

ANALYSIS OF SOLID WASTE GENERATION IN
PENINSULAR MALAYSIA DURING COVID-19 USING
ARTIFICIAL INTELLIGENCE (AI)

BY

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A thesis submitted in fulfillment of the requirement for the
degree of Master of Science Engineering

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ABSTRACT

The waste management process is inherently intricate, involving a complex interplay of technical, climatic, environmental, socio-economic, and demographic factors. This study aims to propose a more adaptable approach to enhance the precision of predictions in volatile scenarios, exemplified by the challenges posed by COVID-19, addressing the limitations of conventional methods' inflexibility. In this analysis, the data on municipal waste collection were collected from the Solid Waste Management and Public Cleaning Corporation (SWCorp) and the National Solid Waste Management Department (JPSPN). Data spans from January 2012 to December 2021 and aims to assess the performance of municipal waste management systems in eight states of Peninsular Malaysia during the pandemic utilizing "Integrated Wasteaware Benchmark Indicators". Moreover, the study utilized a predictive approach using artificial intelligence to forecast waste generation trends up to 2030. The study compares multiple models including artificial neural network (ANN), Gradient boosting (GB), Support vector machine (SVM), Autoregressive Integrated Moving Average (ARIMA), and Vector AutoRegressive (VAR). Each model's accuracy is evaluated using two evaluation metrics, Mean Absolute Error (MAE) and coefficient of determination (R^2). Additionally, this study also studies the impact of data preprocessing on the AI model's performance. The hybrid model of gradient boosting and ARIMA algorithm using preprocessed data was found to have the lowest MAE and the highest R^2 values of 0.341 and 0.954 respectively. The study's findings demonstrate that the developed model can provide targeted parameter predictions and recommendations for more effective strategies for waste management in the future.

APPROVAL PAGE

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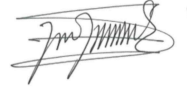
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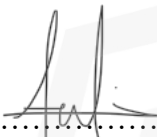


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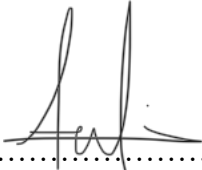
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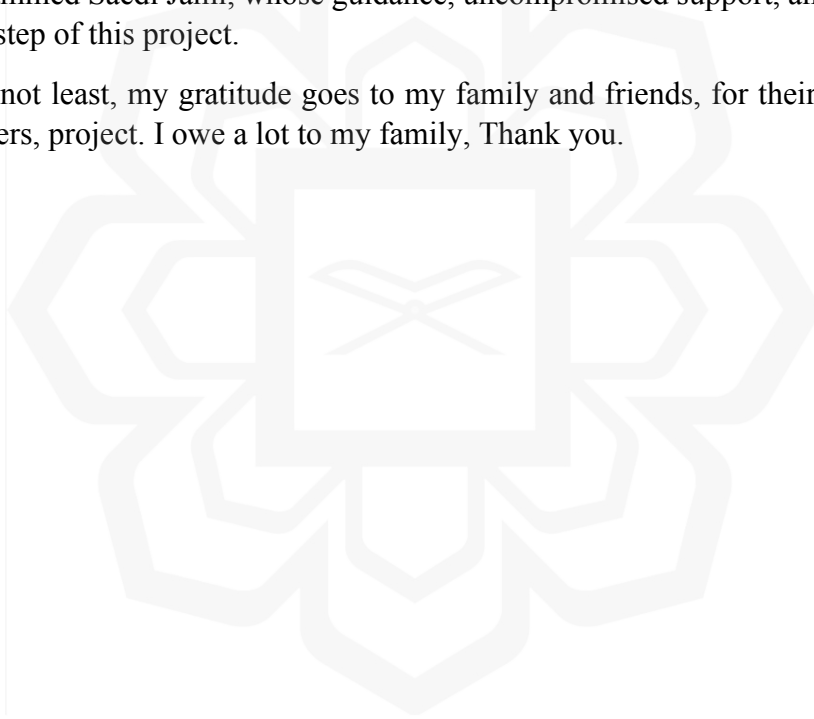


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CHAPTER ONE

INTRODUCTION

1.1 INTRODUCTION

Municipal waste management (MWM) is an essential public health aspect that is often downplayed in its importance in developing countries. The emergence of unexpected public health emergencies such as COVID-19 pandemic exacerbates Solid waste management (SWM) challenges even more, an unprepared system would not be able to sustain the change. The pandemic had plentiful direct and indirect environmental impacts that changed the dynamics of waste generation worldwide in almost all disciplines.

Malaysia is a Southeastern Asian country that spans from the western part of the Malay Peninsula to the northernmost area of Borneo Island in the eastern direction. Peninsula Malaysia consists of 11 states and 2 federal territories representing 40% of Malaysia's total land with an area of 132,265 Km². Region's solid waste is managed and regulated by “Solid Waste Management and Public Cleaning Corporation (SWCorp)” under the “Ministry of Housing and Local Government Jabatan Pengurusan Sisa Pepejal Negara (JPSPN)”. This study is only focused on the territories and states that are in accordance with regulations under the Solid Waste and Public Cleansing Management Act 2007 (Act 672), namely, Kuala Lumpur, Johor, Putrajaya, Negeri Sembilan, Melaka, Kedah, Pahang and Perlis.

COVID-19 emerged as a global pandemic in late 2019, posing significant challenges to public health systems worldwide. The virus primarily spreads through respiratory droplets, leading to a range of symptoms from mild respiratory illness to severe pneumonia and, in some cases, fatalities. The rapid spread of the virus prompted

widespread lockdowns, travel restrictions, and various preventive measures aimed at curbing transmission rates. The pandemic's impact extended beyond health, disrupting economies, education systems, and various sectors, including solid waste management.

As a precautionary measure, Malaysia's government has established several movement restrictions aimed to flatten COVID-19's infections curve, including social movement limitation, travel bans and closure of the national borders, suspension of educational institutions in addition to industrial operations and public transport (Abdullah et al., 2020; Agamuthu & Barasarathi, 2021a; Brohan et al., 2021; Yi et al., 2021).

The Association of waste management in Malaysia (WMAM) data shows that the waste generated in residential areas has surged by 30% from March 2020 to 2021 following the enforcement of the Movement Control Order (MCO).

Furthermore, the study implements AI-based modeling as a predictive method for solid waste generation rates. Predictive analytics, a prominent use of AI, leverages historical data and current trends to forecast future waste generation rates. These models consider multiple factors like population, economic indicators, and seasonal variations to estimate the quantity and types of waste for effective planning and resource allocation.

Moreover, AI-powered smart waste sorting systems utilize machine learning to automate the separation of recyclables, organic waste, and non-recyclables, thereby enhancing recycling rates and minimizing contamination in recycling streams. Additionally, AI algorithms optimize waste collection routes by considering real-time data such as traffic patterns and bin fill levels, leading to reduced collection time and increased operational efficiency.

Furthermore, AI-driven models aid in landfill management by predicting gas emissions like methane, enabling better environmental impact assessment and mitigation strategies. Besides, AI's capability to analyze behavioral patterns and public sentiments aids in developing targeted awareness campaigns to encourage proper waste disposal practices. These applications underscore the transformative potential of AI in revolutionizing SWM, optimizing processes, and fostering sustainability in waste management practices.

Lastly, the effectiveness of a city's waste management system has been suggested as a measure of good governance, indicating a livable and/or investable city. Hence, this study uses the Integrated Solid Waste Management (ISWM) benchmark indicator as an analytical evaluation of Peninsular Malaysia's SWM during the year of 2020. Furthermore, the study implements artificial infiltration as a predictive method for solid waste generation rates.

1.2 PROBLEM STATEMENT

Existing traditional methods of data analysis might lack the depth required to comprehensively understand the unexpected waste patterns in cases such as COVID-19. Studies show that waste forecasts are sensitive to various social-economic indicators (Fan et al. 2021; Vu et al. 2021). Lately, there has been an increase in the application of AI-based methods for modeling waste generation globally (Vu et al. 2021). A few waste-related studies have directly compared Artificial Neural Network (ANN) approaches with regression techniques, showcasing superior model accuracy achieved through the utilization of ANN methods (Jassim, Coskuner, and Zontul 2022; Kulisz and Kujawska 2020; Oguz-Ekim 2021; Oliveira, Sousa, and Dias-Ferreira 2019). Locally, Brohan (2021) studied the impact of movement control orders (MCOs) on the trends of MSW before and during their implementation in Malaysia, the findings offered limited coverage, primarily focusing on overall trends without considering the composition of waste during the MCO period. Overall, most waste modeling studies focus on either total waste estimation or waste fractions prediction. However, no study explicitly considers hybrid models of time series analysis and AI using waste fractions, moreover, the use of Orange data mining software is seldom reported in the literature. Therefore, this study aims to explore the potential of

leveraging artificial intelligence (AI) in analyzing and predicting solid waste generation patterns in Peninsular Malaysia during the COVID-19 pandemic. By incorporating AI-driven methodologies using open-source data mining software, the research intends to delve deeper into the composition and trends of waste generation during the pandemic.

1.3 RESEARCH OBJECTIVES

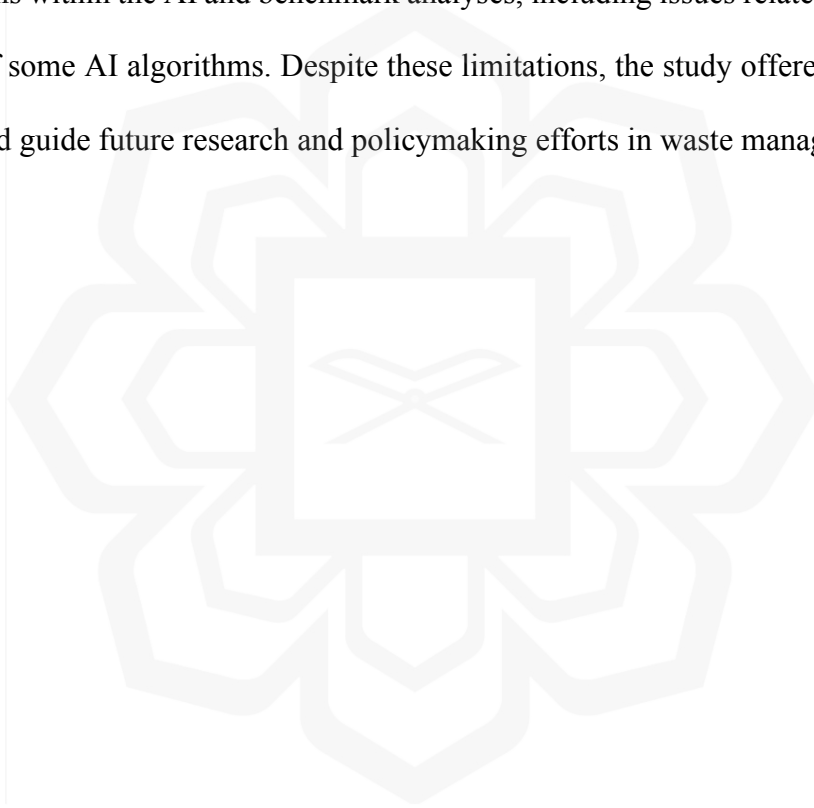
The present study was conducted in order to achieve the following objectives:

1. To analyze raw data from annual statistics of waste management during the Covid-19 pandemic (2020-2021) using ISWM benchmark indicators.
2. To screen for different AI models for the prediction and preprocessing of waste characteristics using an open-source data mining software.
3. To validate the selected model.

1.4 RESEARCH SCOPE

The research focused on investigating the municipal solid waste generation rates during the COVID-19 pandemic, aiming to comprehensively analyze data collected from 'Jabatan Pengurusan Sisa Pepejal Negara (JPSPN)' and 'Solid Waste Management and Public Cleansing Corporation (SWCorp).' The study covered the period spanning 2012 to 2021 across eight states within Peninsular Malaysia, namely Kuala Lumpur, Johor, Putrajaya, Negeri Sembilan, Melaka, Kedah, Pahang, and Perlis. Employing two primary approaches, ISWM benchmark analysis, and Artificial Intelligence, both preprocessed and unprocessed

data underwent analysis using open-source data mining software. The objectives were to understand the pandemic's impact on waste generation patterns, assess the effectiveness of waste management strategies during this period, and uncover insights for potential improvements. While this study aimed to contribute valuable insights to the field of waste management, it recognized limitations such as potential data constraints from selected sources, regulation constraints limiting generalizability, and potential methodological limitations within the AI and benchmark analyses, including issues related to the black box nature of some AI algorithms. Despite these limitations, the study offered critical insights that could guide future research and policymaking efforts in waste management practices.



CHAPTER TWO

LITERATURE REVIEW

2.1 BACKGROUND

With the ballooning populations and rapid growth of cities, challenges arise in sustainable wastes management, particularly in developing countries like Malaysia. The production of waste is an unavoidable result of any human activities and is a significant concern for communities worldwide. In fact, Das et al., (2021) believe that it would play a part in a set of global socio-environmental and geo-economic challenges in the recent future. In 2005, Malaysia reportedly produced 19,000 tons of waste daily, with a recycling rate of only 5%, according to the Malaysian Investment Development Authority (MIDA). Alarmingly, despite the national efforts and the increment of recycling rate up to 17.5% the amount reached 38,000 tons per day in 2018 thirteen years later (MIDA, 2020). Recent studies have specifically studied the recycling of solid waste and municipal solid waste, recognizing their significant potential for producing renewable energy and useful resources through the recovery of waste materials. This method promotes the circular economy by encouraging resource reuse and decreasing waste production.

However, the unprecedented unpredicted coronavirus (COVID-19) outbreak in 2019, has been detrimental to the continuation of solid wastes as a valuable resource for energy (Agamuthu & Barasarathi, 2021c). Artificial Intelligence (AI) and machine learning techniques gained momentum in many technical aspects; offering advanced computational approaches to analyze solid waste management (SWM) processes as an alternative (Abdallah et al., 2020).

2.2.1 Peninsular Malaysia

Peninsula Malaysia consists of 11 states and 2 federal territories and accounts for 40% of Malaysia's total land with an area of 132,265 Km² as shown in Figure 2.1 (a). However, this study only focuses on the states that are in line with to regulations under the “Solid Waste and Public Cleansing Management Act 2007 (Act 672)” as shown in Figure 2.1(b). Act 672 is an Act to coordinate solid waste and public cleansing management with the aim of maintaining proper sanitation. These states census is, Kuala Lumpur (1.9 million), Putrajaya (0.1 million), Johor (4.0 million) Negeri Sembilan (1.2 million), Melaka (1.0 million), Pahang (1.6 million), Kedah (2.2 million) and Perlis (0.3 million) as reported in July 2022 (DOSM, 2022).

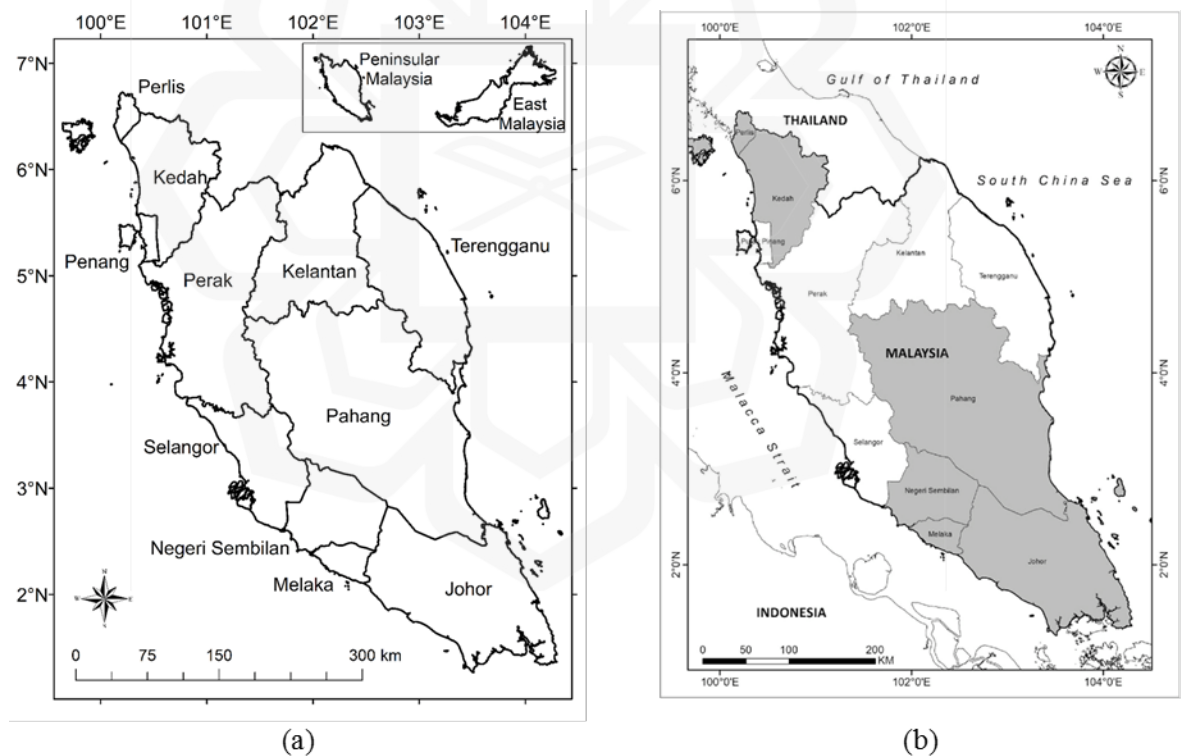


Figure 2. 1: (a) Peninsular Malaysia states and federal territories. (b) states that are pursuant to regulations under the Solid Waste and Public Cleansing Management Act 2007 (Act 672).

2.2 SOLID WASTE STATISTICS

World bank's recent reports showed that globally, the solid waste generated in the year 2020 amounted to 2.24 billion tons, with a projection that municipal solid waste could increase to 3.40 billion tons by 2050 (Kaza et al., 2018; Méndez-Fajardo et al., 2020). East Asia and Pacific region contribute up to 23.3% of it, generating 468 million tons of waste in 2016 (Wee et al., 2017). Malaysia's waste consists of about 64% of domestic and office waste, 25% industrial waste, 8% commercial waste, and around 3% construction waste (Abubakar et al., 2022). SWcorp, managing body of the region's solid waste, reported an increase in medical waste of 7.5% with a total national waste of 4.0 million tons in 2020.

Moreover, statistics reveal that Malaysia generates almost twice the global average of waste per capita per day, and 2.24 times the regional average (Kaza et al., 2018), which is a significant concern due to the country's high population. This results in a huge amount of Municipal Solid Waste, approximately 33,000 tons per day or 1.17 kg per person per day (Iacovidou & Siew Ng, 2020). The states under (Act 672) generated over 3,108.9 thousand tons of solid waste in 2019. Efficient management of Municipal Solid Waste is critical to protect the environment, public health, and resources (Xia et al., 2022). Recent research has focused on the recycling of solid waste and municipal solid waste, which has high potential for generating renewable energy and promoting the circular economy by reducing waste and promoting resource reuse. Figure 2.2 shows waste generation rates in the East Asia and Pacific region according to Kaza et al. (2018).

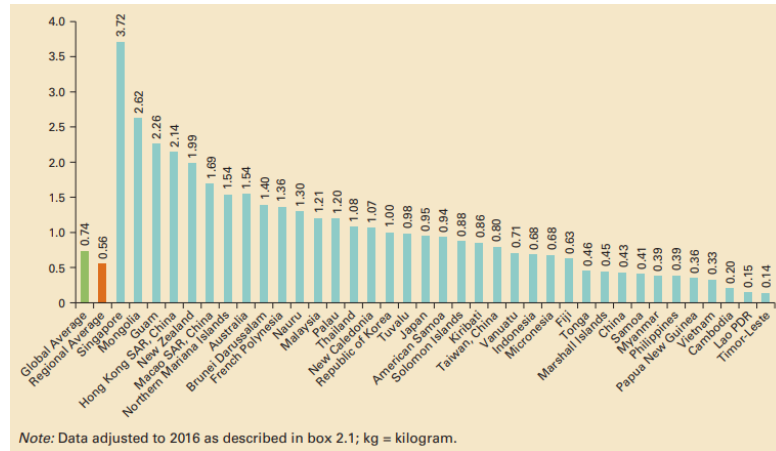


Figure 2. 2: Waste generation rates in East Asia and Pacific region (Kaza et al., 2018).

Moreover, Department of statistics report showed that annual plastic waste generated by Malaysia amounts to 0.94 million tons (DOSM, 2022), on top of that, around 15% to 39% of it ends up washed into the oceans (Tang et al., 2021). Meantime, the pandemic and the applied MCOs has surged plastic detritus from medical sector including masks, gloves, and medical equipment, in addition to takeaway parcels.

2.2.1 Solid Waste during Covid-19

On account of the rapid infection cases recorded globally and regionally, it was anticipated that there would be a surge in the generation of clinical waste (CW). Malaysian healthcare waste is classified into five main categories according to the DOE (2009) (Agamuthu & Barasarathi, 2021), which are, clinical waste (CW); chemical waste; pressurized containers; radioactive waste; and general waste. Around 20% to 40% of the total medical waste generated by hospitals and healthcare centers consists of medical waste that is considered contagious according to DOE (Agamuthu & Barasarathi, 2021) Clinical waste is identified as “the waste produced by health-care establishments, laboratories, research facilities, and similar activities”.

In Furthermore, the term "contaminated medical waste" encompasses waste generated from small or scattered sources, such as home healthcare activities, including swabs, bandages, dressings, dialysis, insulin injections, and more, as defined by the World Health Organization (1999). According to Agamuthu and Barasarathi (2021), the Malaysian Ministry of Health has reported a 27% increase in clinical waste generation by weight in 2020. Table 2.1 shows the percentage of clinical waste generated during the COVID-19 pandemic in Malaysia and other regional countries, compared to before the outbreak.

Table 2. 1: Clinical waste during COVID-19 compared to before the outbreak in Malaysia and regional countries.

Country	CW before COVID-19 (tons/day)	CW During COVID-19 (tons/day)	CW generation increase percentage during COVID-19 (%)	References
KL, Malaysia	35	210	500	(Agamuthu & Barasarathi, 2021c)
Taiwan	35.7	40.4	13.2	(Tsai, 2021)
Jakarta, Indonesia	35	212	506	(Yasri & Wiwanitkit, 2020)
Wuhan, China	50	106.9	113.8	(Asian Development Bank, 2020; (Yasri & Wiwanitkit, 2020)
Bangkok, Thailand	27	160	493	
Manila, Philippines	47	280	496	
Ha Noi, Vietnam	26	154	492	

Contrariwise, during the first stage of the MCO which lasted from 18 March to 12 April 2020, municipal solid waste generation was significantly reduced. Brohan et al., (2021) has conducted an analysis of MSW generation before and during the implementation of the MCO and found that the amount ranged from 549.76 to 118,521.87 tons before the MCO, and 552.54 to 98,844.73 tons after the implementation of the MCO, signifying a significant reduction in the volume of MSW. Table 2.2 shows the percentage change of MSW from selected cities before MCO (I), MCO (II), CMCO, and RMCO in 2020.

Table 2. 2: Relative change of MSW adapted from (Brohan et al., 2021).

State	Municipal solid waste (cumulative tonnage)				Relative change (%)		
	Before MCO	MCO	CMCO	RMCO	MCO	CMCO	RMCO
Kuala Lumpur	118,521.87	98,844.73	111,383.18	348,341.14	-4.01%	3.00%	49.88%
Pahang (Kuantan)	19,731.17	20,209.99	21,754.62	58,737.05	0.10%	0.37%	7.79%
Putrajaya	8540.95	7278.37	8296.80	30,688.52	-0.26%	0.24%	4.71%
Melaka (Melaka Bersejarah)	28,826.96	17,267.04	11,538.18	63,798.81	-2.36%	-1.37%	11.00%
Johor (Johor Bahru)	52,137.85	44,643.93	47,612.43	147,995.60	-1.53%	0.71%	21.13%
Kedah (Alor Setar)	16,300.16	15,539.13	18,283.46	55,308.97	-0.16%	0.66%	7.79%
Negeri Sembilan (Seremban)	17,064.73	24,530.00	26,058.09	52,388.62	1.52%	0.37%	5.54%
Perlis	6888.76	7255.62	8409.87	23,160.81	0.07%	0.28%	3.11%

2.3 SOLIS WASTE MANAGEMENT IN PENINSULAR MALAYSIA

According to SWcorp, the generation of CW increased by 27% (by weight), mostly attributed to Covid-19-related waste (Abdullah et al., 2020; Agamuthu & Barasarathi, 2021a; Yi et al., 2021). This section discusses Covid-19 effects on waste generation and reviews cases studies conducted in Malaysia. Almost all region's solid waste is collected for disposal, reflecting a good waste collection as in developed nations. However, approximately 80% of country's generated MSW is disposed in landfills and open dumps, which are the opposite of sustainable waste management. Moreover, approximately 10% of the total waste generated in Malaysia is a result of illegal dumping. The improper management of waste in Malaysia is believed to be caused by several factors, as stated by (Tang et al., 2021), including a lack and insufficiency of technology, skilled personnel, and facilities.

Following a public outcry in 2007 of a drinking water source contamination as a result of improper landfilling practices, the government made significant changes to the country's waste management strategy (Agamuthu & Fauziah, 2011; Fauziah & Agamuthu, 2012). As a result, parliament passed the “Solid Waste and Public Cleansing Management (SWPCM) Act 2007” at end of August 2007.

Today the act is implemented in 9 of the 13 states of Peninsular Malaysia. Almost all region's waste is collected for disposal, reflecting a good waste collection as in developed nations. However, approximately 80% of country's generated MSW is disposed in open dumps and landfills, which are the opposite of sustainable waste management.

2.3.1 Open Dump

An open dump is an uncontrolled waste disposal site where waste is not covered or protected in any way. These types of dumps are environmentally harmful and are not allowed in many countries. They can lead to the release of pollutants into the air and water and can attract vermin and other pests. They also provide an unsightly appearance to the area. It is generally considered as an illegal practice. However, they are usually the preferred disposable method due to low operation cost and disposal convenience (Yong et al., 2019). Alternatively, proper waste management techniques including landfilling and incineration, are usually used to dispose of waste safely and efficiently.

2.3.2 Landfilling

Landfill operations involve a relatively simple process. Initially, waste is deposited onto a designated area known as the "working face," where it is compacted. Subsequently, a covering layer of soil is applied. In modern landfills, a layering system is commonly employed to facilitate air and water management, thereby preventing contamination. Malaysia established its first municipal solid waste (MSW) sanitary landfill in the early

1990s, alongside an engineered landfill for hazardous waste. These developments occurred after significant advancements in waste management practices throughout Malaysia.

Currently there are 14 landfills in Peninsular Malaysia and 7 in the studied states in this study, Table 2.3 shows the current state of art of landfills in Malaysia.

Table 2. 3: The current state of art of landfills in Malaysia.

State	Sanitary Landfill (a)	Non-Sanitary Sites, Open Category (b)	Non-Sanitary Sites, Stage 1-3 (c)	Number of Operating Discharge Sites (a+b+c)	Transfer Station	Mini Incinerator	Inert Waste Landfill
Perlis	1	0	0	1	0	0	0
Kedah	1	3	2	6	0	1	0
Pulau Pinang	1	0	0	1	1	0	1
Perak	1	13	2	16	0	1	0
Selangor	3	1	1	5	1	0	3
WP Kuala Lumpur	0	0	0	0	1	0	0
Negeri Sembilan	1	2	1	4	0	0	0
Melaka	1	0	0	1	0	0	0
Johor	1	8	3	12	1	0	0
Pahang	2	4	6	12	0	2	0
Terengganu	1	6	2	9	0	0	0
Kelantan	0	10	0	10	0	0	0
WP Labuan	1	0	0	1	0	0	0
Sarawak	3	43	0	46	0	0	0
Sabah	1	21	0	22	0	0	0
Total	18	111	17	146	4	4	4

However, landfills were not the first option to handle Covid-19 related waste. Studies have revealed that the virus can remain viable for different durations, such as up to 3 hours after being aerosolized, up to 4 hours on copper, until 24 hours on cardboard, and up to 2-3 days on stainless steel and plastic (Agamuthu & Barasarathi, 2021a; Moh & Abd Manaf, 2017). Hence, most countries decided to use Incinerators.

2.3.3 Incineration

Incineration is the burning process of solid waste in order to reduce its volume and to convert it into ash, flue gases, and heat. This process is used to dispose of a variety of

materials including medical waste, hazardous waste, and municipal solid waste. Incineration is an effective alternative to reduce waste amounts that needs to be disposed of in landfills. In fact, incineration has the potential to decrease the volume of waste by a significant amount, ranging from 80% to 95% (Yong et al., 2019), in addition, it can also be used to generate energy.

Lastly, incineration also helps in reducing the risk of pollution from leachate and methane gas. However, it does produce air pollutants and ash that must be properly managed to minimize environmental impacts.

2.4 SOLID WASTE MANAGEMENT ASSESSMENT

Sustainable waste management's main aim is to preserve the environment, protect human health, and to conserve resources. Several tools and assessment methods are commonly used to evaluate a city's SW management performance, and these methods are usually helpful methods to support waste management decision making (Allesch & Brunner, 2017). A quick literature analysis shows that majority of research are based on life cycle assessments (Allesch & Brunner, 2014) cost-benefit analysis, multi-criteria decision-making, risk assessments, and benchmarking. Allesch and Brunner (2014) have reviewed 151 articles in terms of objectives, methodologies, systems investigated, and results. Analysis showed that more than 50% of the articles were based on scenario analysis, around 40% were life cycle assessment-based, and only 14% used benchmarking. With the growing options for waste collection and treatment day by day, in addition to the regular change of economic boundary, the question of whether the current waste management system is the most cost-effective way to reach the stated goals.

2.4.1 Benchmark Indicators for Integrated Sustainable Waste management (ISWM)

“Benchmark indicators” are metrics that are used to evaluate the performance of a system, process, or product against a standard or reference point. These indicators can be used to

measure progress, identify areas for improvement, and compare the performance of different systems or organizations (Allesch & Brunner, 2014).

To use benchmark indicators effectively, it is important to select indicators that are relevant to the specific system or process being evaluated, and to establish clear targets or benchmarks against which the performance of the system can be measured.

Benchmark indicators can be used to monitor the progress over time and to identify areas where improvements can be made. They can also be useful for comparing the performance of different systems or organizations, as long as the indicators being used are appropriate and comparable.

There are many different types of benchmark indicators, and they can be used in a variety of fields including business, finance, education, and public policy. Some common examples of benchmark indicators include financial metrics such as profitability, return on investment, and cost-to-income ratio. In the environmental field, common benchmark indicators might include carbon emissions, energy use, and water consumption.

2.4.1.1 Benchmark Indicators for Integrated Sustainable Waste management (ISWM)

"Wasteaware" is a UK-based organization that promotes sustainable waste management practices and works to increase knowledge of the importance of reducing, reusing, and recycling waste. As part of its mission, Wasteaware has developed a set of benchmark indicators for integrated sustainable waste management. These indicators are designed to help organizations measure and track their progress towards more sustainable waste management practices, and to identify areas where improvements can be made.

The Wasteaware benchmark indicators are divided into three main categories: reduction, reuse, and recycling. Each of these categories includes a set of specific indicators that are used to measure and track progress towards more sustainable waste management practices. Table 2.4 shows some specific examples of indicators within each category.

Table 2. 4: Indicators’ main categories with examples

Category	Examples
Reduction	<ul style="list-style-type: none"> • Waste generated per person. • Percentage of waste that is recycled or reused. • Amount of waste prevented through waste reduction efforts.
Reuse	<ul style="list-style-type: none"> • Percentage of materials that are reused. • Number of products that are repaired or refurbished. • Value of materials that are reused
Recycling	<ul style="list-style-type: none"> • Percentage of materials that are recycled. • Amount of energy saved through recycling. • Environmental impact of recycling efforts

Primary, the purpose of using it is to make comparisons between countries, regions, or cities, with the aim of identifying successful strategies and gaining knowledge from each other. According to Wilson et al. (2015), appropriate benchmark indicators should enable a city to evaluate its own performance with regard to SWM services, provide data for decision-making concerning service enhancements, and monitor progress over time. Additionally, Wilson et al. (2015) has developed a framework for Wasteaware, which is a

set of indicators used for Integrated Sustainable Waste Management (ISWM), as shown in Figure 2.3.

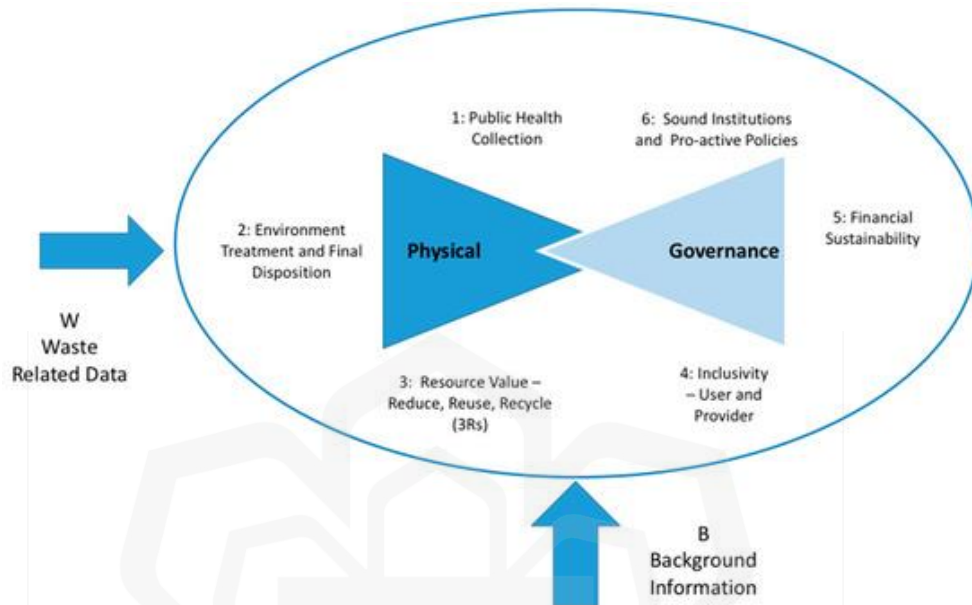


Figure 2. 3: The ISWM framework adapted from (Wilson et al., 2012)

Globally, several research has demonstrated the use of the Wasteaware benchmark indicators as a method for evaluating the performance of SWM systems and identifying opportunities for improvement. In their publication *Solid Waste Management in the World's Cities*, Wilson et al., (2012) carried out a comparison of solid waste management practices across 20 cities in six continents on behalf of UN-Habitat. The first implementation of the Wasteaware ISWM benchmark indicators was in five cities worldwide with different income levels: Monrovia in Liberia, Maputo in Mozambique, Lahore in Pakistan, Guadalajara in Mexico, and Belfast in Northern Ireland. These cities were selected to represent a range of income levels, population sizes, and waste generation rates. To facilitate better understanding, the results from the eight states in Malaysia will be compared to those of these cities.

Table 2.5 shows the summary results for the Wasteaware ISWM benchmark indicators in five case study cities adapted from (Wilson et al., 2012).

Furthermore, to provide a more visually appealing representation the revised metrics, a radar diagram for each city was added. Each diagram includes six indicators, corresponding to the six indicators in the revised metrics. Each indicator is assigned one point, resulting in a total of six points that form an area. The city with the largest area in the diagram is considered to have the best overall performance in solid waste management. Figure 2.4 shows radar diagrams summarizing the 12 Wasteaware ISWM benchmark indicators for the five cities adapted from (Wilson et al., 2012).

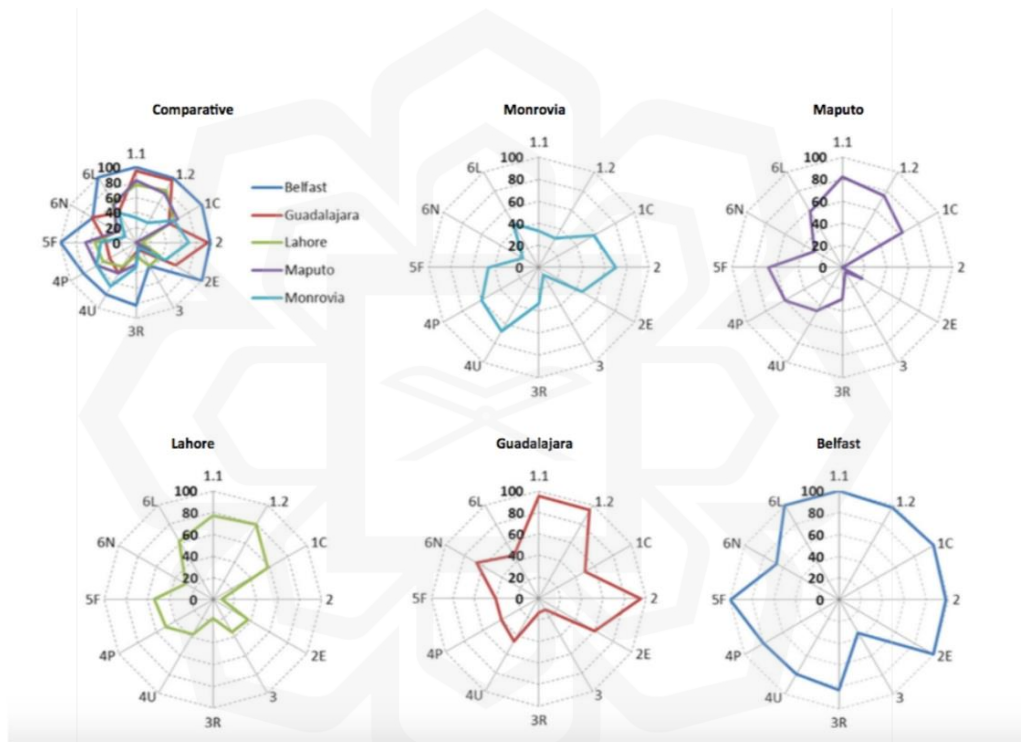


Figure 2.4: Radar diagrams summarizing the 12 Wasteaware ISWM benchmark indicators for the five cities adapted from (Wilson et al., 2012)

Table 2.5: The summary results for the Wasteaware ISWM benchmark indicators in five case study cities adapted from (Wilson et al., 2012)



No	Category	Indicator	Results				
City			Monrovia	Maputo	Lahore	Guadalajara	Belfast
Country			Liberia	Mozambique	Pakistan	Mexico	UK - Northern Ireland
Background information on the city							
B1	Country income level	World Bank income category	Low	Low	Lower-middle	Upper-Middle	High
		GNI per capita	\$370	\$450	\$1,140	\$9,640	\$38,250
B2	Population	Total population of the city	1,021,768	1,131,149	8,160,000	4,664,924	218,000 City only
B3	Waste generation	MSW generation (tonnes/year)	287,000	508,000	1,916,000	2,000,000	149,000
Key Waste-related data							
W1	Waste per capita	MSW per capita (kg per year)	230	316	219	440	683
W2	Waste composition:		4 key fractions - as % of total waste generated				
W2.1	Organic	Organics (food and green wastes)	50%	65%	65%	53%	35.1%
W2.2	Paper	Paper and card	5%	8.5%	2%	9%	21%
W2.3	Plastics	Plastics	13%	8%	12%	10%	6%
W2.4	Metals	Metals	2%	2.5%	0.1%	1.4%	3.3%
Physical Components							
1.1	Public health – waste collection	Waste collection coverage	33% (L)	82% (M)	77% (M)	95% (M/H)	100% (H)
1.2		Waste captured by the system	30% (L)	75% (M)	80% (M)	95% (M/H)	98% (M/H)
1C		Quality of waste collection service	M (58%)	M/H (63%)	M (58%)	M (50%)	H (100%)
2	Environmental control – waste treatment and disposal	Controlled treatment and disposal	70% (L/M)	0% (L)	8% (L)	95% (H)	98% (H)
2E		Degree of environmental protection in waste treatment and disposal	M (45%)	L/M (21%)	L/M (37%)	M (60%)	H (100%)
3	Resource management – reduce, reuse and recycle	Recycling rate	8% (L)	<5% (L)	35% (M)	12% (L/M)	35% (M)
3R		Quality of 3Rs – Reduce, reuse, recycle – provision	L/M (33%)	L/M (29%)	L (17%)	L (13%)	H (83%)
Governance Factors							
4U	Inclusivity	User inclusivity	M/H (67%)	M (46%)	L/M (37%)	M (46%)	M/H (79%)
4P		Provider inclusivity	M (60%)	M (60%)	M (50%)	L/M (40%)	M/H (80%)
5F	Financial sustainability	Financial sustainability	M (46%)	M/H (67%)	M (54%)	L/M (40%)	H (100%)
6N	Sound institutions, proactive policies	Adequacy of national SWM framework	L (17%)	L/M (29%)	L/M (29%)	M/H (67%)	M/H (66%)
6L		Local institutional coherence	M (46%)	M (58%)	M/H (62%)	M (46%)	H (100%)

The researchers utilized a methodology centered on the notion of Integrated and Sustainable Solid Waste Management (ISWM) (Anschütz et al., 2004; Schübeler, 1996). The authors have demonstrated the critical need for good quality data for a comprehensive evaluation. Data's availability and reliability was generally poor, generated waste rates and amounts was not clear; waste weight data was not complete, in addition to the rarity of waste characterization studies or it being mostly out-of-date.

Following the same analytical framework, In Karbala city, Iraq, Abdulredha et al., (2018) has evaluated the SWM system of the city using the benchmark indicators. Results showed a weak system in need for several physical infrastructure and management improvements. Similarly, the SWM status in Lahore, Pakistan was reviewed. The methodology is quite similar and based on the above-mentioned UN-Habitat methodology of city profiling -involving qualitative assessment, systematic quantitative, and governance features- of the current waste management system (Ullah Khan et al., 2019). The assessment was able to spot major flaws and weakness in the current waste management system, results also concluded that only 68% of the city receives waste collection services and merely third of the total waste being managed.

Most recently, Wasteaware indicators were utilized to evaluate the operating system in 11 Pakistani cities. The model aimed to evaluate the current waste management situation and monitor the performance (Iqbal et al., 2022). Results showed that waste collection coverage ranged from 34% (Hyderabad) to 90% (Lahore) among the 11 cities; compared to the assessment done in 2019 (Ullah Khan et al., 2019), that showed that Lahore's waste collection coverage was around 68%, the city's waste management system shows significant improvement in a period of three years.

Overall, the Wasteaware benchmark indicators are intended to provide a comprehensive overview of an organization's waste management practices and to help identify areas for improvement. By tracking and analyzing these indicators, organizations can work towards more sustainable and efficient waste management practices (Abdulredha et al., 2018; Allesch & Brunner, 2014; Srinivasaiah et al., 2021; Vitorino de Souza Melaré

et al., 2017; Wilson et al., 2012, 2015a). However, in Malaysia, Wasteaware benchmark indicators are a relatively less addressed research area, so far.

2.4.2 Life Cycle Assessment (LCA)

Life cycle assessment (LCA) is a tool that is used to assess an environmental impact or load of an activity, process or a product throughout its life cycle from cradle to grave (Roy et al., 2009). It provides the comprehensiveness advantage compared to other methods which help in simplifying issues associated with environmental impact from anthropogenic activities analysis. Many research has used LCA in environmental analysis in general and in solid waste management.

To conduct an LCA, a thorough inventory of all the materials, energy, and emissions associated with a product or process is compiled. This inventory is then used to define the environmental impacts of the product or process across a range of impact categories, including climate change, resource depletion, and air pollution (Sardarmehni, 2022). The results of the LCA are then presented in a report that summarizes the findings and provides recommendations for improvement.

Several southeast Asia countries have utilized the life cycle approach in governmental plans and marketing strategies (Hafizan et al., 2021). Recent research conducted by (Hafizan et al., 2021) provided an overview of the current applications of the LCA in Malaysia. The state of Selangor contributed to the largest percentage of MSW in Malaysia in 2012 alone, 3,923 tons were generated daily (Saheri et al., 2012), as a result, Malaysia has founded the National Green Technology Master Plan (GTMP) with aim of promoting a green culture where life cycle assessment LCA plays a vital role.

2.4.3 System Dynamics Method (SDM)

The system dynamics method (SDM) is usually used complex feedback systems and relationships that influence their behavior over time, it uses the advantage of simulating results based on past data to assess interactions among social, economic, environmental,

demographic and decision-making factors (Sengupta & Agrahari, 2017). It has been used widely, Al-Khatib (2015) has used it to forecast municipal waste generation and costs management in the period of (2002 - 2011). The study was able to decompose general waste into eight main components, considering only the population as the prediction factor of generated and recycled waste in addition to the cost of recycling or disposal.

However, prediction only considered population as a waste source in addition to neglecting further complex factors such as landfill capacity and associated budget allocations. More recent research by (Rafew & Rafizul, 2021) has applied SDM for a long-term prediction of MSW in Khulna city, Bangladesh. According to the simulation results, it is estimated that the amount of waste generated would rise from 168,000 tons in 2020 to 1.2 million tons in 2050, with an increase in per capita generation from 0.117 tons to 0.561 tons. Which hence will result in an increase in the total landfill capacity and collection costs. Nevertheless, the treatment capacity will decrease over time causing a massive pile-up of MSW of 10.3 million tons in 2050.

Overall, the system dynamics approach involves constructing a mathematical model of the system being studied, using a set of equations and variables that represent the key components and relationships within the system. The model is then used to simulate the behavior of the system over time, allowing researchers to understand how different factors influence the system's dynamics and how the system is likely to evolve in the future. Table 2.6 summarizes the most recent publications using statistical analysis in waste management.

Table 2. 6:Recent publication using statistical analysis in waste management.

Reference and Year	Results	Application	Country	Model used
(Saheri et al., 2012)	Landfilling is not a preferable method environmentally.	Environmental analysis of dumps and sanitary landfills	Malaysia	Life Cycle Assessment
(Ravichandran, 2017)	The effective management of radioactive waste within a hospital environment can be achieved by adopting certain measures, such as utilizing temporary storage trolleys for solid wastes of radioactive I ³¹ , implementing a delay tank for liquid wastes, and ensuring proper documentation of waste disposal records.	Waste collection system Radioactivity	Oman	Forecasting
(Azadi & Karimi-Jashni, 2016)	Models showed a proportional relationship. Any increase in parameters increases the mean SMSWG rate increases as well. MLR reported an R ² value of 0.70 when compared to an artificial neural network which resulted in 0.86. Using PCA as a hybrid model with MLR increased the accuracy of the model.	Prediction of the average seasonal municipal solid waste generation rate.	Iran	Multiple Linear Regression
(Vivekananda & Nema, 2014)	Models employed in this study indicated that the trend of waste generation is not only influenced by population, but also by various other socioeconomic factors such as GDP, annual income per capita, and household size. Moreover, the models forecast that Delhi will generate approximately 19,100 tons of MSW per day by the year 2024.	Forecasting of solid waste quantity and composition	India	
(Rafew & Rafizul, 2021)	The system predicted an increase of 1.2 million tons with a per capita generation of 0.561 tons by the year 2050.	Forecasts of waste generation, treatment, and costs	Bangladesh	System Dynamics Methods
(Al-Khatib et al., 2015)	The SDM forecasted the quantity of each generated component for a period of 10 years.	Municipal waste generation prediction and costs management.	Nablus, Palestine	
(Iqbal et al., 2022)	The evaluation process has assisted in identifying the merits and demerit of the current system and in suggesting environmental and economic interventions that could generate income to cover as much as 29% of the operational expenses. This would represent a significant stride towards achieving complete self-reliance in the solid waste management field.	SWM operating system in 11 Pakistani cities.	Pakistan	Wastewater Benchmark Indicators
(Chanthamixay et al., 2017)	The findings indicated that all waste gathered is sent to authorized treatment facilities. Nevertheless, the efficiency of the system is limited by the inadequate enforcement of applicable rules and the execution of the 3Rs.	Assessment of the Bangkok Metropolitan Administration (BMA) system in 2017.	Bangkok, Thailand	

2.5 ARTIFICIAL INTELLIGENCE (AI)

Artificial Intelligence (AI) is the utilization of technology to replicate the functioning of the human brain. Over the years, the use of AI has gained momentum due to its potential to provide alternative computational strategies for solving various problems across multiple domains. Artificial Intelligence (AI) has been utilized in many areas of Solid Waste Management (SWM) to improve the effectiveness and efficiency of waste management processes. It has been found to be more efficient at handling nonlinear, uncertainty, and incomplete data and optimized learning from experience. The most recent applications could be categorized in five categories:

1. Predictive modeling: AI/ML algorithms can be used to predict the volume of the generated waste in a certain area, based on factors such as population density, weather patterns, and economic activity. This information can be used to optimize collection schedules and routes, and to plan for the expansion of waste management facilities. (Abu Qdais & Shatnawi, 2019; Adeleke et al., 2021a, 2021b; Coskuner et al., 2021; Golbaz et al., 2019a, 2019b; Heshmati et al., 2014; Jassim et al., 2022; Kulisz & Kujawska, 2020; Noori et al., 2010; Ozveren, 2016; Solano Meza et al., 2019)
2. Smart waste bins: Smart waste bins equipped with sensors can automatically alert collection teams when they are full, reducing the need for manual inspections. They can also provide data on the waste types that are being generated in an area, which can be used to improve recycling efforts. (Ali et al., 2020; Hannan et al., 2012, 2016)
3. Image recognition: AI/ML algorithms can be used to sort waste into different categories, such as organic waste, recyclable materials, and hazardous waste. This can improve the efficiency of waste sorting facilities and reduce the need for manual labor. (Abdul Rajak et al., 2019; Alsubaei et al., 2022; Hannan et al., 2016; Zhang et al., 2021)

4. Autonomous vehicles: The management and transportation of waste can be facilitated by using AI in autonomous vehicles. This can enhance the efficiency of waste collection routes and reduce the need for human drivers.(Akdas et al., 2021; Amal et al., 2018; Vu et al., 2019)
5. Root cause analysis: AI can be used to identify the root causes of waste management issues, such as littering or illegal dumping, by analyzing data from social media, CCTV cameras and sensor data.(Abdul Rajak et al., 2019; Adeleke et al., 2021b; Bagheri et al., 2017; Pratap Singh et al., 2019; Shahab & Anjum, 2022)

Several studies have compared the use of more than one model for one application, for example, Hospital solid waste (HSW) generation prediction was analyzed by different models both Kernel-based and Neuron-based by Golbaz et al., (2019). Using data from Karaj metropolis hospitals including wards numbers, occupied beds, staff and inpatients, and hospital years of activity as the model inputs. Results were assessed based on the Mean-Square Error (MSE) and coefficient of determination (R^2), which showed that Kernel-based models reported better results compared to Neuron-based (0.82–0.86 for an average R^2 compared to 0.68–0.74). Some other researchers developed a hybrid model combining two or more AI models for a more optimized prediction. For instance, Vu et al., (2019) has combined a waste production model using an artificial neural network (ANN) with a waste collection route optimization using a geographic information system (GIS) model to predict minimal travel distance for optimal waste collection routes in Texas, USA. Results showed a reduction of travel distance by 10.3 to 16.0% and a slight decrease in emissions., however, it increased the collection time by 15.7–19.8%. Table 2.7 summarizes the most recent research that utilized AI in tackling solid waste management problems.

Table 2. 7: Recent publication using AI in waste management.

Reference and Year	Results	Application	Country	Model(s)
(Fan et al., 2022)	Plastic waste generation is anticipated to increase to 17 million Mt/y by 2030. Additionally, the utilization of a combination of 50% recycling, 47.6% energy recovery, and 2.4% landfilling showed the lowest impact on various environmental parameters.	Forecasting plastic waste generation in 2030	EU-27	Neural Network
(Ma et al., 2020)	Effective evaluation of organic waste demonstrated a rising pattern between the years 1990 to 2017, with the regions of East, North, and Central-South China exhibiting greater	Quantitative models between the socio-economic factors of a city	China	Back-propagation (BP) neural
(Golbaz et al., 2019b)	Kernel-based models reported better results compared to Neuron based (0.82–0.86 for average R^2 compared to 0.68–0.74)	Hospital solid waste (HSW) generation prediction.	Iran	MLR, ANN, ANFIS, SVM, LSSVM, FSM
(Oliveira et al., 2019)	Ann presented an R^2 value of 0.98, indicating a 34% increase in comparison to the most effective regression model applied to the identical data set ($R^2=0.73$).	Separately collected packaging waste prediction.	Portugal	ANN, Regression models, Genetic Algorithm
(Rostami & Baghban, 2018)	Results indicated that the proposed model is more precise quantitatively approach as compared to the usual literature correlations.	Higher heating value (HHV)	Iran	Least-square support vector machine (LS-SVM)
(Vu et al., 2019)	Analyzed scenarios indicate that travel distance can be reduced by 10.3 to 16.0%, and emissions can be slightly decreased.	Waste collection route optimization for 2023	USA	ANN-GIS
(Graus et al., 2018)	The model can control energy consumptions in a micro-grid context within the frame of user preference, however, it takes time to learn the feasible solution.	Biological waste treatment process analysis	Germany	SVM
(Shamshiry et al., 2014)	The findings suggested that utilizing diverse input data can lead to a reduction in the number of hidden neurons while improving the accuracy of predictions.	Waste generation rate in Langkawi and cost optimization.	Malaysia	ANN, Response surface model (RSM)

2.6 DATA PREPROCESSING

A model's predictive behavior or accuracy may be affected by many factors, most importantly, the decisions made during the data preprocessing (Gonzalez Zelaya, 2019). Data preprocessing is the process of cleaning, transforming, and organizing data before it is fed into an AI model. It is an essential step in the development of AI models because the quality and structure of the input data carries a significant effect on models' performance. If data is not preprocessed, unexpected behaviors may occur due to inconsistencies in the data. The quality of data may be affected due to many reasons such as human error, measuring devices limitations, or flaws in the data collection stage, as a result, the data set could have missed, inconsistent, or duplicated values. Data preprocessing most common techniques includes,

- Data cleaning: Removing missing or invalid data points.
- Data transformation: Scaling, normalizing, or encoding features.
- Data organization: Splitting data into training, validation, and test sets.

However, it is important to note that it is an iterative process, and it should be done with a clear understanding of the problem and the used model. The field of machine learning models and explain-ability is an active research topic with many applications. While most research focuses on the model's performance, Gonzalez Zelaya's (2019) research has focused more on the decisions affecting the predictive behavior itself. They defined a simple metric - referred to as volatility in the research- to measure the effect in different scenarios including and excluding specific parameters or steps.

2.7 RESEARCH GAP

Solid waste management (SWM) is considered a challenging issue to regulate, as it exhibits characteristics of a nonlinear dynamic process. At the moment, the process of solid waste management is carried out using various statistical methods such as Life cycle assessment (LCA), System Dynamics Method (SDM), and Forecasting among many others. All these methods provide good predictions and analyses but are not sustainable nor convenient in terms of time and cost. This causes many challenges when it comes to performance analysis. Moreover, there are several significant challenges when building predictive models, such as datasets availability, the optimization of processes prior to model development, the minimization of weight, and the avoidance of bias when selecting an appropriate optimization algorithm. These factors can substantially impact the effectiveness of predictive models.

In addition, Wasteaware is a benchmarking tool for waste management developed by the UK government and adopted in several countries, considering the specific regulations, laws, and local context. However, in Malaysia, it is a relatively less addressed research area, so far.

2.8 SUMMARY

In summary, the significance of effective Solid Waste Management (SWM) practices cannot be overstated, especially in the face of unpredictable events like the COVID-19 pandemic and recent floods. These occurrences create fluctuations in waste composition and quantity, putting immense pressure on treatment facilities and waste management systems. Numerous studies used various methodologies to analyze solid waste generation rates and compositions. Among these approaches, Artificial Intelligence (AI) emerges as a standout solution due to its enhanced accuracy and reduced labor intensity in predicting and managing waste characteristics.

Furthermore, the integration of AI-driven methodologies presents an opportunity to streamline waste management strategies, particularly in handling dynamic waste patterns during challenging circumstances. Additionally, the utilization of WasteAware benchmark indicators offers a multifaceted tool for assessing the performance of local authorities in waste management. This tool exhibits several advantages, including transparency, comparability, flexibility, and continuous monitoring. Notably, its cost-effectiveness further solidifies its utility in evaluating and enhancing waste management practices on both local and broader scales.



CHAPTER THREE

METHODOLOGY

3.1 OVERVIEW

This chapter explains a thorough image of the steps that will be undertaken to achieve the stated objectives. It provides detailed study planning, explanation of the techniques used to achieve the study objectives. In this study, WasteAware benchmark indicators and artificial intelligence have been used for the prediction of solid waste generation rates. In this research, data will be collected to provide an overall view of solid waste generation and performance analysis during Covid-19 pandemic.

Next, AI models will be built using default settings, and data will be used with and without preprocessing as input variables for both deterministic models and AI models. Results of the first run will be used to tune models until the optimized result is achieved for both approaches with both cases, processed and unprocessed data. Lastly, results will be represented in graphs for better illustration and recommendations will be given. Figure 3.1 illustrates the research methodology chart.

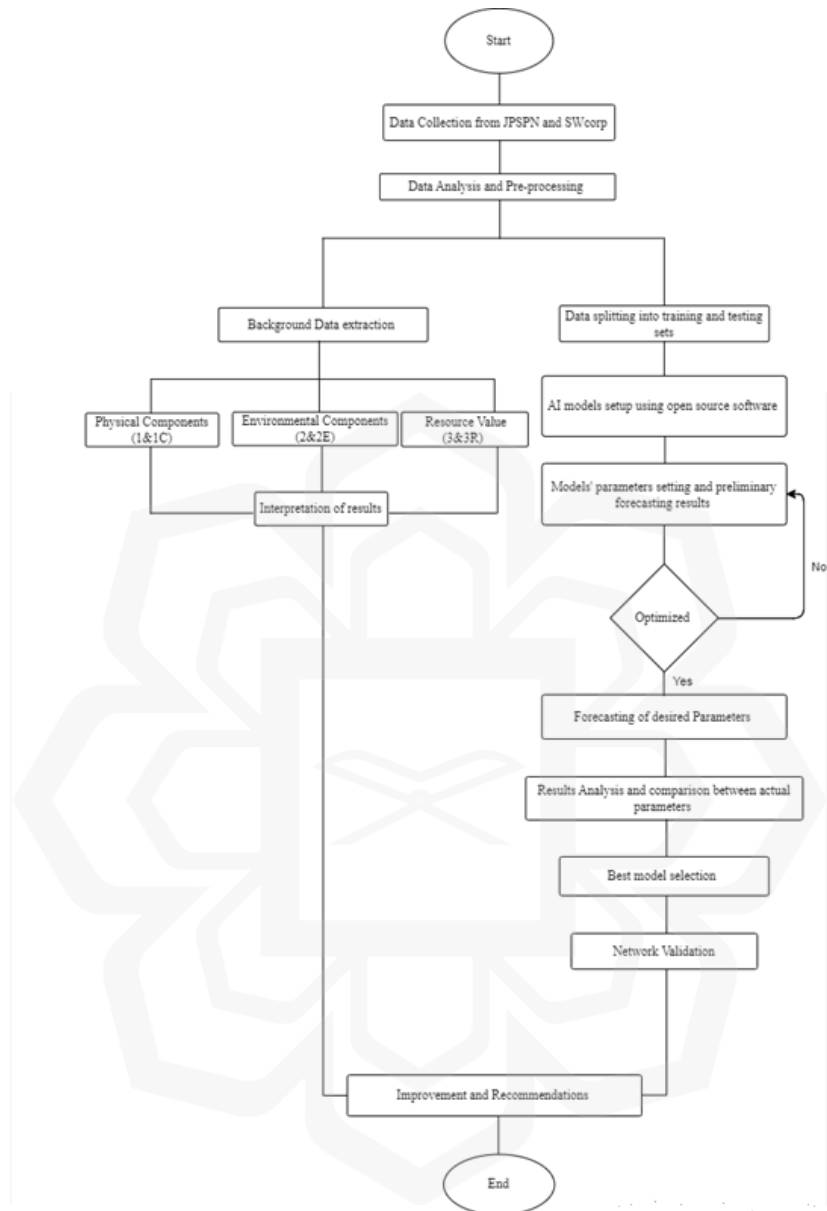


Figure 3. 1: Methodology Chart

3.2 DATA COLLECTION

Data were collected from several sources; some were collected directly from (SWCorp) which is a Malaysian government agency under the Ministry of Housing and Local Government (KPKT) and under the “Solid Waste Management and Public Cleansing Corporation Act (Act 673)”. While some other data were collected from Malaysian Open Data (data.gov.my) server.

The collected data covered 8 states and federal territories namely, Kuala Lumpur, Johor, Putrajaya, Negeri Sembilan, Melaka, Kedah, Pahang and Perlis. Data's timeframe differs from set to set, most of data covers years from 2012 to 2020.

3.3 ‘WASTE AWARE’ BENCHMARK INDICATORS

Benchmark indicator assessment was carried out with refer to Wilson’s (2012) user manual. The user manual provides a step-by-step detailed guideline; each indicator set depends decisively on the input data quality. Hence, data were analyzed critically and separated into 8 excel sheets based on state. Each Excel sheet consists of data for three studied indicators, data used were a results of primary survey work. Table 3.1 shows the followed elements of an ISWM benchmark indicators analytical framework.

Table 3. 1: ISWM benchmark indicators analytical framework elements.

Element	Description
Data collection	This involves collecting data on the various elements of the waste management system, such as rates of waste generation, characteristics of waste, recycling percentages, and waste treatment procedures in all states.
Data analysis	This involves analyzing the collected data to identify trends and patterns, and to calculate the values of the benchmark indicators.
Comparison to targets or benchmarks	This involves assessment of the effectiveness of the waste management system as compared to the benchmark indicators with predetermined benchmarks or targets.

Interpretation of results	The process involves analyzing the results and recognizing the system's strengths and areas for improvement in waste management.
Recommendations for improvement	This involves making recommendations for how the waste management system can be improved based on the analysis results.

The analysis was carried out using Microsoft Excel. Document' preparation was done in four main steps as follows:

3.3.1 Introduction and Background Data

The supporting information include, Country, City, Assessment date, Indicators application date, Population, Gross national income (GNI) per capita in USD, Total municipal solid waste (MSW) generation (tons per year), MSW per capita (in kg/year and kg/day), composition of MSW as generated (Organic, Paper, Plastic, and Metals), waste density, and Moisture content. All the above-mentioned data were collected from existing data or previous research if available or estimated if actual measurements were not available. For each indicator, supplementary details were provided of where and how the measurements were done.

3.3.2 Benchmark Indicators for Physical Components

The supporting information include Waste Collection Coverage (calculated by the percentage of households in the state that have access to a reliable waste collection service), Waste collected by the SWM and recycling system, Quality of waste collection and street cleaning service (a qualitative indicator). This part of the assessment aims to provide a quantitative measure as well as qualitative assessment of the system effectiveness. For each indicator, supporting details were provided of where and how the measurements were done.

3.3.3 Benchmark Indicators for Environmental Components (Waste Treatment and Disposal)

The supporting information include, Controlled treatment or disposal, Protection of the environment in waste disposal and treatment assessment which includes degree of control over waste reception and general site management, The extent to which environmental controls are monitored and verified, Control over waste disposal and treatment, Energy generation and use efficiency, Planning technical competence, management and operation disposal and treatment, and Safety and Occupational health. For each indicator, supporting details were provided of where and how the measurements were done.

3.3.4 Benchmark Indicators for Resource Value (3Rs)

The supporting information includes, Recycling rate, Quality of 3Rs, Separation source of 'dry recyclables', Environmental protection in recycling, and Quality of recycled organic materials. For each indicator, supporting details were provided of where and how the measurements were done.

3.4 AI MODELS

The methodology used the principle of "Perfect model = simple functioning model". Each model was built up simply and optimized after every iteration. All models were built in a supervised manner meaning that data with the specified target was prepared beforehand referring to literature. Model's setup was as shown in Figure 3.2

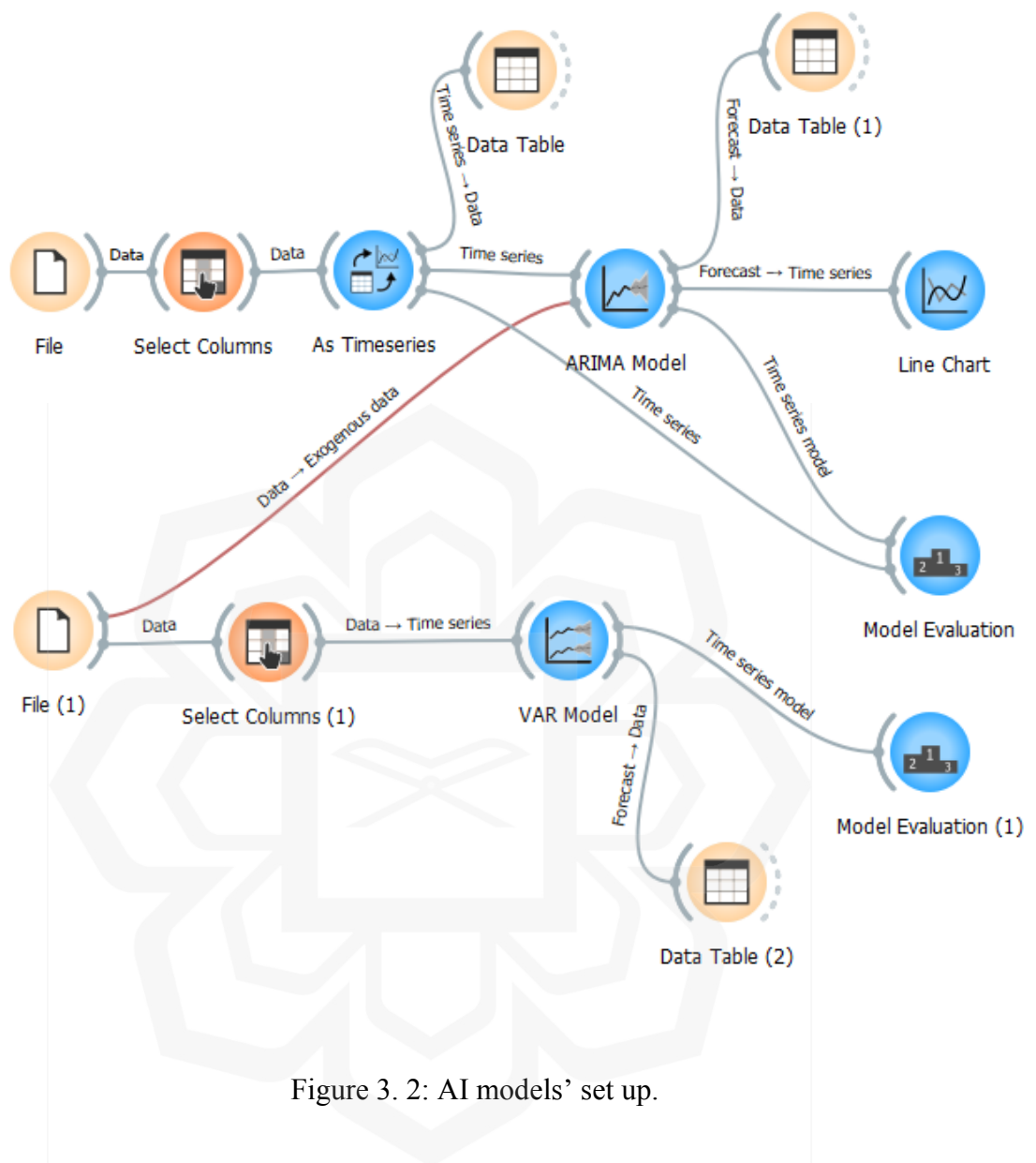


Figure 3. 2: AI models' set up.

Orange data mining was selected for analysis and prediction for many reasons, most importantly it is a commercially available software with an easy setup. First, the collected data were sorted and saved in an Excel file in CVS format. A comprehensive evaluation of diverse AI models was done, each selected for its unique strengths in predicting and preprocessing waste characteristics. The models considered included, Artificial Neural Network (ANN), Support Vector Machine (SVM), VAR (Vector Autoregression), Gradient Boosting (GB), and ARIMA (Autoregressive Integrated Moving Average).

3.4.1 Data Preprocessing

Preprocessing steps aim to prepare data and to facilitate prediction activities. Preprocessing and equality of the data play an important role in the performance of the model algorithm. If data are not preprocessed, the algorithm may behave unexpectedly due to inconsistent data, and performance may be affected (Woo et al., 2020). The quality of data may be affected due to many reasons such as human error, limitations of measuring devices, or flaws in the data collection process, as a result, the data set could have missed, inconsistent, or duplicated values. The first data preprocessing step was outliers' removal, which could be noticed from the statistical analysis of the data. When the standard deviation is high, it indicates that some data points are far from the overall pattern. One class of Support vector machines (SVM) is an unsupervised application algorithm of Support vector machines that were previously discussed.

It detects the outsides of the non-linear radial basis function kernel (RBF) based on the Nu parameter and kernel coefficient. RBF is one of the SVM functions that change with distance from a location, it's commonly used and found to be efficient for overcoming the usual operating conditions errors. (Beghi et al., 2014). Both Nu parameter and kernel coefficient were adjusted until the optimum result was reached. Optimum values were found to be 5% and 0.01 for Nu parameter and kernel coefficient, respectively.

Moreover, normalization is crucial for accuracy, as it standardizes data distribution. With numerous variables and large quantities, a normalization feature was applied, setting a bipolar interval [-1, 1] using the preprocess widget.

Lastly, PCA stands as a valuable multivariate statistical technique to simplifying input variable complexity (Chahboun & Maaroufi, 2021). Determining the ideal number of principal components involved a trial-and-error method, adjusting the number of principal components until achieving optimal outcomes. Through this process, it was identified that the dataset's optimal configuration entailed 10 principal components.

3.4.2 Models' Set up

3.4.2.1 *Data splitting*

After data preprocessing, the dataset is ready for the next phase. The splitting of data for training, validation, and testing depends on the type of the chosen model and the dataset itself. Figure 3.3 shows an approximate division of the data set

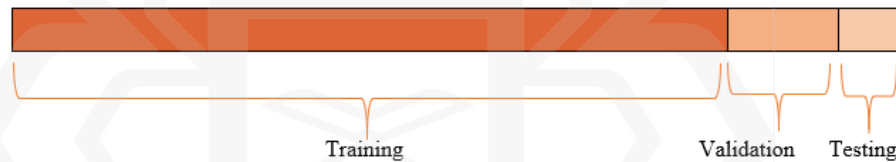


Figure 3.3: Split Ratio

The initial subset, constituting the majority, typically 70-80%, is used as the training set for model training. Following this is the Test Set, comprising around 10-20%, which is used to evaluate the final model's performance on entirely unseen data, mimicking real-world scenarios. Lastly, the Validation Set, a smaller portion (usually 10-15%), is designated for fine-tuning the model's hyperparameters and evaluating its performance during training, mitigating the risk of overfitting. This structured division ensures comprehensive model assessment and robust generalization.

3.4.2.2 *Artificial Neural Network (ANN)*

After reviewing recent literature, one of the widely used ANN modeling algorithms was used, the multi-layer perceptron (MLP) algorithm with backpropagation. The parameters were tested until the optimum values were achieved using 1 hidden

layer, 32 neurons per hidden layer, activation function tanh, solver SGD, regularization of 0.02, and the maximum number of iterations of 200.

3.4.2.3 Support Vector Machine (SVM)

Prediction of the SVM model was optimized using cost function (C) of 5.10, regression loss epsilon (ϵ) of 0.10. The type of kernel used was RBF. Numerical tolerance was set to a default value of 0.0010, while the iteration limit was set to 100.

3.4.2.4 Gradient Boosting (GBM)

Gradient boosting sci-kit-learn was used with a learning rate of 0.120 for training, 100 trees in the forest, subsampling of a total of 0.8, a tree depth of 8, and 5 as minimum subsets split samples.

3.4.2.5 ARIMA

The integration of the ARIMA model involved utilizing time series and Python coding widgets. Optimal parameters were chosen through training an ARIMA model with a one-step prediction, followed by the calculation of error scores for predictions against expected values. The identified optimum parameters for the ARIMA model include Autoregressive terms (p) set at 1, Nonseasonal differences (d) at 5, and a Moving Average factor (q) of 1. This process ensures the ARIMA model is fine-tuned to achieve optimal performance in capturing the underlying patterns within the time series data.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 OVERVIEW

This chapter presents the results of the research study, which were obtained through the analysis of data collected from the regulatory bodies. This chapter provides a comprehensive description of the findings, including both qualitative and quantitative results. The results are discussed in detail and interpreted in the context of the research questions and hypotheses. The chapter also highlights the key findings and their significance, as well as their implications for future research. In addition, any unexpected results are also discussed and explained, providing a comprehensive analysis of the results and their impact on the area of study.

4.2 WASTEWARE BENCHMARK INDICATORS

Data was gathered from 8 states and federal territories in Malaysia from municipal sources, annual reports, and existing literature on the topic of SWM. The collected data included background information on cities, key waste data, physical aspects of the four main components of Municipal Solid Waste, and governance factors. Furthermore, visits were made to selected cities to evaluate the actual quality of services offered by the municipalities.

The primary objective of the Wasteaware ISWM benchmark indicators is to provide a comprehensive assessment of the performance of cities' solid waste management practices based on existing data. The indicators have been designed to be comprehensive and detailed as possible, with each component covering all the fundamental and specific aspects of solid waste management.

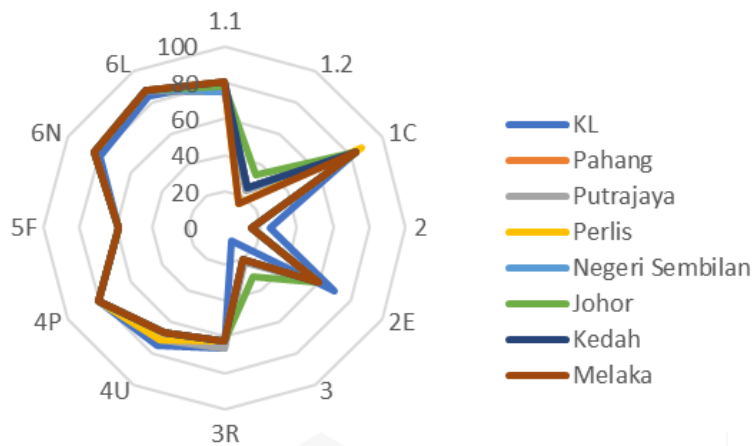
Moreover, in order to make it easier for information users to comprehend the indicators, results are quantified. As such, the results of the assessments have been assigned scores within a certain range, and each range has been color-coded to provide users with a quick visual assessment of the performance. For instance, red code represents a low range of 0-20%, the low/medium range of 21-40% is coded red-orange, the medium range of 41-

60% is coded orange, the medium/high range of 61-80% is coded amber-green, and the high range of 81-100% is coded green. To improve readability even when printed in black and white, the color orange was also used for shading purposes in this application. This color-coding system enables information users to easily and rapidly understand the performance assessment results of different cities or municipalities. Table 4.1 shows a summary of Wasteaware analysis for Kuala Lumpur, the remaining states can be found in the appendix.

Moreover, in evaluating the effectiveness and sustainability of waste management systems, the WasteAware benchmark indicators serve as a comprehensive framework. These indicators encompass various facets of waste management, delineating critical aspects such as waste collection coverage (1.1), the efficiency of waste capture by the system (1.2), and the quality of waste collection services (1C). Additionally, they evaluate controlled treatment and disposal (2), environmental protection during waste treatment (2E), recycling rates (3), and the quality of Reduce, Reuse, Recycle (3Rs) initiatives (3R). Furthermore, these benchmarks assess user (4U) and provider (4P) inclusivity, financial sustainability (5F), adequacy of national solid waste management frameworks (6N), and local institutional coherence (6L). By utilizing this comprehensive set of indicators, this thesis aims to offer an in-depth assessment of waste management practices, facilitating a holistic understanding of the strengths and areas for improvement within waste management systems. Figure 4.1 shows a Radar diagram that summarizes the 12 Wasteaware ISWM benchmark indicators for the eight states for which the data is presented later in this chapter, where the indicator numbers (1.1 to 6L) are also defined.

Table 4. 1: Wasteaware analysis for Kuala Lumpur.

Background information on the city						
City		Kuala Lumpur				
Country		Malaysia				
Date since previous application of indicators:			No known previous application of indicators			
B1	Country income category	World Bank income category	Gross National Income (GNI) per capita			
		<i>Upper middle income</i>	10570			
B2	Population of city	Total population of the city	1,982,112			
B3	Waste generation	Total municipal solid waste generation (tonnes/year)	2319071.04			
No	Category	Data/ Benchmark Indicator	Results	Code		Progress
Key Waste-related data		Data		-	-	-
W1	Waste per capita	MSW per capita	kg per year	1.17	-	-
			kg per day	0.74	-	-
W2	Waste composition:	Summary composition of MSW for 3 key fractions – all as % wt. of total waste generated	-	-	-	-
W2.1	Organic	Organics (food and green wastes) %	44.54	-	-	-
W2.2	Paper	Paper %	6.28	-	-	-
W2.3	Plastics	Plastics %	19.51	-	-	-
W2.4	Metals	Metals %	1.22	-	-	-
W2.5	Solid waste density	Solid waste density	0	-	-	-
W2.6	Moisture content	Moisture content	0	-	-	-
Physical Components		Benchmark Indicator	-	-	-	-
1	Public health – waste collection	1.1 Waste collection coverage	80			
		1.2 Waste Captured by the System	25			
1C		Quality of waste collection service	83			
2	Environmental control – waste treatment and disposal	Controlled treatment and disposal	25			
2E		Quality of environmental protection of waste treatment	70			
3	Resource Management – Reduce, Reuse, Recycle	Recycling rate	8			
3R		Quality of 3Rs – Reduce, reuse, recycle	67			
Governance Factors		Benchmark Indicator	-	-	-	-
4U	Inclusivity	User inclusivity	75			
4P		Provider inclusivity	80			
5F	Financial sustainability	Financial sustainability	58			
6N	Sound institutions, proactive policies	Adequacy of national solid waste management framework	79			
6L		Local institutional coherence	83			



Legends	
1.1	Waste collection coverage
1.2	Waste captured by the system
1C	Quality of waste collection service
2	Controlled treatment and disposal
2E	Quality of environmental protection of waste treatment and disposal
3	Recycling rate
3R	Quality of 3Rs
4U	User inclusivity
4P	Provider inclusivity
5F	Financial sustainability
6N	Adequacy of national SWM framework
6L	Local institutional coherence

Figure 4. 1: Radar diagram of the 12 Wasteware ISWM benchmark indicators for the eight states.

4.2.1 Waste treatment and disposal benchmark

Based on the findings presented in the radar diagram, the evaluated states were observed to have efficient waste management practices, and their performance was relatively similar. The disposal of waste and the total amount of waste treated or disposed of in a controlled facility, as well as the level of environmental conservation, were assessed as key factors. The majority of states scored 82% in the evaluation, while Perlis, Kuala Lumpur, and Putrajaya had a slightly higher rating of 88%. Overall, the waste management quality was deemed to be moderate across all regions.

As discussed in Chapter Two Section 2.3.2 recent data reveals that within the studied area, there are a total of 7 operational sanitary landfills in contrast to 29 non-sanitary sites and open dumps. This distribution accounts for approximately 24% of the waste disposal sites, signifying a notable minority in comparison. However, when compared to another Upper middle-income cities, results are slightly less when compared to 95% and 90% in Guadalajara, Mexico (Wilson et al., 2015b), and Bangkok, Thailand (Chanhthamixay et al., 2017) respectively as represented in Chapter two section 2.4.1.

The analysis highlights the need for further improvements in waste management practices across the evaluated states. While the waste management quality is moderate, there is still room for improvement, particularly in terms of reducing the number of non-sanitary sites and open dumps. The results of the evaluation suggest that there is a need for greater investment in waste management infrastructure and resources to improve waste disposal and treatment processes.

Overall, the evaluation serves as a valuable tool for identifying areas of improvement in waste management practices and highlights the need for ongoing efforts to improve waste management practices and reduce the environmental impact of waste.

4.2.2 Recycling and recovery benchmark

The recycling benchmark measures how well the 3Rs (reduce, reuse, and recycle) are being done, both in terms of quantity and quality. The recycling rates ranged between 20-22% which is a Low/Medium score. The overall benchmark score ranges between 62-67%. Results for each state are attached in the appendix.

Comparing recycling benchmark to other upper middle income shows that all states recycling rate is acceptable at 22%, similar to Bangkok at 23%, and quite high when compared to Guadalajara at 12%. While Bangkok 's recycling rate was the highest, the studied states scored highest in terms of the quality of the 3Rs, with a robust system for reducing and reusing waste, 63% compared to 42%. Guadalajara, on the other hand, scored low in both categories, with a lack of infrastructure for recycling and inadequate education on waste reduction (Wilson et al., 2015b).

Moreover, despite the low to medium score for recycling rates, the overall benchmark score is relatively high, indicating that the states are performing well in other areas such as waste reduction and reuse. However, increasing the recycling rate should remain a priority to further reduce the amount of waste sent to landfills and maximize the use of valuable resources. One possible way to achieve this is through education and awareness campaigns to encourage the public to participate more actively in recycling and composting programs.

Another approach is the promotion of eco-friendly products use and packaging materials, which are easier to recycle or biodegrade. Overall, the recycling benchmark provides valuable insights into the strengths and weaknesses of the solid waste management system in the studied states and can guide policymakers and stakeholders in developing strategies to improve waste management practices.

4.2.3 Governance aspects

The degree to which stakeholders can impact decision-making and operations in a city is measured by the user inclusivity indicator. In Peninsular Malaysia, the score for user inclusivity is high, indicating a positive environment for stakeholder influence. Conversely,

the provider inclusivity indicator assesses the extent to which service providers can access solid waste and recycling niches in the city's economy and operations. Malaysia also scored well on this indicator, with a high-rating for-provider inclusivity. Several literatures have studied the consumer satisfactory regarding the provided states in different states and showed a general satisfactory level (Abas & Wee, 2020; Armi et al., 2013; Husain et al., 2017; Norsa'adah et al., 2020). However, there is room for improvement in this area, as the rating is only average with a normalized score of 58%. One of the key issues identified is the lack of fairness in service provision, especially in densely populated areas where door-to-door waste collection is not available.

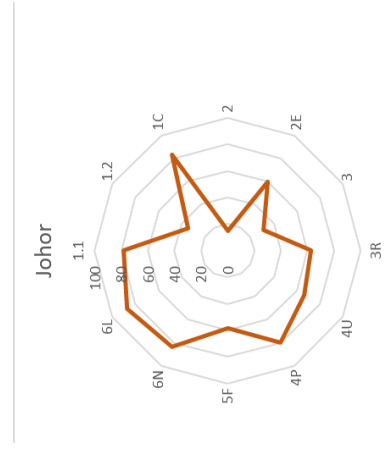
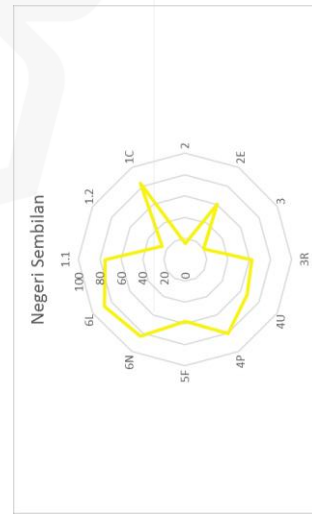
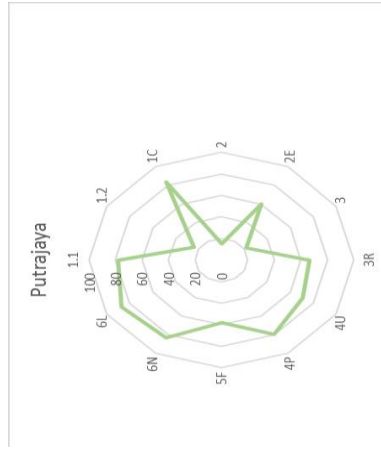
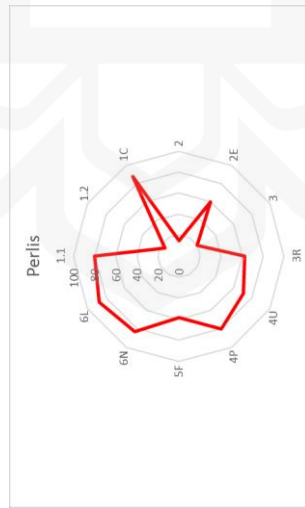
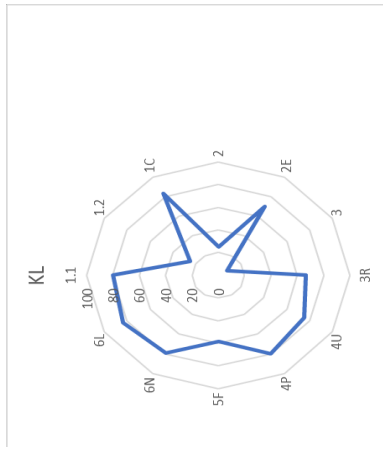
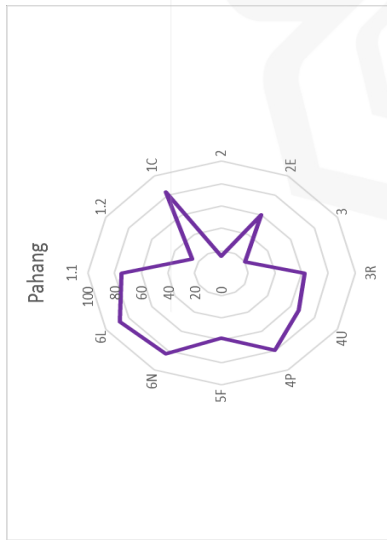
4.2.3 Wasteaware Benchmark Indicators summary

In conclusion, the Wasteaware Benchmark Indicators analysis has been used to assess the current SWM system during COVID-19, more precisely year 2020. The analysis highlighted several strengths and weaknesses in current solid waste management systems across different states. Most of states perform well in terms of waste reduction, recycling, and stakeholder engagement, in comparison with other upper middle-income countries. Results also suggest that there is significant room for improvement in solid waste management practices. Once management prioritize reducing waste generation, promoting recycling, and engaging stakeholders in decision-making processes, states are more likely to achieve environmentally and financially sustainable waste management systems within a short period of time.

Radar diagrams were found to be the most effective and informative visual aid for understanding the six indicators used in the ISWM benchmark. These diagrams provided a comprehensive and comparative assessment of each state's solid waste management performance, representing the data in a clear and intuitive way. The six indicators measured in the study could be plotted on a single chart, making it easier for stakeholders and decision-makers to identify areas for improvement and to make informed decisions about resource allocation and policy development. Specifically, the radar diagrams allowed for a quick comparison of each state's performance in terms of waste generation, collection, disposal, recycling, composting, and informal sector involvement.

The radar diagram offers a comprehensive insight and a visual representation of the Integrated Sustainable Waste Management (ISWM) indicators across eight states in Malaysia, showcasing varied performances. For instance, Kuala Lumpur stands out with an impressive waste collection coverage (1.1) score of 80, signaling extensive waste collection services. It also scores notably high in local institutional coherence (6L) with 83.33, indicating a well-structured waste management framework. Conversely, Pahang and Perlis exhibit lower scores in controlled treatment and disposal (2), both at 15, signaling potential areas for improvement in waste treatment facilities. These states also demonstrate lower recycling rates (3) at 20 and 20, respectively, suggesting opportunities to enhance recycling initiatives. Putrajaya maintains consistent scores across multiple indicators, averaging around 78, reflecting a balanced waste management approach. Notably, Negeri Sembilan and Melaka display strong inclusivity in waste management, scoring 75 and 66.67 in user inclusivity (4U) and 80 in provider inclusivity (4P), indicating robust stakeholder engagement. These numbers underline the diverse performance levels among states, outlining specific areas that require focused attention and improvement in their waste management strategies. Figure 4.3 shows radar diagrams for the eight states, each indicating the relative performance of each city in these six categories.

Figure 4. 3: Radar diagrams for the eight states



Overall, The Wasteaware Benchmark Indicators analysis highlights the need for states to prioritize equitable and inclusive waste management practices that consider the needs and concerns of all stakeholders, including marginalized and vulnerable populations. By prioritizing social and environmental justice in waste management practices, cities can build more sustainable and resilient communities.

4.3 ORANGE DATA MINING SOFTWARE

The used software is Orange software which is an open-source data mining and machine learning software that offers a visual programming interface for creating data workflows. It includes a wide range of tools for data preprocessing, feature selection, machine learning, and data visualization. It can be used for various tasks, such as text mining, image analysis, and bioinformatics, among others. Orange is available for free and can be downloaded for Windows, macOS, and Linux. The data collection was done from variety of sources, which results in having incomplete data sets for all the states with the same parameters. In order to overcome the effect of missing data on any model's behavior, only the complete sets were used for the analysis. Sets included, population, waste per capita, year, and total generated waste in tons, data cover years from 2014 to 2021. Machine learning techniques were used to build a model to forecast solid waste generation. The first analysis used the Time series analysis widget to analyze how solid waste generation has changed over time.

The model used domestic waste quantities data from January 2016 to December 2019 to forecast waste from January 2020 to December 2022. Results showed a fluctuating trend in waste generation over time. Initially, from January 2016 to August 2016, there was a noticeable increase in waste quantities, peaking at 241,654.25 units in August 2016. Subsequently, there was a gradual decline until April 2017, where waste production reached one of its lowest points at 204,983.19 units. Over the following months until July 2018, waste quantities showed a fluctuating but relatively stable pattern. From July 2018 to July 2019, there was a consistent increase, peaking at 240,003.29 units in July 2019. However, the model predicted a subsequent decline until April 2020, marking a notable dip

to 164,697.71 units. A rebound in waste generation was visible from May 2020 to December 2020, reaching 211,990.18 units. Thereafter, the waste quantities displayed a slightly declining trend, maintaining a range of approximately 200,000 to 210,000 units from January 2021 to December 2022. Figure 4.4 shows the trends, patterns, or seasonality in the domestic waste collected up to 2022.

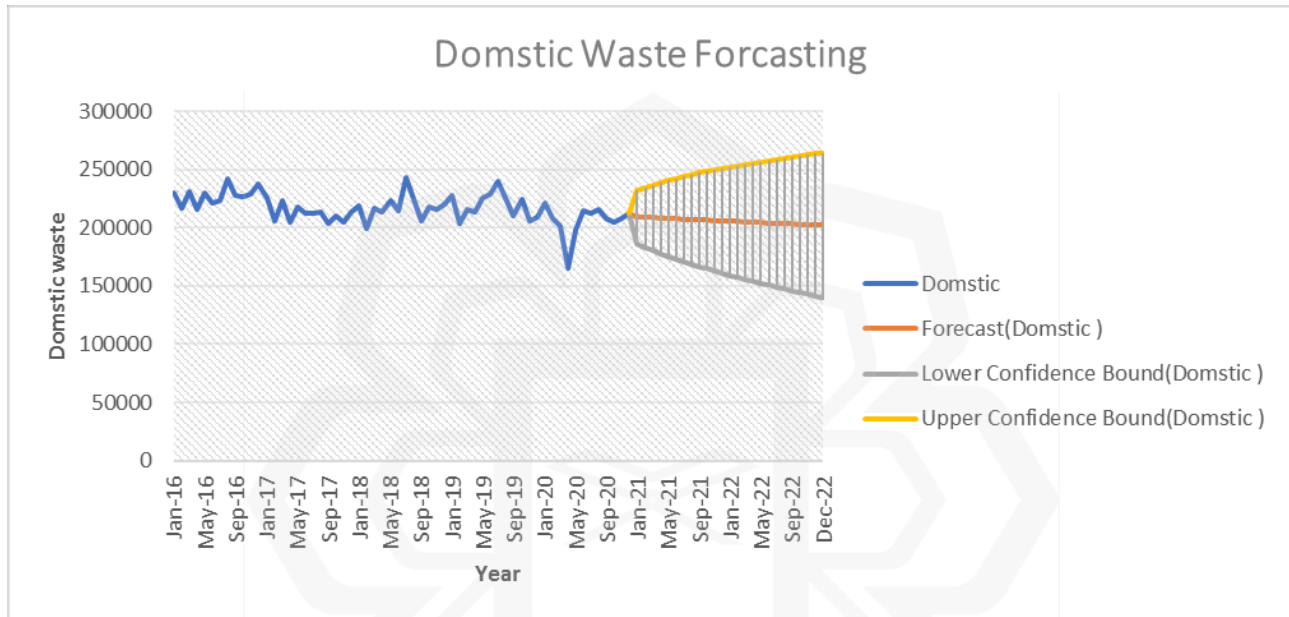


Figure 4. 4: Forecasting of Domestic waste 2020-2022

Additionally, Multiple Regression Analysis was combined with PCA which is a dimensionality reduction, unsupervised learning techniques, was used to identify the most important variables that contribute to the variation in waste generation. The analysis determined that waste production is predominantly influenced by several factors, namely the income, assets, age, and individual outlook of households.

Lastly, the principal model used is ARIMA (AutoRegressive Integrated Moving Average) is a statistical method used for time series forecasting. It models the underlying structure of the data to identify patterns and trends, and then uses this information to make future predictions. ARIMA models use three components to forecast future values:

autoregression (AR), integration (I), and moving average (MA). These components are combined to form an ARIMA model, which can be fine-tuned using parameters such as the order of the autoregression, order of the difference, and the order of the moving average. ARIMA models are widely used in areas such as economics, finance, and operations research. When data were introduced to the model directly it showed poor performance, R^2 was negative which indicates a very poor performance unfortunately without any explanation. A negative R^2 represented a linear regression model that is a poor fit for the data, and the variance of the dependent variable is greater than the variance of the independent variable. A variety of reasons could be behind that for instance:

- The model fits the data poorly, when a model does not fit the data well, R^2 can be negative. This can happen when the correlation between the independent variable and the dependent variable is nonlinear or when the assumptions of the linear regression model are violated.

- The dependent variable is highly variable: If the dependent variable has high variability relative to the independent variable, the model may not be able to explain much of the variation in the dependent variable, leading to a negative R^2 .

- The data has measurement error: If there is significant measurement error in the data, the model may not be able to capture the true relationship between the independent variable and the dependent variable, leading to a negative R^2 .

Since there's no way to understand the specific reason behind the model's behavior, a re-evaluation was done, and tuning parameters was done using trial and error approach. After several data preprocessing steps and parameters tuning an average R^2 of 0.682 was achieved. Figure 4. 5 shows the results of ARIMA model.

Domstic (forecast)	Domstic (96%CI low)	Domstic (96%CI high)
213366	139215	287517
214802	108675	320930
216238	83813.2	348662
217673	61679.6	373666
219108	41127.7	397088
220543	21580.2	419506
221978	2700.9	441255
223413	-15724	462551
224848	-33839.5	483536
226284	-51748.2	504315
227719	-69525.6	524963
229154	-87228.4	545536

Figure 4. 5: ARIMA model results.

The second used model is Vector Autoregressive (VAR) model, which is a statistical model used to analyze the interdependence between multiple time series variables. The data used for this analysis are the waste characteristics and compositions for several years, each variable is modeled as a linear function of its own past values and the past values of other variables in the system. Same as the previous model, it needed several attempts to reach an optimum value of 0.721 R^2 . Model was able to predict the waste composition for year 2022 using data from 2017 to 2021. Figure 4.6 shows the effect of inputting un-preprocessed data on ARIMA and VAR models' Prediction compared to actual results.

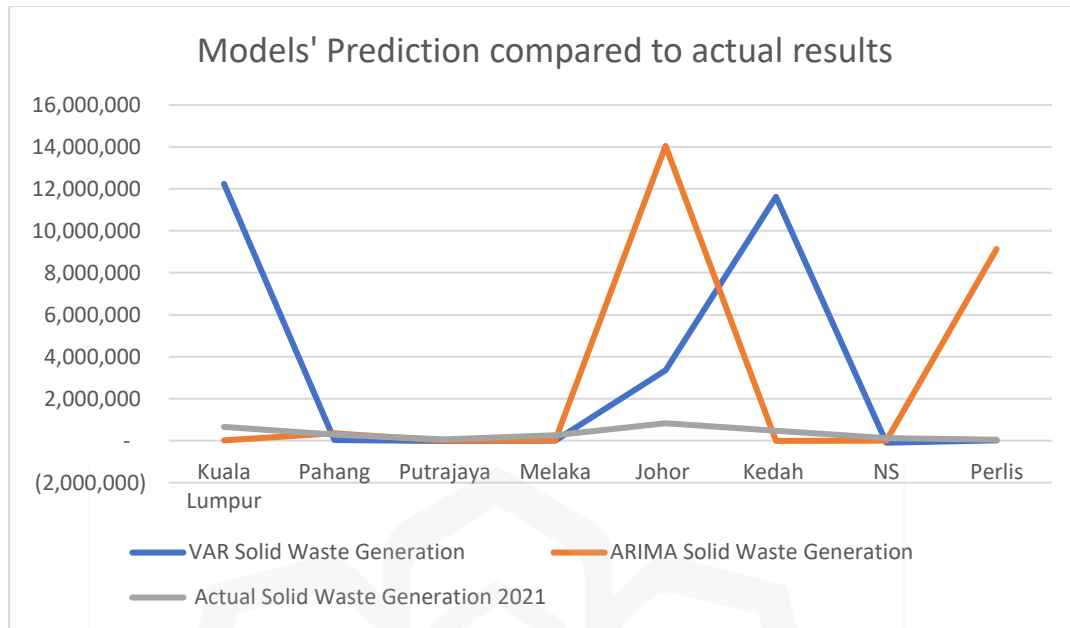


Figure 4. 6: ARIMA and VAR models' Prediction compared to actual results.

Additionally, Orange software allows user to code using python, the feature was used to further analyze and forecast solid waste generation for Malaysia. Code was written based using the following data as an input:

- Demographic data of the population from 2012 to 2021.
- Quantity and composition of solid waste generated before and during COVID-19 pandemic.
- Economic data including income levels, GDP, unemployment rate, etc.

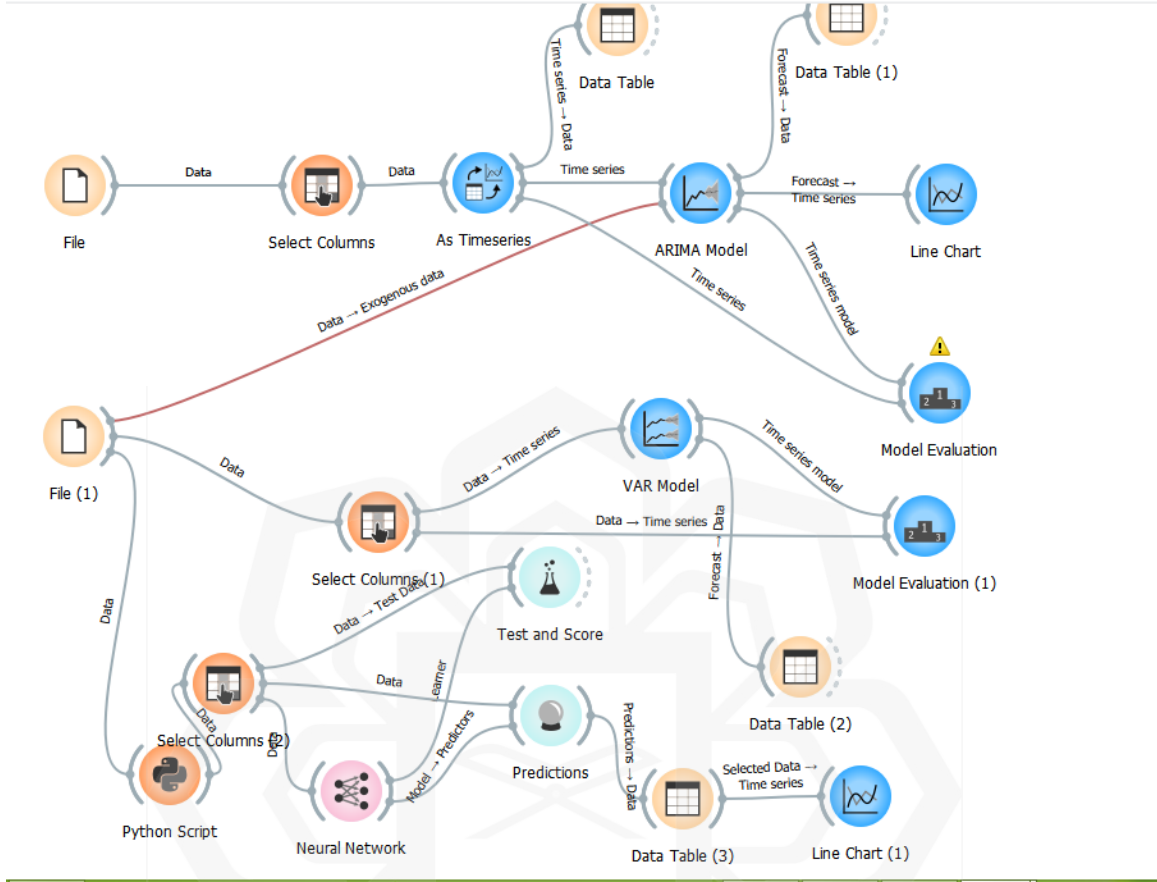


Figure 4. 7: Full models' set-up interface

The Orange interface enables parallel execution of multiple models, each capable of performing independently or in sequence. The optimal setup was achieved by optimizing each model separately, and different datasets were uploaded to be used with different models. Firstly, the 'Column Selection' widget was used to identify the targeted item for prediction. Following that, the data was preprocessed using techniques such as PCA, missing value imputation, and standardization. Next, the nodes were adjusted to create a time-series forecast for the next 7 years.

Initially, a neural network model was used to forecast waste generation, however it showed poor results, with an average R^2 score of 0.439 in testing and 0.578 in validation. To improve the model's performance, several approaches were tested until the optimal

coefficient of determination was achieved. The Python script was used to load the data into a Pandas dataframe, group it by year and month, calculate the total solid waste generated over time, and plot the data. The script then used linear regression to forecast the total solid waste generated over time, resulting in improved model performance of R^2 of 0.892.

To better visualize the results, the predicted outcomes were compared both with an earlier 2018 prediction published by SWCORP and the actual waste generation rates of 2020. The comparison between the estimated annual solid waste generation predicted by the model in 2018 and the actual solid waste generation in 2020 reveals varying levels of accuracy across different states. In Kuala Lumpur, the model's estimate of 677,090.92 tonnes diverged slightly from the actual figure of 658,196.242 tonnes, indicating a relatively close prediction. However, in Pahang and Putrajaya, the model's estimates of 286,741 and 41,574 tonnes respectively significantly deviated from the actual waste generation figures of 284,065 and 54,804 tonnes, suggesting notable inaccuracies. Melaka and Johor also displayed disparities between the model's predictions of 240,297.88 and 878,221 tonnes respectively and the actual waste generation of 255,178 and 831,959.9 tonnes, indicating moderate deviations. Kedah exhibited a similar trend with the model's prediction of 479,660 tonnes differing from the actual 478,560 tonnes. Negeri Sembilan (NS) and Perlis, on the other hand, showed substantial discrepancies with the model's estimates of 284,065 and 45,715.06 tonnes respectively, contrasting significantly from the actual waste generation of 120,041 and 47,916 tonnes. These disparities suggest varying degrees of accuracy in the model's predictions across different states, highlighting the need for further refinement and enhancement of the model's predictive capabilities, particularly in certain regions. Comparison is illustrated in Figure 4.8.

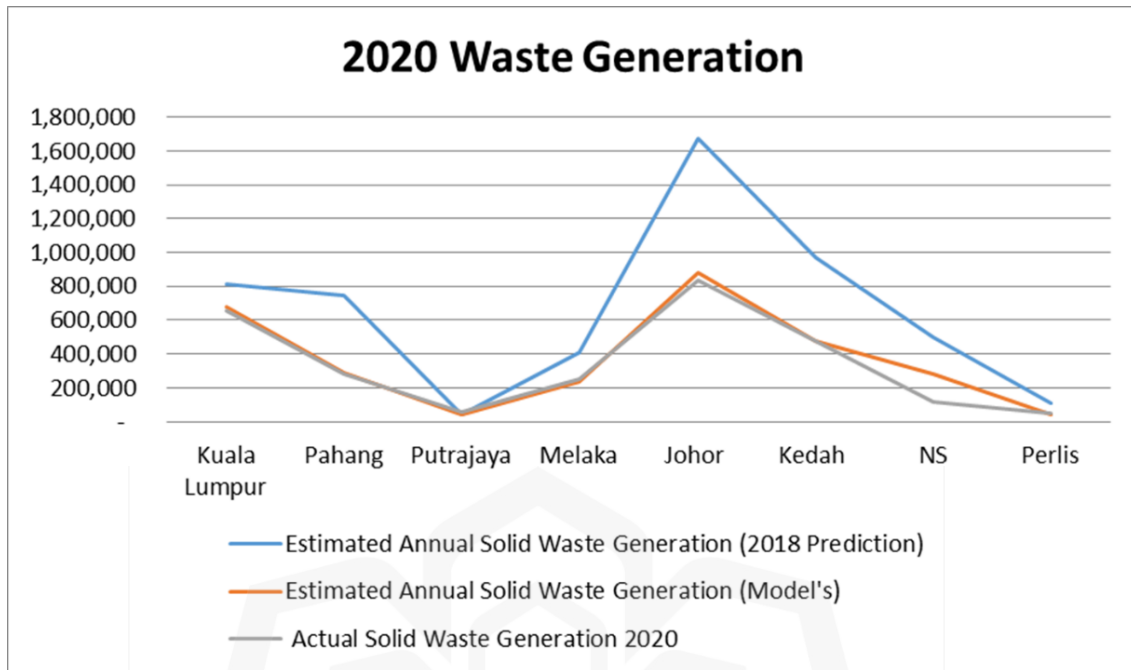


Figure 4. 8: 2020 Solid Waste Generation Comparison.

Following the rigorous optimization of the model and its validation against the 2020 waste generation data, it was ready and reliable for predictive purposes. Leveraging the validated model's efficacy, the study projected waste generation estimates until the year 2030 across the eight states under consideration. Utilizing this optimized model to forecast waste generation for the forthcoming decade offers a glimpse into the potential trends of waste patterns. Table 4.3 shows the prediction until 2030.

Table 4.3: Prediction results until 2030.

Year	Population	Home, industrial, commercial & institutional contents	Home, industrial, commercial & institutional contents (tons\day)	Home, industrial, commercial & institutional contents (tons\year)	Household (tons\day)	Industry, Commercial& Institutional (tons\day)	Industry, Commercial& Institutional (tons\year)
2012	28334135	1.17	33150.94	12100092	21533.94	11617	4240203
2013	28,844,149	1.17	33,747.65	12,317,894	21,921.55	11,826.10	4,316,527
2014	29,363,343	1.17	34,355.11	12,539,616	22,316.14	12,038.97	4,394,224
2015	29,891,883	1.17	34,973.50	12,765,329	22,717.83	12,255.67	4,473,320
2016	30,429,936	1.17	35,603.03	12,995,104	23,126.75	12,476.27	4,553,840
2017	30,977,674	1.17	36,243.88	13,229,016	10,054.05	12687.24	4630843
2018	31490546.27	1.17	36843.94	13448038.13	23932815	12,902.05	4,709,250
2019	32,019,220	1.17	37,462.49	13,673,809	24334608	13,116.86	4,787,656
2020	32,547,895	1.17	38,081.04	13,899,579	24736400	13,331.67	4,866,063
2021	33,076,569	1.17	38,699.59	14,125,349	25138192	13,546.48	4,944,470
2022	33,605,243	1.17	39,318.14	14,351,120	25539985	13761.29	5022876
2023	34,133,917	1.17	39,936.69	14,576,890	25941777	13,976.10	5,101,283
2024	34662591.3	1.17	40555.24	14802660.36	26343569	14,190.91	5,179,690
2025	35,187,315	1.17	41,176.02	15,026,744	26742359	14,405.72	5,258,097
2026	35714672.34	1.17	41,794.98	15251951.69	27143151	14,620.53	5,336,503
2027	36,242,030	1.17	42,413.94	15,477,160	27543943	14835.35	5414910
2028	36,769,387	1.17	43032.9	15,702,368	27944734	15,050.16	5,493,317
2029	37,296,744	1.17	43,651.85	15,927,576	28345526	15,264.97	5,571,723
2030	37,824,102	1.17	44,270.81	16,152,784	28746317	15,479.78	5,650,130

These results were obtained using collected data from 2012 to 2020. Assuming that the waste per capita is constant until 2030 for all type of waste, the amount of waste generated in both households and commercial/industrial/institutional sectors, measured in kilograms per capita and tons per day and year were predicted. The total waste generated is predicted to reach 16.2 million tons by 2030. The majority of the waste is generated by households, while waste generated by the commercial/industrial/institutional sector is much smaller in comparison but has also been increasing steadily over time.

Furthermore, for a more detailed analysis of waste generation prediction, data from each state was used to predict its waste generation rate until 2030. Although the data availability varied among the states, missing values were substituted with the average of

their respective columns. The inputs for the model included population, area, gross domestic product (GDP), and per capita waste generation (represented by a constant of 1.17). After selecting the relevant inputs and target variable, the next step in the modeling process is to select and set up the appropriate model. In the present study, the aim is to predict waste generation rate for all the states, three common machine learning models, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Gradient Booster (GB), were considered. All models have showed promising results in previous waste generation prediction studies that used the same inputs. Therefore, training and testing models using the above-mentioned dataset and input to select the best one that provided the highest accuracy and R^2 score. Gradient Boosting showed the best performance with an R^2 of 0.954. It was then further optimized by adjusting the hyperparameters and fine-tuning the model to achieve the best possible results. Finally, the trained model was used to predict waste generation rate for the states until 2030. A comparison between models' performance is presented in Table 4.4.

Table 4. 4: Models' performance comparison

Model	Testing		Validation	
	R^2	MAE	R^2	MAE
ANN	0.157	3.981	0.257	4.561
SVM	0.450	3.174	0.567	4.931
GB	0.509	5.031	0.954	0.341

One possible reason for Gradient Boosting (GB) model's great performance could be its ability to handle complex and nonlinear relationships between the input variables and the target variable. GB is an ensemble method that combines multiple weak models to create a strong predictor (Cha et al., 2021). Each model in the ensemble focuses on the errors of the previous model, which allows GB to continuously learn and adapt to the data. Additionally, GB has the capability to handle missing values and outliers (Adeogba et al., 2019; Cha et al., 2021; Johnson et al., 2017), which can be common in waste generation data. Therefore, the GB model may have been able to capture the underlying patterns in the

data more accurately and effectively than other models, resulting in a higher accuracy and R^2 score.

Furthermore, Ensemble techniques are particularly beneficial when dealing with limited or small training data (Cha et al., 2021). The reason behind this is that it can reduce the risk of poor classifier selection. It uses its' ability to learn complex relationships between features in the data to optimize individual classifiers. Additionally, Gradient boosting also has the ability to reduce overfitting, which is a common problem when dealing with small datasets (Cha et al., 2021; Namoun et al., 2022). It does this by iteratively adding weak learners to the model and adjusting their weights to minimize errors. Overall, the ability of Gradient boosting to learn complex relationships, reduce overfitting, and handle missing values makes it a powerful machine learning algorithm for the used dataset and explains the outstanding performance. GB validation prediction up to 2030 for each state is shown in Table 4.5.

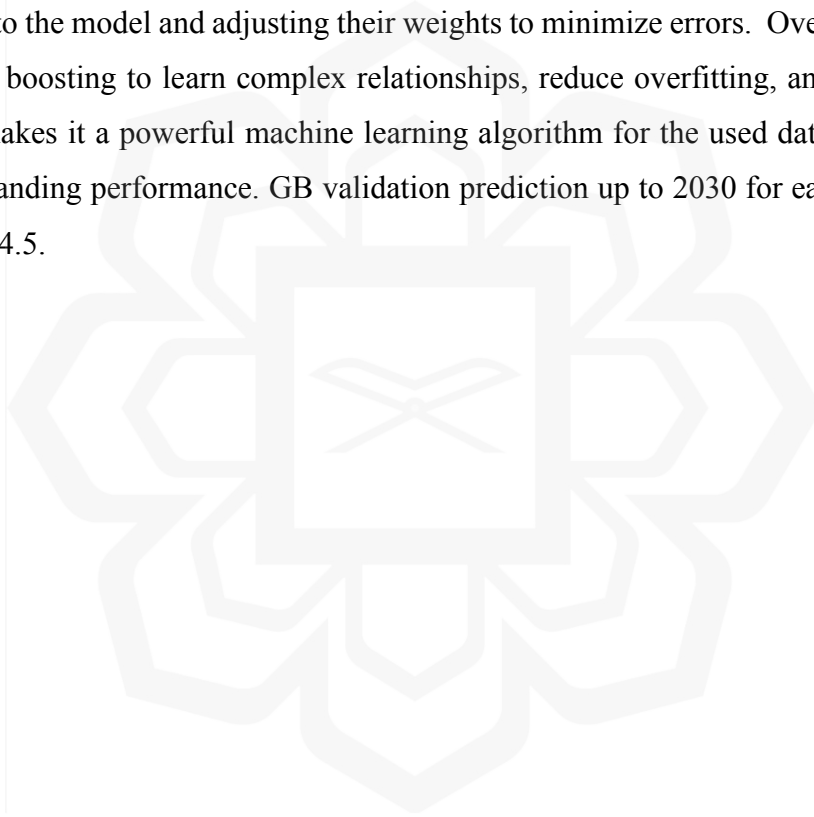


Table 4. 5: Prediction results up to 2030 for each state using Gradient Boosting.

Year	Per capita	Johor P	Johor W	Kedah P	Kedah W	Melaka P	Melaka W	Negeri Sembilan P	Negeri Sembilan W
2014	1.17	3559.8	1520213	2062.7	880876	871.7	372259.5	1079.6	461043.2
2015	1.17	3610.3	1541779	2096.5	895310.3	889	379647.5	1088.8	464972
2016	1.17	3651.8	1559501	2119.7	905217.9	901.1	384814.8	1099.3	469456.1
2017	1.17	3697	1578804	2143.9	915552.5	913.1	389939.4	1114	475733.7
2018	1.17	3742.2	1598107	2163.7	924008.1	922.2	393825.5	1130.1	482609.2
2019	1.17	3764.3	1607544	2180.6	931225.2	930.7	397455.4	1130.3	482694.6
2020	1.17	3817.24	1630152	2209.38	943515.7	945.2933	403687.5	1146.227	489496.1
2021	1.17	3859.051	1648008	2232.674	953463.6	956.9105	408648.6	1157.43	494280.3
2022	1.17	3900.863	1665863	2255.969	963411.4	968.5276	413609.7	1168.632	499064.5
2023	1.17	3942.674	1683719	2279.263	973359.2	980.1448	418570.8	1179.835	503848.6
2024	1.17	3984.486	1701575	2302.557	983307	991.7619	423531.9	1191.038	508632.8
2025	1.17	4026.297	1719430	2325.851	993254.9	1003.379	428493	1202.241	513417
2026	1.17	4068.109	1737286	2349.146	1003203	1014.996	433454.1	1213.444	518201.2
2027	1.17	4109.92	19755141	2372.44	1013151	1026.613	438415.2	1224.647	522985.4
2028	1.17	4151.731	1772997	2395.734	1023098	1038.23	443376.3	1235.85	527769.5
2029	1.17	4193.543	1790852	2419.029	1033046	1049.848	448337.4	1247.052	532553.7
2030	1.17	4235.354	1808708	2442.323	1042994	1061.465	453298.5	1258.255	537337.9

Key: P: Population, E: Waste generation rate. Shaded area represented the predicted rows.

Table 4. 5: Prediction results up to 2030 for each state using Gradient Boosting (continued)

Year	Per capita	Pahang P	Pahang W	Perlis P	Perlis W	Kuala Lumpur P	Kuala Lumpur W	Putrajaya p	Putrajaya W
2014	1.17	1591.7	679735.5	245.1	104670	1737.4	741956.7	80.9	34548.35
2015	1.17	1607.9	686653.7	248.5	106121.9	1780.4	760319.8	83	35445.15
2016	1.17	1626.7	694682.2	251	107189.6	1789.7	764291.4	84.4	36043.02
2017	1.17	1647	703351.4	252	107616.6	1793.2	765786.1	87.5	37366.88
2018	1.17	1665.7	711337.2	253.8	108385.3	1795.2	766640.2	90.4	38605.32
2019	1.17	1674.6	715137.9	254.4	108641.5	1780.7	760447.9	103.8	44327.79
2020	1.17	1696.42	724456.2	257.14	109811.6	1805.873	771198.2	102.3133	43692.91
2021	1.17	1713.797	731877.1	258.9514	110585.2	1813.428	774424.3	106.3076	45398.67
2022	1.17	1731.174	739298	260.7629	111358.8	1820.982	777650.3	110.3019	47104.43
2023	1.17	1748.551	746718.9	262.5743	112132.3	1828.536	780876.4	114.2962	48810.19
2024	1.17	1765.929	754139.8	264.3857	112905.9	1836.09	784102.4	118.2905	50515.95
2025	1.17	1783.306	761560.7	266.1971	113679.5	1843.645	787328.5	122.2848	52221.71
2026	1.17	1800.683	768981.6	268.0086	114453.1	1851.199	790554.6	126.279	53927.47
2027	1.17	1818.06	776402.5	269.82	115226.6	1858.753	793780.6	130.2733	55633.23
2028	1.17	1835.437	783823.4	271.6314	116000.2	1866.308	797006.7	134.2676	57338.99
2029	1.17	1852.814	791244.3	273.4429	116773.8	1873.862	800232.7	138.2619	59044.75
2030	1.17	1870.191	798665.2	275.2543	117547.3	1881.416	803458.8	142.2562	60750.51

Key: P: Population, E: Waste generation rate. Shaded area represented the predicted rows.

The significant amount of the predicted may be overwhelming the existing waste management system, which relies heavily on landfilling as a disposal method. The large amount of waste being generated in the area highlights the need for effective waste management strategies that can help minimize the environmental impact of waste disposal while ensuring that the system can cope with the volume of waste being produced. Alternative waste disposal methods such as recycling, composting, and energy recovery may need to be explored and implemented to reduce the amount of waste being sent to landfills. Additionally, waste reduction and source segregation measures may need to be implemented to encourage individuals and businesses in the area to reduce their waste generation and increase recycling.

Moreover, results also indicate the significant role of data preprocessing. Data preprocessing is the process of transforming raw data into a more useful and suitable format for analysis. It involves a series of techniques and methods that are applied to raw data before it is used in machine learning, data analytics, or other data-driven applications. Data preprocessing typically involves several steps, including data cleaning, data transformation, data reduction, and data normalization.

The quality of the data used to train an AI or ML model can significantly affect its performance and accuracy. Data preprocessing can help to address common issues in data, such as missing values, outliers, and inconsistencies. By removing or imputing missing values, handling outliers, and correcting errors, data preprocessing can improve the quality and accuracy of the data, making it more suitable for training AI and ML models. Table 4.6 shows comparison between models' average results using raw data and after preprocessing using normalization and PCA in terms of R^2 and MAE.

Table 4. 6: Average results using processed and unprocessed data.

Model	Raw data		Preprocessed data	
	R ²	MAE	R ²	MAE
ARIMA (1,5,1)	-10	11704	0.682	2.258
VAR (1, aic, nc)	0.266	3.830	0.721	4.112
ANN	0.439	3.247	0.892	0.316

For the ARIMA model, the R² value significantly improved from -10 on raw data to 0.682 on preprocessed data, indicating a better fit of the model to the data. This could be due to data preprocessing ability to reduce the computational complexity of the data, making it easier and faster for AI and ML models to process. This can result in improved efficiency and reduced processing time. Overall, data preprocessing can improve model performance by reducing noise, removing outliers, filling in missing values, and scaling the data to a suitable range (Gonzalez Zelaya, 2019; Woo et al., 2020). These steps can help the model identify relevant patterns and relationships in the data, leading to more accurate predictions.

In conclusion, using has proven Orange data mining software to be efficient with AI algorithms since it reduces the need for coding. The results of the study provide valuable insights into the current waste management system of eight states in the Peninsular Malaysia, highlighting potential areas for improvement and optimization. Decision-makers and regulatory bodies can implement more effective waste management strategies by leveraging cutting-edge technology and data-driven methods, ultimately contributing to a cleaner and more sustainable environment for current and future generations.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

In conclusion, this thesis analyzed the current SWM system performance of eight states in Peninsular Malaysia using the ISWM Wasteaware benchmark indicators during the COVID-19 pandemic. This study employed Integrated Sustainable Waste Management (ISWM) benchmark indicators to analyze waste management statistics. Applying these indicators allowed for a comprehensive evaluation of waste management practices across various regions. The findings underscored the significance of assessing waste collection coverage, recycling rates, quality of waste collection services, and other critical aspects in understanding the nuances and challenges faced by waste management systems during extraordinary periods like the COVID-19 pandemic. Moreover, the assessment facilitated comparative analyses between the performance of these states and that of other cities and countries, offering valuable perspectives on best practices and areas for improvement in waste management strategies.

Furthermore, a thorough screening process was conducted to evaluate various Artificial Intelligence (AI) models, aiming to select the most suitable models for both predicting and preprocessing waste characteristics. This study extensively explored AI models using open-source data mining software. The primary objective was to uncover and leverage the potential of AI in effectively predicting waste characteristics. Through this extensive exploration, the study aimed to examine each model and optimize the selected parameters. Developed models are suitable for future applications in waste management, especially in predicting waste patterns during challenging circumstances.

Lastly, the validation of the chosen AI model constituted a crucial aspect of this research endeavor. The validation process aimed to ascertain the reliability, accuracy, and robustness of the developed AI model for predicting waste characteristics. By subjecting the model to validation measures and comparing its predictions with actual waste generation data, this study aimed to instill confidence in the model's efficacy and

applicability. The validated AI model could serve as a reliable tool for waste management practitioners and policymakers in forecasting waste patterns accurately.

5.2 RECOMMENDATIONS

The findings and analyses presented in this thesis emphasize the critical importance of employing Integrated Sustainable Waste Management (ISWM) benchmark indicators for evaluating waste management systems, particularly during unprecedented times such as the COVID-19 pandemic. The successful application of these indicators across eight states in Peninsular Malaysia offers valuable insights into the challenges faced by waste management systems. I recommend that other states within Malaysia consider adopting a similar approach by utilizing the ISWM WasteAware benchmark indicators. This proactive step could aid in comprehensively evaluating and benchmarking their waste management systems, facilitating a clearer understanding of strengths, weaknesses, and areas for improvement. Furthermore, leveraging Artificial Intelligence (AI) models, as explored in this study, can significantly benefit waste management strategies, providing predictive capabilities essential for adapting to fluctuating waste patterns. Therefore, I encourage further research and adoption of AI-driven approaches in waste management practices across various states.

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APPENDIX A: Perlis Summary Analysis

Background information on the city						
City		Perlis				
Country		Malaysia				
Date since previous application of indicators:			No known previous application of indicators			
B1	Country income category	World Bank income category	Gross National Income (GNI) per capita			
		<i>Upper middle income</i>	10570			
B2	Population of city	Total population of the city	284,885			
B3	Waste generation	Total municipal solid waste generation (tonnes/year)	333315.45			
No	Category	Data/ Benchmark Indicator	Results	Code		Progress
Key Waste-related data		Data		-	-	-
W1	Waste per capita	MSW per capita	kg per year	1.17	-	-
			kg per day	0.74	-	-
W2	Waste composition:	Summary composition of MSW for 3 key fractions – all as % wt. of total waste generated	-	-	-	-
W2.1	Organic	Organics (food and green wastes) %	35.29	-	-	-
W2.2	Paper	Paper %	4.46	-	-	-
W2.3	Plastics	Plastics %	19.69	-	-	-
W2.4	Metals	Metals %	1.79	-	-	-
W2.5	Solid waste density	Solid waste density	0	-	-	-
W2.6	Moisture content	Moisture content	0	-	-	-
Physical Components		Benchmark Indicator	-	-	-	-
1	Public health – waste collection	1.1 Waste collection coverage	80			
		1.2 Waste Captured by the System	15			
1C		Quality of waste collection service	88			
2	Environmental control – waste treatment and disposal	Controlled treatment and disposal	15			
2E		Quality of environmental protection of waste treatment	60			
3	Resource Management – Reduce, Reuse, Recycle	Recycling rate	20			
3R		Quality of 3Rs – Reduce, reuse, recycle	63			
Governance Factors		Benchmark Indicator	-	-	-	-
4U	Inclusivity	User inclusivity	71			
4P		Provider inclusivity	80			
5F	Financial sustainability	Financial sustainability	58			
6N	Sound institutions, proactive policies	Adequacy of national solid waste management framework	83			
6L		Local institutional coherence	88			

APPENDIX B: Kedah Summary Analysis

Background information on the city						
City		Kedah				
Country		Malaysia				
Date since previous application of indicators:			No known previous application of indicators			
B1	Country income category	World Bank income category	Gross National Income (GNI) per capita			
		Upper middle income	10570			
B2	Population of city	Total population of the city	2,131,427			
B3	Waste generation	Total municipal solid waste generation (tonnes/year)	2493769.59			
No	Category	Data/ Benchmark Indicator	Results	Code		Progress
Key Waste-related data		Data		-	-	-
W1	Waste per capita	MSW per capita	kg per year	1.17	-	-
			kg per day	0.74	-	-
W2	Waste composition:	Summary composition of MSW for 3 key fractions – all as % wt. of total waste generated	-	-	-	-
W2.1	Organic	Organics (food and green wastes) %	20.26	-	-	-
W2.2	Paper	Paper %	13.84	-	-	-
W2.3	Plastics	Plastics %	23.03	-	-	-
W2.4	Metals	Metals %	2.14	-	-	-
W2.5	Solid waste density	Solid waste density	0	-	-	-
W2.6	Moisture content	Moisture content	0	-	-	-
Physical Components		Benchmark Indicator	-	-	-	-
1	Public health – waste collection	1.1 Waste collection coverage	80			
		1.2 Waste Captured by the System	25			
1C		Quality of waste collection service	83			
2	Environmental control – waste treatment and disposal	Controlled treatment and disposal	15			
2E		Quality of environmental protection of waste treatment	60			
3	Resource Management – Reduce, Reuse, Recycle	Recycling rate	20			
3R		Quality of 3Rs – Reduce, reuse, recycle	63			
Governance Factors		Benchmark Indicator	-	-	-	-
4U	Inclusivity	User inclusivity	67			
4P		Provider inclusivity	80			
5F	Financial sustainability	Financial sustainability	58			
6N	Sound institutions, proactive policies	Adequacy of national solid waste management framework	83			
6L		Local institutional coherence	88			

APPENDIX C: Johor Summary Analysis

Background information on the city							
City		Johor					
Country		Malaysia					
Date since previous application of indicators:			No known previous application of indicators				
B1	Country income category	World Bank income category		Gross National Income (GNI) per capita			
		Upper middle income		10570			
B2	Population of city	Total population of the city		4,009,670			
B3	Waste generation	Total municipal solid waste generation (tonnes/year)		4691313.9			
No	Category	Data/ Benchmark Indicator		Results	Code		Progress
Key Waste-related data		Data		-	-	-	
W1	Waste per capita	MSW per capita	kg per year	1.17	-	-	-
			kg per day	0.74	-	-	-
W2	Waste composition:	Summary composition of MSW for 3 key fractions – all as % wt. of total waste generated		-	-	-	-
W2.1	Organic	Organics (food and green wastes) %		42.3	-	-	-
W2.2	Paper	Paper %		7.56	-	-	-
W2.3	Plastics	Plastics %		28.41	-	-	-
W2.4	Metals	Metals %		1.28	-	-	-
W2.5	Solid waste density	Solid waste density		0	-	-	-
W2.6	Moisture content	Moisture content		0	-	-	-
Physical Components		Benchmark Indicator		-	-	-	-
1	Public health – waste collection	1.1 Waste collection coverage		78			
		1.2 Waste Captured by the System		34			
1C		Quality of waste collection service		83			
2	Environmental control – waste treatment and disposal	Controlled treatment and disposal		15			
2E		Quality of environmental protection of waste treatment		60			
3	Resource Management – Reduce, Reuse, Recycle	Recycling rate		31			
3R		Quality of 3Rs – Reduce, reuse, recycle		63			
Governance Factors		Benchmark Indicator		-	-	-	-
4U	Inclusivity	User inclusivity		67			
4P		Provider inclusivity		80			
5F	Financial sustainability	Financial sustainability		58			
6N	Sound institutions, proactive policies	Adequacy of national solid waste management framework		83			
6L		Local institutional coherence		88			

APPENDIX D: Melaka Summary Analysis

Background information on the city						
City		Melaka				
Country		Malaysia				
Date since previous application of indicators:			No known previous application of indicators			
B1	Country income category	World Bank income category	Gross National Income (GNI) per capita			
		Upper middle income	10570			
B2	Population of city	Total population of the city	998,428			
B3	Waste generation	Total municipal solid waste generation (tonnes/year)	1168160.76			
No	Category	Data/ Benchmark Indicator	Results	Code		Progress
Key Waste-related data		Data		-	-	-
W1	Waste per capita	MSW per capita	kg per year	1.17	-	-
			kg per day	0.74	-	-
W2	Waste composition:	Summary composition of MSW for 3 key fractions – all as % wt. of total waste generated	-	-	-	-
W2.1	Organic	Organics (food and green wastes) %	35.7	-	-	-
W2.2	Paper	Paper %	11.7	-	-	-
W2.3	Plastics	Plastics %	25.82	-	-	-
W2.4	Metals	Metals %	2.5	-	-	-
W2.5	Solid waste density	Solid waste density	0	-	-	-
W2.6	Moisture content	Moisture content	0	-	-	-
Physical Components		Benchmark Indicator	-	-	-	-
1	Public health – waste collection	1.1 Waste collection coverage	80			
		1.2 Waste Captured by the System	15			
1C		Quality of waste collection service	83			
2	Environmental control – waste treatment and disposal	Controlled treatment and disposal	15			
2E		Quality of environmental protection of waste treatment	60			
3	Resource Management – Reduce, Reuse, Recycle	Recycling rate	20			
3R		Quality of 3Rs – Reduce, reuse, recycle	63			
Governance Factors		Benchmark Indicator	-	-	-	-
4U	Inclusivity	User inclusivity	67			
4P		Provider inclusivity	80			
5F	Financial sustainability	Financial sustainability	58			
6N	Sound institutions, proactive policies	Adequacy of national solid waste management framework	83			
6L		Local institutional coherence	88			

APPENDIX E: Pahang Summary Analysis

Background information on the city							
City		Pahang					
Country		Malaysia					
Date since previous application of indicators:			No known previous application of indicators				
B1	Country income category	World Bank income category		Gross National Income (GNI) per capita			
		Upper middle income		10570			
B2	Population of city	Total population of the city		1,591,295			
B3	Waste generation	Total municipal solid waste generation (tonnes/year)		1861815.15			
No	Category	Data/ Benchmark Indicator		Results	Code		Progress
Key Waste-related data		Data		-	-	-	
W1	Waste per capita	MSW per capita	kg per year	1.17	-	-	-
			kg per day	0.74	-	-	-
W2	Waste composition:	Summary composition of MSW for 3 key fractions – all as % wt. of total waste generated		-	-	-	-
W2.1	Organic	Organics (food and green wastes) %		28.75	-	-	-
W2.2	Paper	Paper %		6.26	-	-	-
W2.3	Plastics	Plastics %		23	-	-	-
W2.4	Metals	Metals %		4.2	-	-	-
W2.5	Solid waste density	Solid waste density		0	-	-	-
W2.6	Moisture content	Moisture content		0	-	-	-
Physical Components		Benchmark Indicator		-	-	-	-
1	Public health – waste collection	1.1 Waste collection coverage		75			
		1.2 Waste Captured by the System		25			
1C		Quality of waste collection service		83			
2	Environmental control – waste treatment and disposal	Controlled treatment and disposal		15			
2E		Quality of environmental protection of waste treatment		60			
3	Resource Management – Reduce, Reuse, Recycle	Recycling rate		20			
3R		Quality of 3Rs – Reduce, reuse, recycle		63			
Governance Factors		Benchmark Indicator		-	-	-	-
4U	Inclusivity	User inclusivity		67			
4P		Provider inclusivity		80			
5F	Financial sustainability	Financial sustainability		58			
6N	Sound institutions, proactive policies	Adequacy of national solid waste management framework		83			
6L		Local institutional coherence		88			

APPENDIX F: Putrajaya Summary Analysis

Background information on the city						
City		Putrajaya				
Country		Malaysia				
Date since previous application of indicators:			No known previous application of indicators			
B1	Country income category	World Bank income category	Gross National Income (GNI) per capita			
		Upper middle income	10570			
B2	Population of city	Total population of the city	109,202			
B3	Waste generation	Total municipal solid waste generation (tonnes/year)	127766.34			
No	Category	Data/ Benchmark Indicator	Results	Code		Progress
Key Waste-related data		Data	-	-	-	-
W1	Waste per capita	MSW per capita	kg per year	1.17	-	-
			kg per day	0.74	-	-
W2	Waste composition:	Summary composition of MSW for 3 key fractions – all as % wt. of total waste generated	-	-	-	-
W2.1	Organic	Organics (food and green wastes) %	32.17	-	-	-
W2.2	Paper	Paper %	6.28	-	-	-
W2.3	Plastics	Plastics %	19.51	-	-	-
W2.4	Metals	Metals %	1.22	-	-	-
W2.5	Solid waste density	Solid waste density	0	-	-	-
W2.6	Moisture content	Moisture content	0	-	-	-
Physical Components		Benchmark Indicator	-	-	-	-
1	Public health – waste collection	1.1 Waste collection coverage	78			
		1.2 Waste Captured by the System	24			
1C		Quality of waste collection service	83			
2	Environmental control – waste treatment and disposal	Controlled treatment and disposal	15			
2E		Quality of environmental protection of waste treatment	60			
3	Resource Management – Reduce, Reuse, Recycle	Recycling rate	22			
3R		Quality of 3Rs – Reduce, reuse, recycle	67			
Governance Factors		Benchmark Indicator	-	-	-	-
4U	Inclusivity	User inclusivity	71			
4P		Provider inclusivity	80			
5F	Financial sustainability	Financial sustainability	58			
6N	Sound institutions, proactive policies	Adequacy of national solid waste management framework	83			
6L		Local institutional coherence	88			

APPENDIX G: Negeri Sembilan Summary Analysis

Background information on the city						
City		Negeri Sembilan				
Country		Malaysia				
Date since previous application of indicators:			No known previous application of indicators			
B1	Country income category	World Bank income category	Gross National Income (GNI) per capita			
		<i>Upper middle income</i>	10570			
B2	Population of city	Total population of the city	1,199,974			
B3	Waste generation	Total municipal solid waste generation (tonnes/year)	1403969.58			
No	Category	Data/ Benchmark Indicator	Results	Code		Progress
Key Waste-related data		Data		-	-	-
W1	Waste per capita	MSW per capita	kg per year	1.17	-	-
			kg per day	0.74	-	-
W2	Waste composition:	Summary composition of MSW for 3 key fractions – all as % wt. of total waste generated	-	-	-	-
W2.1	Organic	Organics (food and green wastes) %	36.07	-	-	-
W2.2	Paper	Paper %	10.74	-	-	-
W2.3	Plastics	Plastics %	30.13	-	-	-
W2.4	Metals	Metals %	1.69	-	-	-
W2.5	Solid waste density	Solid waste density	0	-	-	-
W2.6	Moisture content	Moisture content	0	-	-	-
Physical Components		Benchmark Indicator		-	-	-
1	Public health – waste collection	1.1 Waste collection coverage	75			
		1.2 Waste Captured by the System	25			
1C		Quality of waste collection service	83			
2	Environmental control – waste treatment and disposal	Controlled treatment and disposal	15			
2E		Quality of environmental protection of waste treatment	60			
3	Resource Management – Reduce, Reuse, Recycle	Recycling rate	20			
3R		Quality of 3Rs – Reduce, reuse, recycle	63			
Governance Factors		Benchmark Indicator		-	-	-
4U	Inclusivity	User inclusivity	67			
4P		Provider inclusivity	80			
5F	Financial sustainability	Financial sustainability	58			
6N	Sound institutions, proactive policies	Adequacy of national solid waste management framework	83			
6L		Local institutional coherence	88			

APPENDIX H: ARIMA and VAR Analysis

The screenshot shows the Orange data mining environment. The 'Data Table (1) - Orange' widget is active, displaying a dataset with 12 instances and 3 features: 'Domestic (forecast)', 'Domestic (96%CI low)', and 'Domestic (96%CI high)'. The data is as follows:

Instance	Domestic (forecast)	Domestic (96%CI low)	Domestic (96%CI high)
1	213366	139215	287517
2	214802	108675	320930
3	216238	83813.2	348662
4	217673	61679.6	373666
5	219108	41127.7	397088
6	220542	21580.2	419506
7	221978	2700.9	441255
8	223413	-15724	462551
9	224848	-33639.5	483336
10	226284	-51748.2	504215
11	227719	-69525.6	524963
12	229154	-87228.4	545536

The screenshot shows the Orange data mining environment. The 'Data Table (2) - Orange' widget is active, displaying a dataset with 24 instances and 72 features. The features include various forecast variables and their confidence intervals. A 'Selected Data' table is also shown, focusing on the 'Forecast (VAR(1,nc))' variable.

Selected Data: Forecast (VAR(1,nc)): 24 instances, 72 variables
 Features: 72 numeric (no missing values)

Instance	ANAN (Avoidable)	NEGERI (forecast)	TAHUN (forecast)	IAN (Non-Avoidable)	STIK (Rigid) (forec)	ISTIK (Firm) (forec)	STIK (Foam) (forec)	RTAS (Newspaper agazines) (forecast)
1	5.46964	7.83452	2020.25	27.4505	7.05485	11.4902	1.50742	2.2413
2	8.18201	6.79381	2020.41	21.8279	8.94229	13.0874	1.61452	2.61899
3	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
4	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
5	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
6	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
7	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
8	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
9	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
10	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
11	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
12	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
13	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
14	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
15	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
16	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
17	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
18	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
19	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
20	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
21	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
22	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
23	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724
24	0.195116	6.49909	2020.47	31.1847	0.47067	13.6066	1.64648	2.80724

