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Research Article

Forecasting Solid Waste Generation in Rodriguez, Rizal Using Artificial Neural Network (Ann) and Regression Analysis: An Input to Municipality's Solid Waste Management Plan

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ARTICLE INFO	ABSTRACT

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Accurate and reliable forecasting of metropolitan solid devastate is extremely significant for an effective solid plan for waste management. Every local government is having a constant review of measure in the implementation of its waste management program to ensure its continuous viability and importance. The aim of this paper is to recognize the several influential variables and expand an effective model for authentic forecasting of 'MSW generation' and offer strategic recommendations that will improve several practices that are associated with waste management practices and several policy making in Rodriguez, Rizal.Solid waste collection of the municipality from 2010-2022, the population, different households, the GDP, commercial establishments and services (CES), and the tourist arrivalfrom 2010 to 2022 were gathered. Two forecasting methods, the "Artificial Neural Network" (ANN) and the multivariable simple regression with the use of Principal Component Analysis (PCA) have been tested that is for their ability for predicting the annual waste production within the municipality. Among the five components, population, Household, and Commercial Establishments have the highest eigenvalues and it account for almost 86% of the total variance in the original data. Furthermore, these components, present the lowestp-values; to which regression model was developed. Artificial Neural Network (ANN) model was has been established through using Multilayer-perceptron Neural Network. The same factors with normalized importance were identified, the Population, Household and Commercial Establishments. Result showed that "ANN" that is Artificial Neural Network has outperformed regression analysis in predicting the solid waste generation having less quantity in terms of the root RMSE. It was also including "mean error" (ME). At the same time, it also include "mean absolute deviation" (MAD) along with "mean percentage error" (MPE). It was in terms of mean "absolute percentage error" (MAPE).A strategic measure has been recommended to enhance waste management practices and policy making of the municipality of Rodriguez that will improve the accuracy as well as effectiveness of its waste management practices and also reduce environmental impacts.

Keywords: Forecasting, "Municipal Solid Waste" (MSW), Multivariate Linear Regression, "Artificial Neural Network (ANN)", Multilayer Perceptor (MLP)

I. INTRODUCTION

The management for waste has been the core problem in the mitigation of the impact of climate change that results in natural calamities and other extreme weather conditions. This has been a constant discussion in organized international forums about the growing concern of its adverse effects and how to effectively contain it. It is a significant area that needs major concern throughout the world for it poses several risks that are associated with the environment and also related to public health and increases within management costs.

The passage of Republic Act 9003, which mandates all local government units, to build a program for accurate waste management that includes the collection of solid waste to dumping in designated landfills aptly addressed waste management issues in the Philippines. However, a constant evaluation of measures in the interpretation of waste management in the locality is imperative to ensure its continuous viability and worthiness. However, it is important to contain an assumption of the "MSW generation" in order to effectively arrange many MSW services. Additionally it also assist in managing expenditures, improve efficiency within waste management. Also, it will be significant in managing the overall brunt mainly on waste recycling and also on landfilling. Hence, effective arrangements of a strong scheme for waste management that further dependent on strong or solid waste production predictability.

Rodriguez, Rizal being a host municipality that is responsible in housing many garbage disposals that is directly from different cities like those and mainly from Metro Manila is geared toward identifying current waste streamswhile determining how much waste is being generated. As the Payatas Sanitary Landfill in Quezon City was permanently closed,the garbage generated in the citiesis now being delivered to Rodriguez landfill. Most of the members who are the part of the Informal Waste Sector within Rodriguez have grown which directly resulted in the opening of several illegal practices associated with waste management. Therefore, a careful plan and strategies for proper waste disposal are indispensable.The municipality enjoins all stakeholders to adhere to the concepts and principles of effective waste management for SWM is the responsibility of all. An important pre required for accurate "solid management of waste" is an effective calculation of "garbage generation". In addition to this, it will also able to effectively design as well as work an accurate collection system of waste with the assistance of generation of MSW.

The paper focus was to know the different variables that are affecting the quantity that is of "MSW generation" and extend an accurate form that estimate accurately the sum of garbage generated in Rodriguez, Rizal that offers strategic measuresfor input to its solid waste management plan.This enables the municipal to address problems in planning waste collection services, and waste management strategies including personnel and truck utilization, monitoring systems, and different recycling activities.

II. OBJECTIVES

The study aimed to identify the significant factors to design an accurate model that forecasts the Generated Solid Waste of Rodriguez, Rizal and to provide an input to the municipality's Solid Waste Management Plan.

Specifically, the study aimed to:

1. collect, analyze, and examine the current waste generation from 2010 – 2022 and identify pattern and trends as well as the key influencing factor in generating solid waste in the municipality of Rodriguez, Rizal.
2. develop a predictive model using Artificial Neural Networks (ANN) and regression analysis for comparative forecasting by considering factors such as Population (Number of Inhabitants), Number of Households, Gross Domestic Product (GDP), Commercial Establishments and Services, and Number of Tourists.
3. Analyze the accuracy as well as the reliability of the performance of ANN and regression model using metrics like "mean squared error" and correlation coefficient.
4. Offer strategic recommendations based on the forecasting models that will improve different practices that is for waste management and also policy making in Rodriguez Rizal.

III. LITERATURE REVIEW

The creation of "MSW" that is MSW has influenced through a variety of factors, including socioeconomic variables, population growth, economic conditions, and household characteristics. Studies have shown that demographic and socioeconomic factors play a crucial role in determining waste production levels.It is constantly changing relation with different factors, such as socioeconomic variables, solid waste can be complicated to manage (Chathong: ANN Bangkok). There are several conventional predicting methods that are for "Solid Waste Generation" habitually depends on the "demographic and also numerous other factors that are socioeconomic and are on per-capita basis. However, the Solid waste production has been directly impacted through numerous factors. The different factors are mainly including economic conditions, growth of population, multiple weather conditions. Additionally there are other factors as well that include geographical situation, different hobbies of the people as well as household size. There are numerous models that have been developed by Several researchers in order to get idea about the sum of MSW generated (Mahmood et al., 2018; Kannangara et al., 2018; Pan et al., 2019; Soni et al., 2019), on the other hand there are other researchers as well who are responsible in analyzing the different variables that are significant in influencing their generation along with composition (Chaya et al., 2018; Grazhdani, 2016; Liu and Wu, 2010; Liu et al., 2019; Rybová et al., 2018). Regrettably, mainly because of the social, economic as well as many geographical heterogeneity of several areas throughout the world, it is quite problematic to establish any kinds of inferences or any tasks with the several models that have been proposed. Therefore, the models along with their overall variables are required to adapt to the situations of many other regions, few times with little achievement. McBean and Fortin have effectively dealt with several certain aspects that are related with MSW management through correlations that is among socioeconomic as well as solid waste composition. As per the view of Intharathirat et al. (2015); Keser et al. (2012); Khan et al. (2016), the quantity of "MSW" and also its work may vary and may also relying on several factors that may be social, environmental or also may be any demographic factors.

Tyson and Chang have measured the impact of several aspects including population, level of income and residence size of unit within a "simple regression model". Beigl et al. has anticipated a form that is for the numerous European cities that are including the numerous descriptive variables. However these variables may include GDP, rate of infant mortality along the size of household. At the same time he has also established a linear model with multiple advisory variables. These variables are education as well as income of each household, and it is also including the overall residents. Buenrostro et al. and Hockett et al. recognized that an overall profit is an important impact on "SWG".

There are multiple works related with literature that reviews in order to recognize the several variables, different tools, and many other techniques as well. This has been done in order to accurately predict 'municipal solid waste generation' from that few concepts have also been associated with the forecasted municipal solid waste generation that have been explained well.

Various forecasting methods are employed to predict MSW generation, including traditional statistical techniques like linear regression and more complex models such as Artificial Neural Networks (ANN). The literature suggests that linear regression models are often preferred for their interpretability and reliability, especially in scenarios with smaller datasets. In the study of (Yang et al 2008) found that regression was more interpretable and easier to validate, they pointed that linear regression outperformed ANN when predicting waste generation in regions where waste generation exhibited a strong linear relationship with factors such as population growth or economic indicators. The study of (Guerra and Mantovani 2012) showed that regression was more reliable for small modalities for data availability while ANN tended to overfit due to insufficient training data. (Chung and Poon 2001) also found out that multiple linear regression is preferred for forecasting municipal solid waste because it allowed policy makers to easily interpret the relationships between independent variables like population, income and organization and waste generation. It is also pointed out by (Mori and Christodoulou,2007) in their study that in predicting specific types of waste like recyclable or organic waste, linear regression models were found to be better suited due to the clear linear relationship between predictors like economic activity and recycling programs, and the outcome. ANN in contrast did not provide significant performance improvement and added complexity to the modeling process. However, ANN can provide high prediction accuracy but may overfit when data is insufficient.

The Multivariate Regression is a straightforward method of determining how the dependent variable is affected by multiple independent variables (ANN and PCA). In waste production forecasts, the significant values are most often the population, level of affluence, and population density (Bocco, Sri Lanka). However, there is a disadvantage of using multivariate regressions is in the preparation of data (Pires et al., 2008 as cited in Waste Management 2). The independent variables are required to be independent in a normal distribution. The power of the connection of the independent variables is measured in Pearson Correlation. Variables that are found to be multicollinear are either simply removed from the regression or treated with Principal Component Analysis (PCA).

As per the view of Navarro-Esbrı et al., examination of trash production that is almost dynamic within environment and can also be effectively proficient with the assistance of information or data mainly in the series of time aspects. It is also encompassing the overall quantity of garbage that is being produced. But at the same time, in recent days there are few investigations that have been systematically conducted in order to accurately assess the ANN "the Artificial Neural Networks" in both of short-term as well as medium-term forecasting. But at the same time, it is also possible that there may not all the efforts that have conducted for long duration forecasting. As stated by Kannangara et al., several models based on artificial intelligence have almost good abilities for prediction in comparison with other regression-based models. It has been identified that in recent days, the "Artificial Neural Network" is much admired for accurately predicting the solid waste amount (Shamshiry, Elmira, et al.). Zadeh et al. has also make assumption on solid waste that is weekly and values with the assistance of the ANN. Noori et al. has added more to the previous study that is through systematically implementing the PCA and also by applying numerous "Gamma test techniques" on the "ANN operation" mainly for forecasting based on weekly. On the other hand, Noori et al. has examined an advanced SVM model that accurately joins the PCA and also SVM technique. The aim behind the combination is to predict solid waste of Mashhad city that generated weekly.

Effective forecasting of “MSW generation” is required for accurate arrangement for waste management. It allows policymakers and stakeholders to make sustainable management structure and allocate require resources. The review emphasizes that reliable historical data is critical for understanding and predicting future waste generation trends. It is true that there will be almost an complexity within making any effective planning associated with MSWM and may also might give outcome in poor MSWM in the upcoming days mainly when forecast data is not accurate, (Buenrostro et al., 2001; Rimaitytė et al., 2012).

Ghinea et al., and (Abassi et al: Forecasting Using Artificial Intelligence) both emphasized that exact projection of numerous “municipal solid waste” sum is significant for the thriving arrangement of an proficient waste management structure ever since numerous areas can control different variable and variations within waste production the use of predictive as well as the application of numerous prognosis models are useful tools, as trustworthy support for different processes that are related with decision-making. They agreed that imprecise forecasts of solid waste can lead to inefficient and ineffective waste processing. (Bocco et al) added that the quantity and also combination of the unnecessary materials or waste that are produced are necessary for accurate decision-making concerning the urban solid waste management.

For that reason, correct prediction of MSW has been assumed as an important establishment for the progress of recent foundation of waste management and optimization of frameworks related to waste management for the upcoming day (Abbasi and El Hanandeh, 2016). Due to this aspect, within enhancing MSWM for the upcoming day, several tools that are required for assumption would be needed for the probable amount prediction of MSW that could be established. Multiple forecasting tools may include “descriptive statistical analysis”. It may include “regression analysis” and may also include “time series analysis”, “material flow analysis” and so on. Apart from all these tools’ efficiencies, they have a set of their strong points and drawbacks (Abbasi and El Hanandeh, 2016; Soni et al., 2019).

The literature highlights the challenges faced in waste management due to the heterogeneity of regions, which complicates the application of forecasting models. Variations in social, economic, and geographical contexts can affect the composition and quantity of waste generated, making it difficult to generalize findings across different areas. The “anthropogenic activities” of mainly the human have constant to enlarge MSW “municipal solid waste” (that is frequently inappropriately arranged because of the insufficient infrastructures of “waste management” (Ayeleru et al., 2018; Madaleno, 2018; Ngoc and Schnitzer, 2009). assessed the impact of climatic environment as well as socioeconomic status on characteristics of solid waste. The shortage of infrastructures of WM has also build ceaseless and exact MSW generation and further it has become a problem of concern for policymakers as well as stakeholders even both locally along with internationally from public health as well as the environment that are being threatened.

In view of these, this study has the aim to give to the body of information through offering two unlike algorithms in order to know that exist more adequate predicting results with respect to accuracy of MSW generation within Rodriguez, Rizal. However, to this end both “Artificial Neural Network” as well as Multivariate Linear Regression have been used mainly in that work because of their high prediction accuracies along with its consistencies that are over many years eager that this gives a reliable information or may also provide an input to the Solid waste Management Plan of Municipality. Effective forecasting of MSW generation is essential for useful planning related with waste management. It allows policymakers and stakeholders to arrange accurate waste management systems and allocate necessary resources efficiently. The review emphasizes that reliable historical data is critical for understanding and predicting future waste generation trends.

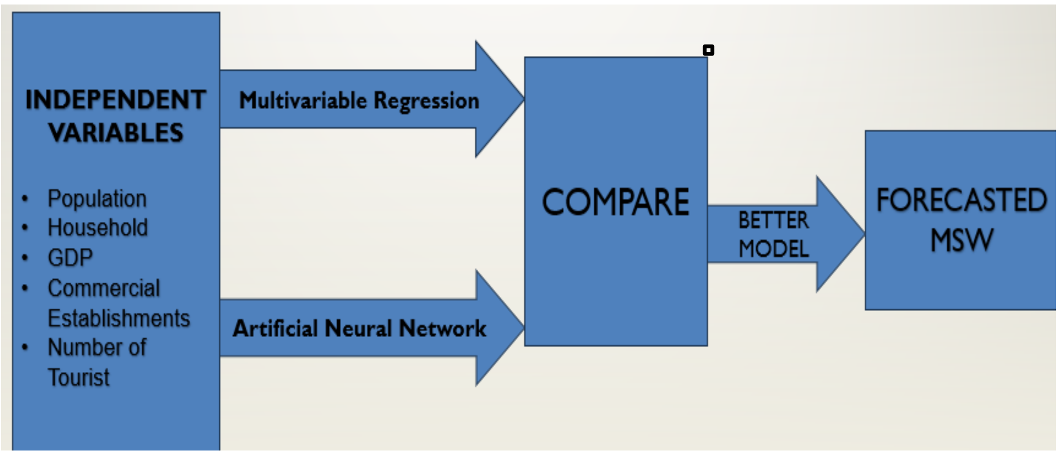
For the administration of MSW to be more effective and also need to be consistent project of rate of the “MSW generation” as well as the MSW composition is very cardinal. Hence, accurate MSWM planning by useful source to know is necessary for well established WM system in the upcoming days (Ghinea et al., 2016; Giusti, 2009; Ngoc and Schnitzer, 2009; Vu et al., 2019). Forecasting is an important tool and technique that is effective in decision-making, being in use in numerous economic sectors or by firms who desire to stay related in today’s spirited world (De Baets and Harvey, 2020; World Meteorological Organization and WHO, 2016). It is frequently well-known on earlier and present data, and most commonly through testing of numerous trends for the future projection (Armstrong and

Green, 2018; De Baets and Harvey, 2020). There are multiple people who are stakeholders that may include "policy makers", different researchers; many municipalities along with several government firms repeatedly use forecasting data in order to arrange MSWM sustainably for future days (Intharathirat et al., 2015; Purcell & Magette, 2007, 2009). When consistent past information and data are accessible, they will offer potential of accepting, arrangement, and forecasting the number of MSW that may be generated in upcoming days (Edjabou et al., 2015, 2017; Ma and Fildes, 2020).

In summary, the literature accurately underscores the complication of waste management, the necessity for accurate forecasting, and the critical need for improved infrastructure to address the challenges posed by increasing waste generation. It advocates for the development of frameworks that incorporate accurate forecasting to optimize waste management strategies.

IV. CONCEPTUAL FRAMEWORK

The development of "solid waste management plan" of Rodriguez, Rizal entails reliable forecasts on the degree of solid devastate has been produced in order to support its strategy formulation. Accurate and reliable forecast can be obtained with the use of model that can be developed based on different factors contributing to the increasing amount of waste generated in Rodriguez, Rizal. Below is the conceptual framework of this study illustrating how a forecasting model is developed.



It started on identifying factors that directly contribute to "solid waste generation" of Rodriguez, Rizal. Regression Analysis and ANN "Artificial Neural Network" were considered as the predictive models to be developed. For the regression model, PCA "Principal Component Analysis" has been applied to recognize the number of principal components from the possible factors while a "Multilayer-perceptron Neural Network" was interpreted to design an Artificial Intelligence model. Metrics such as RMSE "mean squared error", "root mean square error", MAD that is referred to as "mean absolute deviation", and MPE that is mean percentage error and also "mean absolute percentage error" have been computed to determine the more accurate and more reliable model in forecasting MSW of Rodriguez, Rizal. From the result, strategic recommendations were offered as input to Municipal Solid Waste Management Plan of Rodriguez, Rizal. **Done till now**

V. METHODOLOGY

Records and needed data were accessed by getting consent from concerned departments of the municipality of Rodriguez from the Mayor and office heads

The total collection of the Solid Waste Management Office (day-to-day garbage collection) and the waste collection of the MENRO coming from the Material Recovery Facilities (MRF) of every Barangays and the monthly collection from the clean-up drive spearheaded by the agency were added. Factors affecting the generation of MSW were considered. The annual populations, average household, Gross Domestic Product (GDP) were procured from the data of the Philippine Statistics Authority (PSA). Number of commercial establishments in a year was provided by the Business Permit and Licensing Office (BPLO) of the municipality, number of tourists was acquired from the Municipal Tourism and Development Office (MTDO), and other necessary data have been provided by the MPDO

"Municipal Planning and Development Office". Missing or unavailable data were substituted by imputation through average value substitution.

The regression model was developed by determining the linear relationships between variablesusing Pearson Correlation. The factors with highest correlation coefficient, close to 1, were considered as the significant factors while factors with very low correlation coefficients were removed from the independent variable. Next is the application of PCA that is Principal Component Analysis for recognizing how many primary components are there from the possible factors. The factors with Eigen values of at least 1.0 were considered as the principal components. "Regression analysis" is performed to build a model in which factors mainly with "p-value" of decrease or may also be equal to the significance level α of 0.05 will be included in the model.

To develop a model using "Artificial Neural Network", a "Multilayer-perceptron Neural Network" has been used. A low "Sum of Squares Error and Relative Error" suggests the correctness of the model in recognizing the dependent variable, the solid waste generated.

After developing the two models, performance measures were administered. The RMSE "root mean square error", ME "mean error", MAD that "mean absolute deviation" (have been computed. "Mean percentage error" and also "mean absolute percentage error" (MAPE) were also computed. The required form or the model with the lower values was considered more accurate and more reliable in predicting the MSW of Rodriguez, Rizal.

VI. RESULTS AND DISCUSSIONS

1. Collection, analysis, and examination of current waste generation from 2010 – 2022 and identifying pattern and trends, and the key influencing factor in generating "solid waste" mainly within the municipality of Rodriguez, Rizal.

The table below highlights the overall amount of solid waste that has been collected within tons by the different collecting agencies of the municipality of Rodriguez. However, "The Municipal Solid Waste Management Office" oversees the day-to-day collection of garbage among households, commercial establishments that include markets, industries, and institutional services. It is the top collector of solid wastes from 2010 to 2022. The Materials Recovery Facilities of the municipality comes next with a total of 27,588.00 tons. This facility is provided in response to RA 9003 referred to as the Act provided that for an program related with ecological solid waste management that further mandates the establishment of such facility in a barangay or also the cluster of barangays. Moreover, Materials Recovery Facilitiesis established for recovering of wastes that can still be used from recyclable materials to kitchen waste that can be turned into compost. This agency is under the supervision of MENRO- Rodriguez. The clean-up drive programs in support to mandamus ruling of the Supreme Court of the Philippines for the protection of Manila Bay led by ENR that is Environment and Natural Resources Office of the municipality is the third top collector of solid waste.

Table 1. Solid Waste Collection of Rodriguez, Rizal

COLLECTING AGENCY	Amount of Solid Waste Collected (tons)	Rank
MSWMO(Truck Collection)	411,763.00	1
MENRO		
MRF (Materials Recovery Facility)	27588.00	2
Clean-up Drive	130.00	3
TOTAL	**439,481.00**	

Table 2 shows the major sources of solid waste in Rodriguez, Rizal which includes residential (household) required sources, several commercial sources (such as food establishments and service centers while other sources are general stores, and markets), institutional sources (such as institutions and health units), and numerous industrial sources.

Residential waste has effectively constitutes the bulk (74.16%) of MSW which includes several products. It may include kitchen scraps, yard waste, multiple glass bottles and also including plastic containers. Apart from these areas, sand bags, several tissues, diapers as well as special wastes. However these wastes may include batteries, many household cleaning agents. It may be waste electrical and electronic equipment as well.

Table 2. Generation Rates of Solid Waste in Rodriguez, Rizal

Sources/Classification	Solid Waste (tons)	Percentage	Rank
Residential (Household)	325918.95	74.16	1
Commercial Establishments	72646.17	16.53	2
Institutional Services	23468.27	5.34	3
Industries	12876.79	2.93	4
Others	4570.60	1.04	5
Total	**439480.78**	**100**	

Wastes that have been generated within profitable facilities, several stores, supermarkets and it may also include many restaurants, different marketplaces as well as ambulant markets is the second highest source of solid waste comprising 16.53% of the total MSW. The third highest source is coming from governmental and private offices, schools, recreation centers like parks and sports centers with a total of 12876.79 tons or 5.34% while waste produced by industries (production of goods) comprises of 2.93%. Other sources like agricultural wastes, animal husbandry activities, wastes produced within construction as well as demolition sites, and other sectors such as health, automobile maintenance shops, and transportation terminals is 1.04% of the total MSW of Rodriguez.

The SW generation is almost dynamic and also heterogeneous; thus, it is unwavering through several socio-economic variables with disparity impact frequency as per the are evaluated. (Ali Khan and Burney, 1989; Rathje and Murphy, 1992). Due to this, the generation and composition analyses of SW need to be continuously updated to effectively enable the effective use of socio-economic data that is mainly for the assessment that is indirect of different SW materials. For institution drawn in, the ensuing classification of SW is a precious tool for mainly analyses and also for the future planning as well as classification is very necessary for accurately using numerous SW generation information in several required sources and at multiple "geographic scales". (Buenrostro DO, Bocco G, Bernache PG)

2. Development of the predictive models, the Multivariable Linear Regression and the Artificial Neural Networks (ANN) for comparative forecasting by considering factors such as Population (Number of Inhabitants), Number of Households, Gross Domestic Product (GDP), Commercial Establishments and Services, and Number of Tourists.

The Matrix in table 3 shows the correlation coefficients between variables using Pearson Correlation. It shows that population has a strong positive correlation on households and commercial establishments, 0.996 and 0.921 respectively.Household and commercial establishments are also highly correlated (.906) which gives three components- population, household and commercial establishments as the most influential factors in the generation of MSW.

In the study of Mulder (2006), he stated that housing and population relationship is mutual. Population impacted housing through demand of housing. But also, housing effectively has the influences on people and also the households through the anticipation of migrants, also keeping in particular place or may also disassociate the whole population of resident.

Table 3. Correlation Matrix Between Variables

Correlation Matrix

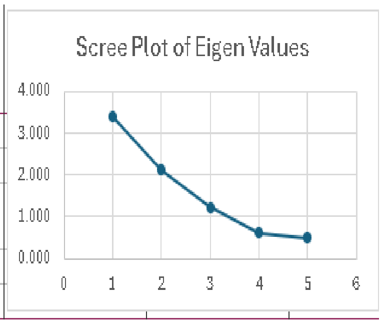
	Population	Household	Commercial_Establishments	Tourist_Arrival	GDP
1 Population	1.000				
2 Household	0.996	1.000			
3 Commercial_Establishments	0.921	0.906	1.000		
4 Tourist_Arrival	0.618	0.634	0.652	1.000	
5 GDP	-0.154	-0.140	-0.100	0.352	1.000

To further examine the interrelations that are among the set of variables, PCA “Principal Component Analysis” has been applied. This is to decrease the dimensionality of the several components while also preserving the most important relationships useful for the regression and classification of data. In table 4,the eigenvalues which represent the total amount of variance for the three principal components Population, Household, and Commercial Establishments comprised a total of 85.834%. Components having eigenvalues of more than one is considered highly significant. Thus, tourist arrival and the GDP were discarded because it is considered as the least significant components.

Table 4. Principal Component Analysis

Total Variance Explained

Component	Initial Eigenvalues Total	% of Variance	Cumulative %
1 Population	3.390	43.125	43.125
2 Household	2.123	27.006	70.131
3 Commercial_Establishments	1.234	15.703	85.834
4 Tourist_Arrival	0.611	7.774	93.608
5 GDP	0.503	6.392	100.000



Extraction Method: Principal Component Analysis.

In developing the model, the p-value for each component was assessed to determine the individual explanatory variable for significance. The p-values of population, commercial establishment and householdin table 5were all less than the significant level of 0.05 which suggests that these are significant and will be included in the model.

Table 5. P-values of the Variables Tested

		P-value
1	Population.	0.0038
2	Commercial Establishments	0.0074
3	Households	0.0089
4	Tourist Arrival	0.3533
5	GDP	0.5462

Table 6. reveals the regression model, with the significant values for Pearson r.

It turns out that number of populations will reach 1,871,205, households will be 437, 723 and 33,039 commercial establishments that yield MSW of 416,609 tons in 2035.

Table 6. Regression Model and Forecasted Populations, Households, Commercial Establishments and MSW for 2035

	Population	Households	Commercial Establishments	Constant
Coefficients	0.025022143	0.826879248	0.989205497	-24839.21

Linear Regression Equation: **Estimated MSW = -24839.21 + 0.025Population + 0.827Households + 0.989Commercial Establishments**

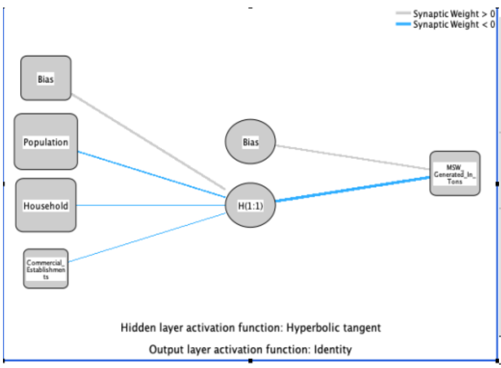
Year	Population	Household	Commercial Establishmen	MSW Generated in Tons
2010	280,904	63,841	1,864	10,928
2011	298,844	66,850	2,430	12,060
2012	320,141	70,702	3,443	15,122
2013	345,571	73,213	3,646	16,663
2014	370,520	77,512	3,994	19,133
2015	392,761	81,308	4,051	22,072
2016	425,803	85,360	4,215	23,864
2017	449,722	90,990	4,379	28,057
2018	467,007	95,838	4,512	31,557
2019	484,195	101,872	4,691	51,243
2020	537,283	107,457	4,743	51,450
2021	570,031	114,106	4,966	76,371
2022	588,452	117,173	5,447	80,962
2023	636,377	133,531	5,958	107,392
2024	691,472	143,551	6,586	117,677
2025	758,018	173,590	7,399	144,985
2026	821,500	186,616	8,502	158,436
2027	891,869	201,740	9,564	173,753
2028	959,566	219,177	10,054	190,350
2029	1,033,309	239,203	12,312	210,987
2030	1,118,807	262,154	14,708	234,475
2031	1,201,667	288,433	17,011	260,556
2032	1,310,868	318,516	20,645	291,758
2033	1,452,865	352,965	24,396	327,507
2034	1,636,124	392,442	28,007	368,307
2035	1,871,205	437,723	33,039	416,609

Note: MSW Generated in Tons from 2023-2035 are forecasted figure

To develop an ANN “Artificial Neural Network” model, an effective “Multilayer-perceptron Neural Network” is used. “Multilayer Perceptrons” are considered as “feedforward artificial neural network” that is the key source in generating outputs directly from set of many inputs. It is a deep method of learning that further uses “backpropagation” in order to train the network that having almost three types of layers and these layers may include input, output, as well as hidden. The input sheet also receives the input signal for accurately processing. On the other hand, the output layer also performs several tasks including classification and prediction. The right computational engine of Multilayer Perceptrons mainly conatined of an arbitrary number of several hidden layers that is between inputs as well as several output layers. Same like that, the data that flow from the input layer that is to the output layer within a Multilayer Perceptron. Along with that, “the Multilayer Perceptrons” are accurately built in order to estimate any kind of function which can also solve multiple issues which are almost not “linearly detachable”.

The primary goal of the MLP is to minimize the error, the same as the perceptron’s goal. But the MLP has a little bit different process called backpropagation. It is run by selecting a number of training instances a network will process each time and it passes the training instances into the input sheet to the unseen coat and to the output coat in which the production error mainly based on the output from the ‘output layer’ is computed. To measure how each connection is related to the output error go through the network in a reverse order and update the weights to reduce the output error. It’s a matter of repetition until it covers every training instance.

Table 7. Network Information



Network Information

Input Layer	Covariates	1	Population
		2	Household
		3	Commercial_Establishments
	Number of Units[a]		3
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		1
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	MSW_Generated_In_Tons
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

In table 7, the diagram of the neural network is shown. It is asingle-layer ANN having one layer of input nodes, it constitutes of almost three layers, viz., input, hidden, as well as output. The nodes in the input layer are the independent variables including the bias. There are 2 nodes in the hidden layer that feeds information to the output which is the dependent variable- the MSW generated in tons. The straight lines connecting the nodes depict the flow of information carrying the magnitude of each variable. The network information indicates, the 3 covariates (most influential factors)–the population, household and commercial establishment. One hidden layer with one unit and in the output layer the dependent variable which is the MSW generated in tons.

Table 8. The Model Summary

Model Summary

Training	Sum of Squares Error	.065
	Relative Error	.014
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	.003
	Relative Error	.042

Dependent Variable: MSW_Generated_In_Tons

a. Error computations are based on the testing sample.

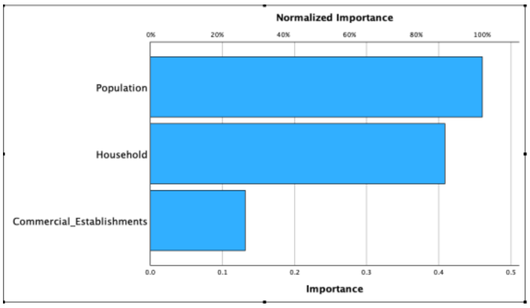
It can be gleaned in the above table the snapshot of the Neural network predictive or the classification accuracy. The sum of the square error is 0.003 indicating that the predictive accuracy of the model is 99.997%. The relative error is also relatively high, at most 0.42. This shows that the model can predict at 99.58% accuracy.

The significance of a self-governing variable is a compute of how much the model-predicted value of the network changes for diverse values of the self-determining variable. Normalized substance is simply the significance values that are divided by the largest important values as well as expressed as percentages. From table 9, population is the most important (46%), household is 40.8% and commercial establishment is 13.2%. The greater the importance the more useful the variable in predicting the outcome.

Table 9. The Independent Variable Importance

Independent Variable Importance

	Importance	Normalized Importance
Population	.460	100.0%
Household	.408	88.8%
Commercial_Establishments	.132	28.6%



In table 10,forecasted population, number of households, and commercial establishments and servicesusing Artificial Neural Network (ANN) until year 2035 is shown. By year 2035, population reach to 1,871,205, there will be 437,723 households and commercial establishment will increase to 274,543.

Table 10. Forecasted Populations, Households, CES

and MSW Using ANN for 2035

Year	Population	Household	Commercial Establishment	MSW Generated in Tons
2010	280,904	63,841	1,864	10,928
2011	298,844	66,850	2,430	12,060
2012	320,141	70,702	3,443	15,122
2013	345,571	73,213	3,646	16,663
2014	370,520	77,512	3,994	19,133
2015	392,761	81,308	4,051	22,072
2016	425,803	85,360	4,215	23,864
2017	449,722	90,990	4,379	28,057
2018	467,007	95,838	4,512	31,557
2019	484,195	101,872	4,691	51,243
2020	537,283	107,457	4,743	51,450
2021	570,031	114,106	4,966	76,371
2022	588,452	117,173	5,447	80,962
2023	636,377	133,531	5,958	88,306
2024	691,472	143,551	6,586	96,549
2025	758,018	173,590	7,399	106,144
2026	821,500	186,616	8,502	115,780
2027	891,869	201,740	9,564	125,970
2028	959,566	219,177	10,054	136,395
2029	1,033,309	239,203	12,312	147,455
2030	1,118,807	262,154	14,708	160,571
2031	1,201,667	288,433	17,011	173,138
2032	1,310,868	318,516	20,645	189,945
2033	1,452,865	352,965	24,396	211,516
2034	1,636,124	392,442	28,007	239,065
2035	1,871,205	437,723	33,039	274,543

Note: MSW Generated in Tons from 2023-2035 are forecasted figure

3. Assessment of accuracy and reliability of the performance of ANN and regression model using metrics such as mean squared error and correlation coefficient.

Upon developing the two different models, measure of performance is done to select which is more reliable. Table 11 below, effectively reveals the 'comparison of performance' between the regression and Artificial Neural Network Models.

Table 11. PerformanceMeasure of Regression and ANNModels

Performance Measure	Model 1 Regression	Model 2 ANN
RMSE	5907.3	93.8
ME	3.4	88.2
MAD	4650.7	75.7
MPE	1.09%	0.3%
MAPE	14.15%	0.3%

The two most used performance procedures that confine the amount of the issues are "RMSE" root means 'square error' and also include "mean absolute deviation" (MAD). It has been identified that both range from 0 to ∞, and also with inferior values demonstrating an enhanced prediction model. Due to that RMSE is also provides a comparatively high weight to huge problems, it is more functional when huge errors are predominantly adverse. The model with the lowest RMSE or MAD will always be preferred over competing models. Looking at the table, ANN has a lower RMSE and MAD compared to regression. The mean percentage errors (MPE) and the MAPE "mean absolute percentage error" are also lower for ANN, except for the Mean Error (ME). Hence, ANN is considered themore accurate and more preciseforecasting model.

VII. SUMMARY AND CONCLUSIONS

There were several factors considered in the generation of MSW of Rodriguez, Rizal which includepopulation, commercial establishments, number of households, tourist arrivals and the gross domestic product of the municipality. Pearson correlation, Principal Component Analysis and Regression Analysis showed that population, commercial establishments, and the accurate household's number are the most influential factors that effectively put in to the generation of MSW of Rodriguez, Rizal. Furthermore, Artificial Neural Network (ANN) model was developed showing the same significant factors and found to be a better and more reliable forecasting model than regression having lesser values that is mainly in the terms of RMSE 'root mean square error', MAD that is "mean absolute deviation". Also in terms of other values including mean MPE "percentage error" and "MAPE" "mean absolute percentage error".

VIII. IMPLICATIONS AND RECOMMENDATIONS

As per the outcomes of the study, the "Artificial Neural Network" is highly recommended in identifying the "municipal solid waste" that could be used in updating a useful Municipal Solid Waste Management Plan for succeeding years. The model is highly suggested especially in the conduct of WACS that is "waste analysis and characterization study" of the Solid Waste Management Committee along with other concerned LGU officials.

LGU officials and the "Municipal Solid Waste Management" Board should use the model as a basis in constructing additional facilities that could accommodate the forecasted solid waste that are generated through the municipality for the coming years. It is also recommended to conduct accuracy of the same study after 5 years to update input data and improve the forecasts.Below are strategic recommendations that can be made to enhance waste management practices and policy making of the municipality:

STRATEGIC RECOMMENDATIONS	ACTION	OUTCOME
Data driven waste management policies	Use ANN models to forecast waste generation patterns and establish a data	Proactively allocate resources such as waste collection

	collection framework to consistently gather information on population growth, household numbers and commercial establishment.	schedules, infrastructure development and recycling efforts, based on precise future waste estimates.
Dynamic waste collection schedules	Use ANN generated forecast to adjust waste collection schedules based on expected waste volume fluctuations like population surges and commercial activity spikes.	More efficient waste collection with reduce operational cost, less environmental impact and minimize overflow of waste bins in critical areas.
Targeted waste reduction campaigns	Use the ANN model to identify key areas where waste generation is projected to be high and design and implement localized waste reduction campaign that address this specific types of waste likely to increase in these areas	More effective public awareness programs that lead to behavioral changes reducing waste at the source and promoting sustainable practices like recycling and composting.
Infrastructure development based on forecasting	Plan and construct waste treatment facilities and recycling plants based on long-term forecast generated by ANN models.	Optimize placement of insight structure, reduces waste transportation cost and enhances processing efficiency contributing to better overall waste management.
Incentive programs for waste minimization	Develop incentive programs that encourage households and businesses to minimize waste production, informed by the ANN's prediction of waste sources. It may also offer financial incentives tax breaks or recognition awards for entities that successfully reduce waste below forecasted levels.	Encourages community and business participation in waste reduction leading to less waste being generated and the more sustainable waste management system.
Real time monitoring and adjustment	Integrate real time data collection with ANN model to monitor actual waste generation against forecasts. Use this data to make rapid adjustment to waste management practices such as scaling up waste collection efforts when spikes are observed or relocating resources to areas facing higher waste generation.	A responsible waste management system that adopts quickly to real-word conditions reducing inefficiencies and addressing issues like unexpected waste surges.

By adapting these strategic measures, the municipality of Rodriguez can improve the accuracy and helpfulness of its practices related to waste management and reduce environmental impacts and make informal policy decisions that cater to future waste trends.

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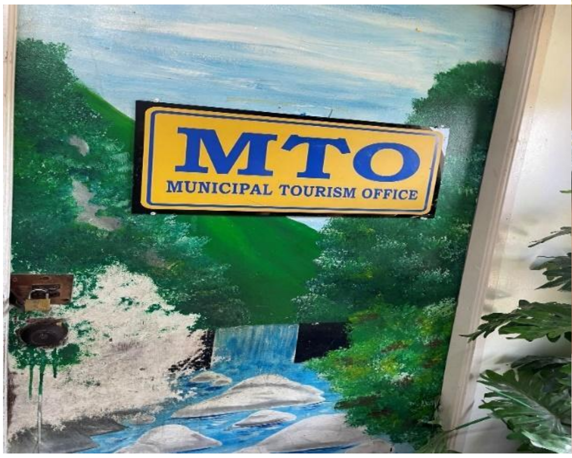
XI. DOCUMENTATION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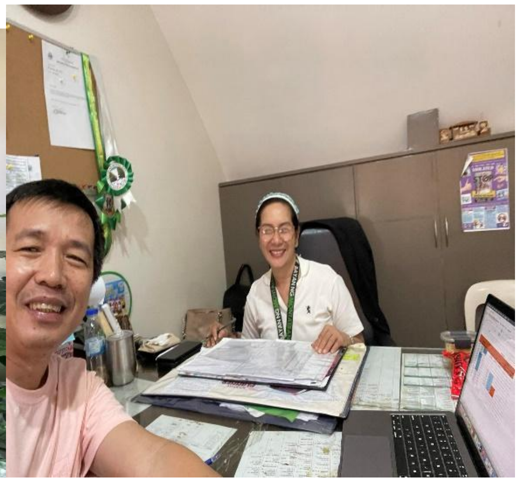


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