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*RESEARCH ARTICLE*

# THE APPLICATION OF LINEAR REGRESSION AND ARTIFICIAL NEAURAL NETWORKS TO FORECAST THE AMOUNT OF ELECTRONIC WASTE IN THAILAND

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## Abstract

This research aims to investigate the input factors influencing e-waste generation and analyze their predictive capabilities using linear regression techniques and neural networks. The study utilizes data collected from the population, Gross Domestic Product (GDP), inflation, and the amount of e-waste obtained from the Pollution Control Department. By comparing the performance of linear regression and neural networks, this research seeks to identify the most effective approach for modeling and forecasting e-waste generation based on the selected input factors. The findings will contribute to improved understanding and prediction of e-waste patterns, aiding policymakers and waste management authorities in developing sustainable strategies for e-waste management. The data were forecast the possible volume of e-waste in the future. A model using neural network modeling techniques be dividing data into different layers:3 input layers,3 hidden layers,1 bias, and 1 output layer.The effect of deep learning is to get a Learning Rate: LR = 0.01 that doesn't increase the loss value. This allows the model to be trained as fast as possible, with a loss of0.0056, Os 92 ms/step. Neural Network learned with data, and reworked it to fit this data 500 times (Epochs = 500), where Root Mean Squared Error: RMSE= 0.0751, RMSE approaches 0, showing that the model is highly accurate.



## Introduction:-

The concern of e-waste related to the growth of its volume every year caused by the increase of consumption and short lifespan. E-waste is considered the most rapidly growing waste in the past decade (3-4% per year), while only 15% of them are recycled [2] During 2004-2020, most of the researches discussed or conducted in the Asia region (64.2%) and mainly focused on China (22.4%) and India (11.9%). associated with the fact that China is the major contributor because of the import of e-waste and rapid economics and industrial development [4]According to the UN's Global E-Waste Monitor 2020, e-waste volumes surged to 53.6 million metric tons worldwide in 2019, signifying a notable 21% increase over the span of five years. Regrettably, a mere 17.4% of this colossal e-waste

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output was appropriately directed to recycling facilities. Thailand, in particular, grapples with a worrisome annual production of over 400,000 tons of e-waste from local communities. Consequently, one might ponder if Thailand's capacity to manage electronic waste will be overburdened. Alas, a mere 7.1% of the collected waste finds its way to proper recycling channels. The accumulation of e-waste poses a formidable challenge, as a multitude of considerations must be weighed in planning effective waste management operations. These include storage, consolidation, material recovery, as well as the indispensable tools, machinery, equipment, personnel, and systems necessary to avert environmental pollution. Indeed, the detrimental consequences of e-waste mismanagement extend to soil, water, and air pollution. Given the exponential growth of e-waste volumes in recent years, it becomes imperative to devise policies and strategies that prioritize recycling and reusing scarce minerals, such as rare earth, thereby diminishing the need for resource-intensive underground mining. Forecasts serve as indispensable tools in designing and implementing environmentally conscious engineering and inspection practices, which in turn inform the development of a sustainable e-waste system in Thailand.The classification and its percentage as in Table 1.[1] The awareness of e-waste has emerged since 2002 in the Basel Convention and “European Union Waste of Electronic and Electrical Equipment Directive”.

**Table1:-** The classification of WEEE.

| Classification of WEEE | % |
|---|---|
| Large household appliance | 49 |
| Small household appliance | 7 |
| IT and telecommunication | 16 |
| Consumer electronics | 21 |
| Lighting equipment | 2.4 |
| Electrical and electronic tools | 3.5 |
| Toys, leisure and sport equipment | 0.1 |
| Medical devices | 0.1 |
| Monitoring and Control equipment | 0.2 |
| Automatic dispensers | 0.2 |

**The tool to manage e-waste**

The previous research comprehensively delved into an array of tools utilized in the management of e-waste. These tools encompassed Extended Producer Responsibility (EPR), Life Cycle Assessment (LCA), Material Flow Analysis (MFA), and Multi-Criteria Analysis (MCA). The articles further offered valuable insights and recommendations to enhance the e-waste management system. These suggestions spanned various areas, including device design, e-waste collection, recycling, and initiatives aimed at raising awareness [3]. Some studies focused on scrutinizing existing management strategies while proposing global solutions, such as establishing recycling plants, internalizing prices, and fostering reduction and reuse [5-6]. Additionally, comparative studies were conducted to discern disparities between developed and developing nations [7-8]. Furthermore, research endeavors explored innovative approaches, such as the design of mobile plants, the implementation of autonomous robots in recycling facilities, and the utilization of cyber-physical systems for e-waste management [9-11]. In order to estimate the volume of e-waste, forecasting techniques were employed, leveraging production data of Electrical and Electronic Equipment (EEE) while considering the proportion of End-of-Life (EOL) devices discarded and recycled [12]. Questionnaires adapted from the United Nations Environment Program (UNEP) were also utilized to analyze the potential generation and flow of e-waste, although the accuracy of the data relied on the role and expertise of respondents in the EEE or Waste Electrical and Electronic Equipment (WEEE) life cycle[13]. Common models employed for estimating e-waste generation include Material Flow Analysis and Population Balance Model [14]. Furthermore, system dynamics modeling revealed that factors such as population growth, economic development, and changes in consumption patterns influenced the escalating number of EOL EEE [15]. Overall, the research aimed to explore effective management strategies, estimate e-waste generation, and comprehend the intricate dynamics entwined within e-waste management systems. In developing countries, the reverse e-waste supply chain network typically encompasses four to six key stakeholders, namely end-users (households, institutions, or corporates), collectors (scavengers and service centers), secondhand markets, sub-dealers or recyclers, refurbishment entities, and dealers engaged in exporting non-recyclable e-waste [16-18]. The substances in e-waste and the impact on health.Table 1 [19-25] presents a comprehensive list of the substances found in e-waste and their impact on human health.E-waste can be classified based on a physical and chemical constituent. The classification of its characteristics in references is presented in Table 1. The differences in physical and chemical composition may come from different years of the data.

**Table 1:-** The differences in physical and chemical composition.

| **Constituents (%)** | 2014 | 2004 | 2012 | 2015 |
|---|---|---|---|---|
| **Metals** | 60.2 | 49 | 13 | 39.50 |
| Copper | | | 7 | 20.10 |
| Iron | | | | 8.1 |
| Tin | | | | 4 |
| Nickel | | | | 2 |
| Lead | | | | 2 |
| Aluminium | | | | 2 |
| Zinc | | | | 1 |
| Silver | | | | 0.20 |
| Gold | | | | 0.10 |
| Palladium | | | | 0.01 |
| **Plastics** | 15.2 | 33 | 21 | 30.30 |
| Metal-plastic mixture | 5 | | | |
| Cables | 2 | | | |
| Screens (CRT and LCD) | 11.9 | 12 | | |
| PCB | 1.7 | | | |
| Others | 1.4 | 1 | | |
| Pollutants | 2.7 | | | |
| Wood | | 5 | | |
| Refractory Oxides | | | | 30.20 |

A study conducted in Vietnam confirmed the presence of dioxin compounds in soil at e-waste processing sites, surpassing the maximum acceptable concentration set by WHO regulations. This pollution primarily stems from the practice of open burning and storage [26]. Improper recycling activities, such as open burning and manual dismantling, have led to soil and river contamination in Vietnam. Fire retardants have been detected in soils and river sediments, providing evidence of this detrimental pollution [27]. Furthermore, residents living near e-waste burning sites exhibited the highest levels of exposure, as evidenced by blood analyses. The study concluded that open burning conducted by the informal waste sector significantly contributes to air contamination, leading to elevated heavy metal exposure for these residents [28]. In line with a study conducted in India, a separate investigation conducted in urban areas of Vietnam's informal e-waste recycling sites revealed higher levels of PCBs (polychlorinated biphenyls) and BFRs (brominated flame retardants) in indoor dust compared to non-e-waste households [29-30]. The contamination of cadmium in groundwater systems exceeded regulatory thresholds, indicating severe toxicity concerns. Additionally, the process of e-waste recycling resulted in increased blood lead levels (BLLs), particularly among children and adolescents, surpassing recommended levels [30-31]. Another study examined the exposure to phthalic acid esters (PAEs), which are prevalent in e-waste recycling areas. Urine samples from residents were analyzed, shedding light on the presence of PAEs and their potential health implications [32].

**E-waste in Thailand**

In Thailand, the sources of electronic waste are primarily divided into three main parts:

1. Industrial Waste: Refers to electronic waste generated within factories, including components with chemical substances and leftover scraps from the production process. This category also includes products that do not meet the standards for recycling or disposal.
2. Household Waste: Refers to electronic waste generated from everyday use by individuals, including waste from households, companies, and various stores. This includes waste generated from the use of products until they reach the end of their lifespan, are outdated, or become damaged beyond repair.
3. Import Waste: Refers to electronic waste that is imported from foreign countries, as regulated by the Hazardous Substances Act of 1992.

The situation of waste from electrical and electronic equipment (WEEE) in Thailand in the year 2020 was as follows: There was a total amount of 418,113 tons of waste from electrical and electronic equipment generated. The majority of these waste products were collected at households, totaling 214,056 tons. Additionally, 170,545 tons were sold to second-hand shops for purchase of used goods. The community-based waste separation resulted in

43,152 tons of waste from electrical and electronic equipment being sorted, while local government organizations collected 360 tons. Based on Table 2

**Table 2:-** The quantity of waste from electrical and electronic equipment between the years 2017 to 2020.

| No. | Product | Amount WEEE ton/year | | | |
|---|---|---|---|---|---|
| | | 2017 | 2018 | 2019 | 2020 |
| 1 | Television | 98,369.71 | 98,612.65 | 99,447.71 | 100,515.36 |
| 2 | Air condition | 75,419.61 | 76,653.41 | 77,653.41 | 78,639.32 |
| 3 | Refrigerator | 63,884.71 | 64,970.07 | 65,995.07 | 66,880.48 |
| 4 | Washing Machine | 60,851.64 | 61,927.60 | 62,807.60 | 63,719.55 |
| 5 | Computer | 56,087.54 | 58,261.41 | 59,711.41 | 60,756.21 |
| 6 | CD/DVD Player | 30,436.42 | 32,630.77 | 32,830.77 | 33,175.65 |
| 7 | Telephone | 8,797.58 | 11,824.85 | 12,915.30 | 14,240.98 |
| 8 | Digital Camara | 7,540.00 | 9,773.73 | 9,973.73 | 10,185.45 |
| **Total** | | **401,387.21** | **414,654.49** | **421,335.00** | **428,113.00** |

**Source:** Industrial and Electronic Appliance Data Center, Electricity and Electronics Institute.

Based on Table 2, which shows the quantity of waste from electrical and electronic equipment between the years 2017 to 2020, it was found that the amount of waste products has been continuously increasing. This is a result of rapid technological advancements leading to frequent changes in electrical and electronic products to keep up with the latest technology. The importation of low-quality products has also contributed to shorter product lifespans and increased generation of waste products. Furthermore, a significant portion of the population disposes of waste products improperly by mixing them with general waste or selling them to informal waste collectors, resulting in inadequate management of these waste products. This situation has adverse impacts on public health and the environment.

**Environmental and Health Effect**

In Thailand, it is common for general public entrepreneurs to engage in the dismantling and separation of electronic waste. This process typically takes place within residential areas, where the electronic waste is dismantled and sorted before being sold as recyclable materials to secondhand shops or recycling businesses. These general public entrepreneurs may have varying levels of expertise and specialization in dismantling different types of electrical appliances, such as televisions, fans, air conditioners, refrigerators, computers, and mobile phones. The activities involved in this process are similar and usually occur in the areas beneath houses and their surroundings. The process itself involves manual dismantling and separation, with some individuals wearing minimal personal protective equipment, such as gloves and face masks, to ensure their personal safety. In order to extract valuable metals, television and computer screens are often smashed, while compressors from air conditioners and refrigerators are dismantled to separate copper and steel. Unfortunately, this process results in oil residues contaminating the soil, as some individuals collect and store the oil for resale. To extract valuable metals from small-sized electrical wires, burning is often employed. This burning is typically done on one's own land, rented land, or in local government waste pits. However, this practice releases toxic fumes, including lead vapor, dust, hazardous gases, dioxins, and furans, into the environment. In addition to these practices, there is improper disposal or burning of electronic waste that cannot be easily sold or decomposed. Television screens and foam insulation from refrigerators are sometimes left on roadsides, public areas, or mixed with general waste. The burning of such waste in unregulated areas or waste pits generates thick smoke and foul odor, spreading with the wind and causing inconvenience and distress to both the local community and nearby communities not engaged in this activity**.**Entrepreneurs involved in the dismantling and separation of electronic waste without proper personal protective equipment, such as N95 masks and thick rubber gloves, are at risk of inhaling hazardous chemicals or dust contaminated with dangerous heavy metals. This poses significant health risks to them. Pregnant women or breastfeeding mothers can transmit these chemicals, particularly heavy metals like lead, to their fetus or infant through breast milk. Lead, being a highly toxic heavy metal, is of particular concern, especially for children under the age of six living in areas where electronic waste is being dismantled and separated. These children are at a high risk of accumulating dangerous levels of lead, which can lead to lead poisoning. Lead dust that clings to the clothing of caregivers can also be transmitted to children through the respiratory system or through behaviors like touching objects and putting their hands in their mouths. This increases the risk of lead exposure through the digestive system. Moreover, young children's bodies can absorb and retain lead more efficiently through the digestive system compared to adults, up to forty-five times more. This is especially concerning for children who lack essential nutrients like calcium. The accumulation of lead in the bodies of young children can impair their nervous system, affecting brain development and the central nervous system. This can result in lower IQ, delayed development, growth impairment, decreased attention span, and anemia. Apart from lead, electronic waste contains various other dangerous heavy metals and substances that can have long-term health impacts and accumulate in both the environment and the human food chain.

The activities involved in the dismantling and separation of electronic waste, such as burning wires or plastic scraps, as well as smashing and disposing of glass from television screens, possess the potential to spread and contaminate hazardous substances in the environment. This contamination can affect various aspects of environmental quality, including soil, surface water, and groundwater. Firstly, the water quality in community water sources for consumption may be compromised due to the presence of these hazardous substances. Secondly, the soil quality in residential areas can deteriorate. For instance, the disposal of refrigerator condenser coils can render the soil slippery. Moreover, contamination of soil in agricultural areas can lead to the infiltration of heavy metals into crops or other plants, posing risks to food safety. Furthermore, the air quality can be significantly impacted by these activities. Burning wires, foam insulation from refrigerators, or large quantities of plastic scraps can release toxic air pollutants. These pollutants can disperse through the wind and affect communities unrelated to the occupation of electronic waste dismantling and separation. Several examples of identifiable air pollutants include:Burning wires made of PVC plastic to extract copper can generate smoke, fine dust, and toxic gases like hydrogen chloride (HCl). Burning wires made of PVC plastic mixed with other types of waste in landfills, which contain substances from the polyaromatic hydrocarbon (PAHs) group, can produce dioxins and furans. These persistent toxic substances can accumulate in the environment for extended periods and possess high toxicity levels. Burning plastic scraps containing polyethylene, polypropylene, and polystyrene can emit smoke, fine dust, volatile organic compounds (VOCs), and carbon monoxide (CO). Burning foam insulation made of polyurethane can release smoke, fine dust, and toxic gases like hydrogen cyanide (HCN). These pollutants not only pose risks to the environment but also to the health and well-being of individuals residing in these areas. It is essential to address and mitigate these environmental hazards associated with electronic waste dismantling and separation to safeguard both the ecosystem and human health.

**The problems and obstacles in managing the disposal of electrical and electronic product waste are as follows:**

Addressing these problems and overcoming the obstacles requires a comprehensive approach involving government regulations, public awareness campaigns, investment in infrastructure, and collaboration between various stakeholders including manufacturers, recyclers, and consumers. In Thailand from the implementation of projects or activities under the strategic plan, it has been found that some problems have been alleviated or resolved. However, the current situation reveals that there are still several unresolved issues, including the emergence of new product-related problems resulting from technological, economic, social, and environmental changes, such as:

1. The quantity of electronic and electrical waste products has increased significantly due to rapid technological changes. This has led to a higher frequency of replacing electronic and electrical appliances, including the importation of low-quality products with short lifespans that are not cost-effective to repair.
2. There is a lack of specific legislation governing the management of waste products, resulting in a lack of systematic mechanisms for waste management. While government agencies may provide disposal services for waste products to ensure proper handling, the quantity collected in each period remains minimal. The majority of the population tends to sell their waste products to appliance repair shops, secondhand stores, scrapyards, or dispose of them as general waste.
3. The collection and database systems for product and waste-related information among relevant public and private entities are not interconnected on a national level. Furthermore, there are no requirements for businesses to compile waste quantity data from the outset. Consequently, it is challenging for government agencies or research institutions to establish comprehensive databases, leading to potentially unreliable data and the formulation of plans or policies that do not reflect the rapidly changing economic, social, and technological landscape.
4. Business establishments involved in dismantling and separating waste from electronic and electrical appliances, such as buy-and-sell shops or community-based operations, often do not adhere to the necessary regulations or guidelines, despite the existence of controlling laws.
5. Recycling facilities for plastic and metal scraps derived from the dismantling and separation of electronic and electrical waste products are predominantly located in central and eastern regions of the country. This results in high transportation costs for plastic and metal scraps from manufacturing facilities in other regions, necessitating frequent

large-scale transportation using trucks operated by intermediaries. During certain periods when the prices of plastic and metal scraps are low, smaller-scale dismantlers find it economically unviable, leading to the accumulation of plastic and metal scraps in significant quantities in the area. This situation poses a risk of fire outbreaks, causing inconvenience and potential hazards to nearby communities.

6. Research and development in the field of waste management technology and innovation are still limited and do not cover all types of waste products. As a result, the recycling of valuable plastic and metal scraps from waste products often reenters the production process inefficiently or relies on outdated technologies that have adverse effects on the health of workers and neighboring communities. This is particularly evident in metal smelting operations, which frequently release a high volume of air pollutants, such as particulate matter, metal fumes, and various toxic gases, depending on the type of metal involved. Consequently, communities often voice complaints and engage in protests against such operations.

7. The control of imports for used electrical and electronic products from foreign countries does not cover all types of such products. According to the announcement of the Department of Industrial Works on the conditions for permitting the importation of used electrical appliances and electronic equipment as hazardous substances into the Kingdom (Version 3, 2007), the scope of controlled electrical appliances and electronic equipment is defined by 32 specified items and their components or parts, which require authorization from the officials for importation into the country. However, in the case of used electrical appliances and electronic equipment that are not listed in the announcement, they can be imported into the country without any conditions. Consequently, a large number of foreign used electrical products are imported into the country. These products often have a short lifespan and are not cost-effective to repair or lack repair shops, leading to their disposal as electronic waste in a short period of time.

8. The public is still not aware of the hazardous dangers posed by waste products and their impacts on health, the environment, and lacks motivation to separate waste products from general waste. As a result, they often opt for methods of managing waste products by selling them to appliance repair shops, second-hand stores, scrapyards, or simply disposing of them together with general waste, instead of following the designated collection points established by local authorities.

9. The future technological advancements will lead to the generation of electronic waste from components or discarded products, for which there is currently no preparedness. It remains unclear which agencies will be responsible for establishing efficient collection systems, recycling, and waste management. If adequate preparations are not made, it will become a burden for local government organizations that will require a significant allocation of resources for future management, such as electric vehicle (lithium-ion) batteries and various types of solar cells made from monocrystalline, polycrystalline, amorphous silicon, cadmium telluride, or copper indium gallium selenide/sulfide. These electronic waste materials can be a significant source of heavy metal pollution to the environment.

From the preliminary issues regarding the collection and database systems for product and waste-related information, which are not interconnected among relevant public and private entities on a national level, and the absence of requirements for businesses to compile waste quantity data from the outset, there is a lack of beneficial data for development and management in the realm of e-waste. Therefore, this research study has undertaken the examination and creation of a predictive model for estimating the quantity of e-waste in Thailand. This is accomplished through the utilization of data that can be collected from the public sector, with the identified factors that have an impact on the amount of e-waste in Thailand being Population (X1), Gross Domestic Product (X2), and Inflation (X3). A linear regression model and neural networks have been employed to forecast the future amount of electronic waste in Thailand.

## Materials and Methods:-

The objective of this research is to examine the utilization of linear regression and neural network techniques for forecasting the volume of electronic waste in Thailand. The study focuses on three factors: Population (X1), Gross Domestic Product (X2), and Inflation (X3). A linear regression model and neural networks are employed to predict the future amount of electronic waste in Thailand. Data from 2008 to 2020 is collected for X1, X2, and X3 to forecast the potential volume of electronic waste.

**The models using Linear Regression technique yielded three models, which are as follows:**

**1. Linear regression** is a statistical technique used to model the relationship between a dependent variable and one or more independent variables. In the context of the given research objective, linear regression is utilized to forecast the volume of electronic waste in Thailand based on the three factors: Population (X1), Gross Domestic Product (X2), and Inflation (X3).

2. **The linear regression mode**l assumes a linear relationship between the independent variables (X1, X2, and X3) and the dependent variable (volume of electronic waste). It aims to find the best-fit line that minimizes the difference between the predicted values and the actual values of the dependent variable.
3. **To perform the linear regression analysis**, data from the years 2008 to 2020 for the three factors (X1, X2, and X3) are collected. These factors are used as predictors or inputs for the linear regression model. The corresponding volumes of electronic waste serve as the dependent variable.

The data used in the research is time series data, obtained from the population statistics provided by the Ministry of Interior of Thailand on December 31st of each year. The data is derived from the central registration authority, under the signature of the Director-General of the Department of Provincial Administration, as published in the Royal Gazette regarding the total number of citizens throughout the kingdom, based on the evidence of citizen registration as of December 31st of each year. This is done in accordance with the authority granted by Section 45 of the Registration Act of 1991. The Director-General of the Department of Provincial Administration announced the total number of citizens throughout the kingdom based on the evidence of citizen registration on December 31st, 2008, until 2020.For the import of data related to Gross Domestic Product (GDP) in billion baht and inflation rate (%) from the National Economic and Social Development Council and the Budget Bureau of the Thai Parliament and the Bank of Thailand, the data covers the period from 2008 to 2020. This data is used for predicting the quantity of electronic waste.

**Table 1:-** Data from years 2008-2020.

| Year | E-waste (Metric ton) | Population (person) | GDP (Billion baht) | Inflation Rate (%) |
|---|---|---|---|---|
| 2008 | 322,380 | 63,389,730 | 7,710 | 5.51 |
| 2009 | 332,839 | 63,525,062 | 7,657 | -0.81 |
| 2010 | 341,989 | 63,878,267 | 8,232 | 3.26 |
| 2011 | 350,939 | 64,076,033 | 8,302 | 3.81 |
| 2012 | 359,070 | 64,456,695 | 8,903 | 3.01 |
| 2013 | 368,314 | 64,785,909 | 9,142 | 2.18 |
| 2014 | 376,801 | 65,724,716 | 9,232 | 1.9 |
| 2015 | 384,233 | 65,729,098 | 9,521 | -0.9 |
| 2016 | 380,605 | 65,931,550 | 9,849 | 0.18 |
| 2017 | 393,070 | 66,188,503 | 10,260 | 0.67 |
| 2018 | 414,600 | 66,413,979 | 10,690 | 1.07 |
| 2019 | 420,000 | 66,558,935 | 10,932 | 0.7 |
| 2020 | 428,113 | 66,186,727 | 10,265 | -0.85 |

**Source:** Department of Pollution Control, Ministry of Interior, National Economic and Social Development Council, Budget Bureau of the Thai Parliament, and Bank of Thailand.
4. The linear regression model estimates the coefficients or weights for each independent variable, indicating the strength and direction of their influence on the volume of electronic waste. These coefficients help determine the contribution of each factor to the overall prediction.
5. Once the linear regression model is trained using the collected data, it can be used to forecast the potential volume of electronic waste in Thailand for future periods. By inputting the values of X1 (Population), X2 (Gross Domestic Product), and X3 (Inflation) for the desired forecast period, the model generates a predicted value for the volume of electronic waste.

**The model utilizes the technique of Neural Networks**

The model utilizes the technique of Neural Networks, which classify data into different layers. It consists of 3 input layers, 3 hidden layers, 1 bias layer, and 1 output layer.The effect of deep learning is to get a Learning Rate: LR = 0.01 that doesn't increase the loss value. This allows the model to be trained as fast as possible, with a loss of0.0056, Os 92 ms/step. Neural Network learned with data, and reworked it to fit this data 500 times (Epochs = 500)

```
[ ]  # Declare input for train to find model
     # Z = ปี, Y = ปริมาณขยะ, X1 =จำนวนประชากร, X2 = GDP ประเทศ, X3 = เงินเฟ้อ(Inflation)
     # data = df[['X1','X2','X3']].apply(lambda x: (x - x.min()) / (x.max() - x.min()))  #normalize

     feature = df[['X1','X2','X3']].apply(lambda x: (x - x.min()) / (x.max() - x.min()))  #normalize
     label = df[['Y']].apply(lambda x: (x - x.min()) / (x.max() - x.min()))  #normalize
```

```
[ ]  lr = 0.01
     epochs = 500

     model = build_model(lr)
     history = model.fit(X, Y, epochs=epochs, verbose=0)
```

**Experimental tests:-**

Forecasting the quantity of electronic waste is essential for planning waste management systems to accommodate the increasing amount of waste generated from electrical and electronic products. One important factor to consider is the population of consumers who contribute to the disposal of electronic waste each year or in the future. This population can be determined based on the registered population records, which refer to the population registered with local authorities. The data on population changes in each region throughout Thailand is collected by the Ministry of Interior, Department of Provincial Administration. The Director-General of the Department of Provincial Administration announces the total number of citizens throughout the kingdom based on the evidence of citizen registration on December 31st of each year, as published in the Royal Gazette.

Additionally, economic statistics, especially the Gross Domestic Product (GDP) in billion baht, obtained from the National Economic and Social Development Council, Budget Bureau of the Thai Parliament, and Bank of Thailand, are important import factors that influence the quantity of electronic waste. In other words, when the economy is doing well, consumers tend to spend more on electrical and electronic products, resulting in an increase in electronic waste. Furthermore, the inflation rate is another import factor that indicates whether the prices of goods are cheap or expensive, affecting consumption. When the inflation rate is low, the prices of electrical and electronic products are not expensive, leading to increased consumption. As consumption increases, the quantity of electronic waste also increases. By considering these import factors and analyzing statistics, it is possible to calculate and forecast the quantity of electronic waste in the future.

## Test Results and Discussion:-

1.The models using Linear Regression technique yielded three models, which are as follows:
1.1. The relationship between population size (X1) and the quantity of electronic waste (Y).

```
[ ]  # Linear Model
     # y = (coerf_ * x_train) + intercept_
     # know "coerf_" and "intercept_" from model then we can predict value


     # Make a prediction
     y_pred = lr.predict(x_train)

     # visualise the model VS actual data
     plt.figure(figsize=(10,7))
     plt.scatter(x_train, y_train)
     plt.plot(x_train, y_pred, color="red", linewidth=3)  # value from prediction, plot the graph for evaluation
     plt.xlabel("Population")
     plt.ylabel("E-Waste Quantity")
     plt.show()

     # if the line pass from many point then this model is the most of accuration
```

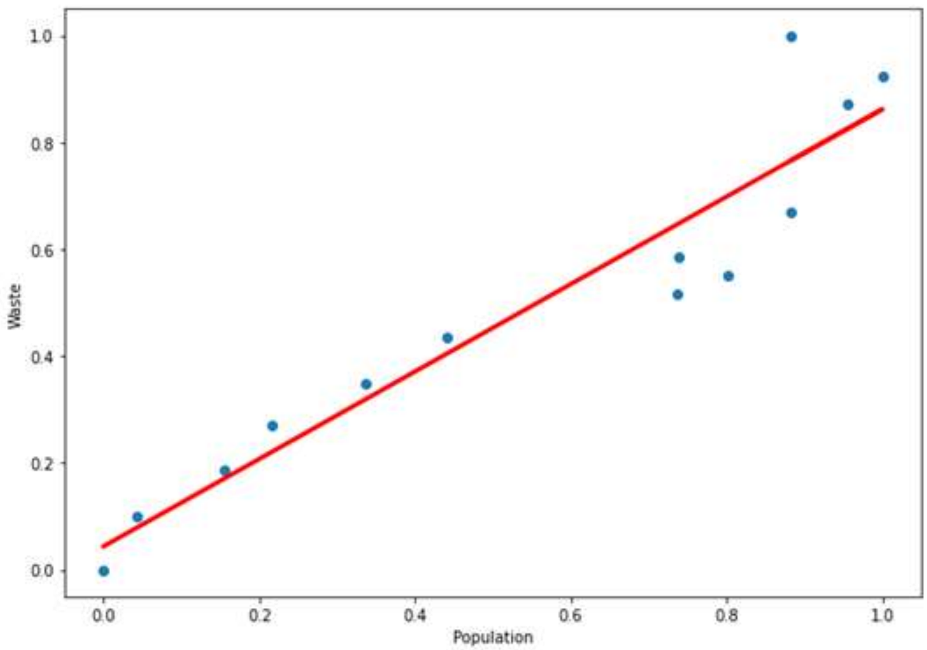


**Figure 1**:- Line graph showing the relationship between population size and the quantity of electronic waste.

From the self-generated machine learning equation (Machine Learning: ML) as shown in equation 1, which demonstrates the relationship between the population size (X1) of a country and the quantity of electronic waste (E-Waste Quantity) (Y), the correlation coefficient or slope is 0.8182669. This indicates a positive linear relationship between the independent variable, population size, and the dependent variable, e-waste quantity. In other words, as X1 increases, Y increases. This means that as the population size increases, the e-waste quantity also increases at a rate of 0.8182669 metric tons per person per year. Additionally, there is a constant value of 0.04377163, representing the intercept on the Y-axis. This means that even without any population, there is a constant e-waste quantity of 0.04377163 metric tons per year.The training set accuracy is 0.8991089548206352, which indicates the testing accuracy of the model or equation. It is measured by R-square, where a value close to 1 indicates high accuracy. In this case, the tested model has an R-square value of 0.8991089548206352, indicating a relatively high level of accuracy.

$$Y= (0.81826609)\ X1+0.04377163 \qquad (1)$$

1.2. The relationship between the Gross Domestic Product (GDP) (X2) of a country and the quantity of electronic waste (Y).

```
# Declare input for train to find model
# Z = ปี, Y = ปริมาณขยะ, X1 =จำนวนประชากร, X2 = GDP ประเทศ, X3 = เงินเฟ้อ(Inflation)
x_dataset = df['X2']  # independent variable  (value for train model)
y_dataset = df['Y']   # dependect variable  (value that we predict)
```

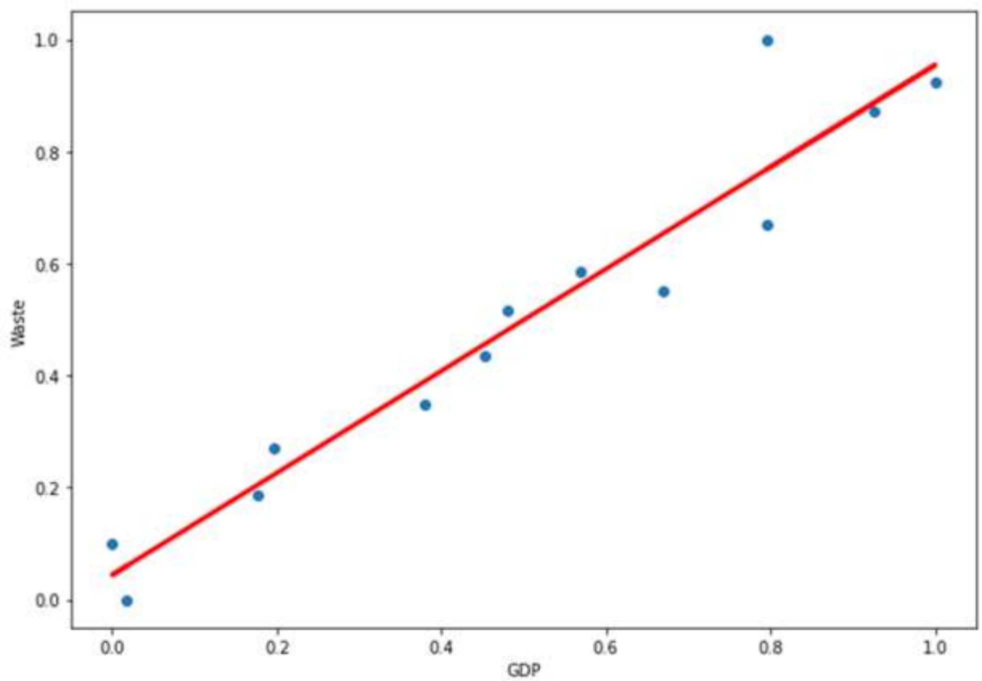


**Figure 2:-** Line graph showing the relationship between Gross Domestic Product (GDP) and the quantity of electronic waste.

From the self-generated machine learning equation (Machine Learning: ML)as shown in equation 2, which demonstrates the relationship between the Gross Domestic Product (GDP) (X2) of a country and the quantity of electronic waste (E-Waste Quantity) (Y), the correlation coefficient or slope is 0.91029688. This indicates a positive linear relationship between the independent variable, Gross Domestic Product (GDP), and the dependent variable, e-waste quantity. In other words, as X2 increases, Y increases. This means that as the GDP increases, the e-waste quantity also increases at a rate of 0.91029688 metric tons per billion dollars of GDP per year. Additionally, there is a constant value of 0.04388535, representing the intercept on the Y-axis. This means that even without any GDP, there is a constant e-waste quantity of 0.04388535 metric tons per year.The training set accuracy is 0.9265369547129064, which indicates the testing accuracy of the model or equation. It is measured by R-square, where a value close to 1 indicates high accuracy. In this case, the tested model has an R-square value of 0.9265369547129064, indicating a relatively high level of accuracy.

$$Y= (0.91029688)\ X2 + 0.04388535 \qquad (2)$$

1.3 Relationship between Inflation (X3) and the volume of electronic waste (Y)

```
# Declare input for train to find model
# Z = ปี, Y = ปริมาณขยะ, X1 =จำนวนประชากร, X2 = GDP ประเทศ, X3 = เงินเฟ้อ(Inflation)
x_dataset = df['X3']  # independent variable  (value for train model)
y_dataset = df['Y']   # dependect variable  (value that we predict)
```

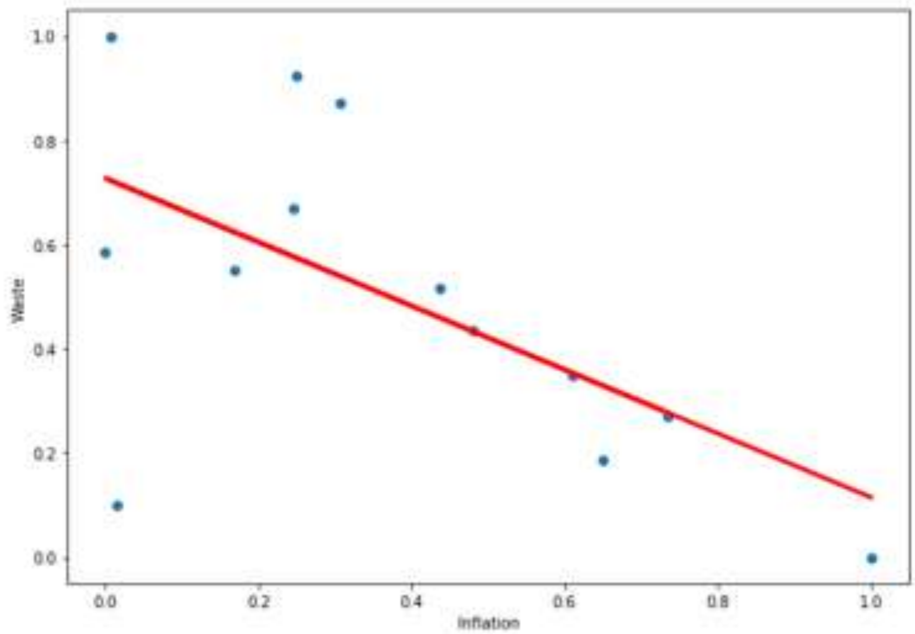


**Figure 3**:- Line graph showing the relationship between the inflation rate and the quantity of electronic waste.

From the self-generated machine learning equation (Machine Learning: ML)as shown in equation 3, which demonstrates the relationship between the inflation rate (X3) of a country and the quantity of electronic waste (E-Waste Quantity) (Y), the correlation coefficient or slope is -0.61222847. This indicates a negative linear relationship between the independent variable, inflation rate, and the dependent variable, e-waste quantity. In other words, as X3 decreases, Y increases. This means that as inflation decreases, the e-waste quantity increases at a rate of 0.61222847 metric tons per 1% decrease in inflation. Additionally, there is a constant value of 0.72709675, representing the intercept on the Y-axis. This means that even without any inflation, there is a constant e-waste quantity of 0.72709675 metric tons per year. The training set accuracy is 0.36059465893933307, which indicates the testing accuracy of the model or equation. It is measured by R-square, where a value close to 1 indicates high accuracy. In this case, the tested model has an R-square value of 0.36059465893933307, indicating a relatively low level of accuracy. This could be due to high variability in the inflation data, as there are noticeable differences between observed values and calculated values, resulting in lower accuracy.

$$Y = (-0.61222847)\,X3 + 0.72709675 \quad (3)$$

2.**The model utilizes the technique of Neural Networks**, which classify data into different layers. It consists of 3 input layers, 3 hidden layers, 1 bias layer, and 1 output layer.

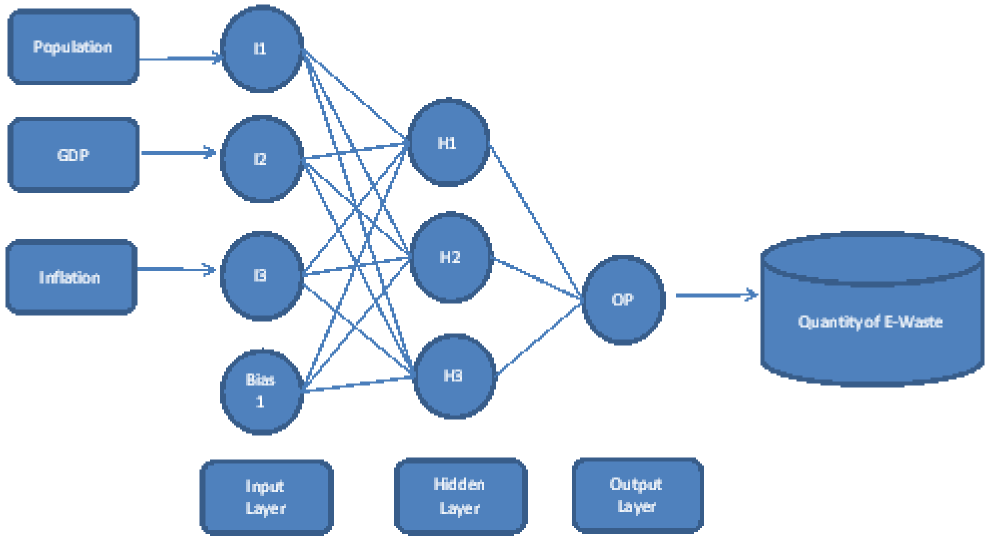


**Figure 4**:- Neural Network model for predicting the quantity of electronic waste.

## Summary and Conclusion:-

It was found that the deep learning model achieved a learning rate (LR) of 0.01, which did not increase the loss value. This allowed the model to train at the fastest speed, resulting in a decreased loss value of 0.0056. The training process took an average of 92 milliseconds per step. The neural network learned from the data by adjusting its values to fit this specific dataset. This process was repeated 500 times (epochs = 500), resulting in a continuous decrease in the loss value. The root mean squared error (RMSE) reached a value of 0.0751, which indicates a close fit to the data (approaching 0).

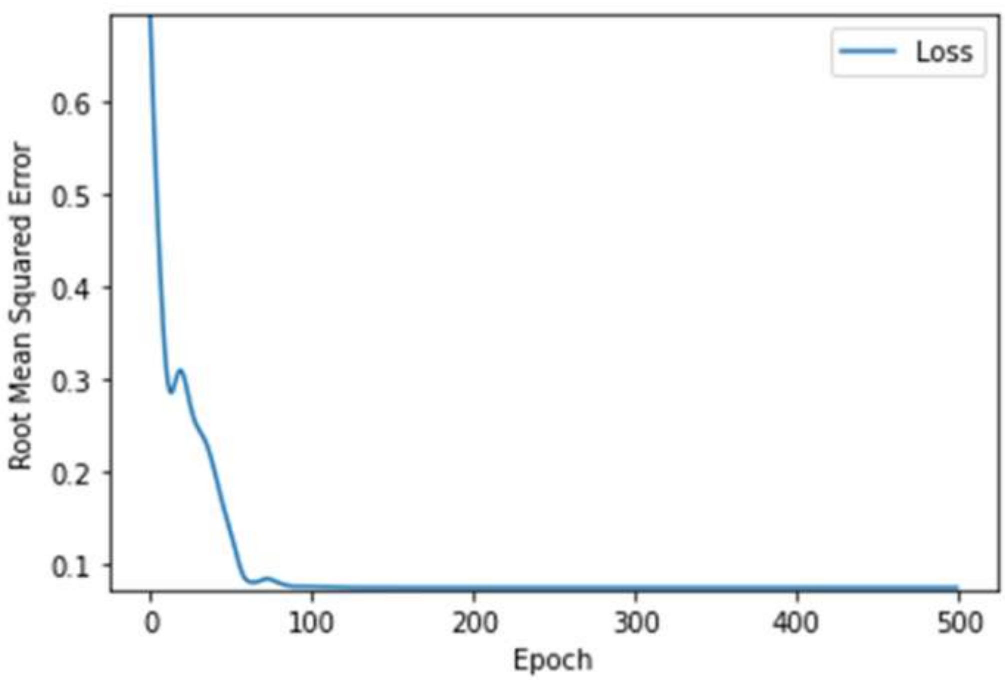


**Figure 5**:- Graph showing the values of RMSE (Root Mean Squared Error) against Epochs.

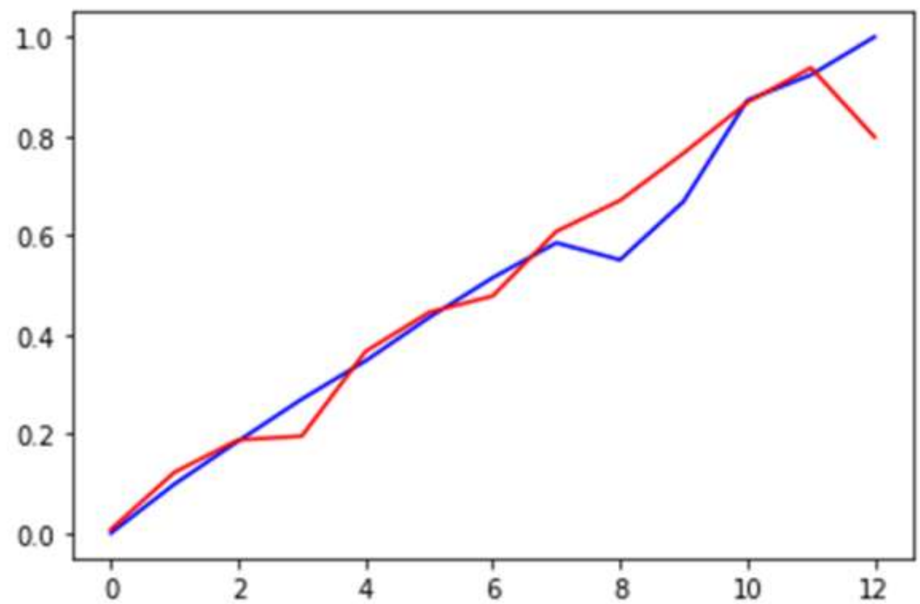


**Figure 6**:- Graph showing the relationship between predicted values and observed values of electronic waste quantity.

The red line representing the predicted values and the blue line representing the observed values of electronic waste quantity show a close and accurate relationship. The RMSE value of 0.0751 indicates a high level of accuracy, as the Root Mean Squared Error (RMSE) approaching 0 suggests that the model has a high level of accuracy.

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