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Research Article

Modelling and Forecasting Fresh Agro-Food Commodity Consumption Per Capita in Malaysia Using Machine Learning

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This study focuses on identifying and analyzing spending trend profiles and developing the per capita consumption models to forecast the fresh agro-food per capita consumption in Malaysia. Previous published works have looked at statistical and machine learning methods to forecast the demand of agro-food such as ARIMA and SVM methods. However, ordinary least squares (OLS) and neural network (NN) methods have shown better results in modelling time series data. For that reason, the primary objective of this study is to model and forecast the consumption per capita (PCC) of several selected fresh agro-food commodities in Malaysia using the OLS and NN methods. The secondary objectives of the paper include investigating the performance of OLS against NNs with three different topologies, discussing the correlation between Malaysia GDP per capita and the agro-food commodity PCC, and finally assessing whether the PCC data are increasing over time or decreasing over time and whether the trend in either direction is statistically significant by using the Mann–Kendall statistical test. Based on the results of the agro-food consumption per capita (PCC) forecasting, several critical agro-food commodities are also identified in this work. The material of the study consists of the per capita consumption of thirty-three (33) agro-food items that can be categorized into rice, livestock, vegetables, fisheries, and fruits, total gross domestic product (GDP) per capita, and the total population of Malaysia between 2010 and 2017. Based on the results obtained, the neural network (NN_{T_1}) model was found to produce the lowest total MSE of 17.95, for all 33 fresh agro-food investigated in this study. Several agro-food commodities have been identified as having significant positive (e.g., rice, spinach, cabbage, celery cabbage, eggplant, cucumber, poultry, lamb, squid, tuna, star fruit, jackfruit, durian, sweet corn, and coconut) or negative (e.g., pork, mackerel, papaya, guava, mangosteen, pineapple, banana, rambutan, and watermelon) trends using the Mann–Kendall trend test. This study also demonstrated that the production of critical agro-food commodities (e.g., rice, chili, cabbage, celery cabbage, poultry (chicken/duck), beef, lamb, crab, mango, and coconut) should be improved to ensure self-sufficiency ratios (SSRs) of more than 100% to accommodate the increased projected consumption in Malaysia by the year 2025. This paper concludes that neural network methods produce better prediction, and future works include forecasting agro-food demand based on other independent variables such as weather conditions, disease outbreak, and stock market trends. There is a need to explore further the capability of ensemble models or hybrid models based on deep learning methods using multi-source data, as these have been shown to improve the performance of the base model. With these ensemble models combined with multi-source data, a more comprehensive analysis of the PCC can be obtained.

1. Introduction

The current global population of 7.8 billion (2020) persons is expected to reach 9.7 billion by 2050. It is expected that the world would require 70% more food than what is available at the moment with less natural resources like land and water due to urbanization, soil erosion, climatic changes, water shortages, and excessive use by livestock [1]. The agriculture sector is one of the main contributors to Malaysia's national gross domestic product (GDP). For instance, the agriculture sector contributed 8.2% (RM96.0 billion) to GDP in 2017 and 7.3% (RM99.5 billion) in 2018, and one of the major contributors in this sector is palm oil by contributing 37.9% of the total contribution from the agriculture sector in 2018 [2]. Malaysia has been giving more concentration towards the agricultural sector related to palm oil, cocoa, and rubber due to its export value, and these products are important to the local manufacturing sector. However, less attention is paid towards agrofood in agribusiness due to a good and excellent production in agriculture sector through palm oil, cocoa, and rubber prduction in Malaysia..

Agro-food refers to food production that is produced agriculturally which includes the use of compost and precision fertilizers, irrigation monitoring, the adoption of no-till farming practices, and the use of less-input-dependent crop varieties and animal breeds. In 2019, the government of Malaysia had released a document that highlighted a five-point security plan, including a set of strategies and initiatives to be implemented towards ensuring food security and boosting revenue in the agricultural sector particularly in agro (or agri) food system, called "Malaysia's Agro-Food Policy (NAP 2011–2020)—Performance and New Direction" [3]. Agro-food system defines a system concept that applies to agro-food sector which comprises activities related to the production, processing, distribution, sale, preparation, and consumption of food such as crops, livestock, forestry, aquaculture, and fisheries.

Malaysia's population had shown an increasing trend approximately from 30.68 mil to 32.68 mil from 2016 to 2019 [4] and is projected to increase up to 40.5 mil in 2050 [1]. Food security may be in a risky situation in the future as we face global population growth and climate change caused by the increasing competition for land and water resources from industrial and urban growth. Thus, there is a need for our country to increase agricultural productivity as per capita consumption is highly likely to increase when Malaysia's population increases to ensure food security in our country. The purpose of this paper is to contribute to the improvisation to the agricultural industry by modelling and forecasting agro-food consumption per capita in Malaysia. Factors that affect the value of consumption per capita will be elaborated in this paper as it is important to understand these to build an accurate model for forecasting its values.

Consumption per capita or per capita consumption (PCC) can be measured by dividing the quantity of goods consumed by the total population. It is an average quantity for a person concerning the good's gross quantity consumed. In general, PCC is necessary to measure and assess the median standard of consumers [5, 6]. This method will allow and accurately assess whether food security can be ensured in our country or vice versa. Thus, it is very important to understand factors that are affecting the PCC of certain agricultural commodities. By understanding and forecasting the value of PCC in the future, the agricultural industry will be able to plan and execute the prepared policy to manage consumer expectations. For instance, if there is an increase in PCC of certain agricultural commodities in the following year, Malaysian agri-food system must respond to such changes in consumer demand and be prepared for the future food supply system. It will allow the nation to combat hunger and poverty and achieve food security.

Due to low agricultural productivity, Malaysia needs to improve their yields significantly in order to double output by 2050 and keep up with increased demand. The domestic agricultural production is expected to be especially vulnerable to the impacts of climate change over the next 30 years. [7]. Forecasting PCC in Malaysia is important as it will contribute to the agriculture industry to evaluate and estimate Malaysia's agro-food product, make the agricultural sector more competitive in various sector and global market, increase trade balance value in our country, and ensure food security for our country that will also encourage economic growth and reduction in import agro-food. Thus, this study focuses on identifying and analyzing spending trend profiles and developing the per capita consumption models to forecast the fresh agro-food per capita consumption in Malaysia. This is why forecasting the per capita consumption is crucial issue for addressing food security.

Previous published works have looked at statistical and machine learning methods to forecast the demand of agro-food such as ARIMA and SVM methods [8–12]. Ordinary least squares (OLS) and neural network (NN) methods have shown better results in modelling time series data [8, 11, 13, 14]. For that reason, the main objective of this study is to model and forecast the consumption per capita (PCC) of several selected fresh agro-food products in Malaysia by employing two main models, namely, ordinary least squares (OLS) and neural network (NN), with three different topologies and evaluate the forecasting capability of the developed models.

2. Related Works

A complete food supply transformation-based operational paradigm may consist of four main stages which are food sourcing, food processing, food packaging and warehousing, and food transportation and logistics [15]. Firstly, the food sourcing stage looks at responsible sourcing, plantation, and harvesting. In order to have sustainable food sourcing, machine learning (ML) methods are designed to improve smart farming and harvesting using robots and drones [16, 17], perform predictive market demand forecasting [18], and also use blockchain and smart contracts with the integration of Internet of Things (IoT) devices in pre-harvesting and post-harvesting to track and trace the workflow of agricultural food supply chains [19]. Next, in the food processing stage, issues related to food ingredient safety and sustainable processing technology are addressed. Thus, real-time traceability using IoT and blockchain (BC) is required [20, 21]. In addition to that, food inspection and smart nutrient composition can be addressed using the BC and artificial intelligence (AI) technologies [22, 23]. Then, in the food packaging and warehousing stage, smart packaging and anti-counterfeiting technologies are required. These technologies include contactless smart packaging [24], smart label and ledger using RFID, IoT, and BC [25], and finally automated warehouse logistics that require the integration of RFID, big data, and cyber-physical system [26, 27]. Finally, in the food transportation and logistics stage, cold chain optimization and on-time delivery are very important issues that need to be addressed efficiently and effectively [28, 29]. Thus, the application of reinforced learning and prescriptive intelligence in route optimization is required using AI and ML [30]. Data-driven simulation modelling of food systems is also required to ensure on-time delivery [31]. This paper addresses the predictive agro-food demand forecasting based on Engel's law.

Engel's law has stated that the households' demand for food increases less than proportionally, as income increases [5]. According to Engel's law, the linear food demand of a consumer can be formulated as follows:

$$q_i = b \times y_i + a_i, \tag{1}$$

where q_i denotes the food demand, a_i can be interpreted as a minimum consumption level of food, y_i is income, and the observations are indexed across the i-th households or individuals [6]. Applying Engel's law, gross domestic product (GDP) per capita can be used to represent the income in order to forecast the food consumption per capita. Cirera and Masset have introduced and simulated simple simulations to predict growth in food demand under the effect of changes in income distribution on food demand within an economy [5]. In this work, the basic assumption that was outlined is that the average food consumption can be computed based on both the average income and variance of income as shown below:

$$\overline{q} = b \times \left(\ln \overline{y} - \frac{\sigma_y^2}{2} \right) + a, \tag{2}$$

where $\overline{q}$ is the average food consumption, $\overline{y}$ is the average income, and σ_y^2 denotes the variance of income.

In addition to that, besides GDP, other factors also may influence the consumption per capita of certain agricultural commodities, such as social science factors [32]. For instance, Kearney examined the main drivers largely responsible for the observed food consumption trends that include income, urbanization, trade liberalization, translational food corporations, retailing [33], food industry marketing, and finally consumer attitudes and behaviour, and it was concluded that the level of urbanization has significant effects on the observed changes in dietary patterns [34]. In a separate work, a projected demand of Indonesian food consumption for 2025 and 2045 was built using the functional relationship between income and food consumption [35].

Candy et al. modelled the availability of food and impact on environmental due to shift of dietary patterns in Australia by using the Australian Stocks and Flows Framework (ASFF) to model different diet scenarios [36]. Based on the findings obtained, changes in diet had little effect on environmental impact due to the amount and nature of Australian exports. Othman et al. studied the consumption pattern on fruits and vegetables among adults in Malaysia. Based on their findings, it stated that that chili, cabbage, cucumber, leaf mustard, tomatoes, and water convolvulus were most favorable to consume by adults [37].

The factors that influence the application on machine learning (ML) algorithms in the food supply chain depend highly on the types of tasks that need to be performed in the production planning and control, food processing, distribution, and consumption. The ML algorithms used to develop sustainable food supply chain are grouped into two categories, namely, supervised and unsupervised learning [38, 39].

Several methods used to model food supply chain related to neural network and deep learning are reviewed in [40, 41]. Most of the best methods found to be more effective in predicting time series data are those related to neural network family. The experimental results showed the consistent performance improvements by the proposed deep learning approaches over other representative linear and non-linear methods on multiple real-world datasets [42–46]. Thus, this work employs two models, namely, ordinary least squares (OLS) and neural network (NN), in order to model and forecast the consumption per capita (PCC) of several selected fresh agro-food commodities in Malaysia. This paper also investigates the performance of NN with three different topologies.

3. Materials and Methods

3.1. Materials. In this study, thirty-three fresh agro-food products, which can be categorized into rice, livestock, vegetables, fisheries, and fruits, will be used and the per capita consumption (PCC) secondary data of these products for the last eight (8) years (e.g., 2010 to 2017) [3, 47] were used to develop models using the ordinary least squares (OLS) and neural network (NN). These models will be used to forecast the consumption per capita for selected fresh agro-food products from 2018 to 2025. Secondary data on the per capita consumption of fresh agro-food products for 2018 were also obtained from two resources (e.g., Department of Statistics Malaysia (DOSM) [2] and Research on the Use of Fresh Agro-Food in Malaysia (KPASM-Kajian Penggunaan Agromakanan Segar di Malaysia) [48]) for evaluation purposes. Besides the PCC, secondary data related to the total gross domestic product (GDP) per capita [49] and the total population of Malaysia between 2010 and 2018 are also used in this study. Table 1 tabulates the per capita consumption of all the 33 selected fresh agro-food items (kg).

Figure 1 depicts the GDP per capita (USD) for Malaysia from 2010 to 2019 [49].

Table 1: Per capita consumption of 33 selected fresh agro-food items (kg) [3, 47].

Agro-food	2010	2011	2012	2013	2014	2015	2016	2017	2018#	2018*
Rice	79.6	92.7	90.8	83.8	87.9	87.5	79.5	78.2	76.1	74.4
Vegetables										
Spinach	1.0	1.2	1.5	1.5	1.4	1.4	1.5	1.9	2.0	1.9
Lady's finger	0.7	0.8	0.8	1.0	1.3	1.5	1.4	1.5	1.5	1.4
Chili	1.1	1.1	1.9	2.4	1.8	2.1	2.0	1.6	1.4	1.7
Long beans	1.1	1.2	1.3	1.6	1.5	2.0	1.8	1.6	1.7	1.6
Cabbage	5.9	7.0	4.6	5.4	10.8	10.1	4.9	5.4	5.6	6.1
Celery cabbage	3.9	4.1	5.5	7.9	8.8	6.9	6.9	4.4	6.3	4.0
Eggplant	0.9	1.0	1.1	1.6	1.5	1.5	1.3	1.1	1.2	1.0
Cucumber	1.6	2.0	2.9	3.5	2.9	3.1	2.6	2.3	2.9	2.3
Tomato	3.2	3.2	2.8	4.6	3.5	3.5	5.4	3.9	3.8	4.2
Livestock										
Chicken and duck	41.2	40.5	43.6	46.0	50.3	50.5	53.7	52.0	50.9	51.0
Pork	21.0	19.1	18.9	18.5	18.3	18.8	16.6	16.3	14.5	17.9
Beef and buffalo meat	4.9	5.2	5.5	5.9	5.8	6.2	5.8	5.6	6.3	5.7
Lamb	0.9	0.7	0.9	1.0	1.2	1.2	1.2	1.3	1.6	1.3
Chicken and duck egg	16.7	17.2	17.2	18.1	19.6	21.1	21.6	22.2	24.2	22.8
Fisheries										
Crab	0.5	0.4	0.5	0.5	0.4	0.4	0.4	0.4	0.6	0.4
Mackerel	8.2	7.4	7.5	7.1	6.7	6.9	7.2	5.2	5.2	5.5
Squid	2.1	2.2	2.6	2.4	2.7	2.1	2.3	2.1	2.2	2.1
Tuna	2.1	2.7	2.8	2.8	2.8	2.6	2.4	2.5	2.4	2.1
Prawn	4.7	4.1	4.6	4.4	4.7	4.6	4.1	3.9	3.6	4.4
Fruits										
Star fruit	—	0.2	0.4	0.3	0.2	0.2	0.2	0.2	0.2	0.1
Papaya	—	0.7	0.5	0.2	1.0	1.1	1.2	1.7	1.1	1.0
Jackfruit	1.7	1.7	1.7	2.0	1.6	1.8	1.6	1.5	1.5	1.6
Durian	9.9	11.8	11.0	11.6	10.9	11.2	9.1	6.4	6.1	9.8
Sweet corn	1.6	1.9	2.6	2.6	1.8	1.7	1.8	1.9	2.1	1.8
Guava	0.8	0.8	1.2	0.8	1.1	1.7	1.9	2.5	3.3	1.1
Coconut	18.4	17.7	21.5	18.5	18.8	17.3	17.0	19.4	15.7	21.5
Mango	1.8	2.0	2.2	1.7	1.6	1.9	1.7	2.0	2.0	1.9
Mangosteen	1.0	0.8	0.8	0.8	0.7	0.8	0.6	0.4	0.5	0.6
Pineapple	8.3	7.7	7.7	5.8	7.8	10.6	8.9	7.6	7.5	7.2
Banana	10.2	9.2	8.9	8.9	9.4	9.5	8.9	10.0	12.0	9.4
Rambutan	2.4	2.1	2.1	2.1	1.9	2.0	1.8	1.1	1.0	1.5
Watermelon	5.9	5.5	5.6	4.9	3.4	3.4	3.7	3.3	3.7	2.6

*DOSM [2]; #KPASM [48].

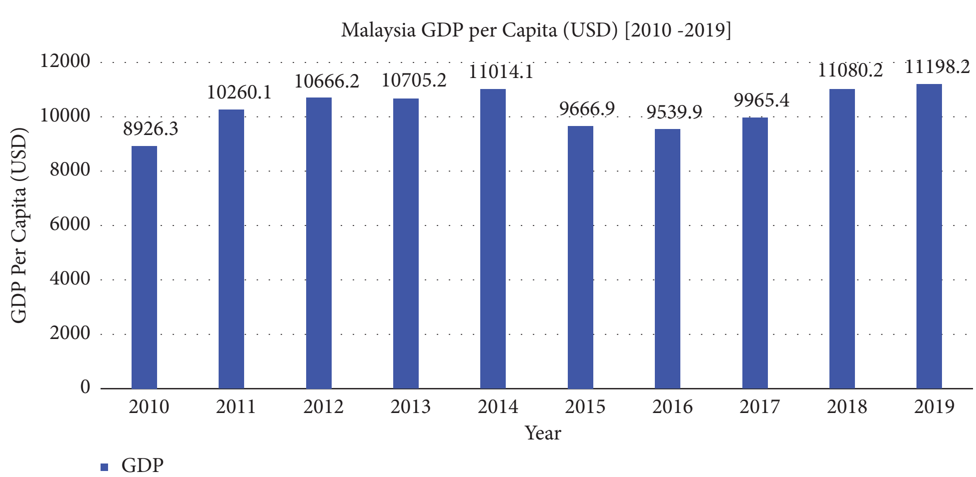

Figure 1: GDP per capita (USD) for Malaysia from 2010 to 2019 (source: http://www.ceic.data.com).

3.2. Methods. The modelling of the per capita consumption (PCC) projection is limited to only a few selected fresh agro-food products only. In this paper, two models will be applied, namely, ordinary least squares (OLS) and neural network (NN), to model and forecast the consumption per capita (PCC) of several selected fresh agro-food products in Malaysia.

3.2.1. Ordinary Least Squares (OLS). The following is a linear regression model [50] used to estimate PCC_i:

$$\mathrm{PCC}_i = \alpha + \beta \times \mathrm{GDP}_{\mathrm{percapita}_i} + \varepsilon_i, \tag{3}$$

where PCC_i is the i^{th} estimated consumption per capita (dependent variable) based on $\mathrm{GDP}_{\mathrm{percapita}_i}$ which is the i^{th} total of gross domestic product per capita (independent variable) of Malaysia, ε_i is the error term, and α, β are the true (but unobserved) parameters of the regression. In this work, GDP per capita is used to estimate PCC since there is a strong relationship between consumption, income, and GDP for low and middle-income countries, such as Malaysia [51].

3.2.2. Neural Network (NN). In this work, a resilient backpropagation neural network (RBNN) is applied [52]. This is one of the backpropagation neural network models which is a learning scheme that performs a direct adaptation of the weight step based on local gradient information [53, 54]. In terms of topology, Figure [[displays three types of topology for the neural network that will be applied in this work, namely,

(1) NN_{T_1}: 1-10-1 (1 input, 1 layer with 10 neurons, and 1 output)—see Figure 2.

(2) NN_{T_2}: 1-5-5-1 (1 input, 2 layers having 5 neurons each, and 1 output)—see Figure 3.

(3) NN_{T_3}: 1-4-3-3-1 (1 input, 3 layers (having 4 neurons, 3 neurons, and 3 neurons each), and 1 output)—see Figure 4.

For instance, Figure 2 visualizes the computed neural network with 1 input, 1 hidden layer having 10 neurons, and 1 output. The black lines show the connections with weights. The input will be the GDP and the output will be the forecasted agro-food commodity consumption per capita (PCC). The weights are calculated using the back-propagation algorithm. The blue line displays the bias term. In this work, we are not going to investigate the most optimized topology of the neural network. As there are instances in which high accuracy can be obtained without any hidden layers, varying the number of hidden layers and neurons is just a trial and error effort in order to investigate the effects of applying different numbers of layers and neurons on the mean square error of the neural network models. The data are split into 90% train set and 10% test set in a random way for 5 times (5 cross validation) and the fitting and forecasting effect of these two models are estimated using the mean square error (MSE) [55].

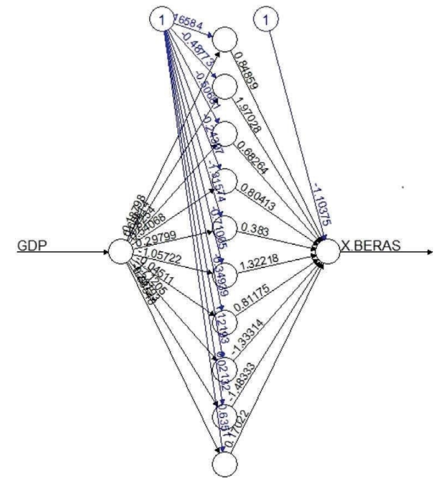

Figure 2: NN with 1-10-1 topology.

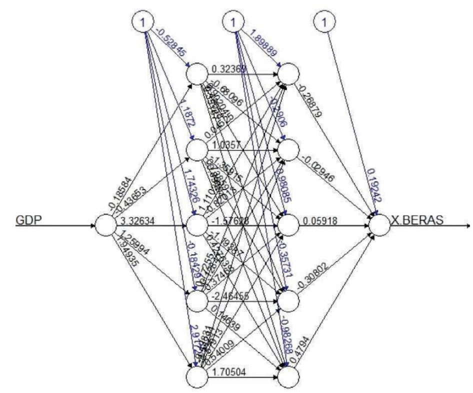

Figure 3: NN with 1-5-5-1 topology.

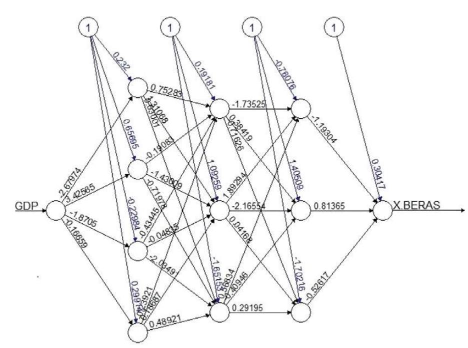

Figure 4: NN with 1-4-3-3-1 topology.

3.2.3. Mean Square Error (MSE). In this work, we compute the mean square error (MSE) [55] to assess the performance of the models. MSE measures the average of the squares of the differences between the actual and predicted values. MSE can be computed as follows:

$$\mathrm{MSE} = \frac{1}{n} \sum \left(x_i - y_i\right)^2, \tag{4}$$

where n is the number of observations and x_i and y_i represent the i th observation of the actual and predicted values.

3.2.4. Mann–Kendall Test. The trends of PCC forecasted for a period of eight years are then evaluated using trend testing called the Mann–Kendall test [56, 57]. This statistical test is performed to determine whether a trend has a monotonic upward or downward trend or constant (i.e., no trend) over the eight-year projection. The Mann–Kendall test does not require that the data be normally distributed or linear but the data should not be serially correlated [58]. The presence of serial correlation among the data should be investigated first by computing the autocorrelation and partial autocorrelation corresponding to the time series of the data. In this work, we apply the acf() and pacf() functions in R [59].

In determining the presence of monotonic trend in a time series, the Mann–Kendall [60] test defines the null hypothesis (H_0) as the data come from a population where random variables are independent and do not follow any monotonic trend over time. On the other hand, the alternative hypothesis (H_a) is said to have the data that follow a monotonic trend over time. The computation of the Mann–Kendall test statistic is calculated according to

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \operatorname{sign}\left(x_j - x_k\right), \tag{5}$$

where $j > k$, and

$$\operatorname{sign}(x) = \begin{cases} 1, & \text{if} x > 0, \\ 0, & \text{if} x = 0, \\ -1, & \text{if} x < 0. \end{cases} \tag{6}$$

Kendall's tau, τ, rank correlation coefficient is determined to show the sign of the relationship between time and the variables. Kendall's tau, τ, is computed according to

$$\tau = \frac{S}{D}, \tag{7}$$

where

$$D = \left[\frac{1}{2}n(n-1) - \frac{1}{2}\sum_{j=1}^{p} t_j\left(t_j - 1\right)\right]^{(1/2)} \left[\frac{1}{2}n(n-1)\right]^{(1/2)}, \tag{8}$$

where p is the number of tied groups in the dataset and t_j is the number of data points in the j-th tied group. Decision about the statistical significance will be made using empirical significance level (p – value) compared to $\alpha = 5\%$.

4. Results

The discussion of the results of this paper is divided into four sections, namely, (a) Assessment of Model Performances; (b) Projections and Trends of Agro-Food Consumption Per Capita; (c) Correlation between GDP and PCC; (d) Forecasted Demand for Agro-Food Commodities in Malaysia.

4.1. Assessment of Model Performances. The performances of the neural network models and OLS are assessed based on the MSE measures. In addition to that, the projected PCC for all fresh agro-food products is also compared with the actual PCCs reported by DOSM [2] and KPASM [48] for the year 2018 only. Table 2 tabulates the performance assessment of the neural network (NN_{T_1}, NN_{T_2}, NN_{T_3}) and OLS models in modelling the per capita consumption of 33 selected fresh agro-food items (kg) [3, 47].

Among all the RBNN models, the NN_{T_1} produced the lowest total MSE of 17.95, for all 33 fresh agro-food investigated in this study. We also compared the forecasted consumption per capita (PCC) with the consumption per capita (PCC) for the year 2018 reported by DOSM [2] and KPASM [48]. The total MSE for both the NN and OLS models is also tabulated in Table 2, and the neural network model (NNT_1) produced better forecasting results as it produced lower MSE values compared to the OLS model. For instance, for the DOSM and KPASM data that were produced for the PCC in the year 2018, the total MSEs of all fresh agro-food commodities for NN_{T_1} model are lower than the total MSEs produced by the OLS model. The total MSEs produced by the NN_{T_1} model for the DOSM and KPASM data are 274.93 and 288.33, respectively.

Based on Table 2, the trends of agrofood commodities per capita consumption (PCC) were modelled using the OLS and NN for rice, vegetables, livestock, fisheries, and fruits.

The slopes of the trend lines forecasted by the OLS model for most of the agro-food commodities are higher compared to the ones forecasted by the neural network models. For instance, the slopes of the trend lines for the forecasted PCCs of rice, spinach, chili, cabbage, celery cabbage, and cucumber by the neural network (NN) are lower.

Similar trends can be seen for other agro-food commodities such as pork, beef or buffalo meat, chicken or duck egg, mackerel, squid, tuna, papaya, durian, coconut, banana, and watermelon. In short, it can be concluded that the OLS model produced a more aggressive slope by having high vertical change in consumption per capita (PCC) and low horizontal change in year. As a result, the total MSE for OLS is much higher compared to the total MSE produced by the NN_{T_1} model.

4.2. Projections and Trends of Agro-Food Consumption Per Capita. Table 3 tabulates the projections of fresh agro-food consumption per capita (kg) for the year 2019 through 2025. In this work, in order to determine the statistical significance of the monotonic trend, H_0 is defined as there is no trend in the series, and alternatively H_a is defined as there is a positive or negative trend. Based on Kendall's tau (τ), the Mann–Kendall trend test was used to detect monotonic trends in the time series. Then, the statistical significance of the monotonic trend can be determined by comparing the p value to $\alpha = 5\%$. If the two-tailed Mann–Kendall test p value is greater than 0.05 (p value $>r$bin 5%), H_0 is accepted (there is no trend in the series); otherwise, H_a is accepted (there is a positive or negative trend).

Table 2: Performance assessment of the neural network (NN_{T_1}, NN_{T_2}, NN_{T_3}) and OLS models in modelling the per capita consumption of 33 selected fresh agro-food items (kg) [3, 47].

Agro-food	MSE			MSE^{*}_{2018}		$MSE^{\#}_{2018}$	
	NN_{T_1}	NN_{T_2}	NN_{T_2}	NN_{T_1}	OLS	NN_{T_1}	OLS
Rice	5.87	6.45	7.34	220.52	227.93	173.98	180.56
Vegetables							
Spinach	0.03	0.56	0.76	0.14	0.12	0.18	0.17
Lady's finger	0.00	0.05	0.04	0.08	0.08	0.16	0.16
Chili	0.05	0.23	1.45	0.08	0.10	0.34	0.39
Long beans	0.02	0.54	1.34	0.01	0.01	0.01	0.02
Cabbage	0.15	0.23	0.28	1.75	1.88	3.47	3.65
Celery cabbage	2.39	4.34	3.45	10.97	11.95	1.00	1.32
Eggplant	0.01	0.34	0.32	0.16	0.18	0.06	0.08
Cucumber	0.47	0.45	1.34	0.57	0.73	0.01	0.05
Tomato	0.08	0.87	0.99	0.36	0.35	0.04	0.04
Livestock							
Chicken and duck	3.11	2.67	4.33	12.87	13.56	12.30	12.98
Pork	0.38	0.67	0.45	0.04	0.01	12.82	12.10
Beef and buffalo meat	0.04	0.34	11.77%	0.01	0.01	0.24	0.20
Lamb	0.01	0.23	0.56	0.07	0.07	0.34	0.33
Chicken and duck egg	0.38	0.99	1.45	15.02	15.88	28.14	29.33
Fisheries							
Crab	0.00	0.6	1.4	0.00	0.00	0.02	0.02
Mackerel	0.21	0.87	0.34	1.58	1.46	2.37	2.22
Squid	0.09	0.92	1.56	0.19	0.23	0.11	0.14
Tuna	0.19	0.65	0.98	0.61	0.67	0.22	0.25
Prawn	0.01	0.43	0.67	0.00	0.00	0.78	0.77
Fruits							
Star fruit	0.01	0.66	1.01	0.04	0.04	0.00	0.00
Papaya	0.89	1.92	2.3	0.15	0.26	0.26	0.39
Jackfruit	0.00	0.89	0.98	0.02	0.02	0.06	0.07
Durian	1.50	1.56	1.78	1.25	1.87	23.23	25.68
Sweet corn	0.09	0.45	0.23	0.31	0.29	0.09	0.08
Guava	0.14	0.23	0.65	0.00	0.00	4.59	4.63
Coconut	0.60	0.45	0.23	4.74	4.03	13.34	14.62
Mango	0.01	0.54	1.32	0.00	0.00	0.02	0.02
Mangosteen	0.00	0.01	0.34	0.01	0.01	0.03	0.03
Pineapple	0.75	1.45	2.34	0.02	0.04	0.21	0.26
Banana	0.31	0.45	0.78	0.14	0.18	8.67	8.98
Rambutan	0.05	0.56	0.34	0.17	0.14	0.77	0.72
Watermelon	0.12	1.45	1.89	3.06	2.92	0.45	0.39
Total	17.95	33.05	44.13	274.93	285.02	288.33	300.62

*DOSM [2]; #KPASM [48].

4.2.1. Rice. Figure 5 illustrates that there is a significant positive trend for the consumption of rice per capita. The forecasted consumption per capita of rice in 2025 is 110.3 kilograms per person annually. Malaysia has set up some initiatives to increase rice production by 5% [61]. Similar trends are also found in other studies [8].

4.2.2. Vegetables. Figure 6 illustrates that there are significant positive trends for the consumption per capita of spinach, chili, cabbage, celery cabbage, eggplant, and cucumber. However, there are no significant trends for the consumption per capita of lady's finger, long beans, and tomato. These findings are supported by previously conducted research in which it stated that that chili, cabbage, cucumber, leaf mustard, tomatoes, and water convolvulus were most favorable to consume by adults [37].

Healthy foods like cabbage is also getting more popular [62]. It has also been reported that there will be an increase in vegetable market for the next few years in Malaysia [63]. The chili consumption per capita is increasing as the agriculture ministry has set up a taskforce to keep local chilies competitive [64]. In 2025, the chili consumption per capita in Malaysia was forecasted to about 3.0 kilograms per person annually.

4.2.3. Livestock. Figure 7 illustrates that there are significant positive trends for the consumption per capita of chicken/duck and beef/buffalo meat. At the same time, there is also

Table 3: Projections of fresh agro-food consumption per capita (kg).

Agro-food	2019	2020	2021	2022	2023	2024	2025	τ	p-val	Trend
Rice	89.8	93.6	96.7	99.9	103.3	106.9	110.3	0.6	0.0019	△
Vegetables										
Spinach	1.5	1.6	1.7	1.8	1.8	1.9	2.0	0.8	0.0001	△
Lady's finger	1.1	1.1	1.1	1.1	1.1	1.1	1.1	0.0	1.0000	⊘
Chili	2.0	2.2	2.4	2.5	2.7	2.9	3.0	0.7	0.0001	△
Long bean	1.5	1.5	1.6	1.6	1.6	1.6	1.6	−0.2	0.4391	⊘
Cabbage	7.5	8.1	8.6	9.1	9.6	10.2	10.7	0.5	0.0039	△
Celery cabbage	7.5	8.5	9.3	10.2	11.0	11.8	12.6	0.8	0.0001	△
Eggplant	1.4	1.6	1.7	1.8	2.0	2.1	2.2	0.7	0.0001	△
Cucumber	3.1	3.5	3.8	4.0	4.3	4.6	4.9	0.8	0.0001	△
Tomato	3.6	3.4	3.3	3.2	3.1	3.0	2.9	−0.3	0.1140	⊘
Livestock										
Chicken and duck	47.4	47.6	47.7	47.8	47.9	48.1	48.2	0.4	0.0217	△
Pork	18.0	17.7	17.5	17.2	16.9	16.6	16.4	−0.8	0.0001	∇
Beef and buffalo meat	5.8	5.9	6.1	6.2	6.3	6.4	6.6	0.8	0.0001	△
Lamb	1.0	1.0	1.0	1.0	0.9	0.9	0.9	−0.1	0.6830	⊘
Chicken and duck egg	18.9	18.6	18.4	18.2	17.9	17.7	17.4	−0.2	0.4170	⊘
Fisheries										
Crab	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.1	0.8430	⊘
Mackerel	6.7	6.5	6.3	6.2	6.0	5.8	5.6	−0.8	0.0001	∇
Squid	2.6	2.8	2.9	3.1	3.2	3.4	3.6	0.7	0.0001	△
Tuna	2.9	3.2	3.3	3.5	3.7	3.8	4.0	0.8	0.0001	△
Prawn	4.4	4.5	4.5	4.6	4.6	4.6	4.7	0.2	0.3411	⊘
Fruits										
Star fruit	0.3	0.3	0.4	0.4	0.5	0.5	0.5	0.7	0.0005	△
Papaya	0.6	0.2	0.0	0.0	0.0	0.0	0.0	−0.6	0.0015	∇
Jackfruit	1.7	1.7	1.8	1.8	1.8	1.8	1.8	0.5	0.0098	△
Durian	11.0	11.6	12.1	12.6	13.1	13.7	14.2	0.6	0.0019	△
Sweet corn	2.4	2.7	2.9	3.2	3.4	3.7	3.9	0.7	0.0001	△
Guava	1.1	1.0	0.8	0.7	0.6	0.4	0.3	−0.4	0.0301	∇
Coconut	19.4	20.1	20.7	21.4	22.1	22.8	23.6	0.7	0.0003	△
Mango	1.9	1.9	1.9	1.9	1.9	1.9	1.9	0.1	0.8024	⊘
Mangosteen	0.7	0.6	0.6	0.6	0.6	0.5	0.5	−0.7	0.0002	∇
Pineapple	6.9	6.0	5.3	4.6	3.8	3.0	2.2	−0.7	0.0002	∇
Banana	9.0	8.7	8.5	8.3	8.1	7.9	7.8	−0.7	0.0002	∇
Rambutan	1.9	1.9	1.9	1.8	1.8	1.8	1.7	−0.8	0.0001	∇
Watermelon	4.3	4.2	4.2	4.1	4.1	4.0	4.0	−0.4	0.0214	∇

△: there is a significant positive trend, ∇: there is a significant negative trend, and ⊘: there is no significant trend.

significant negative trend for the consumption per capita of pork. However, there are no significant trends for the consumption per capita of lamb and chicken/duck egg. Malaysia's poultry meat consumption per capita is increasing as majority of Malaysians indicated that they would not willingly give up meat in their diets [65]. In 2025, the poultry consumption per capita in Malaysia was forecasted to about 48.2 kilograms per person annually. Similarly, the beef and buffalo meat consumption per capita in Malaysia has positive trend also [66], and in 2025, it was forecasted to amount to about 6.6 kilograms per person annually. Unlike poultry meat and beef consumption, pork meat consumption in Malaysia had been declining over the years [67], and in 2025, it was forecasted to amount to about 16.4 kilograms per person annually. This is most probably due to the African swine fever [68]. There is no significant trend found in the consumption per capita for lamb as it, in particular, is perceived as a superior meat among many consumers, for which they are willing to pay a premium [69]. Malaysia's lamb meat consumption volume was at approximately 43,000 tonnes carcase weight equivalent (cwe) in 2018 and forecasted to grow by 4% by 2022 [70]. However, the lamb consumption per capita shown in Table 3 shows that there is no significant trend exists and it was estimated that the lamb consumption per capita in Malaysia to about 0.9 kilograms per person annually in 2025.

4.2.4. Fisheries. Figure 8 illustrates that there are significant positive trends for the consumption per capita of squid and tuna fish. At the same time, there is also significant negative trend for the consumption per capita of mackerel fish. However, there are no significant trends for the consumption per capita of crab and prawn.

The positive trend of squid consumption per capita shows increasing demand for squid, and in 2025, the squid consumption per capita in Malaysia was forecasted to about 3.6 kilograms per person annually. This positive trend can be seen

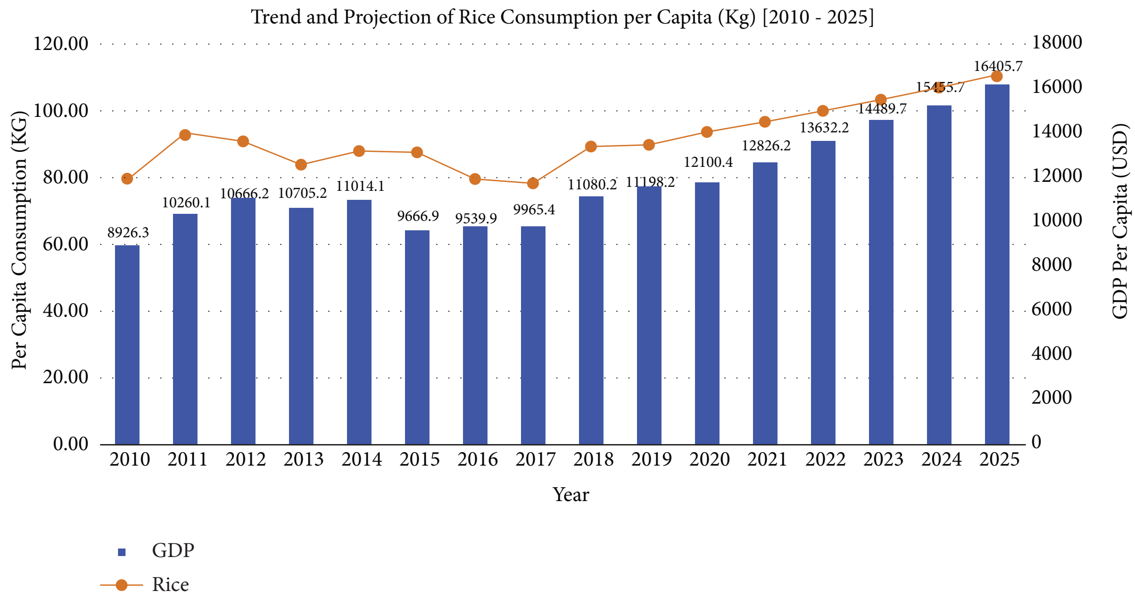

Figure 5: Projection of rice consumption per capita (kg) (2018–2025) based on secondary data obtained from 2010 to 2017.

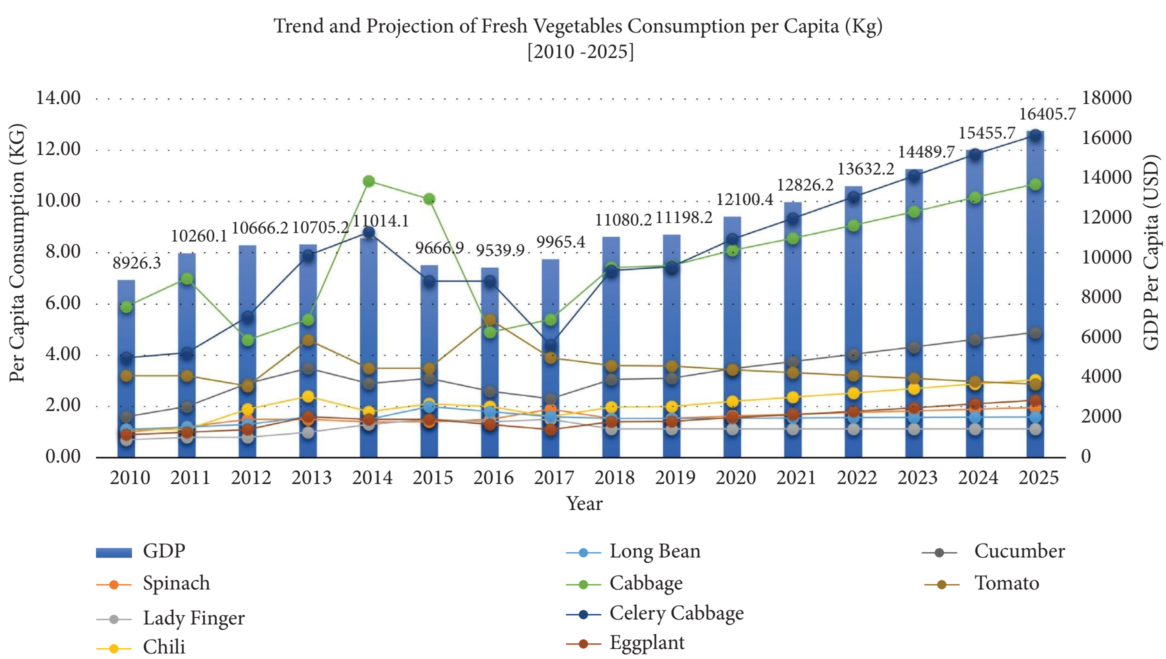

Figure 6: Projection of fresh vegetable consumption per capita (kg) (2018–2025) based on secondary data obtained from 2010 to 2017.

most probably because squid dishes are said to be able to reduce blood pressure or have other positive benefits [62]. Malaysia is one of the Asian countries which continue to demand more squid [71] and deliveries for squid have always been stable [72].

The demand for prawns in the local market is increasing but not significant and more initiatives have been taken to support the local prawn farming industry [73]. As prawns are one of the most popular seafood types [74, 75], in 2025, the prawn consumption per capita in Malaysia was forecasted to about 4.7 kilograms per person annually. They provide numerous health benefits due to its contents that can be used to improve bone and brain health [96].

The global crab market, which is dominated by Asia-Pacific, is estimated to grow at a CAGR of 5.5%, during the forecast period (2020–2025) [77]. However, the estimated projected consumption per capita of crab is about 0.4 kilograms per person annually in Malaysia, and there is no significant trend shown in Table 3.

Labuan waters has potentially become one of the hot spots for tuna fishing with high-valued catches [78]. The increased number of licences issued by the Fisheries Department in Labuan from 22 to 27 last year indicates that the demand for tuna-based products, which are locally manufactured, has increased [79]. The tuna consumption

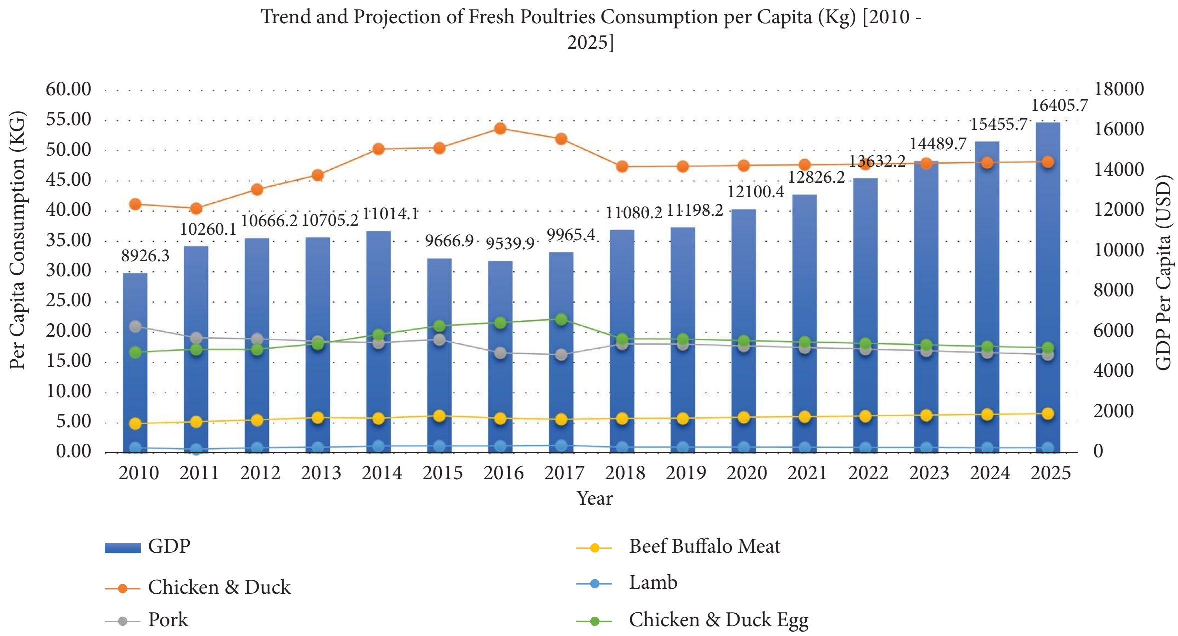

FIGURE 7: Projection of fresh livestock consumption per capita (kg) (2018–2025) based on secondary data obtained from 2010 to 2017.

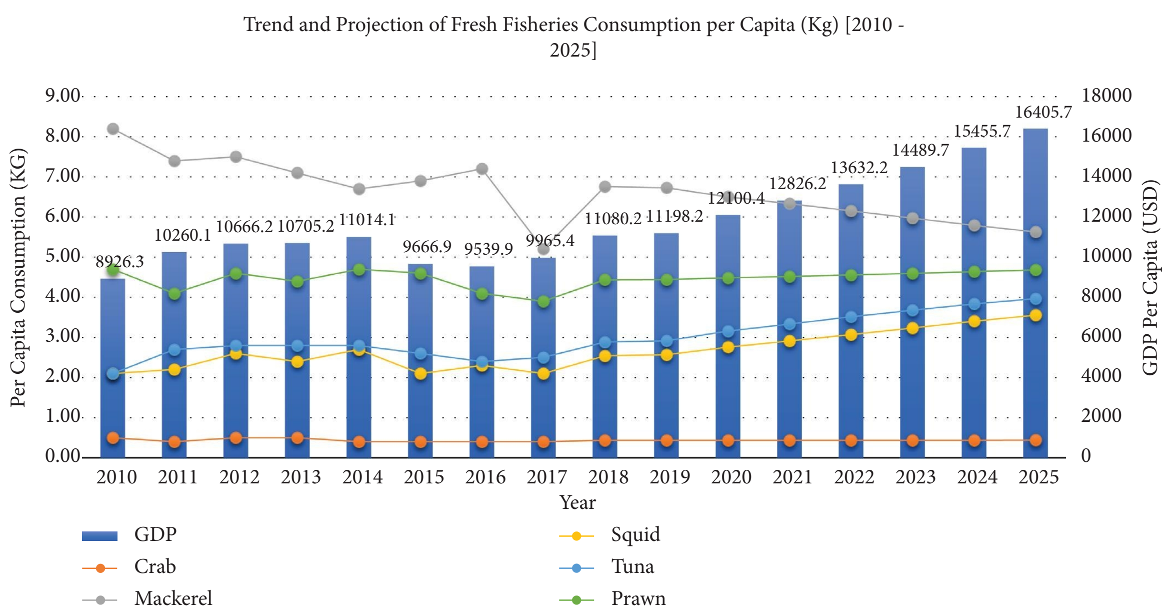

FIGURE 8: Projection of fresh fishery consumption per capita (kg) (2018–2025) based on secondary data obtained from 2010 to 2017.

per capita in Malaysia was forecasted to about 4.0 kilograms per person annually and the total forecasted consumption of tuna is expected to increase by 52.8% in 2025 (see Table 4).

The forecasted consumption per capita of mackerel fish is declining over the years until 2025. In 2025, the estimated projected consumption per capita of mackerel is about 5.6 kilograms per person annually and the total forecasted consumption of mackerel fish is expected to decrease by 16.7% (see Table 4). It is most probably because the price of mackerel fish (ikan kembung) has soared recently [80, 81].

4.2.5. Fruits. Figure 9 illustrates that there are significant positive trends for the consumption per capita of big size fruits such as durian and coconut. At the same time, there is also significant negative trend for the consumption per capita of other big size fruits such as pineapple, banana, and watermelon.

Coconuts are Malaysia's fourth largest industrial crop after oil palm, rubber, and rice. Malaysia is among the top 10 coconut exporters in the world and most of the plantations are found in Sabah and Sarawak [82]. Recently, coconuts are becoming popular as prices have gone up. The production of coconut is expected to increase by 2020 [83] as the demand

Table 4: Projections of fresh agro-food consumption ('000 tonnes metric).

Agro-food	2020	2021	2022	2023	2024	2025	Changes (%)	
Population ('000)	32370.0	32780.0	33180.0	33580.0	33970.0	34350.0		
Consumption ('000 ton metric)								
Rice	3047.5	3194.5	3355.3	3526.9	3717.4	3907.6	860.1	28.2
Vegetables								
Spinach	54.3	58.0	62.0	66.4	71.3	76.2	21.9	40.3
Lady's finger	36.0	36.4	36.7	36.9	37.2	37.4	1.4	3.8
Chili	73.8	81.1	89.1	97.8	107.6	117.5	43.6	59.1
Long bean	48.4	48.8	49.2	49.6	49.9	50.2	1.7	3.6
Cabbage	265.6	286.0	308.7	333.1	360.5	388.0	122.4	46.1
Celery cabbage	288.5	326.1	368.2	413.7	465.2	517.0	228.5	79.2
Eggplant	52.0	56.8	62.3	68.1	74.7	81.3	29.4	56.5
Cucumber	120.2	134.8	151.1	168.8	188.7	208.8	88.5	73.6
Tomato	111.8	109.6	106.8	103.6	99.8	95.9	−15.9	−14.2
Livestock								
Chicken and duck	1534.8	1556.5	1578.0	1599.7	1621.4	1642.6	107.8	7.0
Pork	567.2	563.6	558.3	551.9	543.4	534.6	−32.6	−5.7
Beef and buffalo meat	194.8	202.0	209.9	218.2	227.4	236.5	41.7	21.4
Lamb	33.2	33.4	33.5	33.5	33.5	33.5	0.3	0.9
Chicken and duck egg	595.7	593.7	590.1	585.6	579.2	572.5	−23.2	−3.9
Fisheries								
Crab	14.2	14.4	14.6	14.8	15.0	15.1	0.9	6.7
Mackerel	206.6	201.7	195.6	188.7	180.5	172.1	−34.6	−16.7
Squid	92.4	100.0	108.4	117.5	127.7	137.9	45.5	49.3
Tuna	105.4	114.6	124.9	136.0	148.4	160.9	55.6	52.8
Prawn	144.6	147.3	150.2	153.1	156.2	159.2	14.7	10.1
Fruits								
Star fruit	11.8	13.6	15.5	17.6	20.0	22.4	10.6	89.4
Jackfruit	57.5	59.1	60.8	62.6	64.6	66.6	9.1	15.8
Durian	392.6	420.0	450.3	482.9	519.4	555.9	163.3	41.6
Sweet corn	87.5	97.1	107.8	119.4	132.5	145.6	58.1	66.4
Guava	30.4	26.0	20.8	15.2	8.7	2.1	−28.3	−93.1
Coconut	661.7	692.2	725.6	761.1	800.5	839.8	178.1	26.9
Mango	60.4	61.2	61.9	62.7	63.5	64.3	3.9	6.4
Mangosteen	20.8	19.9	18.9	17.7	16.4	15.0	−5.8	−27.7
Pineapple	191.6	168.7	142.4	113.5	80.0	46.3	−145.3	−75.9
Banana	277.0	270.8	263.3	254.7	244.3	233.8	−43.3	−15.6
Rambutan	59.0	58.4	57.5	56.6	55.3	54.1	−4.9	−8.3
Watermelon	134.3	132.2	129.7	126.7	123.0	119.3	−15.0	−11.1

for the coconut increases based on the projection of the coconut consumption per capita (PCC) which was forecasted to about 23.6 kilograms per person annually [83].

The rising awareness about health benefits of durian has also been fueling the demand for the product across the world [84]. In 2025, the expected consumption per capita for durian is about 14.6 kilograms per person annually.

The demand for pineapple continues to rise worldwide [85]. However, the supply of pineapple in Malaysia was affected and has suffered losses following the problem faced by the Malaysian Pineapple Industry Board (MPIB) in retrieving the MD2 pineapple seeds under the Rompin Integrated Pineapple Plantation (RIPP) recently [86]. The trend of pineapple consumption per capita shows decreasing trend. In 2025, it was forecasted that the pineapple consumption per capita (PCC) in Malaysia decreases to about 3.0 kilograms per person annually.

The consumption per capita of banana is declining as shown in Table 3. The estimated projected consumption per capita of banana is declining to about 7.9 kilograms per person annually in 2025 and the total forecasted consumption of banana is expected to decrease by 15.6% in 2025 (see Table 4). The sudden spike of banana import in Malaysia may indicate there were potential shortages or inconsistent supply of local production which required additional supply [87].

The watermelon demand is declining worldwide (e.g., Malaysia [88], Australia [89], and Myanmar [90]). There is a significant negative trend forecasted for the consumption per capita of watermelon in Malaysia over the next five years. In 2025, the watermelon consumption per capita in Malaysia was forecasted to about 4.0 kilograms per person annually and the total forecasted consumption of watermelon is expected to decrease by 11.1% (see Table 4).

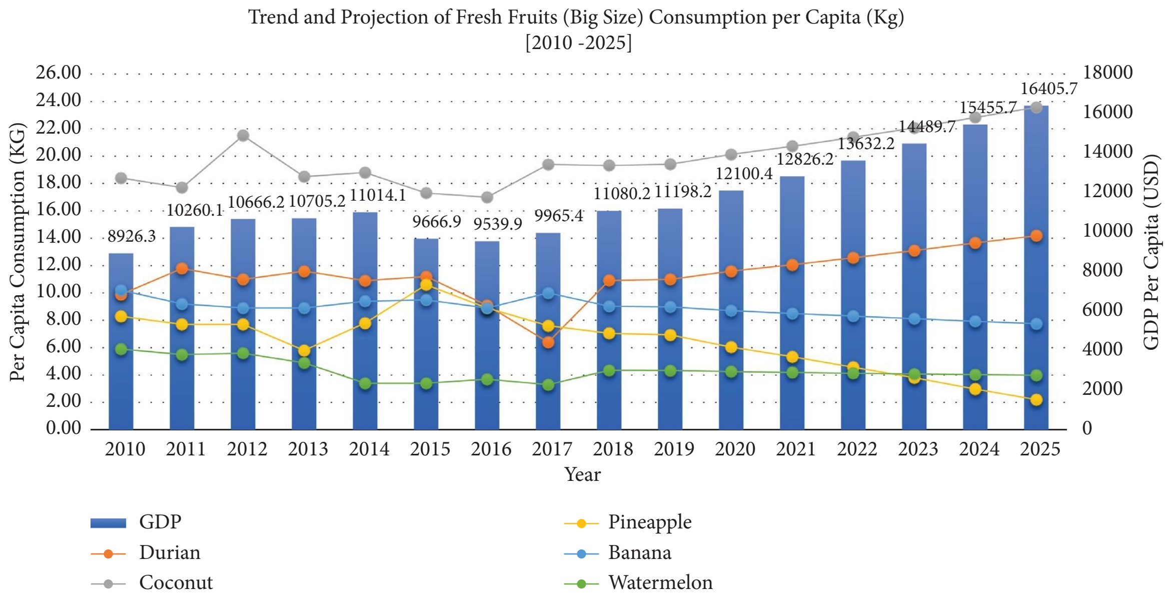

FIGURE 9: Projection of fresh fruit (big size) consumption per capita (kg) (2018–2025) based on secondary data obtained from 2010 to 2017.

Figure 10 illustrates that there are significant positive trends for the consumption per capita of small size fruits such as star fruit, jackfruit, and sweet corn. At the same time, there is also significant negative trend for the consumption per capita of other small size fruits such as papaya, guava, mangosteen, and rambutan [88]. However, there are no significant trends for the consumption per capita of mango. These findings are in line with the findings of a study on vegetable and fruit intake among Malaysians that showed there is only a small percentage of consumers who actually buy and consume enough fruits and vegetables as per the dietary guidelines [91]. Star fruit is gaining popularity recently [62] as it is loaded with healthy fiber and vitamin C which is useful to reduce fatty liver risk [92]. The consumption per capita of star fruit is projected to about 0.7 kilograms per person annually.

The consumption per capita of papaya is predicted to be decreasing due to limited supply as the papaya industry is facing various disease issues that jeopardize its production [93].

4.3. Malaysian GDP Per Capita and Agro-Food Consumption Per Capita (PCC). This section analyzes the correlation between Malaysian GDP per capita and the selected agro-food consumption per capita (PCC). Table 5 tabulates all the agricultural commodities that have strong positive or negative correlation values between the consumption per capita (PCC) in kilogram and the Malaysian national gross domestic product per capita (USD).

4.4. Significant Positive Trends. The present study demonstrated that with the increase in the gross domestic product (GDP) per capita, the consumption per capita for several fresh agro-food commodities is also increasing. For instance, Figures 5 and 6 depict significant positive trends that include rice, spinach, chili, cabbage, celery cabbage, eggplant, and cucumber. There are strong positive correlations between the GDP and the PCC of rice, celery cabbage, eggplant, and cucumber with correlation values of 0.95, 0.91, 0.91, and 0.93, respectively.

For the livestock and fishery categories, Figures 7 and 8 display significant positive trends for chicken/duck, beef/buffalo meat, squid and tuna. Based on the observation, the positive correlation values between GDP and the PCC of squid and tuna are quite high, which are 0.98 and 0.99. Finally, Figures 9 and 10 depict significant positive trends for star fruit, jackfruit, durian, sweet corn, and coconut. Only three commodities have strong positive correlation values with GDP which are star fruit (0.91), sweet corn (0.96), and coconut (0.90).

4.5. Significant Negative Trends. At the same time, the present study also demonstrated that with the increase in the gross domestic product (GDP) per capita, the consumption per capita for several fresh agro-food commodities is also decreasing. For instance, Figures 7 and 8 depict significant negative trends for livestock and fisheries that include pork and mackerel. For the fruit category, Figures 9 and 10 display significant negative trends for papaya, guava, mangosteen, pineapple, banana, rambutan, and watermelon. There are strong negative correlations between the GDP and the PCC of papaya, pineapple, and banana with correlation values of −0.95, −0.94, and −0.90, respectively.

4.6. Forecasted Demand for Agro-Food Commodities in Malaysia. This section discusses the forecasted Malaysia demand for the agro-food commodities based on the forecasted Malaysia population [94], up to the year of 2025. The projected demands for agro-food commodities will be generated by using the projected consumption per capita of

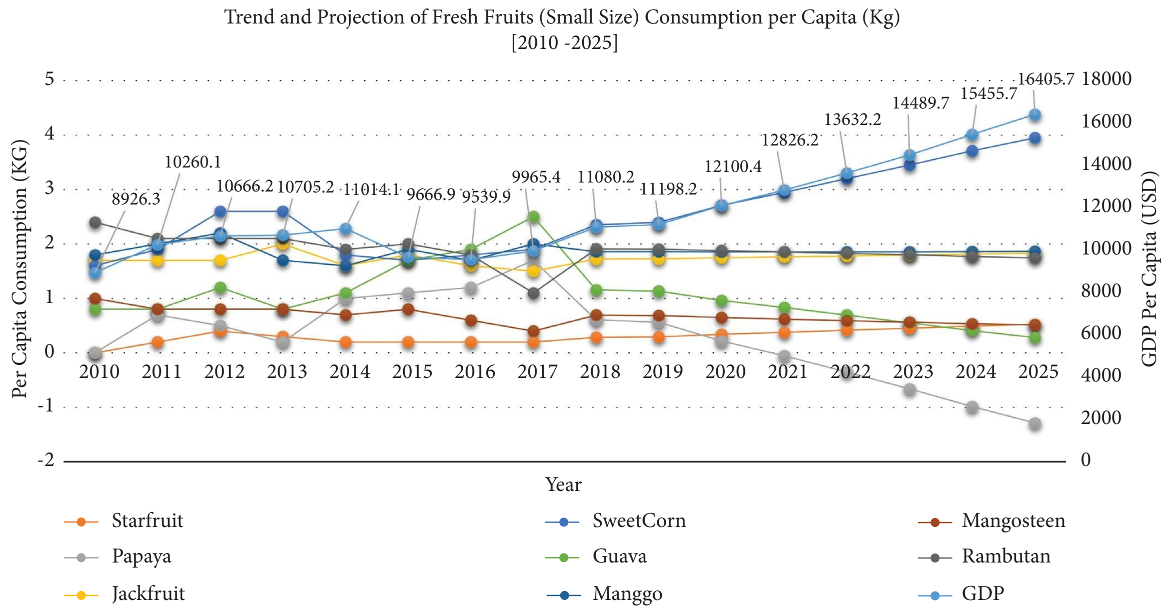

Figure 10: Projection of fresh fruit (small size) consumption per capita (kg) (2018–2025) based on secondary data obtained from 2010 to 2017.

Table 5: Agricultural commodities that have strong positive or negative correlation values between the consumption per capita (PCC) in kilogram and the Malaysian national gross domestic product per capita (USD).

Relationship	Agro-food	Corr.
Positive	Rice	0.95
	Celery cabbage	0.91
	Eggplant	0.91
	Cucumber	0.93
	Squid	0.98
	Tuna	0.99
	Star fruit	0.91
	Sweet corn	0.96
	Coconut	0.90
Negative	Papaya	−0.95
	Pineapple	−0.94
	Banana	−0.90

all the 33 selected agro-food commodities in this work that can be referred from Table 3.

There are 22 out of 33 agro-food commodities that were most commonly consumed which have self-sufficiency ratios (SSRs) of more than 100% with agricultural products (i.e., eggplant, cucumber, spinach, and eggs), but a few of them have self-sufficiency ratios (SSRs) of less than 100% with rice (70.0%), chili (31.9%), cabbage (38.7%), celery cabbage (97.6%), mango (23.3%), coconut (68.8%), guava (94.0%), mackerel (86.5%), crab (86.9%), chicken and duck (98.1%), pork (91.9%), beef and buffalo meat (23.9%), and lamb (11.2%) [2].

Referring to Table 4, several agro-food commodities have been identified as critical commodities that require self-sufficiency ratios (SSRs) of more than 100%. For instance, the consumption of rice in Malaysia increases by approximately 860.1 million metric tonnes from year 2020 to 2025, which has an increase of demand by 28.2%. For vegetables, the consumption of chili, cabbage, and celery cabbage is projected to increase by 59.1%, 46.1%, and 79.2% in 2025. The SSRs for poultry (chicken/duck), beef, and lamb in 2018 were estimated to be 98.1%, 23.9%, and 11.2%, respectively, and the projected consumption for these agro-food commodities was estimated to increase by 7.0%, 21.4%, and 0.9%, respectively. Malaysia's agricultural productivity is estimated to be 45% of the average among high-income countries [95]. For fisheries, the critical agri-food commodities include crab and mackerel. However, the projected consumption for mackerel decreases by 16.7% in 2025. On the other hand, the consumption of crab is projected to be increased by 6.7% in 2025. Finally, for fruits, the forecasted consumption for mango and coconut was 6.4% and 26.9% in 2025. There is an urgent need for reforming and expanding the agricultural sector's contribution to the country's development trajectory [96]. Thus, more initiatives should be planned and executed by the Ministry of Agriculture and Agro-Based Industry (MoA) to ensure that the supply of these critical agri-food commodities is sufficient by the year 2025. In short, the results have shown a huge gap between the consumption per capita and self-sufficiency ratios (SSRs) of various crops which is comparable to those findings found previously [10].

5. Conclusion

In general, the neural network model was the best prediction model and is a potential decision-supportive tool for the Ministry of Agriculture and Agro-Based Industry to strategize and implement all programmes that have been outlined in the next National Agro-Food Policy 2021–2030. This study will give ideas to future studies focusing on different agro-food sub-sectors. The present study demonstrated that with the increase in the gross domestic product (GDP) per capita, the consumption per capita for several fresh agro-food commodities is also increasing (e.g., rice, spinach, chili, cabbage, celery cabbage, eggplant, cucumber, chicken/duck, beef/buffalo meat, squid, tuna, star fruit, jackfruit, durian, sweet corn, and coconut). At the same time, with the increase in GDP per capita, the consumption per capita for several fresh agro-food commodities is also decreasing that includes pork, mackerel, papaya, guava, mangosteen, pineapple, banana, rambutan, and watermelon. Several agro-food commodities have also been identified as having significant positive (e.g., rice, spinach, cabbage, celery cabbage, eggplant, cucumber, poultry, lamb, squid, tuna, star fruit, jackfruit, durian, sweet corn, and coconut) or negative (e.g., pork, mackerel, papaya, guava, mangosteen, pineapple, banana, rambutan, and watermelon) trends using the Mann–Kendall trend test. This study demonstrated that the production of critical agro-food commodities (e.g., rice, chili, cabbage, celery cabbage, poultry (chicken/duck), beef, lamb, crab, mango, and coconut) should be improved to ensure self-sufficiency ratios (SSRs) of more than 100% to accommodate the increased projected consumptions in Malaysia by the year 2025. The results have shown a huge gap between the PCC and SSRs of various crops which is comparable to those findings found in previously published works. There are a few limitations of this work. This includes modelling the dependent variable (e.g., PCC) against only one independent variable (e.g., GDP). In order to get a more comprehensive understanding, more future works should be conducted involving several independent variables such as weather conditions, disease outbreak, and stock market trends. Next, there is a need to explore further the capability of ensemble models or hybrid models based on deep learning methods using multi-source data, as these have been shown to improve the performance of the base model. With these ensemble models combined with multi-source data, a more comprehensive analysis of the PCC can be obtained.

Data Availability

In this study, thirty-three fresh agrofood products, which can be categorized into rice, livestock, vegetables, fisheries, and fruits and the per capita consumption (PCC) secondary data of these products for the last eight years (e.g., 2010 to 2017) will be used. These data are obtained from the Federal Agricultural Marketing Authority (FAMA), Ministry of Agriculture and Food Industry, Malaysia, and Department of Statistics Malaysia (DOSM).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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