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Development of Automatic Object Detection and IoT for Garbage Pickup Assignment Problem

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***Abstract*—Waste management remains a challenge in certain cities, particularly in allocating fleets responsible for collecting garbage from temporary disposal sites. Inadequate planning can lead to the accumulation of substantial waste piles. This study aims to enhance truck assignment by considering truck capacity and the collection route. The assignment process incorporates the fundamental concept of the transportation problem, precisely the northwest corner method. The volume of waste transported aligns with the resident or industrial population within the designated service area. The waste generation capacity determines the future fleet and quantity, forming a crucial element of the ensuing distribution channel. A monitoring system integrating object detection and the Internet of Things (IoT) has been devised to ensure effective garbage collection. Cameras strategically positioned at temporary disposal sites transmit real-time images. The system evaluates garbage collection capacity through object detection facilitated by neural network training. The research outcomes demonstrate the system's capability to identify waste pile levels and validate the garbage pickup process by the designated fleet. Future research should focus on assignment and scheduling in waste transportation, enabling fleet allocation within specific timeframes. Additionally, an object detection algorithm refinement is necessary for more precise identification of waste pile locations.**

***Keywords*—IoT; object detection; scheduling; neural network training.**

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I. INTRODUCTION

Garbage is a by-product produced by humans every day. Waste is generated in household activities, industry, and other activities. Garbage is all forms of waste generated from human and animal activities, usually in solid form and generally not helpful or no longer needed. Garbage management involves collecting it from the service point and moving it to the temporary or final disposal site. Service point locations are spread across residential and industrial areas. Along with the growth of an area, the population in an area will grow to be more. This will have consequences, namely increasing the amount of waste because waste is a consequence of human activities. Increasing the amount of waste will lead to several problems, such as flooding, reducing the city's beauty, causing unpleasant odors, and others. Based on Indonesian Law No.18 of 2008 concerning Waste Management, there are several types of waste, including household waste, a kind of household waste, and specific waste.

One of the problems in waste disposal includes frequent delays in picking up garbage, lack of capacity in picking up, and the availability of a fleet for picking up trash. The distribution of waste disposal locations, both service and final disposal points, forms a distribution network that can be identified and optimized to reduce problems. Another issue is that after the fleet assignment, it turns out that the truck does not pick up garbage at a predetermined location but serves other consumers who are not in the service coverage. The lack of a monitoring system is the cause of this problem [1]. Trucks are only assigned without evaluating their performance in distributing solid waste [2]. In this study, we will assign the fleet to collect garbage using trucks according to their available capacity. After completing the assignment, the next step is to design a real-time monitoring system that ensures the assigned truck has completed the task at the service point.

II. MATERIAL AND METHOD

A. Neural Networks

The first proposed computational model using neural networks was in 1943 by McCulloch and Pitts. The idea revolves around several interconnected layers, forming a network [3] A feed-forward neural network (FFNN) can be considered in terms of neural activation and the binding strength between connections of each pair of neurons(cit.). In FFNN, the neurons are interconnected with clear start and stop places, i.e., the input and output layer [4].

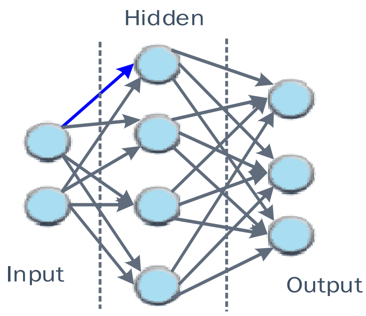

Fig. 1 Typical network architecture

The hidden layers between the input and output layers are the hidden layers. The hidden layer will determine the learning process by adjusting weight, while the goal is to minimize the error between the output layers and the input in the input layers. The weights undergo adjustment through backpropagation, involving the calculation of the partial derivative of the error concerning the last layer of weights. This weight adjustment process is iteratively repeated in a recursive process.

B. Convolutional Neural Networks (CNN)

The main advantage of using CNN over any other neural network is its superiority in image data processing. CNN is a variant of Multi-Layer Perceptron (MLP). These filters are local in input space, thus giving an advantage in 2D image processing [5]. CNN consists of three layers, namely the convolution layer, the sub-sampling layer, and the output layer [6]. Convolution Layer is the first layer of CNN. It comprises a convolution mask, bias terms, and a function expression. Together, these generate an output of the layer [7].

Figure 2 describes a 5x5 mask performing convolution over a 32x32 input feature map, which should result in a 28x28 matrix. Proceed with adding a bias and sigmoid function applied to the matrix.

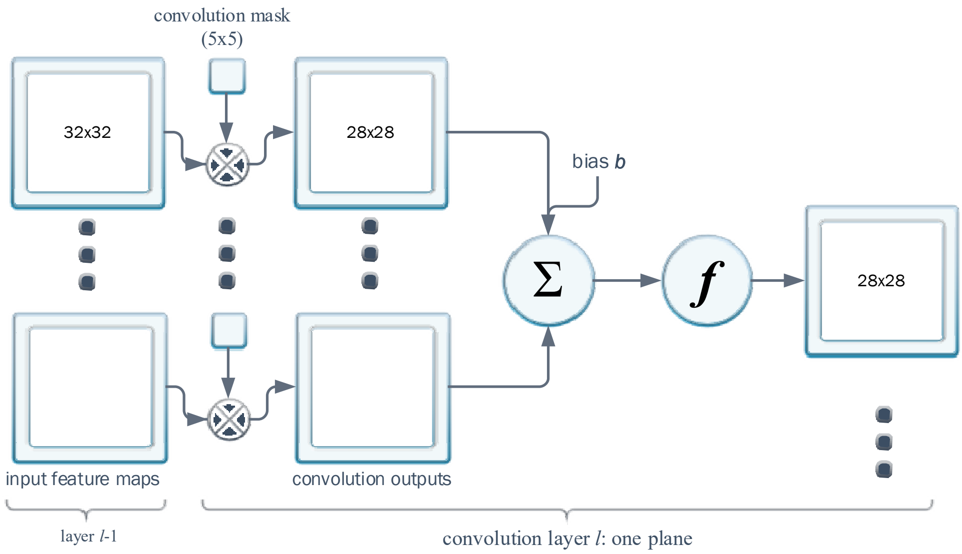

Fig. 2 Mask performing convolution

Subsampling layers come after the convolutional layer. Having the same number of planes as the preceding layer, the primary function of this layer is to decrease the size of the feature map (as depicted in Figure 3). It divides the image into 2x2 blocks and conducts averaging. The subsampling layer retains the relative information between features rather than maintaining the exact relationships.

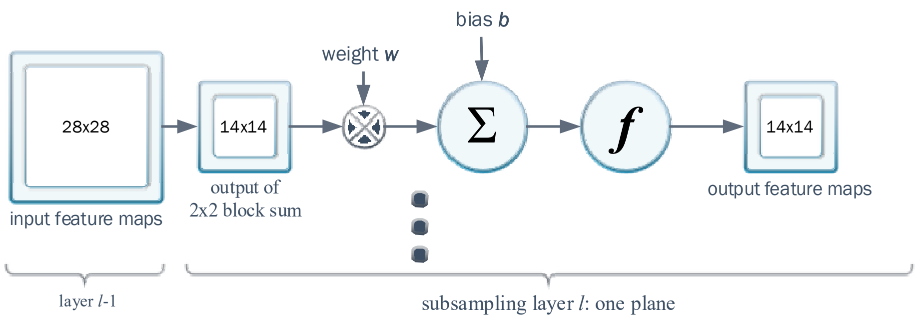

Fig. 3 Sub-sampling Process

C. Method

In this study, geographical data will be collected regarding the location of each waste distribution point. The location of the service point and the final disposal location are identified to determine the distance between the final collection point and the pick-up location. The location of each point will be mapped using the Geographic Information System Application to determine the retrieval distance. The capacity for transporting waste is determined by the number of residents or the quantity of industries within the service area. The capacity for waste generation is crucial in determining the future fleet and its amount. This factor constitutes one of the elements that shape the resulting distribution channel.

Fleet data is needed to identify the capacity of each fleet, fleet class, and the number of fleets available each day [8]. Capacity is used to determine how many vehicles are needed to pick up trash at a point. Fleet class is used to identify roads that can be passed by vehicles [9]. The fleet class will be combined with previously identified road infrastructure data using GIS. Location data, garbage collection requests, and the type and number of fleets will be input into the assignment model. This model will plan the type of vehicle assigned to pick up garbage at a specific location.

For evaluation, a real-time monitoring system was developed [10]. The monitoring system developed is based on object detection, which will evaluate the amount of waste piled up at the temporary garbage site using multi-objective criteria [11]. This evaluation is in the form of urgency level: empty, regular, and emergency. The blank review states that the garbage has been collected, the standard assessment states that the trash is complete, while the emergency states that the waste has piled up and scattered. The classification algorithm is used to solve these steps [12].

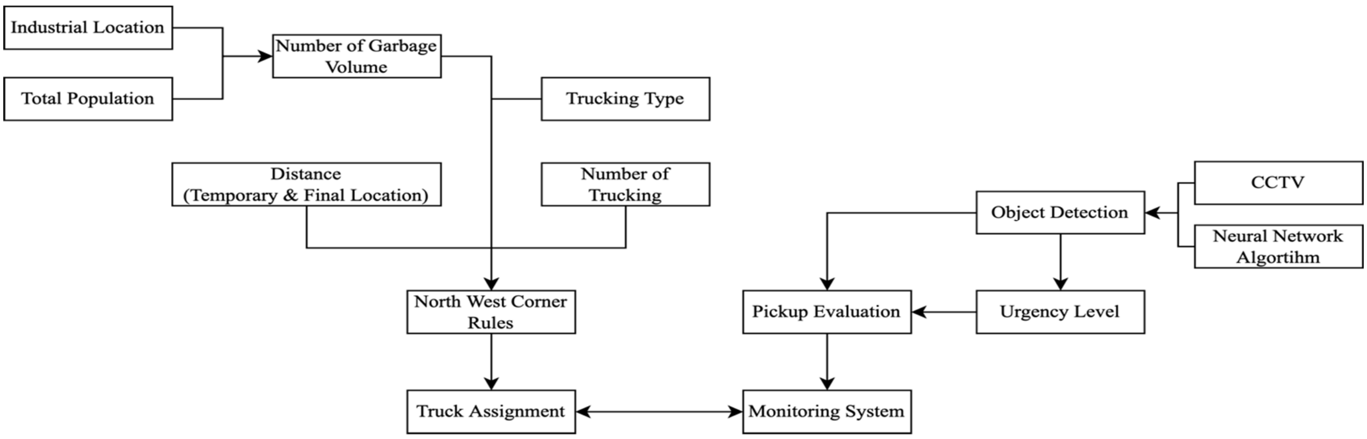

Fig. 4 Method

III. Result and Discussion

A. Vehicle Characteristics

First, it is necessary to define the fleet and its capacity. One fleet will operate for six working days and eight hours daily. The data is presented in Table I.

TABLE I
VEHICLE CHARACTERISTICS

Truck ID	Truck Capacity (m^3/rit)	Truck Capacity (m^3/rit)
T-001	10	60
T-002	6	36
T-003	4	24
T-004	6	36
T-005	6	36
T-006	6	36
T-007	6	36
T-008	6	36
T-009	6	36
T-010	6	36
T-011	6	36
T-012	6	36
T-013	10	60
T-014	6	36
T-015	6	36
T-016	6	36
T-017	6	36
T-018	6	36

B. Capacity of Temporary Dump

Another parameter that needs to be determined is the capacity of the temporary dump. This capacity will be used as input demand which will be executed using the northwest corner rules assignment algorithm [13]. The data capacity of the temporary dump is shown in Table 2.

TABLE III
CAPACITY OF TEMPORARY DUMP

Location Code	Capacity (m 3)	Number of RIT/Week	Total	Location Code	Capacity (m 3)	Number of RIT/Week	Total
Loc_1	6	1	6	Loc_28	6	1	6
Loc_2	6	1	6	Loc_29	6	1	6
Loc_3	6	1	6	Loc_30	6	1	6
Loc_4	6	1	6	Loc_31	6	2	12
Loc_5	6	1	6	Loc_32	6	1	6
Loc_6	6	1	6	Loc_33	6	1	6
Loc_7	6	1	6	Loc_34	10	6	60
Loc_8	6	1	6	Loc_35	6	1	6
Loc_9	6	1	6	Loc_36	6	1	6
Loc_10	6	2	12	Loc_37	6	1	6
Loc_11	6	1	6	Loc_38	6	1	6
Loc_12	6	1	6	Loc_39	6	1	6
Loc_13	6	1	6	Loc_40	6	1	6
Loc_14	6	1	6	Loc_41	6	1	6
Loc_15	10	6	60	Loc_42	6	1	6
Loc_16	6	1	6	Loc_43	6	1	6
Loc_17	6	1	6	Loc_44	6	1	6
Loc_18	6	1	6	Loc_45	6	1	6
Loc_19	6	2	12	Loc_46	6	1	6
Loc_20	6	1	6	Loc_47	6	1	6
Loc_21	6	1	6	Loc_48	6	1	6
Loc_22	6	1	6	Loc_49	6	1	6
Loc_23	6	1	6	Loc_50	6	1	6
Loc_24	6	1	6	Loc_51	6	1	6
Loc_25	6	1	6	Loc_52	6	1	6
Loc_26	6	1	6	Loc_53	6	1	6
Loc_27	6	1	6	Loc_54	6	2	12

C. Assignment for Transshipment Problem

This method is one of the procedures in the transportation model that starts the calculation at the top left of the table and systematically allocates shipping units. The weakness of the NWC method is that each allocation does not pay attention to the cost per unit [14]. The criteria demanded are the base cells in the top left and bottom right corner. The northwest-corner method requires that the calculation start at the top left of the table and allocate units to the shipping route as follows:

- Empty supply (truck capacity) on each row before moving to the next bottom row.
- Deplete each column's requirement (temporary dump capacity) before moving to the next column on the right side.
- Ensure that all supply and demand are met.

The NWC method does not consider costs in optimizing transshipment. We chose this because the institution that carries out waste transportation is a non-profit organization that prioritizes service, so it does not consider transportation costs. The goal to be achieved is the fulfillment of the need for waste transportation by the truck it owns.

NWC Algorithm Steps:

1) Step 1: Choose the cell in the transportation matrix's upper left corner and assign the minimum value between s1 and d1.

2) Step 2: Deduct this value from the supply and demand of the corresponding row and column. If the supply becomes 0, mark (strike) that row and proceed downward to the next cell. If the demand reaches 0, mark (strike) that column and advance horizontally to the next cell. In cases where supply and demand are reduced to 0, mark (strike) the row and column and move diagonally to the next cell.

3) Step 3: Continue performing these actions until all the supply and demand values are reduced to zero. The assignment's result is in Table III.

TABLE III
ASSIGNMENT RESULT

TrunkID	Trunk Capacity (m 3)	Assignment Day 1	Assignment Day 2	Assignment Day 3	Assignment Day 4	Assignment Day 5	Assignment Day 6
T-001	10	Loc_1 Loc_2	Loc_2 Loc_3 Loc_4	Loc_2 Loc_6 Loc_7	Loc_6 Loc_7 Loc_8	Loc_8 Loc_9 Loc_10	Loc_11
T-002	6	Loc_10 Loc_12 Loc_13	Loc_10 Loc_12 Loc_14	Loc_10 Loc_15	Loc_11 Loc_15	Loc_16 Loc_18 Loc_19	Loc_17 Loc_19
T-003	4	Loc_20 Loc_21	Loc_21	Loc_22	Loc_23 Loc_24	Loc_24 Loc_25	Loc_26 Loc_27

TrunkID	Trunk Capacity (m 3)	Assignment Day 1	Assignment Day 2	Assignment Day 3	Assignment Day 4	Assignment Day 5	Assignment Day 6
T-004	6	Loc_28 Loc_29 Loc_30	Loc_31 Loc_32	Loc_33 Loc_34 Loc_35	Loc_36 Loc_37 Loc_38	Loc_38 Loc_39 Loc_40	Loc_28 Loc_29 Loc_30
T-005	6	Loc_30 Loc_31	Loc_31 Loc_32 Loc_33	Loc_32 Loc_33	Loc_34 Loc_35 Loc_36	Loc_37 Loc_38	Loc_39 Loc_40 Loc_41
T-006	6	Loc_42 Loc_43 Loc_44	Loc_31 Loc_32 Loc_33	Loc_32 Loc_33	Loc_34 Loc_35 Loc_36	Loc_37 Loc_38	Loc_39 Loc_40 Loc_41
T-007	6	Loc_42 Loc_43 Loc_44	Loc_45 Loc_46	Loc_47	Loc_49	Loc_50 Loc_51	Loc_52 Loc_53 Loc_54

D. Darknet Framework & YOLOv4

Darknet is an open-source neural network framework written in C and CUDA. Darknet is used as a backbone for image training. The version used is Darknet -53; just like the name suggests, it uses 53 convolutional layers [15]. Darknet-53 exhibits superior performance in comparison to Darknet-19. Moreover, it outperforms ResNet-101 and operates at a speed that is 1.5 times faster [16]. In contrast to ResNet-152, Darknet-53 demonstrates equivalent performance while being twice as speedy, boasting a BFLOP/s rate. Additionally, regarding the overall score, Darknet-53 outperforms Darknet-19, ResNet-101, and ResNet-152. This indicates that Darknet-53's network architecture effectively leverages GPU capabilities, improving efficiency and faster processing. This efficiency is notably enhanced compared to ResNet, which is hindered by its excessive layer count and suboptimal efficiency.

The YOLO (You Only Look Once) algorithm, created by Joseph Redmon in 2016, is designed to handle datasets from video, image, and real-time camera feeds. It employs darknet as its underlying framework for training on image data. [17]. Numerous investigations have employed YOLO for waste detection. For instance, a study conducted by [18] utilized YOLOv3 to develop a Smart Waste Management system. The outcomes of the experiments showed promising results, with YOLOv3 achieving a mean average precision (mAP) of 94.99%, while YOLOv3-tiny lagged at 51.95%. Research by [19] researched employing YOLO for waste classification and sorting, achieving an impressive accuracy rate of up to 98%. Additionally, research by [20] utilized YOLO for waste container identification, demonstrating detection capabilities through images, video, or real-time video capture with an accuracy of 90%. Another investigation explored Smart Bin technology in Modern Waste Management, enabling the classification of waste types, monitoring bin fill levels, tracking trucks, and optimizing routes for drivers, yielding a mean average precision (mAP) of 84.44%. In a separate study, [21] applied YOLOv3 to vision-based water surface waste detection using a robot, achieving a noteworthy mAP of 91.45%.

E. System Setup

A camera will be installed at a temporary garbage collection point. The camera will be connected to a feed server and should be accessible by the main system for image data training and data collection. If a garbage collection point has a previous security camera installed, it will be used instead, provided the primary system can access the camera feed (See Figure 4).

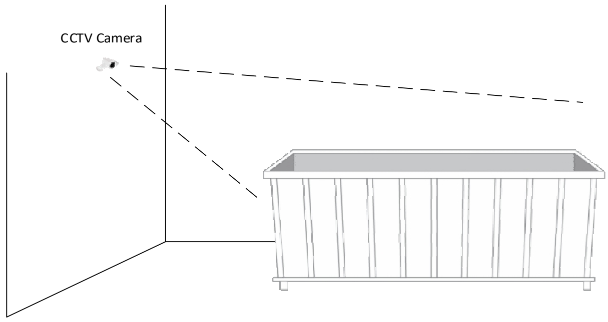

Fig. 4 Camera Setup

The video captured will be used as a training dataset for the early stages of deployment. However, the system should also be trained for at least 100 images per garbage collection point beforehand (Figure 5).

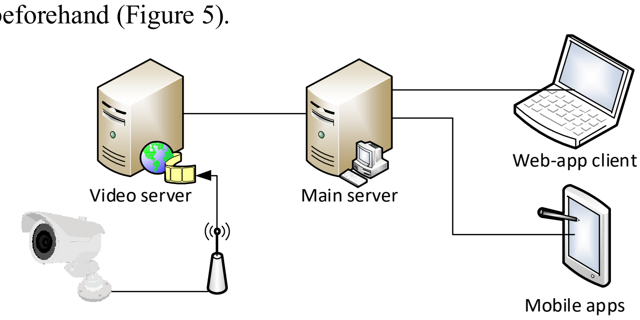

Fig. 5 Camera Setup

F. Training Image/Video Data

The first step in training is dataset collecting [22]. The data set used for training is a collection of garbage container's images of a certain site. For data validation, a set of validation image should be prepared [23]. The validation image should represent the condition of capacity percentage of a container, i.e., 10% capacity, 20% capacity, etc. All the image size should not be lower than 300x300 pixel.

The next stage involves preprocessing the dataset, wherein all dataset images are meticulously labeled using annotation tools, resulting in a text file containing information about each image. Alongside labeling, the preprocessing dataset incorporates an augmentation process. Data augmentation is a method of altering or modifying data without compromising its core characteristics. In this context, the augmentation technique applied is mosaic data augmentation [24].

The subsequent phase involves training and validation at Google Laboratory. In this step, the training dataset prepared in advance serves as the input, and the outcome is a weight file generated during this process, which will be applied in subsequent real-time testing [25]. In this phase, the transfer learning procedure takes place, drawing from the AlexeAB repository that was previously trained on the COCO dataset. The COCO dataset, originating from Microsoft, comprises 80 distinct classes. In the case of YOLOv4, the specific file used is yolov4.conv.137 (see Figure 6).

```
   layer   filters  size/strd(dil)      input                output
   0 Create CUDA-stream - 0
 Create cudnn-handle 0
conv     32       3 x 3/ 1    416 x 416 x   3 ->  416 x 416 x  32 0.299 BF
   1 conv     64       3 x 3/ 2    416 x 416 x  32 ->  208 x 208 x  64 1.595 BF
   2 conv     64       1 x 1/ 1    208 x 208 x  64 ->  208 x 208 x  64 0.354 BF
   3 route  1                                    ->  208 x 208 x  64
   4 conv     64       1 x 1/ 1    208 x 208 x  64 ->  208 x 208 x  64 0.354 BF
   5 conv     32       1 x 1/ 1    208 x 208 x  64 ->  208 x 208 x  32 0.177 BF
   6 conv     64       3 x 3/ 1    208 x 208 x  32 ->  208 x 208 x  64 1.595 BF
   7 Shortcut Layer: 4,  wt = 0, wn = 0, outputs: 208 x 208 x  64 0.003 BF
   8 conv     64       1 x 1/ 1    208 x 208 x  64 ->  208 x 208 x  64 0.354 BF
   9 route  8 2                                  ->  208 x 208 x 128
  10 conv     64       1 x 1/ 1    208 x 208 x 128 ->  208 x 208 x  64 0.709 BF

                                   ...

 151 route  147                                     ->   26 x  26 x 256
 152 conv    512       3 x 3/ 2     26 x  26 x 256 ->   13 x  13 x 512 0.399 BF
 153 route  152 116                              ->   13 x  13 x1024
 154 conv    512       1 x 1/ 1     13 x  13 x1024 ->   13 x  13 x 512 0.177 BF
 155 conv   1024       3 x 3/ 1     13 x  13 x 512 ->   13 x  13 x1024 1.595 BF
 156 conv    512       1 x 1/ 1     13 x  13 x1024 ->   13 x  13 x 512 0.177 BF
 157 conv   1024       3 x 3/ 1     13 x  13 x 512 ->   13 x  13 x1024 1.595 BF
 158 conv    512       1 x 1/ 1     13 x  13 x1024 ->   13 x  13 x 512 0.177 BF
 159 conv   1024       3 x 3/ 1     13 x  13 x 512 ->   13 x  13 x1024 1.595 BF
 160 conv     27       1 x 1/ 1     13 x  13 x1024 ->   13 x  13 x  27 0.009 BF
 161 yolo
```

Fig. 6 Validation State YOLOv4

After the best weights model generated from the training and validation process, real-time testing conducted with input images, and or, videos of the garbage site [26].

For loss function in YOLOv4, it uses Complete Intersection over Union (CIoU), rather than mean square error (MSE) like the predecessor.

The CIoU loss function is as follows:

$$LOSS_{CIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \tag{1}$$

where $\rho^2(b, b^{gt})$ It signifies the Euclidean distance between the center points of the predicted box and the ground truth, where 'c' denotes the diagonal distance of the smallest enclosed area capable of simultaneously encompassing both the prediction box and the ground truth.

For calculate total loss function for YOLOv4, we use model from [27]:

$$\begin{aligned} Loss &= 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \\ &- \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} \left[\hat{C}_i \log(C_i) + (1 - \hat{C}_i) \log(1 - C_i)\right] \\ &- \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{noobj} \left[\hat{C}_i \log(C_i) + (1 - C_i) \log(1 - C_i)\right] \\ &- \sum_{i=0}^{S^2} I_{ij}^{obj} \sum_{c \in classes} \left[\hat{p}_i(c) \log(p_i(c)) + (1 - \hat{p}_i(c)) \log(1 - p_i(c))\right] \end{aligned} \tag{2}$$

The model has been trained for over 3000 iterations as can be seen in Figure 7.

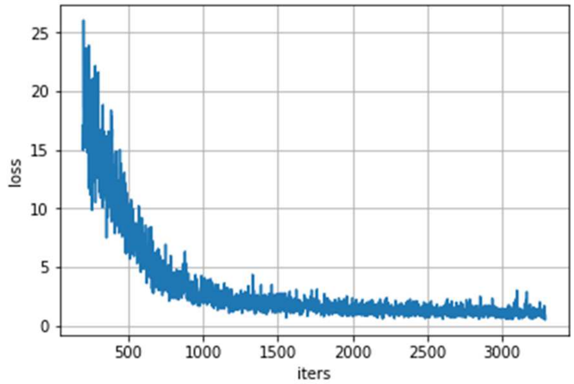

Fig. 7 Model Iteration

After the best weights model generated from the training and validation process, real-time testing conducted with input images, and or, videos of the garbage site.

G. Pre-Requisites

Video feed from the garbage collection sites should be always on record. Any cloud server solution for recording and sending live feed is applicable. If the provider provides the necessary to access the feed such as API endpoint, API documentation and necessary credential access. Once the live feed is successfully retrieved, then the system will use the feed to process video as the YOLOv4 input. For example, let's pick a popular brand for CCTV/security cameras, HIKVISION. For third-party integration, they provide an OpenAPI solution. From the API, we can access the live feed of the camera, the status of the camera, the camera URL, and the API key and secret.

H. System Synthesis

Using the SQL database, the system will have 4 tables for a rough cutdown version (Figure 8). The tables consist of 3 entities: collection sites, carrier vehicles, and drivers. Then, we store vehicle assignments as a many-to-many relation intermediate table with pivots such as urgency level, date-time of an assignment, estimated cost, and timestamp when the assignment has been done.

The collection site entity is the garbage collection site observed with live cameras. The system stores the site's basic information, such as name, site code, location on the map, and address. The table also stores camera credentials access as JSON objects. The system also stores the current capacity status of a garbage collection site. The status will be updated hourly based on the monitoring system [28].

Vehicle and Driver entities are meant to store their data respectfully. The vehicle assignment table is a record of vehicle assignments. On a single assignment, there will be one vehicle assigned and one driver on duty [29]. An assignment is finished when the monitoring system recognizes the garbage collection is empty or minimal.

I. Monitoring and Dispatch System

The process flow of the Monitoring & Dispatch System is shown in Figure 9. Monitoring on each collection site will commence every 30 minutes. On monitoring, the system will determine by feed testing on YOLOv4 how much garbage has filled the container [30].

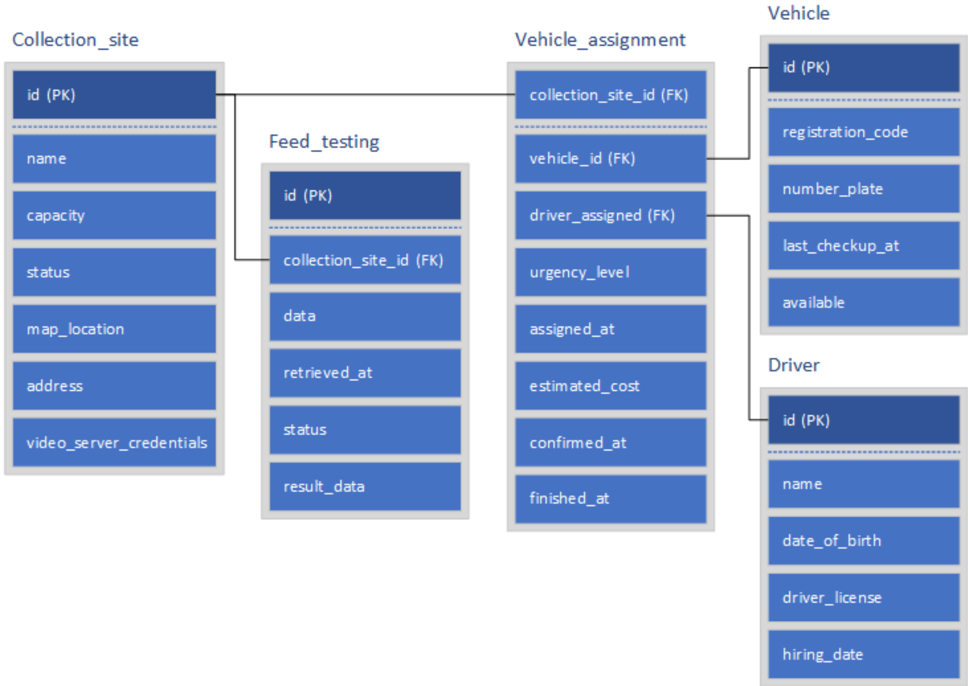

Fig. 8 ERD of SQL Database

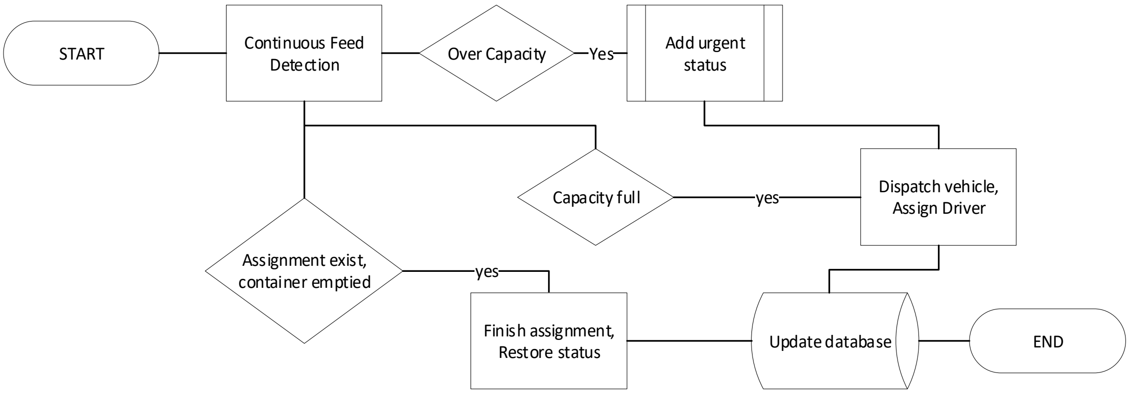

Fig. 9 Process Flow of Monitoring & Dispatch System

The result will be in percentage. The monitoring system will do nothing while the garbage has filled less than 80% (Figure 10). If the capacity is already 80% or more, the monitoring system then flags the database on the collection sites table as full, and then sends order to dispatch system to begin a new assignment to specified collection site.

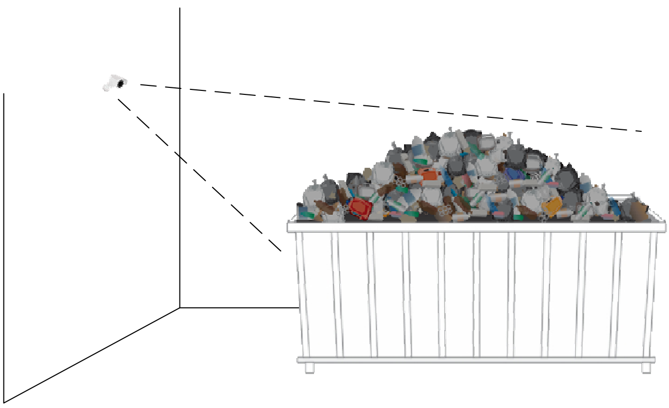

Fig. 10 Garbage Container Box Filled Less Than 80%

There's also a case when an assignment is delayed too long for it to begin, and for any reason, the monitoring system will declare urgency on a said garbage collection site. The condition is defined as overload capacity, which is marked by any other garbage piling up visually outside the container (Figure 11). When the container overloads, the system will flag the assignment as urgent with a red code, meaning the assignment should be prioritized by drivers and vehicles.

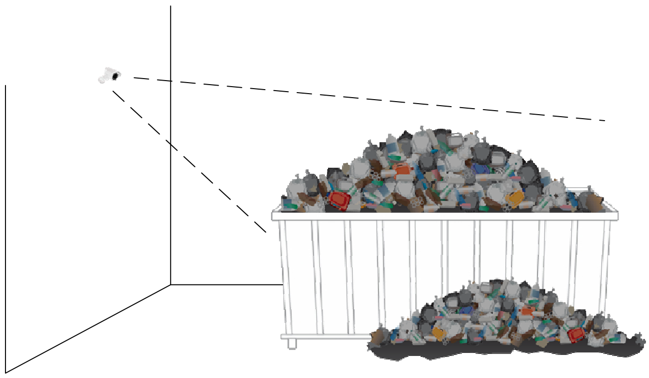

Fig. 11 Garbage Container Box Filled More Than 80%

When a new assignment is created, the system also looks for an available vehicle and driver. The system notifies the appointed driver through a messaging app (WhatsApp) or SMS. If the driver agrees to take the assignment, the system flags the assignment as ongoing.

J. System Interface

On the System web application client, it will display all the registered garbage collection sites (Figure 12 and Figure 13). The data on the list are collection site id, site address, last assignment done, current garbage load on the container. The video feed status is also listed here. Downtime in the video server should be expected, either caused by a technical problem in the camera itself or the video server under maintenance. For further information about a specific collection site, the user can navigate through menu-dots on the table row to the single collection site page. On a single collection site page, the data displayed include but is not limited to the latest feed received from the camera, the collection site address, and the last assignment history; also, if there’s a current assignment in progress, the page should also present the assignment’s information.

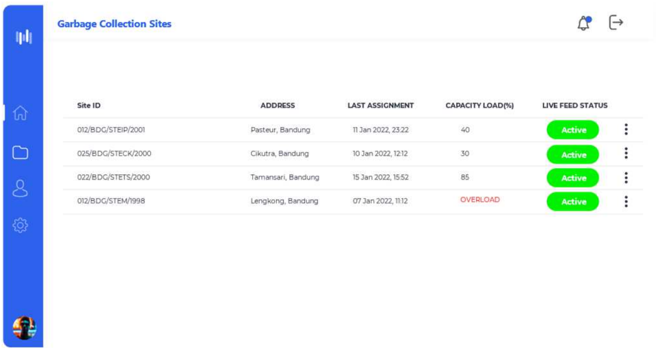

Fig. 12 Garbage Container Box Filled More Than 80%

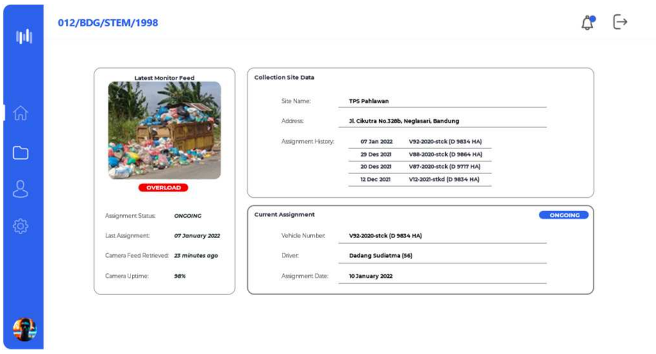

Fig. 13 Garbage Container Box Filled More Than 80%

IV. Conclusion

This paper aims to solve the problem of transporting waste. The first step is to do trucking assignments to collect garbage. This aims to optimize and ensure all waste in temporary disposal sites can be transported by available trucks. A simple NWC algorithm is used to solve this problem by considering the amount of garbage transported and the truck's carrying capacity. We did not consider the cost because the appointed case study was of a company engaged in the service sector. Another obstacle faced, due to human factors, is that sometimes trucks do not pick up garbage according to a predetermined schedule but instead serve garbage collection from private companies. To overcome this, we propose an actual monitoring system based on object detection. The object detection that we propose uses a neural network algorithm. The object detection algorithm's result shows the garbage's fullness level. These results will be combined in a dashboard that is integrated with the assignment system that has been carried out. For further research, it is considered related to transport costs and calculated the usefulness level of implementing this system.

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