Konsumsi Makanan Per Kapita Per Bulan di Kabupaten Simalungun Tahun 2018-2019*. https://repositori.usu.ac.id/handle/123456789/6778

Schröer, C., Kruse, F., & Gómez, J. M. (2021). A Systematic Literature Review on Applying CRISP-DM Process Model. *Procedia Computer Science*, *181*, 526–534. https://doi.org/10.1016/J.PROCS.2021.01.199

Sharma, S., Bansal, M., & Saxena, A. K. (2022). Forecasting of GDP (Gross Domestic Product) per Capita Using (ARIMA) Data-Driven Intelligent Time Series Predicting Approach. *2022 International Conference on Sustainable Islamic Business and Finance, SIBF 2022*, 85–90. https://doi.org/10.1109/SIBF56821.2022.9939928

Suriani, N., & Noviar, H. (2022). Analisis Trend Pengeluaran Konsumsi Pangan Di Provinsi Aceh. *Jurnal Ilmiah Ekonomi Terpadu*, *2*(2), 84–93. http://jurnal.utu.ac.id/jimetera/article/view/5904

UN Statistics Division. (2016). *Goal 2: End hunger, achieve food security and improved nutrition and promote sustainable agriculture — SDG Indicators*. https://unstats.un.org/sdgs/report/2016/goal-02/

Voumik, L. C., & Smrity, D. Y. (2020). Forecasting GDP Per Capita In Bangladesh: Using Arima Model. *European Journal of Business and Management Research*, *5*(5). https://doi.org/10.24018/EJBMR.2020.5.5.533

Wardani, S., Solikhun, S., & Andani, S. R. (2019). Jaringan Saraf Tiruan Memprediksi Rata-Rata Pengeluaran Perkapita Untuk Makan dan Bukan Makanan Menurut Provinsi. *Seminar Nasional Sains Dan Teknologi Informasi (SENSASI)*, *2*(1), 630–635. http://prosiding.seminar-id.com/index.php/sensasi/article/view/378

WHO. (2022). *Global Hunger Index (GHI)*. https://www.who.int/data/nutrition/nlis/info/global-hunger-index-(ghi)

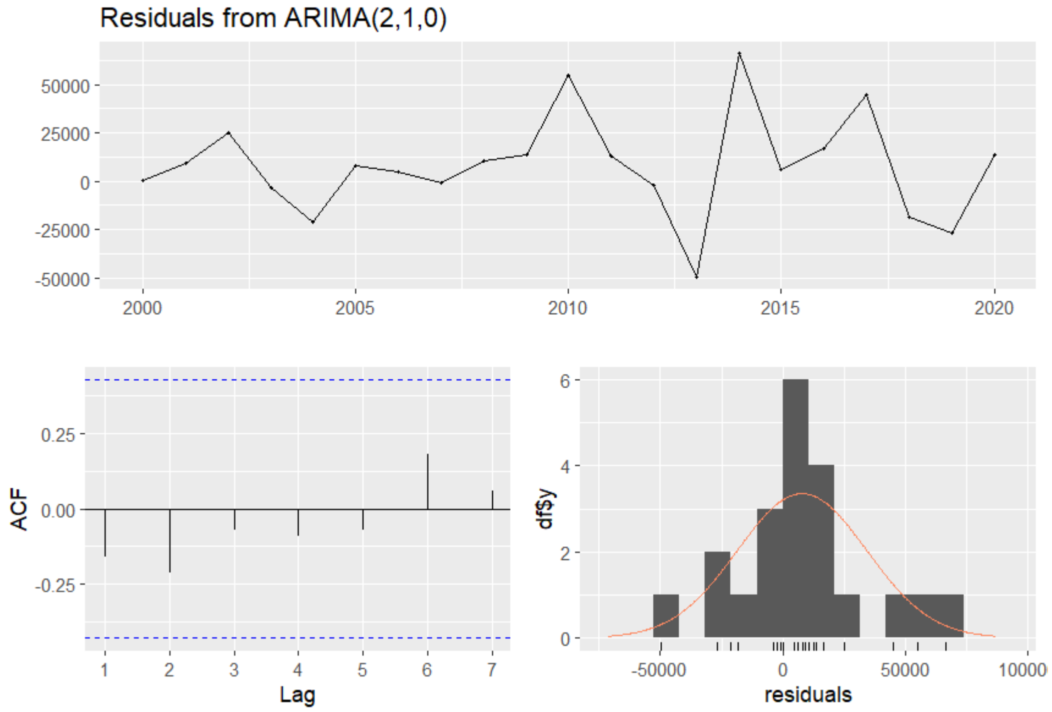
Zeng, G., Zhang, C., Li, S., & Sun, H. (2021). The Dynamic Impact of Agricultural Fiscal Expenditures and Gross Agricultural Output on Poverty Reduction: A VAR Model Analysis. *Sustainability 2021, Vol. 13, Page 5766*, *13*(11), 5766. https://doi.org/10.3390/SU13115766

Zhang, B., & Nguyen, B. H. (2020). Real-time Forecasting of the Australian Macroeconomy Using Flexible Bayesian VARs. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3716598

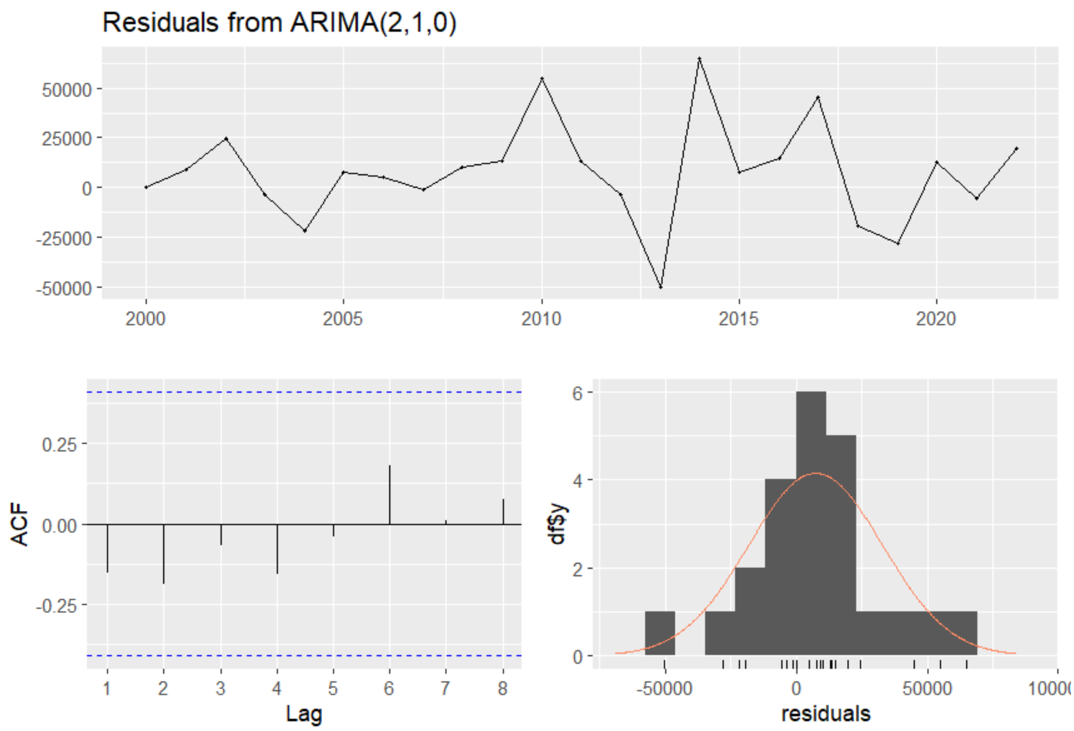
Zheng, A., Fang, Q., Zhu, Y., Jiang, C., Jin, F., & Wang, X. (2020). An application of ARIMA model for predicting total health expenditure in China from 1978-2022. *Journal of Global Health*, *10*(1). https://doi.org/10.7189/JOGH.10.010803

APPENDIX A – ARIMA Model Residuals

ARIMA_210



ARIMA_210_Whole



APPENDIX B – ADF Test of Variables

ADF on Original Data

```
    Augmented Dickey-Fuller Test on "AllSpend"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = 1.0213
 No. Lags Chosen        = 1
 Critical value 1%      = -3.788
 Critical value 5%      = -3.013
 Critical value 10%     = -2.646
 => P-Value = 0.9945. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Rice_Grains"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -0.4612
 No. Lags Chosen        = 0
 Critical value 1%      = -3.77
 Critical value 5%      = -3.005
 Critical value 10%     = -2.643
 => P-Value = 0.8994. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Tubers"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = 2.9028
 No. Lags Chosen        = 1
 Critical value 1%      = -3.788
 Critical value 5%      = -3.013
 Critical value 10%     = -2.646
 => P-Value = 1.0. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Fish"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = 1.7684
 No. Lags Chosen        = 6
 Critical value 1%      = -3.924
 Critical value 5%      = -3.068
 Critical value 10%     = -2.674
 => P-Value = 0.9983. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Meat"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -0.7028
 No. Lags Chosen        = 8
 Critical value 1%      = -4.012
 Critical value 5%      = -3.104
 Critical value 10%     = -2.691
 => P-Value = 0.846. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Eggs_Dairy"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -0.033
 No. Lags Chosen        = 1
 Critical value 1%      = -3.788
 Critical value 5%      = -3.013
 Critical value 10%     = -2.646
 => P-Value = 0.9557. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Vegetables"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = 2.1937
 No. Lags Chosen        = 3
 Critical value 1%      = -3.833
 Critical value 5%      = -3.031
 Critical value 10%     = -2.656
 => P-Value = 0.9989. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Legumes"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = 1.0785
 No. Lags Chosen        = 1
 Critical value 1%      = -3.788
 Critical value 5%      = -3.013
 Critical value 10%     = -2.646
 => P-Value = 0.995. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Fruits"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = 0.1222
 No. Lags Chosen        = 1
 Critical value 1%      = -3.788
 Critical value 5%      = -3.013
 Critical value 10%     = -2.646
 => P-Value = 0.9675. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Oils_Fats"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = 1.2077
 No. Lags Chosen        = 9
 Critical value 1%      = -4.069
 Critical value 5%      = -3.127
 Critical value 10%     = -2.702
 => P-Value = 0.996. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Beverages"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = 1.1793
 No. Lags Chosen        = 2
 Critical value 1%      = -3.809
 Critical value 5%      = -3.022
 Critical value 10%     = -2.651
 => P-Value = 0.9958. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Spices"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = 2.2768
 No. Lags Chosen        = 9
 Critical value 1%      = -4.069
 Critical value 5%      = -3.127
 Critical value 10%     = -2.702
 => P-Value = 0.9989. Do not reject H0.
 => Series is Non-Stationary.
```

```
   Augmented Dickey-Fuller Test on "Other_consumables"
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level     = 0.05
Test Statistic         = 2.0468
No. Lags Chosen        = 9
Critical value 1%      = -4.069
Critical value 5%      = -3.127
Critical value 10%     = -2.702
=> P-Value = 0.9987. Do not reject H0.
=> Series is Non-Stationary.


   Augmented Dickey-Fuller Test on "Prepared_Food"
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level     = 0.05
Test Statistic         = -1.1092
No. Lags Chosen        = 9
Critical value 1%      = -4.069
Critical value 5%      = -3.127
Critical value 10%     = -2.702
=> P-Value = 0.7114. Do not reject H0.
=> Series is Non-Stationary.


   Augmented Dickey-Fuller Test on "Tobacco"
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level     = 0.05
Test Statistic         = 0.8084
No. Lags Chosen        = 1
Critical value 1%      = -3.788
Critical value 5%      = -3.013
Critical value 10%     = -2.646
=> P-Value = 0.9918. Do not reject H0.
=> Series is Non-Stationary.
```

ADF on 1st Order Differenced Data

```
Augmented Dickey-Fuller Test on "AllSpend" Diff 1
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -4.6892
 No. Lags Chosen        = 0
 Critical value 1%      = -3.788
 Critical value 5%      = -3.013
 Critical value 10%     = -2.646
 => P-Value = 0.0001. Reject H0.
 => Series is Stationary.


    Augmented Dickey-Fuller Test on "Rice_Grains" Diff 1
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -5.3544
 No. Lags Chosen        = 0
 Critical value 1%      = -3.788
 Critical value 5%      = -3.013
 Critical value 10%     = -2.646
 => P-Value = 0.0. Reject H0.
 => Series is Stationary.


    Augmented Dickey-Fuller Test on "Tubers" Diff 1
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -3.2042
 No. Lags Chosen        = 9
 Critical value 1%      = -4.138
 Critical value 5%      = -3.155
 Critical value 10%     = -2.714
 => P-Value = 0.0197. Reject H0.
 => Series is Stationary.
```

```
   Augmented Dickey-Fuller Test on "Fish" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level     = 0.05
Test Statistic         = -2.3383
No. Lags Chosen        = 9
Critical value 1%      = -4.138
Critical value 5%      = -3.155
Critical value 10%     = -2.714
=> P-Value = 0.1599. Do not reject H0.
=> Series is Non-Stationary.


   Augmented Dickey-Fuller Test on "Meat" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level     = 0.05
Test Statistic         = -2.4777
No. Lags Chosen        = 3
Critical value 1%      = -3.859
Critical value 5%      = -3.042
Critical value 10%     = -2.661
=> P-Value = 0.121. Do not reject H0.
=> Series is Non-Stationary.


   Augmented Dickey-Fuller Test on "Eggs_Dairy" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level     = 0.05
Test Statistic         = -6.1849
No. Lags Chosen        = 0
Critical value 1%      = -3.788
Critical value 5%      = -3.013
Critical value 10%     = -2.646
=> P-Value = 0.0. Reject H0.
=> Series is Stationary.
```

```
   Augmented Dickey-Fuller Test on "Vegetables" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -2.6954
No. Lags Chosen       = 2
Critical value 1%     = -3.833
Critical value 5%     = -3.031
Critical value 10%    = -2.656
=> P-Value = 0.0748. Do not reject H0.
=> Series is Non-Stationary.
```

```
   Augmented Dickey-Fuller Test on "Oils_Fats" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -7.6794
No. Lags Chosen       = 8
Critical value 1%     = -4.069
Critical value 5%     = -3.127
Critical value 10%    = -2.702
=> P-Value = 0.0. Reject H0.
=> Series is Stationary.
```

```
   Augmented Dickey-Fuller Test on "Legumes" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -5.9418
No. Lags Chosen       = 0
Critical value 1%     = -3.788
Critical value 5%     = -3.013
Critical value 10%    = -2.646
=> P-Value = 0.0. Reject H0.
=> Series is Stationary.
```

```
   Augmented Dickey-Fuller Test on "Beverages" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -3.2972
No. Lags Chosen       = 9
Critical value 1%     = -4.138
Critical value 5%     = -3.155
Critical value 10%    = -2.714
=> P-Value = 0.015. Reject H0.
=> Series is Stationary.
```

```
   Augmented Dickey-Fuller Test on "Fruits" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -7.6653
No. Lags Chosen       = 0
Critical value 1%     = -3.788
Critical value 5%     = -3.013
Critical value 10%    = -2.646
=> P-Value = 0.0. Reject H0.
=> Series is Stationary.
```

```
   Augmented Dickey-Fuller Test on "Spices" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = 0.2412
No. Lags Chosen       = 9
Critical value 1%     = -4.138
Critical value 5%     = -3.155
Critical value 10%    = -2.714
=> P-Value = 0.9745. Do not reject H0.
=> Series is Non-Stationary.
```

```
   Augmented Dickey-Fuller Test on "Other_consumables" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = 0.4842
No. Lags Chosen       = 9
Critical value 1%     = -4.138
Critical value 5%     = -3.155
Critical value 10%    = -2.714
=> P-Value = 0.9844. Do not reject H0.
=> Series is Non-Stationary.
```

```
   Augmented Dickey-Fuller Test on "Prepared_Food" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = 0.3427
No. Lags Chosen       = 8
Critical value 1%     = -4.069
Critical value 5%     = -3.127
Critical value 10%    = -2.702
=> P-Value = 0.9792. Do not reject H0.
=> Series is Non-Stationary.
```

```
   Augmented Dickey-Fuller Test on "Tobacco" Diff 1
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -2.8941
No. Lags Chosen       = 7
Critical value 1%     = -4.012
Critical value 5%     = -3.104
Critical value 10%    = -2.691
=> P-Value = 0.046. Reject H0.
=> Series is Stationary.
```

ADF Test on 2nd Order Differenced Data

```
Augmented Dickey-Fuller Test on "AllSpend" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -9.3182
 No. Lags Chosen       = 0
 Critical value 1%     = -3.809
 Critical value 5%     = -3.022
 Critical value 10%    = -2.651
 => P-Value = 0.0. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Rice_Grains" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -6.5615
 No. Lags Chosen       = 1
 Critical value 1%     = -3.833
 Critical value 5%     = -3.031
 Critical value 10%    = -2.656
 => P-Value = 0.0. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Tubers" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -2.5132
 No. Lags Chosen       = 8
 Critical value 1%     = -4.138
 Critical value 5%     = -3.155
 Critical value 10%    = -2.714
 => P-Value = 0.1123. Do not reject H0.
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "Vegetables" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -5.5074
 No. Lags Chosen       = 2
 Critical value 1%     = -3.859
 Critical value 5%     = -3.042
 Critical value 10%    = -2.661
 => P-Value = 0.0. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Legumes" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -11.2373
 No. Lags Chosen       = 0
 Critical value 1%     = -3.809
 Critical value 5%     = -3.022
 Critical value 10%    = -2.651
 => P-Value = 0.0. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Fruits" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -5.0822
 No. Lags Chosen       = 2
 Critical value 1%     = -3.859
 Critical value 5%     = -3.042
 Critical value 10%    = -2.661
 => P-Value = 0.0. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Fish" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -3.7234
 No. Lags Chosen       = 5
 Critical value 1%     = -3.964
 Critical value 5%     = -3.085
 Critical value 10%    = -2.682
 => P-Value = 0.0038. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Meat" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -3.8071
 No. Lags Chosen       = 4
 Critical value 1%     = -3.924
 Critical value 5%     = -3.068
 Critical value 10%    = -2.674
 => P-Value = 0.0028. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Eggs_Dairy" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -5.1901
 No. Lags Chosen       = 2
 Critical value 1%     = -3.859
 Critical value 5%     = -3.042
 Critical value 10%    = -2.661
 => P-Value = 0.0. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Oils_Fats" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -4.3262
 No. Lags Chosen       = 8
 Critical value 1%     = -4.138
 Critical value 5%     = -3.155
 Critical value 10%    = -2.714
 => P-Value = 0.0004. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Beverages" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -4.534
 No. Lags Chosen       = 3
 Critical value 1%     = -3.889
 Critical value 5%     = -3.054
 Critical value 10%    = -2.667
 => P-Value = 0.0002. Reject H0.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "Spices" Diff 2
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
 Test Statistic        = -8.3449
 No. Lags Chosen       = 8
 Critical value 1%     = -4.138
 Critical value 5%     = -3.155
 Critical value 10%    = -2.714
 => P-Value = 0.0. Reject H0.
 => Series is Stationary.
```

```
   Augmented Dickey-Fuller Test on "Other_consumables" Diff 2
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -1.7373
No. Lags Chosen       = 8
Critical value 1%     = -4.138
Critical value 5%     = -3.155
Critical value 10%    = -2.714
=> P-Value = 0.412. Do not reject H0.
=> Series is Non-Stationary.


   Augmented Dickey-Fuller Test on "Prepared_Food" Diff 2
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -4.0723
No. Lags Chosen       = 7
Critical value 1%     = -4.069
Critical value 5%     = -3.127
Critical value 10%    = -2.702
=> P-Value = 0.0011. Reject H0.
=> Series is Stationary.


   Augmented Dickey-Fuller Test on "Tobacco" Diff 2
   -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -9.4875
No. Lags Chosen       = 0
Critical value 1%     = -3.809
Critical value 5%     = -3.022
Critical value 10%    = -2.651
=> P-Value = 0.0. Reject H0.
=> Series is Stationary.
```

APPENDIX C – VAR Regression Model Equations

VAR 2021-2022 Model

```
  Summary of Regression Results   
==================================
Model:                         VAR
Method:                        OLS
Date:           Sat, 09, Mar, 2024
Time:                     20:04:41
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                    70.3764
Nobs:                     18.0000    HQIC:                   69.5236
Log likelihood:          -706.648    FPE:                1.44708e+30
AIC:                      69.3871    Det(Omega_mle):     5.42840e+29
--------------------------------------------------------------------
Results for equation AllSpend
===================================================================================
                      coefficient       std. error           t-stat            prob
-----------------------------------------------------------------------------------
const                 -323.758296      5501.961193           -0.059           0.953
L1.AllSpend             -0.747462         0.485221           -1.540           0.123
L1.Vegetables            2.423078         1.522473            1.592           0.111
L1.Fruits               -3.097190         2.308996           -1.341           0.180
L1.Prepared_Food         0.609559         0.663189            0.919           0.358
===================================================================================

Results for equation Vegetables
===================================================================================
                      coefficient       std. error           t-stat            prob
-----------------------------------------------------------------------------------
const                  123.594291       597.155854            0.207           0.836
L1.AllSpend              0.359133         0.052664            6.819           0.000
L1.Vegetables           -0.675691         0.165242           -4.089           0.000
L1.Fruits               -1.504499         0.250607           -6.003           0.000
L1.Prepared_Food        -0.430083         0.071979           -5.975           0.000
===================================================================================

Results for equation Fruits
===================================================================================
                      coefficient       std. error           t-stat            prob
-----------------------------------------------------------------------------------
const                  -65.605671       502.860950           -0.130           0.896
L1.AllSpend             -0.102339         0.044348           -2.308           0.021
L1.Vegetables            0.442472         0.139149            3.180           0.001
L1.Fruits               -0.428190         0.211035           -2.029           0.042
L1.Prepared_Food         0.178788         0.060613            2.950           0.003
===================================================================================

Results for equation Prepared_Food
===================================================================================
                      coefficient       std. error           t-stat            prob
-----------------------------------------------------------------------------------
const                  189.661614      4184.809465            0.045           0.964
L1.AllSpend             -0.247561         0.369061           -0.671           0.502
L1.Vegetables            2.458315         1.157998            2.123           0.034
L1.Fruits               -0.155594         1.756230           -0.089           0.929
L1.Prepared_Food        -0.221929         0.504424           -0.440           0.660
===================================================================================

Correlation matrix of residuals
                 AllSpend  Vegetables    Fruits  Prepared_Food
AllSpend         1.000000    0.352597  0.133922       0.905376
Vegetables       0.352597    1.000000 -0.415656       0.318516
Fruits           0.133922   -0.415656  1.000000       0.055195
Prepared_Food    0.905376    0.318516  0.055195       1.000000
```

VAR 2023-2027 Model

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sun, 10, Mar, 2024
Time:                     00:02:44
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                    69.2251
Nobs:                     22.0000    HQIC:                   68.4669
Log likelihood:          -855.432    FPE:                4.43952e+29
AIC:                      68.2332    Det(Omega_mle):     1.95691e+29
--------------------------------------------------------------------
Results for equation AllSpend
==================================================================================
                   coefficient       std. error           t-stat            prob
----------------------------------------------------------------------------------
const             -11222.204493     20890.702359           -0.537           0.591
L1.AllSpend            2.076243         0.455011            4.563           0.000
L1.Vegetables         -2.659446         2.406299           -1.105           0.269
L1.Fruits             -8.630075         4.497050           -1.919           0.055
L1.Prepared_Food      -1.059333         0.591840           -1.790           0.073
==================================================================================

Results for equation Vegetables
==================================================================================
                   coefficient       std. error           t-stat            prob
----------------------------------------------------------------------------------
const              -1225.952419      2716.403852           -0.451           0.652
L1.AllSpend            0.169360         0.059165            2.863           0.004
L1.Vegetables         -0.108535         0.312889           -0.347           0.729
L1.Fruits             -1.012967         0.584748           -1.732           0.083
L1.Prepared_Food      -0.094867         0.076957           -1.233           0.218
==================================================================================

Results for equation Fruits
==================================================================================
                   coefficient       std. error           t-stat            prob
----------------------------------------------------------------------------------
const               1213.920001      1782.793731            0.681           0.496
L1.AllSpend            0.082558         0.038830            2.126           0.033
L1.Vegetables         -0.020160         0.205351           -0.098           0.922
L1.Fruits             -0.580430         0.383774           -1.512           0.130
L1.Prepared_Food      -0.005539         0.050507           -0.110           0.913
==================================================================================

Results for equation Prepared_Food
==================================================================================
                   coefficient       std. error           t-stat            prob
----------------------------------------------------------------------------------
const             -16325.289291     14371.042380           -1.136           0.256
L1.AllSpend            0.697710         0.313009            2.229           0.026
L1.Vegetables         -1.958381         1.655331           -1.183           0.237
L1.Fruits             -3.992384         3.093592           -1.291           0.197
L1.Prepared_Food       0.128815         0.407136            0.316           0.752
==================================================================================

Correlation matrix of residuals
                AllSpend  Vegetables    Fruits  Prepared_Food
AllSpend        1.000000    0.054405  0.645871       0.869399
Vegetables      0.054405    1.000000 -0.550504      -0.167704
Fruits          0.645871   -0.550504  1.000000       0.685915
Prepared_Food   0.869399   -0.167704  0.685915       1.000000
```

APPENDIX D – 2023-2027 Forecast Numbers

ARIMA (2,1,0) Forecast Result Details (IDR)

ARIMA (2,1,0) Forecast 2023-2027					
	Point Forecast	Low 80	High 80	Low 95	High 95
2023	Rp736,324.30	Rp700,559.70	Rp772,088.80	Rp681,627.10	Rp791,021.50
2024	Rp761,160.70	Rp704,306.90	Rp818,014.40	Rp674,210.40	Rp848,111.00
2025	Rp775,149.00	Rp688,589.70	Rp861,708.20	Rp642,768.00	Rp907,529.90
2026	Rp791,701.20	Rp677,341.40	Rp906,061.00	Rp616,803.00	Rp966,599.50
2027	Rp803,068.40	Rp658,637.70	Rp947,499.20	Rp582,180.60	Rp1,023,956.30

VAR Forecast Result Details (IDR)

Year	AllSpend	Vegetables	Fruits	Prepared_Food
Existing				
2000	96,732	7,124	4,683	13,928
2001	109,119	7,580	4,914	17,865
2002	144,352	10,962	7,853	30,584
2003	155,686	12,159	8,908	34,915
2004	155,169	11,282	8,254	37,048
2005	168,765	12,182	9,088	41,282
2006	176,753	13,029	8,556	43,581
2007	184,740	13,876	8,023	45,880
2008	201,218	14,220	11,346	52,116
2009	222,980	15,878	10,824	62,776
2010	291,678	19,093	14,829	89,258
2011	332,509	25,355	15,200	111,584
2012	375,110	25,051	19,079	112,566
2013	356,435	31,158	16,379	92,254
2014	439,770	30,177	23,106	142,784
2015	457,312	27,450	24,342	145,416
2016	520,631	35,213	23,889	177,775
2017	590,082	43,178	27,531	220,882
2018	620,962	40,522	34,018	237,326
2019	637,132	38,316	31,979	251,129
2020	670,304	46,252	34,908	257,945
2021	681,278	54,678	30,832	242,214
2022	721,084	55,679	35,233	246,924
Forecasted				
2023	772,210	55,739	37,805	268,886
2024	832,740	59,702	40,410	297,000
2025	895,608	64,217	43,660	324,691
2026	956,753	68,456	46,719	350,306
2027	1,018,890	72,822	49,764	375,750