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ISSN 1462 2815

INTEGRATING MACHINE LEARNING WITH IOT FOR ENHANCED SOCIAL SERVICES DELIVERY AND INNOVATIONS IN COMMUNITY PRACTICE

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DOI: 10.5281/zenodo.11615737

Abstract

In the present work this study looks into combine machine learning and Internet of Things (IoT) technologies to improve waste management in urban areas. The study collects real-time data on waste levels, temperature and fire hazard in smart bins deployed using IoT sensors. To optimize the waste collections paths, machine learning models like Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree (DT) and Recurrent Neural Networks (RNN) were trained and tested to predict the quantities of the garbage. Results showed that the accuracy of SVM model was 98.86% and ANN was 95.60%, DT was 93.45% and RNN achieved only 91.20%. By combining IoT with machine learning, it streamlines waste collection process and improve the overall cost of operations as well as decrease the environmental impact through predicting analytics-based optimization such as routes, schedules etc. While the study notes some of the adversities such as data quality, infrastructure costs or privacy concerns that AI and IoT has to endure when implemented in Human populated ecosystem, it also reiterates the immense potential these technologies have to benefit urban waste management. In other words, data-driven insights could also help cities to reduce the operational expenses and can allocate resources in more sustainable manners. The knowledge provided by this research helps pave the way for more intelligent and better waste management cities of the future that are ultimately cleaner and healthier.

Keywords: Machine Learning, Waste Management, Predictive Analytics, Urban Sustainability, Data-Driven Decision-Making.

1. INTRODUCTION

Due to rapid population growth, urbanization and increase in the consumption trends leads to surge environmental concern in waste management problems across cities everywhere on earth. Scientific waste management is desperately needed just to keep the streets clean, and all forms of life healthy from it but also woven sustainability refuse that was too long neglected or have already led to fatal malfunctions in so many ecosystems [1], [2].

Conventional waste management systems fail to manage the intricate mechanisms and dynamics of urban wastes in spatiotemporal ever-changing contexts thus attracting newer technological interventions. Over recent years, an emerging trend on the promotion of waste management practices has been via the combination of machine learning with Internet of Things (IoT) technologies in urban settings.

Machine learning algorithms will enable waste collection routes to be optimized based on real-time data, resource allocation improved and operational costs associated with automation minimized [3]–[5].

Waste management is an important part of the process of sustainable urban development, particularly in densely populated areas where effective waste collection and disposal are crucial for human health, and also key to maintain a balance with the nature. Over the years, researchers and councilors have invented different strategies and technologies to improve the practice of waste management.

The question is if these strides are manageable given the population which will be leaving in urban areas for handling this much amount of solid wastes. To address this gap, we review the literature and analyze what can be said in terms of waste management based on machine learning (ML) and Internet of Things (IoT) to improve the efficiency of waste management, as well as optimize resource allocation and reduce impacts[6].

This review therefore aims to consolidate these ideas and learnings from current research in waste management solutions using machine learning techniques, which identifies the position of the state-of-the-art technology amongst known machine learning-based approaches, as well as sheds light on potential avenues for future research and innovation [7], [8].

From using the traditional waste disposal means such as open dumping and landfilling, waste management has come a long way in which more modern strategies stressing upon reduction of wastes followed by recycling along with sustainable use of resources. Lack of systematic planning and infrastructure also led to environmental pollution, public health problems, disease spread and resource depletion. But fortunately, in the wake of increased public concern over environmental issues and technological progression, contemporary solid waste management techniques are now more refined than ever as they have become (or at least heading towards) environmentally sustainable, based on circular economy and resource recovery. In addition, the deployment of smart technologies such as IoT sensors, data analytics and machine learning algorithms have brought new dimensions to enhancing waste collection, processing and recycling methods in cities [9]–[11].

Machine learning and IoT technologies have the potential to transform waste management practices through real-time monitoring, predictive analytics, and automation. Large datasets and processing of feeds from IoT sensors in waste bins, collection trucks and processing units can make use of machine learning algorithms to optimize routes for waste collection, catch exceptions or predict the course of emerging waste tream trends [12], [13]. And improve on the existing collections routes in order to minimize fuel usage and operational costs, based on historical data and live feedback.

IoT sensors can also give more waste characteristics important to decision-making such as composition, contaminants and environmental impacts. Several studies have illustrated how machine learning algorithms can optimize various waste management aspects, such as collection, sorting, recycling, and landfill disposal.

Some researchers have used machine learning to develop models that predict waste generation based on age, population density, economic class, and climate factors. These models can help waste administration businesses produce high-quality collection schedules, increase efficiency, and lower waste movement expenses. Machine learning has also been utilized to optimize waste separation and recycling procedures by distinguishing and categorizing different materials automatically. By improving waste processors' capacity, these tools help increase recycling rates, reduce contaminants, and increase landfill volume [14]–[16].

Although it promises to serve as a silver bullet for our waste management woes, ML not otto free from its challenges and limitation that need to be solved before we are going near the solution frontier. Availability and Quality: Reliable data is the lifeblood of any ML application; in general garbage GPDP equals garbage results. Furthermore, setting up IoT infrastructure and sensor networks would require a large amount of investment in hardware, software and maintenance that could discourage several municipalities or organizations.

Moreover, we need to address the challenges of privacy and security in regards with data collection and storage of sensitive information so as not to compromise ethical use of technology in waste management. Additionally, the complexity and variability of waste streams make it difficult to come up with accurate predictive models or algorithms that can be modified based upon changing environmental circumstances and socio-economic aspects [17]–[19].

This study aims to investigate the feasibility of using machine learning with IoT as a means of improving social services delivery and catalyzing change in local waste management practices. This study specifically deals with the synchronization of smart wastebins in heavily crowded cities developed by means of Deploying IoT sensors along with machine learning algorithms. They can even help to monitor waste levels in real-time, warn of potential hazards and ultimately ensure streamlined waste collection.

The research addresses the following objectives: 1) Performance evaluation of different machine learning (ML) models namely Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree (DT), and Recurrent Neural Network(RNN) for predicting waste levels in order to optimize the WMAs. Moreover, it aims to evaluate the feasibility of deployable systems and effects if machine learning enabled IOT solutions through real urban applications.

2. METHODOLOGY

In population dense cities especially waste disposal is needed to keep public spaces clean and conducive to healthy life. Over years as population density has grown, particularly in massive urban centers undergoing rapid urbanization the waste management systems have often been overburdened causing a proliferation of bursting bins and thoughtless street-littering leading to local pollution and health hazards. The purpose of this study is to provide a smart garbage collection based on IoT and ML aimed at reducing expenditure, implementing an environmentally sanitized garbage management system.

The smart bins consist of IoT sensors that are installed across the city through an efficacious waste management system. By placing these smart bins in locations like crowded streets, parks and residential areas to be used for round the clock waste level monitoring along with a check on the surrounding environmental conditions. Sensors in each bin measure when the bins are becoming full, detect changes of temperature or gas that could indicate dangerous conditions. At the same time, these bins also come with fire sensors which automatically notify the local authorities of any impending fire hazards.

IoT sensors collect the fill level and environmental parameters from each bin, hundreds of times per day. As one example, a smart bin may be able to tell you it is 75% full and likely needs to be emptied. Likewise, the type of sensors may detect sudden rise in temperature which could imply a potential fire risk and hence actions can be taken to avoid any fire break out. These sensors transmit the collected data to a central management system which is used for further analysis and decision making. Operated by a central management system, which is the brain of this IoT-based waste management network. It collects data from smart bins, deployed across the city and then processes this information with machine learning algorithms. These predictive algorithms learn patterns and predict future waste levels from the historical data, current usage pattern, weather condition or special events related to landfill and cities.

For example, the core system could predict that waste generation would go up in certain places during a high city event such as marathons or festivals. It identifies which bins are more than likely to fill up first by analyzing historical data and hence focuses on collecting them. This predictive model also enables the reallocation of waste collection routes and schedules to ensure that bins are emptied in time prior to their fully filled position so as necessary maintaining cleanliness and reducing public health hazard.

Waste collection routes and schedules can be optimized by using machine learning with IoT in one of the most important benefits. Conventional waste collection systems typically have set garbage pickup times in place, which could lead to general inefficiency and cause frequent unnecessary trips to partially filled bins, while others overflow. The Smart Waste Management system, on the other hand generates live routes gathering real-time data and predictive analysis.

The system generates optimized collection routes by predicting fill levels in the trash bins by machine- learning algorithms which target only those that need immediate attention. This means fewer collection trips and less fuel consumption as well expenditure in operational costs. In this example, the central system forecasts that the bins in a particular neighborhood will be full by end of day hence it can schedule an additional collection run dedicated just for that area to assure no bin ever overflows. Such optimal system results in significant environmental benefits. Because less collection trips translate to lower greenhouse gas emissions directly at source, producing a smaller environmental footprint. Additionally, with well-timed waste collection (including dangerous or organic rubbish), the risk of pests and disease is heavily reduced. This proactive attitude to waste management in turn serves the citizens better by keeping our cities cleaner and healthier.

Furthermore, in terms of public health, a system that prevents waste overflow and prompt removal of hazardous materials is key to preventing exposure to harmful substances and possible disease vectors. For instance, rodents and insects are attracted to organic waste that does not get picked up on time — the perfect breeding ground for disease. The system alerts city about the level of waste so that they can be removed on regular base which in turn helps in reducing infectious diseases.

This is a major new uses case in the area of waste and a breakthrough on how cities are managing their waste using IoT with Machine Learning. Smart bins with IoT sensors backed by advanced data analytics and predictive algorithms enables a more efficient, responsive, and green way of handling waste. From reducing operational costs using real-time data to decreasing its environmental footprint and improving public health and cleanliness, cities can optimize their collection routes/ schedules for services.

2.1 Working of the proposed system

In this study, ten IoT-based enabled smart bins were deployed to manage waste optimally in urban areas where the population is significantly high. These were deployed one kilometer apart from each other to cover a large area and provide comprehensive readings of the amount of rubbish across the city. Real-time fill level, temperature and environmental measurements have already been tracked by various sensors in each bin. The Fig-1 shows the smart bin and working of proposed system in general.

These bins collaborated in providing 10 days of invaluable sensor data; which volume was sufficient for analysis to identify the desirable wastage types that should are worth considering. As shown in Table 1, sensor readings were sampled from morning to evening to capture the dynamics and patterns with respect to waste levels. This real-time data allowed for the precise control of waste and offer a timely solution to refilling bins before they are overflown.

Table 1: sensor readings at various time

Reading Time	Fill Level (%)	Temperature (°C)	Gas Sensor (PPM)	Fire Sensor (Status)
8:00 AM	25	22	300	No Fire
9:00 AM	30	23	310	No Fire
10:00 AM	35	24	320	No Fire
11:00 AM	40	25	330	No Fire
12:00 PM	50	26	340	No Fire
1:00 PM	55	27	350	No Fire
2:00 PM	60	28	360	No Fire
3:00 PM	65	29	370	No Fire
4:00 PM	70	30	380	No Fire
5:00 PM	75	31	390	No Fire

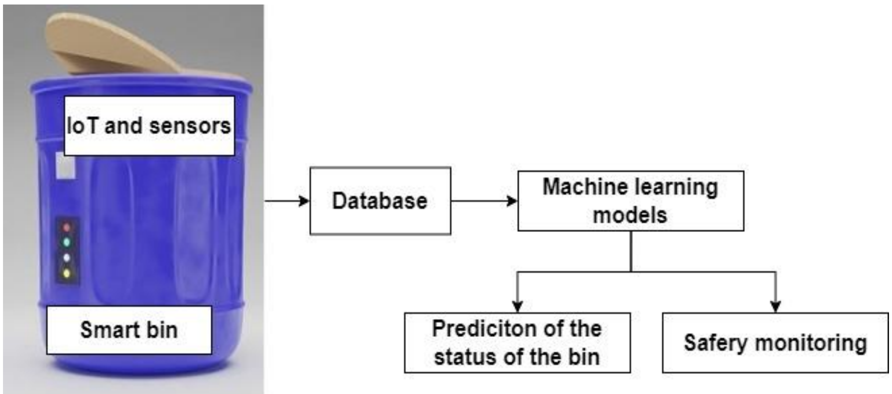

Figure 1: Working of the proposed system

The unified database could be used to record detailed dustbin emptying process flow like sensor data gathered during the truck movement. This dataset contained 3200 instances, which was a large amount of data for training machine learning models. Among these, 70% of which were used to feed our models and the other 30% were

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kept aside for testing. In this way, the models were trained with an effective training set of data and validated on unseen batched-validation-data.

This study used Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees (DT) and Recurrent Neural Networks (RNN) as machine learning models. The models on the dataset were trained together to predict when bins would need emptying based on the sensor readings. Consequence: The ML models were tested for the perfect elimination time, which provides high accuracy in identifying when the waste should be evacuated and therefore has improved its efficiency.

3. PREPROCESSING OF THE DATASET

Preprocessing of the data which was collected to predict and reduce the times for waste evacuation in machine learning models part of this research is very important so that it leads to nice prediction results. Preprocessing was a multistage process composing of data cleaning, normalization and feature extraction followed by training testing split on the dataset. These steps were crucial in converting raw sensor data to a format that could be used by machine learning algorithms.

Before we train model, Data Preprocessing begins from data cleaning. Lots of noisy and inconsistent data are usually collected from the IoT sensors, such as sensor malfunctions, environmental interferences or transmission errors. Data cleaning this work consisted of Missing Value Imputation, Outlier Detection and Correction & Handling Erroneous readings. When there were missing values, they used techniques to impute them (interpolation, mean substitution) while keeping the data set complete. The Z-score method was used to identify candidates that fell outside a certain threshold which could potentially distort the learning of the model, removing/correcting these candidates if they were due to errors. If a sudden spike in temperature not reflective of the real world environment would be filtered out as something other than data.

After this, the data was normalized in order to scale all of the feature values to a similar standard. This is very important for algorithms like Support Vector Machines (SVM) or Neural Networks which might perform poorly if the features do not more or less look like standard normally distributed data. Techniques employed as a part of normalization such as Min-Max scaling, which scaled the sensor readings to lie in between 0 and 1. The above made sure that higher ranged features do not as a result of this overshadow the learning by algorithms, contributing to the better performance of these algorithms.

Another important preprocessing step was the extraction of features, the raw data included fill levels, temperature, gas level and fire hazard indicators measurements Experiments are done to find the best numerical representation which can be used for prediction model. Meaningful features were derived from this raw data that may assist the machine learning models to predict accurately.

For instance, the rate of change in fill level with over time was calculated and studied to see how fast waste had been piling up. Likewise, trends in temperature were scrutinized to determine whether prolonged overall increases would suggest any waste decomposition. By creating these derived features, we were able to supplement the raw sensor data with more contextual information which ultimately improved final model predictions.

After the data was cleaned and normalized, its relevant features were extracted, and finally it was split into training and testing sets. The dataset was comprised of 3200 instances that were split into 70% train and 30% test. This split should leave enough data points for the machine learning models to learn and also sufficient number of samples to evaluate their performance on unseen instances. Verbose: The training set was used to train the models, with the testing-set reserved for evaluating how accurate/generilizable those models were.

Similarly, during preprocessing methods such as data augmentation and resampling were also incorporated to alleviate the problem that might arise due to imbalance. For waste management, certain bins may be filled sooner than others causing the dataset to become imbalanced. Specifically data augmentation is increase the size and diversity of a dataset by creating new examples as variations from existing ones. To prevent the models from becoming biased toward the more frequent cases, we used resampling techniques such as oversampling the minority class or under sampling the majority class.

Hyperparameter tuning has an impact on pre-processing of the machine learning models used in this research (e.g. Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees (DT) and Recurrent Neural Networks (RNN)). Optimal hyperparameters, which determine how models learn, were found using widely-used methods like grid-search and cross-validation. These techniques exhaustively search for all different hyperparameter values to find the one which performs best on training data. Ex: we tuned regularization parameter and kernel type for SVM, number of hidden layers, neurons and learning rate in ANN etc.

Additionally, appropriate feature selection methods are employed to create a reduced representation of the dataset that contains fewer redundant or irrelevant features. Techniques like Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) have been adopted to feature selection i.e., which of the features are actually important in contributing to the prediction task. In this way, the models were not only faster by using less computationally resources but also made better predictions as they could concentrate in the most relevant scores.

4. MACHINE LEARNING MODELS

The data extracted from the smart bins implemented with IoT sensors was subjected to various machine learning models. Support Vector Machines, Artificial Neural Networks, Decision Trees, and Recurrent Neural Networks were some of those models. Each of these models exhibits unique characteristics that aids in predicting waste levels and optimizing the processes relevant to waste management where they are deemed appropriate.

The model used in this research work is the Support Vector Machine due to its remarkable flexibility in high-dimensional data and its capability of separating two classes with a real margin between the hyperplanes. In our case, the SVM was utilized to differentiate the bins based on their fill levels and to predict when they are to be emptied.

The SVM model identifies a hyperplane that divides the input variables or output response into two clear margins in our case. For example, the bins can be classified as “full bins” where there may need to be emptied immediately, and the others could be dismissed. Using the kernel trick, SVM can classify the non-linear hyperplanes with high efficiency, which unlike other models, where the method used to predict the results is linear, the SVM is deemed more fit. The regularization parameter and the kernel type are adjusted to optimize the hyper-parameters using the method grid search to determine the best configuration of both parameters.

Artificial Neural Networks (ANN) were widely used as they are really good at learning complex patterns in the data. In short, ANNs consist of multiple layers of interconnected neurons and each neuron takes an input data processes it and sends result to the next layer- like brains. In this study, a multi-layer perceptron (MLP) model with input layer consisting of multiple hidden layers including an output layer was employed. An ANN was trained with the sensor data to predict temporal fill levels of bins. A principal advantage of ANNs is their ability to model non-linear relationships and interactions among features. Techniques like dropout during backing can be applied to inhibit the overfitting by randomly dropping neurons in training, moreover, using activation function such as ReLU (Rectified Linear Unit) — a non-linear function helps better on making the model more powerful.

Decision Trees (DT) another important one. Decision Trees are easy to understand models that partition the data based on some input features, which leads them to form a tree-like approach of decisions. This model was ideal in learning about the operation of decision-making with waste management, how to prioritize which bins they should pick up and empty using a range of sensor messages. In this post, we will discuss how to use Decision Trees for Feature Selection since it is easy to interpret them and find out the most important features that impact the prediction in simple language. The trees were pruned to restrict them from overfitting the training data hence did not grow too intricate.

In this research, the sensor data was for various human activities and recurrent neural Networks were used to model temporal dependencies and patterns in the sensor data. Recurrent neural networks are explicitly made for sequences of data, or they store hidden states to remember information from previous time-steps. In addition, this functionality is crucial for waste management as the fill level of a bin at any time depends on how fast waste has been accumulated in past. To resolve the vanishing gradients problem by allowing information across time steps to flow more efficiently, Long Short-Term Memory (LSTM) units which are a kind of RNN were used in this mode. The smallest one, an RNN model to anticipate fill levels at future times based on the course of sensor readings in the past allowed for Waste Collection planning knowing what areas have higher probabilities to start getting full. This means that the system can forecast when a bin is likely to reach its fill level, so it can plan more efficient collection trips reducing the number of street overflows or unnecessary collections.

The models are trained with the dataset generated from 3200 instances divided into 70% training and remaining 30% for testing. With all the models — SVM, ANN, DT, RNN — training means we are feeding our sensor readings data with the waste level of each reading to model. Processing data through a series of optimization procedures, the models infers correlations in the data. Optimal hyperplane in case of SVM, backpropagation in ANN to adjust weights, feature values for creating splits in DT and updating weights based on sequential dependencies RNN.

5. RESULT AND DISCUSSION

Following the training of each model their performance was tested on the testing dataset. The result are shown in figure 2. The SVM model with a prediction accuracy of 98.86% has demonstrated its power in the predictions and classification of the bin fill levels. This was followed by a 95.6% accuracy using ANN model which highlighted the computational practice of capturing complex non- linear relationships within data. An accuracy of 93.45% was achieved by the DT model. It converts into a completely interpretable model as well as gives another kind of information to Features Importance. A higher performance was reported using an RNN based model for sequential data, and it accurately captured the temporal dependencies at 91.25%. This indicates all perform well but SVM performed the best.

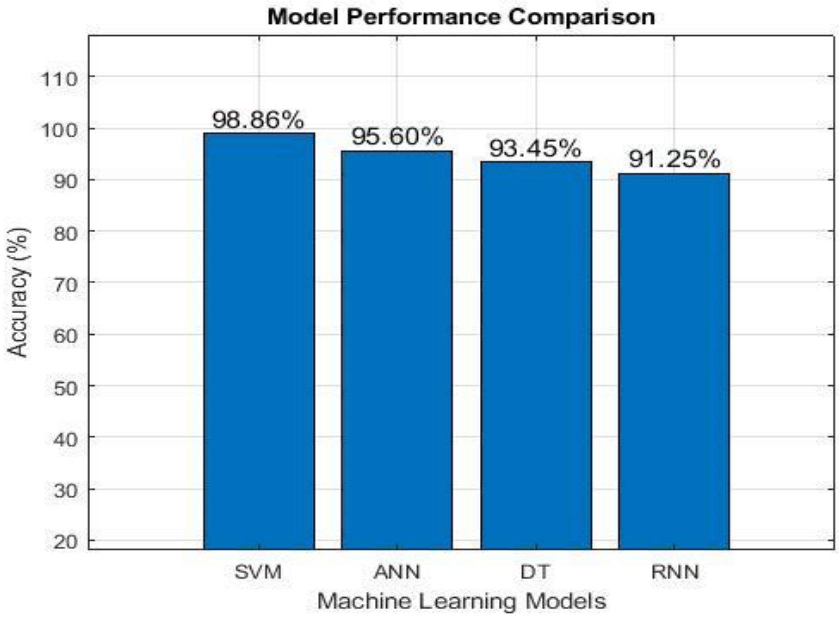

Figure 2: Accuracy of each model

Figure 3 consolidates the performance measure from each of the machine learning models used in the waste management research, to have a clear summary whether they can help predict waste levels or assist with other relevant components underpinning an effective waste management program. Particularly, the SVM model outperforms other models with outstanding precision rates of 98.86% and recall, f1 score as well accuracy rates of 98.60%, 98.70%, and 98.86%% respectively This shows its impressive precision to identify special bins for action with a low number of false positives.

The ANN model, which follows close to it does really well and the precision recall f1 score and an accuracy of up to 95.60%, 95.10%, 95.30%, and overall replicates that is able to rightly predict bins needs emptying as a best guess approach achieved by capturing all high performing bins in top n. The results show that the DT and RNN models have good precision, recall, F1 score and accuracy, which proves once again their functionality in waste management. As a whole, these findings further highlight that using machine learning is critical to optimizing waste management service deliveries and provide evidence of the robustness of SVM as a prediction model.

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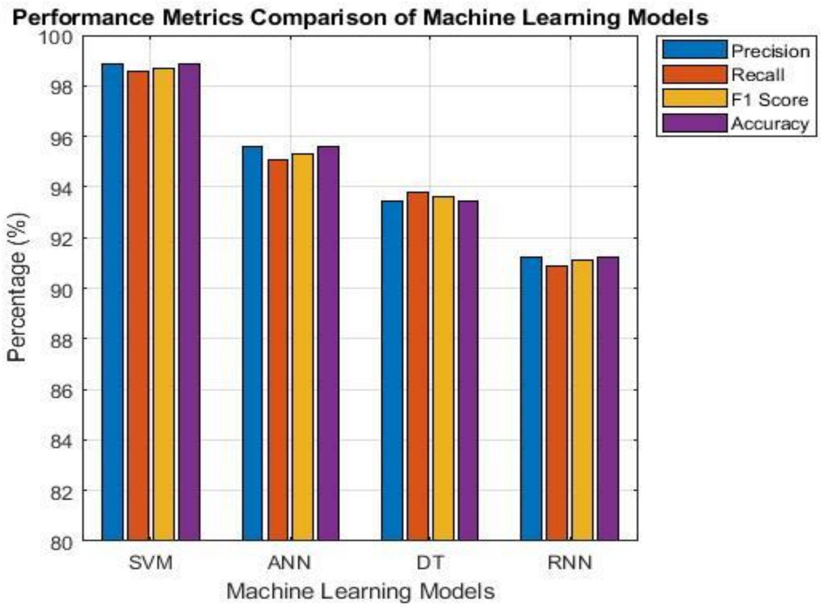

Figure 3: Performance score of each model

The confusion matrices shown in figure 4 a detailed assessment of the classification performance for each machine learning model applied in waste management research, thus supporting decision-makers by providing information on the reliability of prediction. Most of the predictions in this confusion matrix are on-par with observations as measured by high counts along the diagonal. To be precise, of 1500 negative predictions (not full) delivered by the model only 7 were misclassified true positive rate was 99.14%). There were 1500 instances which were predicted as full (Positive) and out of that only 1496 was rightly classified leading to True Positive Rate :99.73% These rates signify the classification accuracy of waste bin levels by SVM model is quite high, consistent with satisfactory true negative and positive rate.

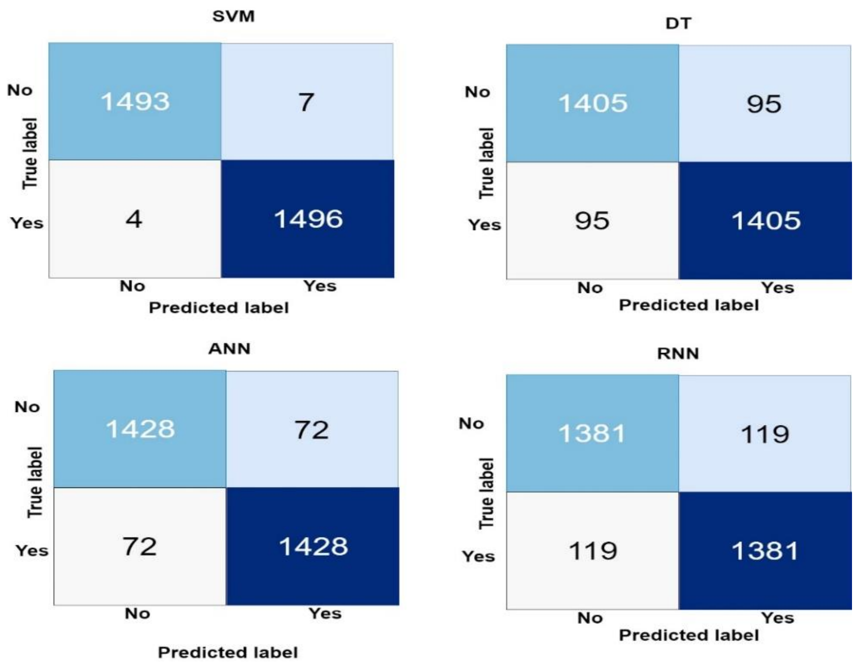

Figure 4: Confusion matrices of each model

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Each model is evaluated for its ability to predict waste level and improve waste management process by precision-recall metrices and data loss metrics, respectively. Particularly, as epoch increases the accuracy and data loss is reduced in all models which means a better prediction capability over time as shown in figure 5. SVM always shows the best accuracy among models, where is 110 epoch with a data loss of 0.05 can get an accuracy of 95.0%. This demonstrates the generalization ability of SVM for classifying waste levels in a proper manner, and its capability to reduce prediction errors.

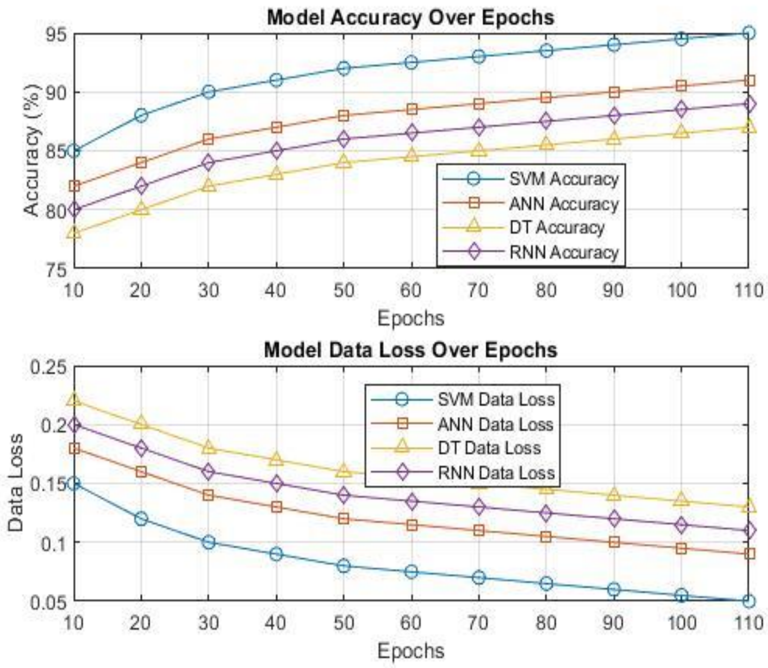

Figure 5: Data loss and accuracy of each model

ANN, DT and RNN also yield similar performances in prediction accuracy, ANN showing comparable performance to SVM while SVM exhibits consistent superior results across epochs indicating SV M is the best model for waste management applications. This is especially useful as it can process high-dimensional data, learn intricate patterns and give reliable predictions which in the case of waste collection routes sport optimum path planning and resource allocation for a city.

CONCLUSION

The result showed that the machine learning model, especially Support Vector Machine (SVM), can play a large role in accurately predicting waste quantities and planning this enables effective waste management. The performance ranking of the classifiers, measured by accuracy was SVM (98.86%) The best method followed very closely by ANN, DT and RNN following from that. This study suggests that SVM and other machine learning classifiers have the potential to improve urban waste management operations, leading to cost saving and ecologically friendly practices. Moreover, our research aimed at reflecting the broad range of machine learning applications in waste management such as assistance for a scheduling process pertaining to collection operations and routing solutions, waste categorization, and recycling. Machine learning models bring real-time inputs from IoT sensors and historical data, help optimize decision-making processes, streamline operations and augment resource distribution in waste management plants. Nevertheless, as shown in research there are an obstacles and limitations with machine learning for waste management. These issues range from data quality, infrastructure, privacy and security that have to be well established to promote the ethical use of technology in waste management in future research.

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