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Machine Learning Application in Solid Waste Management: A review of Literature

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--***ABSTRACT***---
In this paper, we present a comprehensive review of research dedicated to applications of machine learning in Solid waste management. The works analyzed were categorized in classes of three generic categories; namely, prediction of waste generation model, waste detection models, optimization of collection and disposal models. The paper reviewed studies from 2008 that focusing the three domain and the different machine learning models used to solve waste management challenge. The analysis prioritized domain in prediction of generation, detection and finally optimization of collection solid waste, the findings indicated GIS-based optimized using ArcGIS Network Analyst tool applied on variables such as cost, route distance and number of trucks, gives the best results. Further research will be carried out in future to realize and validate the tool.
Keywords: *Artificial Intelligence, Machine Learning, Modeling, Optimization, Deep learning, Neural network*

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I. Introduction

Cities generate economic growth accompanied by solid waste depending on various urban forms (Lehmann,2011). The problem of Solid Waste Management (SWM) is multidimensional and is best appreciated in the light of rapid urbanization (Oteng-Ababio, 2010). Solid waste management (SWM) plays a critical role in the global economy. Pressure on management of the waste system increases with the continuing expansion of the human population. On the other hand, adapting to new technology improves the precision of collection from generation to disposal. Machine learning is one of the new scientific fields that uses data-intensive approaches leading to accurate and faster decision-making for effective management of waste.

Machine learning is the core area of Artificial Intelligence (Dasgupta &Nath, 2016). Machine learning and artificial intelligence has merged with big data analytics has improved performance computing to create new opportunities for data intensive science in the multi-disciplinary domain (Liakoset al., 2018). It employs variety of statistical, probabilistic and optimization techniques that allows computers to "learn" from past examples and to detect hard-to-discern patterns from large, noisy or complex data sets (Cruz & Wishart, 2006).

In this paper, we present a comprehensive review of the application of ML in solid waste management (SWM). A number of relevant papers are presented that emphasize key and unique features of popular ML models. The paper is structured in sections as follows: Section 2 the definition of terms used in ML, most common models and algorithms. Section 3 presents the implemented methodology for the collection and categorization of the presented works. Finally, in Section 4, the strengths derived from the implementation of ML in SWM are listed, as well as the future expectations in the domain.

Machine learning is a branch of artificial intelligence research that employs a variety of statistical, probabilistic and optimization tools to "learn" from past examples and to then use that prior training to classify new data, identify new patterns or predict novel trends (Mitchell, 1997). According to (Liakoset al., 2018), ML methodologies involve a learning process with the objective to learn from "experience" (training data)to perform a task.

Machine learning, like statistics, is used to analyze and interpret data. Unlike statistics, though, machine learning methods can employ Boolean logic, absolute conditionality, conditional probabilities and unconventional optimization strategies to model data or classify patterns (Cruz, & Wishart, 2006). Data in ML consists of a set of examples. Usually, an individual example is described by a set of attributes, also known as features or variables. A feature can be nominal (enumeration), binary, ordinal, or numeric.

Effectiveness of ML is not always guaranteed. This is to mean that if the data is of poor quality, the result will be of poor quality. The performance of the ML model in a specific task is measured by a performance metric that is improved with experience overtime. To calculate the performance of ML models and algorithms, various statistical and mathematical models are used. After the end of the learning process, the trained model can be used to classify, predict, or cluster new examples (testing data) using the experience obtained during the training process. Machine learning studies how to automatically learn to make accurate predictions based on past observations.

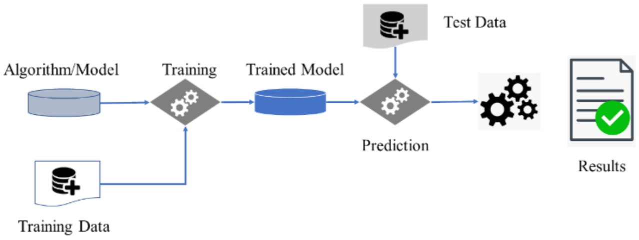

Figure 1: Machine Learning Process

Likewise, not all machine learning methods are created equal. Some are better for certain kinds of problems while others are better for other kinds of problems. This is why it is critically important to try more than one machine learning method on any given training set to get optimum results.

ML are classified into the three broad categories into 1) supervised learning with a given set of inputs with their desired outputs (Dasgupta & Nath, 2016); 2) unsupervised learning that finds a good internal representation of the input; 3) reinforcement learning which learns how to act given an observation in a dynamic environment (Liakos, et al., 2018).Between supervised and unsupervised learning is semi-supervised learning ,where the machine is provided with a training set with some (often many) of the target outputs missing (Dasgupta& Nath,2016).

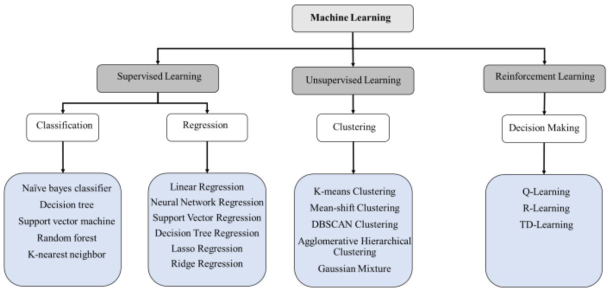

Figure 2: Machine Leaning Algorithms

Asupervisedlearningalgorithmsupervisesthetrainingdataandproducesageneralrule(function), which can be used for mapping new inputs. The algorithm can perform classification and regression analysis for image classification, diagnostics, forecasting and prediction. Unsupervised learning algorithms include approaches to create clusters from raw, unlabeled or unclassified data into hierarchical clustering and K-means clustering algorithms (Khanum et al 2015). Reinforcement learning models provide significant insight into the neural basis of a variety of cognitive processes for decision making (Miletić et al.,2020).

II. Methodology

The reviewed articles have been, on a first level, classified in three generic categories; namely, prediction of waste generation models, waste detection models, collection and disposal models. The search engines implemented were Scopus, ScienceDirect and PubMed. The selected articles regard works presented solely in journal papers. Application of different technologies like GIS and IoT, although very important, were included. Finally, all articles presented here regard the periodfrom2008 up to the present.

III. Related Studies

3.1 Prediction of Waste Generation Models

Understandingbehavioralpatternsinthegenerationofhouseholdwasteisacriticalcomponentforefficient collection (Meza, et al, 2019), and to design incentives that encourage recycling and composting (Kontokosta et al., 2018). Forecasting waste, with minimum errors is essential. The study by (Meza, et al, 2019), uses machine learning algorithms to predict waste generation from timeseries. It also highlights that Artificial Neural Networks (ANN) have greater precision due to their non-linear nature compared to multiple linear regression models (Azadi&Karimiashni,2016). The aim of this work was to perform a comparative analysis of various predictive models for the generation of solid urban waste.

Another study that used models for prediction was by (Kannangara, et al, 2018) that used two machine learning algorithms, namely decision trees and neural networks, were applied to build the models. Results showed that machine learning algorithms can be successfully used to generate waste models with good prediction performance. Neural network models had the best performance. In another study (Ahmad, & Kim, 2020) applied GIS as descriptive analysis and compared with time series prediction models for the analysis of waste amount, location-based analysis of waste amount, and analysis of the numbers of trucks. It developed and used a Support Vector Machine Regression (SVR) based time series model. The study compared different regression methods for waste, prediction topics SVR, Random Forest and LassoLars Regression. Its findings produced in-time waste information utilized by waste management authorities for the effective planning of waste management.

Ina similar study, (Kontokosta et.al.,2018) aimed to predict weekly and daily municipal waste generation from residential properties at the building level using a data mining and machine learning approach. The study developed a predictive model by comparing the performance of gradient boosting regression tree (GBRT) and Neural Network (NN) machine learning algorithms to estimate weekly waste generation.

Study by (Kolekaretal.,2016), aims to review the published models related to prediction of MSW generation. This paper reviewed 20 MSW generation prediction models from 2006 to 2014. The models which were generally used to predict MSW generation within 2006-2014 are suppor tvector machine (Abbasi et al. 2012), wavelet transform (Noori et al. 2009;Kolekar et al., 2012), artificial neural network (Noori et al. 2009; Abdoli et al. 2011; Antanasijevic et al. 2013), system dynamic(Kollikkathara et al. 2010;Chen et al. 2012), multiple regression analysis (Shan 2010; Dai et al.2011; Keser et al. 2012), fuzzy logic (Karadimas and Orsoni, 2006; Lozano-Olvera et al. 2008;Oumarou et al. 2012), geographical information system (Purcell and Magette, 2009; Keser et al.2012), single regression analysis (Ojeda-Benitez et al. 2008; Thanh et al. 2010; Lebersorger and Beigl, 2011; Li et al.2011), analytic hierarchy process (Li et al.2011), gray model (Liu and Yu,2007)and time series analysis (Owusu-Sekyereetal.2013; Mwenda et.al. 2014).

3.2 Detection of Waste Models

The emerging artificial intelligence (AI)techniques are said to be well-suited for application in the SWM field (Vitorino et al., 2017). AI technology deals with the design of computer systems and programs that are capable of mimicking human traits such as problem solving, learning, perception, understanding, reasoning, and awareness of surroundings. AI models such as artificial neural network (ANN), expert system, genetic algorithm (GA), and fuzzy logic (FL) have the capability to solve ill-defined problems, configure complex mapping, and predict results (Yetilmezsoy et al., 2011).

AI has been widely implemented to solve problems related to air pollution, water and waste water treatment modelling, simulation of soil remediation and ground water contamination as well as planning of SWM strategies (Yetilmezsoy et al., 2011). The paper will review studies focused solely on identifying the AI models used to predict MSW generation rate based on economic and socio-demographic parameters (Goel et al., 2017; Kolekar et al., 2016). Finally, Melaré et al. (2017) discussed the use of AI-based optimization techniques in SWM to predict waste generation, manage waste collection systems, monitor waste containers, and locate disposal sites (Vitorino et.al., 2017).

The study by (Geetha, S. et al., 2022), uses waste detection and classification methods which employ deep neural networks model. The trained neural network model is integrated into a mobile-based application for trash geotagging based on images captured by users on their smartphones. The tagged images are then connected to the cleaners' database, and the nearest cleaners are notified of the waste. In a similar study, (Hewiagh, Ali, et al., 2021) used three machine learning algorithms, random forest, support vector machine, and multi-layer perceptron. The study identified the best detection model based on the model's performance. Results show that each of these algorithms can be used for fraud detection in waste management with high accuracy. The random forest algorithm produces the optimal model with accuracy.

Improving the efficiency of waste collection, several studies have applied ML algorithms to realize waste bin detection, which can be regarded as a classification problem. (Hannan et al., 2014) used an ANN with a Hough transform model or Gabor wavelet filters to classify the level of solid waste inside the bin, and the output was divided into five classes: empty, medium, full, flow, and overflow. Combined with gray-level co-occurrence matrix feature extraction methods, (Arebey et al., 2012) adopted ANN and KNN for solid waste bin level detection and found that the KNN classifier performed better than ANN with the same dataset. Based on the data collected from the sensor mounted inside the container, (Rutqvist et al., 2020) treated the waste bin level detection as a two-class classification problem: emptying and non-emptying, and ANN, KNN, LR, SVM, DT, and RF were selected as classification algorithms, among which RF performed best.

3.3 Optimization of Collection and Disposal of Waste Models

In a study by (Romero-Gazquez et al., 2018) on finding an optimal path planning for selective waste collection in smart cities, the study developed an optimal path planning algorithm togetherwithapracticalsoftwareplatformforcomputingtooptimizethenumberoftruckstouseandtheirwaste collection routes. The results from the study indicate that for trucks with low capacity, the waste collected per truck is lower than the current path for almost all thresholds evaluated. It further indicates the optimal path for waste collection strongly depends on the input parameters.

In a similar study by (Kallel et al., 2016), uses GIS-based tools to optimize the actual state was evaluated, and by modifying its particular parameters, other scenarios were generated and analyzed to identify optimal routes. The results showed that the three scenarios guarantee savings compared to in terms of collection time and distance.

In another study by (O'Connor, 2013), solid waste collection vehicle route optimization was addressed with different types of mathematical algorithms. Routing algorithms use a measuring system called a path length to determine the ideal route to a defined destination. The optimal routes are then determined by comparing the different paths. These paths can be calculated by different types of algorithms. Some of the routing algorithms used include Simulated Annealing, TabuSearch, Genetic Algorithm, AntColony Optimization, and Dijkstra's algorithm (UlusamSeçkineretal., 2021).

This study focused mainly on the use of Esri products, Network Analyst extension to ArcGIS, and Vehicle Routing Problem solver has many advanced features and allows users to customize different parameters already built on a GIS platform. The results of this project show the Vehicle Routing Problem VRP solver is not ideal for calculating route optimization for large clusters of points.

In a related study by (Luetal.,2017) the study demonstrates a multi-constrained and multicompartment routing problem modeled with roll-on roll-off scheduling strategies in a two-stagedecision-makingprocesstoexhibitthehighestcomplexityofitskindinpracticalimplementation. Results indicate that differentiated collection increases opportunities to pursue the best routing strategies with sustainable implications through sensitivity analysis at the expense of higher collection costs. The analysis concludes with the perspectives of a smart and green waste collection system designed to create a more sustainable waste management system in the future.

Previous studies by (Ulusametal.,2021) that minimize solid waste collection route using ant colony algorithm. The results show that optimization for distance will also increase the efficiency of the SWMS as the same; even better, activities are performed at less cost and relatively less time.

Yet in another research (Hina, 2016) applies GIS/RS techniques to evaluate communal solid waste depots by developing Decision Support System (DSS) to find the optimal routes for solid waste disposal and select potential sites for dumping. The study used Arc-GIS 10.0 Network Analyst (NA) and its route optimization solvers. The results indicated by using advanced route solving software, the cost can be reduced significantly, decrease mileage driven, fuel consumption. To enhance the quality of the model, other spatial data can be added like generation capacity of various residential areas, types of dumping vehicles, enhanced road network for operations.

Table 1: Summary review of literature

Article Title	Goal	Technique/ Tool	Functionality	Model/Algorithm	Remarks/Significant results
(Romero-Gazquez etal.,2018)	Find an optimalpath planning forselective wastecollection. The IntegerLinearProgramming(ILP)	Net2Planand QuantumGIS(QGIS)	variable cost,route distance,numberoftrucks,distance	The algorithmseeks tominimize thecost, fuelcomposition,CO2emissions	Inthisstudy,theresearcherwillborrowsome ofthe parameter used such as;route distance, number of trucks,distance. The researcher will also use QuantumGIS (QGIS) to perform process notsupportedbyArcGIS.QGISisalsoanopen source with different capabilitiestoArcGIS.
(Kallel etal.,2016)	Scenariosgenerated andanalyzed toidentify optimalroutes	ArcGISNetworkAnalysttool	collection time,distance, cost, collectionroute/binsposition	GIS-basedoptimizedscenariosimprovecollection/transportation ofsolidwaste	Distanceasaparameterwastakenalreadyin thepreviousliterature. TheresearcherwilluseArcGISNetworkAnalyst tool.
(O'Connor, 2013)	Simulated Annealing, Tabu Search, Genetic Algorithm, Ant Colony Optimization, and Dijkstra's algorithm	ArcGIS - Network Analyst extension, Vehicle Routing Problem solver	Distance and optimalroute	The Network Analyst Route solver was used to calculate shortest distance and quickest route. It eventually reduces the cost for sanitation collection and transportation.	Distance as a parameter was taken already in the previous literature. The researcher will use ArcGIS Network Analyst tool extension.
(Lu et al., 2017)	Unified heuristic algorithm	Vehicle routing problems (VRPs) and Geographic al information System	Cost, time windows, and intermediate facilities,	Machine learning models and algorithms integrated with GIS data contribute to smart waste management	The machine learning models and algorithms similar to the proposed study.
(UlusamSeçkineretal.,2021)	The purpose is todetermine theshortest wastecollection andtransportationroutecoveredbyawastecollectiontruck. Compared antcolonyalgorithm with mixed-integerprogramming modelsolutions.	ArcGIS–ArcMap'snetworkanalysttool. Ant colonyalgorithmonMATLAB. Mixed-integerlinearprogramming onLINGO Travelsalesmanproblem tooptimizeroutedeterminationon	Locationofwastecontainers. Distance. Costoffuel.Laborcost	ACO algorithm, itwas able toapproximatepromisingsolutions withgoodconvergenceand diversitymaintenancefor most of theoptimizationproblems. Shortestpossible route(near-optimaldistance) wasdetermined	Theresearcherwillusethecostoffuelasan added parameter. The researcher will use ArcGISNetworkAnalysttoolextensionthathasalreadybeen selected in theprevious.
(Hina,2016)	To apply GIS/RStechniques toevaluatecommunal solidwaste depots bydevelopingDecisionSupportSystem (DSS) tofind the optimalroutes for solidwaste disposaland selectpotential sites fordumping. UsedArc-GIS 10.0 NetworkAnalyst(NA)andits routeoptimizationsolvers	NetworkAnalyst ofArcGIS10.0 version. Routingsolver,Closestfacilityand OD costmatrixsolver	Distance, Cost, Time takento disposal, route,dumpsite, truckcapacity, truckspeed per quantityof waste, truckspeedanddistance traveled,loading time	Promote theuse ofemergingtechnologiessuch as GIS &remote sensingto planning,managementand decisionmaking. Dijkstra'salgorithmisthe simplestpath findingalgorithm ascompared toothercontemporaryalgorithmsbecause itreduces theamount oftimeand effortrequiredtofindtheoptimal or best path(Sivanandam, etal 2009).	Inthisstudy,theresearcherwillborrowsome ofthe parameter used such as;timetakentodisposal, truckcapacity. The researcher will use ArcGISNetworkAnalysttoolextensionthathasalreadybeen selected in theprevious.

IV. Discussions

The study reviewed 40journal articles in total, all papers were categorized in the identified generic categories related to applications of ML in solid waste management. The distribution of the articles according to these application domains and to the defined sub-categories; 28 articles on prediction of waste generation, 6 on detection and optimization of solid waste respectively. The analysis showed that ML model used were more focused on supervised learning that are based on classification and regression methods.

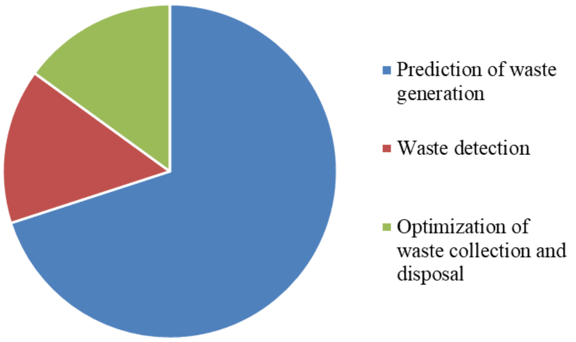

Figure 3: Articles Reviewed

From the analysis of these articles, it was found that 26 ML models have been implemented in total. More specifically, 12ML models were implemented in the approaches on prediction of waste generation where the most popular models were ANNs and SVMs. In waste detection category, 7 ML models were implemented, with most popular, models being ANNs and SVMs. Finally, in optimization of waste collection and disposal in particular route classification and estimation, 7 ML models were implemented and the most frequently implemented were ILPs.

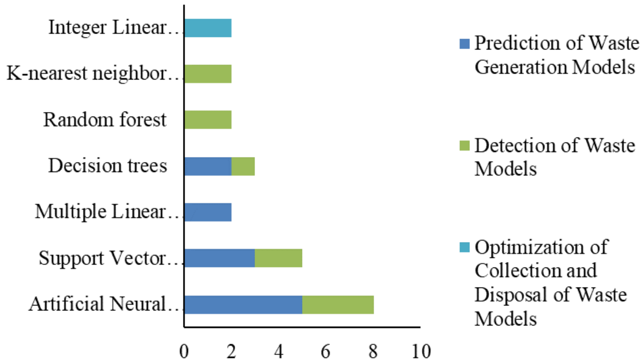

Figure 4: Machine Learning Models

In Figure 4, the eight ML models with their total rates are presented, and in Figure 3 and Table 2, the ML models for all studies according to the application domains are presented.

Table 2: Machine Learning Models reviewed

Domains	Models/Algorithms used
Prediction of Waste Generation Models	Artificial Neural Networks (ANN), Multiple linear regression models, Decision trees, Support vector machines, Artificial neural networks, Neural network models, Decision trees, Support Vector Machine Regression (SVR), Neural Network (NN), Support Vector Machine (SVM), Wavelet Transform (WT), Artificial Neural Networks (ANN), Multiple Linear Regression (MLR), Fuzzy Logic (FL), Geographical Information System (GIS), System dynamics, Single regression analysis, Analytic hierarchy process (AHP), gray model (GM), Time series analysis.
Detection of Waste Models	Neural network model, Random Forest, Support vector machine, and multi-layer perceptron, Artificial neural networks (ANNs), K-nearest neighbor (KNN), and multi-layer perceptron (MLP), Artificial neural networks (ANNs), K-nearest neighbor (KNN), Logistic Regression (LR), Support vector machine (SVM), Decision tree (DT), Random Forest (RF).
Optimization of Collection and Disposal of Waste Models	Integer Linear Programming (ILP), Simulated Annealing, Tabu Search, Genetic Algorithm, Ant Colony Optimization, Dijkstra's algorithm, Unified heuristic algorithm, Ant colony algorithm, mixed-integer programming model.

V. Conclusion

Our study on machine learning algorithms for intelligent applications on waste management opens several research issues in the area. Thus, in this section, we summarize conclusions that have potential research opportunities and future directions.

The study critically reviewed application of machine learning models in the three domains of waste management. It is also evident from the analysis that most of the reviewed articles used ANN and SVM machine learning models. More specifically, the application of ANN was mostly for prediction of waste generation. The evolution and application of artificial intelligence systems in providing innovative solutions to societal challenges. They provide recommendations and insights for decision makers for possible actions. This dynamic shift builds on the future application of machine learning models that unlock greater possibilities in solid waste management.

A successful machine learning model heavily depends on data and the performance of the learning algorithms. For optimal results learning algorithms then need to be trained through the collected real-world data and knowledge related to the target application before the system can assist with intelligent decision-making. Based on the review above, machine learning has been applied to solve solid waste challenges in the three domains. The study recommends to use ML models in finding the optimal route for collection and disposal of solid waste. It deduces the use integer linear programming model (ILP), GIS-based optimized using ArcGIS Network Analyst tool applied on variables such as cost, route distance and number of trucks, gives the best results. Further research will be carried out in future to realize and validate the tool.

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