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Smart Garbage Collector Vehicle: A Steps towards Swachh Bharat

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A B S T R A C T

Garbage collection is one of the most hazardous jobs in our country, and workers should avoid direct contact with hazardous trash. This paper is devoted to the design of a garbage collection vehicle that can be operated automatically. The creation of cutting-edge deep learning-based data processing technologies in recent years has sped up this rise. Furthermore, major automakers produce cars capable of partially or completely autonomous driving on public roadways. Contrarily, self-driving vehicles are now only permitted on multi-lane highways, such as interstates, and are not yet ready for urban areas or residential complexes. Because the autonomous garbage collection vehicle is battery-powered, the quantity of pollution it emits is insignificant in nature.

Keyword: automated vehicle, YOLOPV8 v5 algorithm, LiDAR, GPS, RTK sensor, garbage collector, clean city, pollution free

1. INTRODUCTION

In the modern age of rapid modernization, many new advanced methods are being introduced in various fields of engineering. One of the most often debated topics is the necessity for self-driving automobiles. Recognizing the environment around the automobile is crucial in the development of such self-driving vehicles. In order to do this, autonomous vehicles are equipped with tools including ultrasound, LiDAR, radar, and video. These characteristics are subsequently analysed in order to identify the vehicle's surroundings. With the rapid growth of deep learning, technology for recognising the immediate surroundings via sensor data has lately evolved significantly.

As previously noted, self-driving automobiles have a wide range of applications. This research focused largely on the construction of an autonomous automobile to collect waste, such as domestic debris, in residential areas. In complicated situations, such as residential areas, the automated driving system must be more dynamic in order to react to unexpected events, as they are more inclined to occur compared to motorways. Furthermore, two workers are typically needed for basic garbage collection activities. One is typically in charge of driving, while the other is in charge of gathering trash and putting it into the car. The person (shown in figure 1) who is constantly in touch with the dangerous refuse that could spread diseases during the waste-gathering process. As worker safety is also essential, this could be accomplished in this endeavour.

Fig 1: A worker collecting garbage

In this article, we created an automated moving car for trash pickup in residential areas and verified its operation in a real-world residential area. The basic working of automatic self-driving vehicle, was first specified in Section 3. We selected and positioned the sensor's field of view (FOV) in Section 4 while taking into account the sensor's field of vision. Additional external equipment are mounted onto the car in addition to deal with unforeseen occurrences. In Section 5, we created an autonomous driving system that incorporated vehicle modelling, a sensor-based recognition method, a vehicular pose estimation strategy, and a vehicular route planning algorithm. Taking about the hardware part only for garbage collector bin that is attached with truck is discussed in Section 6

2. LITERATURE SURVEY

People typically see lanes and travel along roadways while driving. Similarly, lane detection is a vital part of traveling along a lane in automated driving. Lane detection is commonly performed by automated driving systems using a camera attached to the car, just as a person recognizes lanes by gazing at them with their eyes. As deep learning research has become busier, so has studied lane detection using it. By building a LaneNet and using the clustering loss function to instantly acquire the next-best instance segmentation, Neven et al. [1] showed lane identification. A perspective transform layer was added to CNN in Yu et al.'s [6] construction, allowing for effective semantic lane classification even when the pixels are scaled down to match the lane's apparent spacing in the picture. Zheng et al. [5] used a recurrent feature-shift aggregator (RESA) to derive enhanced lane features from normal CNN features by utilising spatial linkages of pixels across rows and columns. Self-attention distillation (SAD) was employed by Hou et al. [7] to enhance ENet [2] performance without the use of additional data or labels.

According to ongoing deep learning research, current environmental identification techniques like lane recognition and semantic segmentation have produced many outcomes as previously mentioned. The gathering and labelling of datasets is one of the most important elements for these deep learning networks. Many datasets linked to autonomous driving have recently been developed and released. Six cameras, five radars, and one LiDAR were used to collect data every 20 seconds in 1000 situations by Caesar et al. [8]. They then released a fully annotated dataset with 3D bounding boxes for 23 classes of eight attributes. Yu et al.'s [9] collection of 100 K driving movies from various weather conditions, landscapes, and daylight hours were classified using scene labelling, object bounding boxes, drivable zones, lane markers, and full-frame instance segmentation.

Another crucial element of autonomous driving is figuring out where a vehicle is right now. However, determining the exact position necessitates the use of an accurate GPS sensor, which is quite costly. As a result, numerous studies have been performed to enhance efficiency by merging a standard GPS sensor alongside a camera sensor. Chen et al. To overcome the limitations of the GNSS sensor, [10] developed the Global Navigation Satellite System-Visual-ORB-SLAM (GVORB) technique for a monocular camera using ORB-SLAM [11] and low-cost GNSS [10]. The discrepancies between the lanes visible through a monocular camera and those shown on an HD map were used in Cai et al.'s [12] demonstration of the vehicle's precise localization technique to bridge the gap between the GPS sensor's estimation of the vehicle's position and the lanes' actual visibility.

In this proposal paper, for increasing the accuracy level and decreasing the noise effect in object detection YOLO-V8 algorithm is used. For getting the shortest path plaining Floyd-Warshall Algorithm is used. In order to reduce the vehicle pollution solar energy is being used. And the mechanical design of the robotic arm for lifting the bin is being designed completely by us.

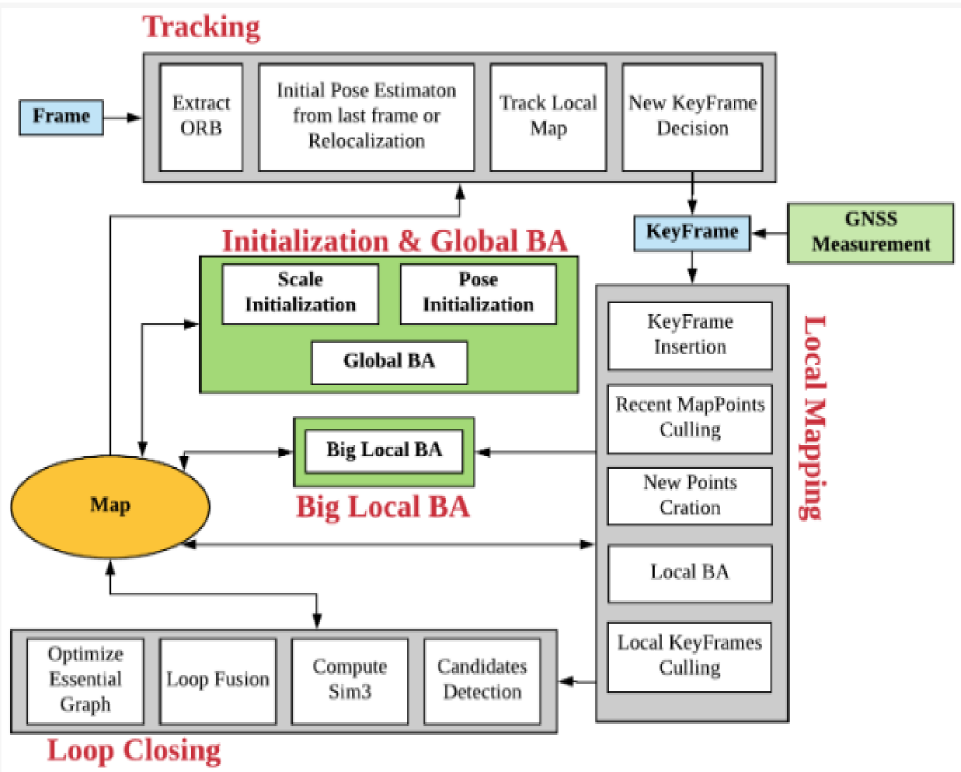

Fig 2: (GVORB) system overview [10].

3. WORKING OF SELF-DRIVING CAR

Automated decision-making algorithms are what self-driving cars do. Data streams from cameras, LiDAR, RADAR, GPS, and inertia sensors can be handled. After this information has been collected, deep learning algorithms are used to simulate the information, which makes choices in accordance with the environment in which the vehicle is operating.

To comprehend the operation of self-driving cars, we must first investigate the four major components:

i. *Perception* - Perception, which enables the vehicle to see its surroundings and identify and categorize what it sees, is one of the most crucial qualities that self-driving vehicles must possess. The car must be able to recognize objects instantly to make sound choices.

Thus, the vehicle must be able to recognize and identify traffic signals, road signs, pedestrian paths, parking spaces, lanes, and a variety of other objects. Not only that, but it must also know the precise distance between its own and any items in its vicinity.

ii. *Localization* - In self-driving cars, localization algorithms use a field of science called visual odometry to determine the location and orientation of the vehicle as it navigates. (VO). It functions by comparing key points in successive video frames.

iii. *Prediction* - Self-driving vehicles' sensors enable them to perform tasks such as image categorization, object recognition, segmentation, and localization. Through the use of several data representations, the vehicle may predict the objects in its immediate vicinity. A deep learning system is capable of analysing such data (pictures and cloud points of data from RADAR's and LiDAR's) during training. When making inferences, a comparable model can help the car get ready for any probable moves, like braking, halting, slowing down, changing lanes, and so forth.

iv. *Decision Making* - Decision-making is crucial in self-driving cars. They demand a dynamic and precise system in an unpredictable world. It must take into consideration the reality that not all sensor data will be correct, and that humans might make rash judgements while driving. These characteristics are difficult to quantify. Even if we could quantify them, we couldn't precisely foresee them.

For running a vehicle automatically in residential as well as industrial area smoothly so we are using Operational Design Domain (ODD) and Simultaneous Localisation and Mapping (SLAM) technologies for proper accuracy and avoid accident. The vehicle will halt at various locations along the path to collect garbage.

4. VEHICLE HARDWARE

4.1 Sensors

Four cameras, four radars, one LiDAR, six ultrasonic sensors, and one real-time kinematic (RTK) sensor are all used to comprehend the world around the car. We established and positioned the cameras on the roof of the car before the setup to get a clear view.

The radar was installed on each side of the car to identify things from all directions. In addition, a LiDAR camera was mounted on the vehicle's front grille to identify items and obstructions in front of the vehicle. The ultrasonic sensors were strategically placed around the car to identify obstacles near to the vehicle and thus avoid accidents. For receiving the signal at its strongest, we mounted the RTK module's transmitter on the carport collection box.

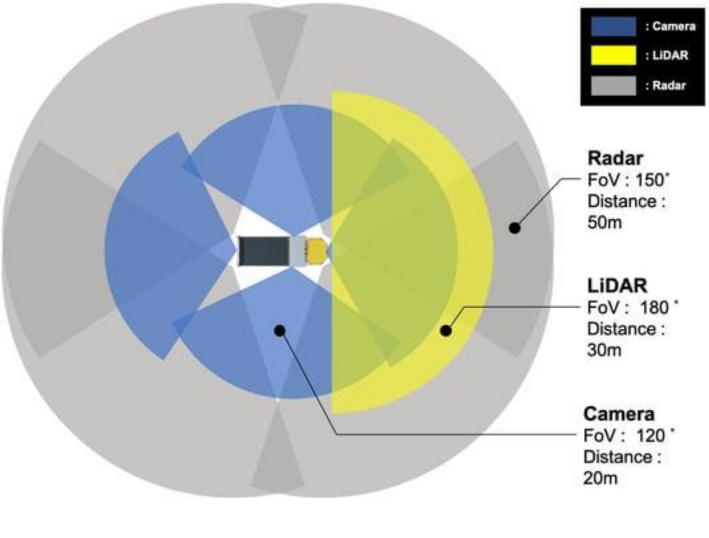

Fig 3: Sensor coverage.

4.2 Module box

The autonomous navigation module was split into sub-modules. This arrangement (shown in figure 4) is because when the camera, LiDAR, radar, ultrasonic, and RTK signals are managed in one module, a considerable amount of processing power is needed. The price of the host computer rises quickly as computing power grows. As a result, we designed the automated driving module with separate sub-modules to process information effectively by spreading abundant processing capability to the sub-modules. Because picture analysis needed more computing capacity instead of additional data, each camera received one module. This article needs more processing capacity as we've employed the network [42] to identify objects and barriers in the video and the system [1] for lane identification.

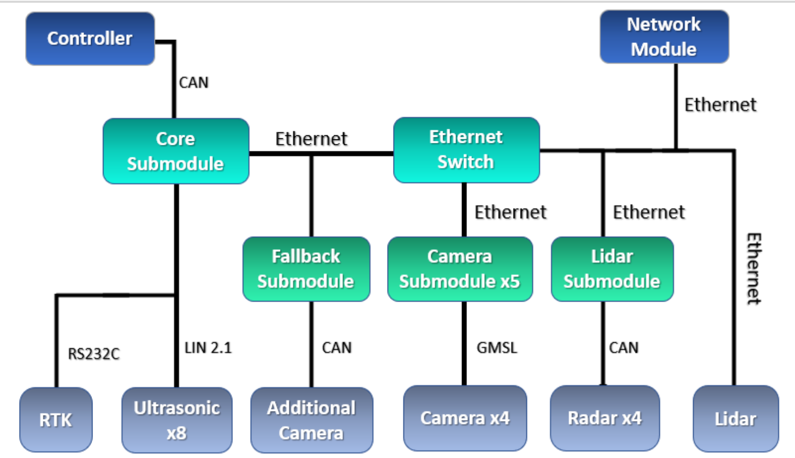

Fig 4: Module box Structure

4.3 User Interface

Our autonomous vehicle's client interface (UI) points to accurately working the driving framework and screening the independent driving system's state. Each item's Driven pointer is green when everything is fine and ruddy when something is off-base, such as being unplugged or not getting detecting information. The automated driving framework gets a still crisis caution from the car in the case the slightest one of the Driven signs is failing. The middle board, in comparison, appears as an HD map.

4.4 Control Button

Safety should come first in self-driving vehicles. As a consequence, we increased the number of control knobs in the vehicle. These control keys enable you o operate the vehicle from the inside, outside, or via an external device. Safety workers in an emergency can prevent future protection-related events by pressing any of the additional buttons given.

In this essay, a driverless car has two roles: manual and automatic mode. The automatic driving system stops the vehicle on its own when a risk factor is detected because it can recognize its environs and recognize any dangerous or odd situations.

5. VEHICLE SOFTWARE

5.1 Overall System

As shown in Figure 5, we developed our automated transportation system. Using different sensor data, an automated driving system recognises its environment. Through segmentation data of the immediate world, the awareness module recognises lane information, object information, and road information. The information gathered is then used in the stance estimator and behaviour planning tools. The posture estimation module constantly calculates the vehicle's posture using various sensor data combined with the vehicle's speed, direction, HD map information, and information recognised by the module identity. Based on the expected posture of the car, a global path can be generated from HD maps in the global path planning module and transmitted to the action planning module.

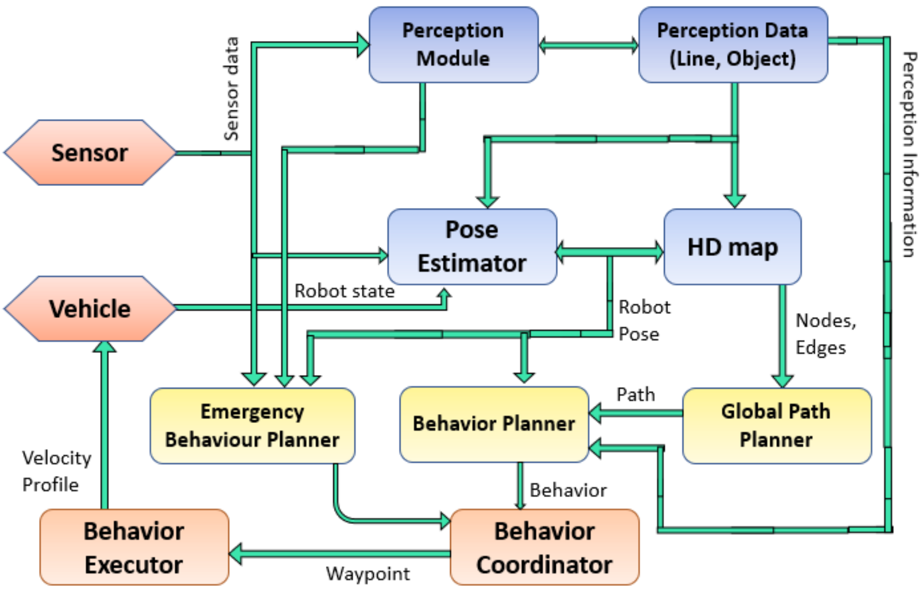

Fig 5: Overall software System

5.2 Object detection

Object recognition is typically accomplished through a mix of feature-based and appearance-based modelling. Images hold more information than laser images and can be used for both feature- and appearance-based modelling. In this piece, images are primarily used to classify them, while LiDAR is used to determine the object's location relative to the car.

The laser scanning, in conjunction with the vehicle's position, contributes to the creation of a 3D point cloud of the surroundings. This is then superimposed on the picture. A pinhole camera model was used to translate the 3D data from LiDAR scanning into 2D picture pixels. Equation 1 is used to transform the LiDAR coordinates (x, y, z) to pixels (u, v) in the picture.

$$u = \frac{f}{z}x + u_0 \quad (1)$$

$$v = \frac{f}{z}y + v_0, \quad (2)$$

where f – camera focal length,

and u_0, v_0 *are the camera*

For object recognition and categorization, we utilize the YOLOV8 algorithm. The benefit of using YOLOV8 is that it is quicker (64 fps) compared to other algorithms while keeping high precision. Other algorithms recognize items by iteratively repeating the picture via region recommendation or sliding window techniques.

Typically, for object recognition simulations, the loss function is the total of the Bbox regression loss, classification loss, and confidence loss expressed in [13]. For confidence and categorization losses, binary cross-entropy (BCE) was used, and EIoU loss was utilized for Bbox regression loss.

$$L = \boldsymbol{\lambda}_1 L_{obj} + \boldsymbol{\lambda}_1 L_{cls} + \boldsymbol{\lambda}_1 L_{box}, \quad (3)$$

$$L_{obj} = -\frac{1}{N}\sum_i (O_i ln\,(C_i) + (1 - O_i)\,ln(1 - C_i)), \quad (4)$$

$$L_{cls} = -\frac{1}{N_{pos}}\sum_{i\epsilon pos}\sum_{j\epsilon cls} O_{ij} ln(C_{ij}) + (1 - O_{ij}) ln(1 - C_{ij}), \quad (5)$$

$$L_{box} = L_{EIoU} = L_{IoU} + L_{dis} + L_{asp}$$

$$= 1 - IoU + \frac{\rho^2(b, b^{gt})}{C^2} + \frac{\rho^2(w, w^{gt})}{C_w^2} + \frac{\rho^2(h, h)}{C_h^2} \quad (6)$$

Each loss's coefficients, or hyperparameters, are represented by $\boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2, \boldsymbol{\lambda}_3$ in equation (1). In equation (2), $O_i\varepsilon[0,1]$ stands for the predicted bounding box and gross truth. C_i is the predicted value, $C_i = sigmoid(C_i), and\ N$ is the number of positive and negative samples, and N is the number of positive and negative samples. In equation (3), the variable $O_i\varepsilon[0,1]$, i_{th} class in the i_{th} represent the prediction value, C_{ij} the prediction value, and N_{pos} the number of positive samples, respectively. In equation (4), $\rho^2(b, b^{gt})$ stands for the Euclidean distance between the centres of the two boxes and the GT, C also stands for the diagonal and width and height of the minimum bounding rectangle of the two boxes are denoted by C_w, C_h.

5.3 Lane Detection

Lane recognition is accomplished by merging three types of sensor data. To begin, lane information is extracted from a binary picture. The lane information is then obtained via the lane recognition network [1] and lastly obtained from the lane recognition camera. As shown in figure. 6, we utilised the polynomial line extraction technique [14] with the sliding window approach to detect the lanes from the binary picture after utilizing the perspective transformation to the binary image received from the front camera.

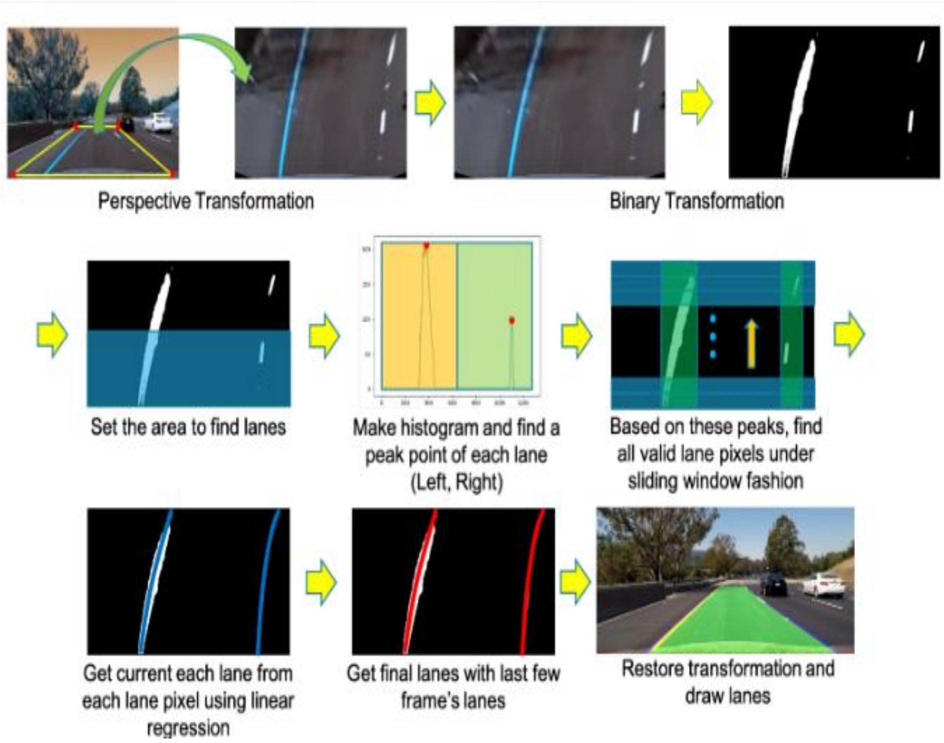

Fig 6: Lane recognition process using binary images

For each outline, we figure each lane as a set of second-order polynomial conditions. All of our lines are drawn utilizing the condition x=ay^2+by+c. Here, as already expressed, we utilize three unmistakable sorts of information to recognize paths. On each piece of data, we perceive the closest cleared-out and right path. We recognize three sorts of data:

$$L_b = \begin{matrix} a_{b_r} & b_{b_r} & C_{b_r} \\ a_{b_t} & b_{b_t} & C_{b_t} \end{matrix} \quad (7)$$

$$L_n = \begin{matrix} a_{n_r} & b_{n_r} & C_{n_r} \\ a_{n_t} & b_{n_t} & C_{n_t} \end{matrix} \quad (8)$$

$$L_m = \begin{matrix} a_{m_r} & b_{m_r} & C_{m_r} \\ a_{m_t} & b_{m_t} & C_{m_t} \end{matrix} \quad (9)$$

where b, n, m, l, and r means binary, network, lane camera, left lane, and right lane inputs, resultantly. As already mentioned, lane detection could be improved and it would be best if lane detection could identify the lane during the t-1 frame, but not necessarily in subsequent frames.

$$L_{q_l} = \sum_{i=q}^{size(Q_l)} Q_l(i)/q \quad (10)$$

$$L_{q_r} = \sum_{i=q}^{size(Q_r)} Q_r(i)/q \quad (11)$$

where L_{q_l} and L_{q_r} are, correspondingly, the extra paths made from the left and right paths. Since the paths can sometimes have particular shapes, we utilize the lines separately for the left and right paths.

5.4 Global Path Plaining

Global path planning for automatic vehicles involves determining the optimal route or path for a vehicle to follow from its current location to a desired destination, taking into account various constraints and objectives. In this paper the shortest path algorithm is also being highlighted. The main methodology or objective of this section is real time monitoring/tracking system on truck route whose system architecture is shown in figure 7 and providing the shortest route to truck for collecting garbage from house. In figure 8, every truck is appointed to a range of area from where they collect garbage and return to disposal site. If anytime any truck has met the capacity of garbage storage, then using shortest path they will return back to disposal area. For finding the shortest path, this Floyd-Warshall Algorithm is used. This algorithm is not determined from a single source. In other words, instead of calculating from a single node, it calculates the shortest distance between each combined node within the arrange. It understands the shortest path issue by dividing the major issue into smaller ones and then combining the responses. It creates multi-stop routes since it defines the shortest way between all pertinent nodes. As a result, no matter where you're on the map, this algorithm will discover the shortest way to any other node.

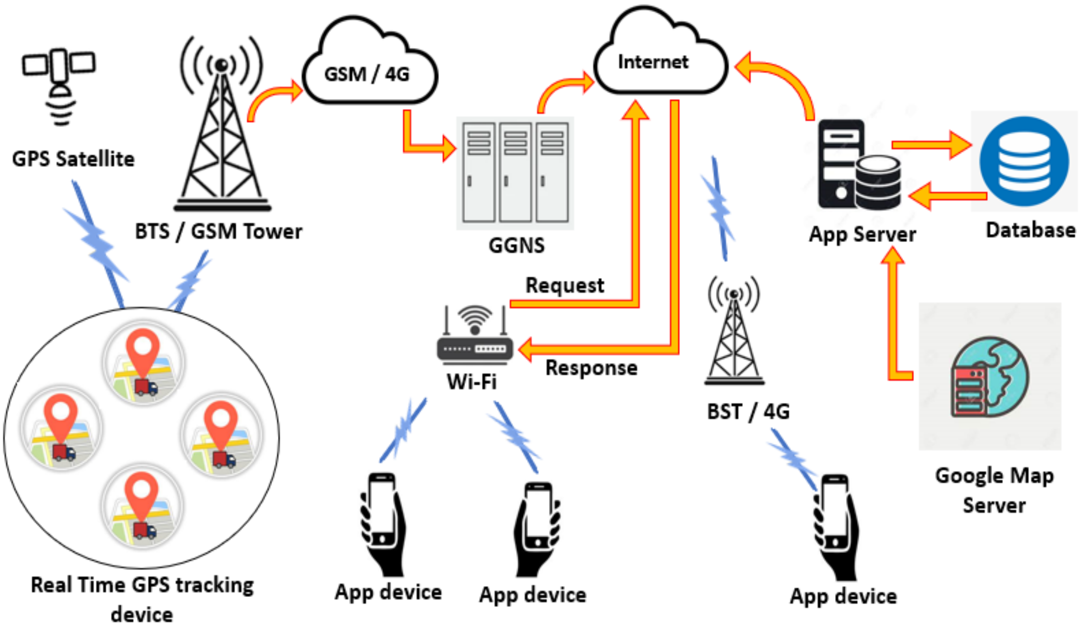

Fig 7: System Architecture of Vehicle Tracking System

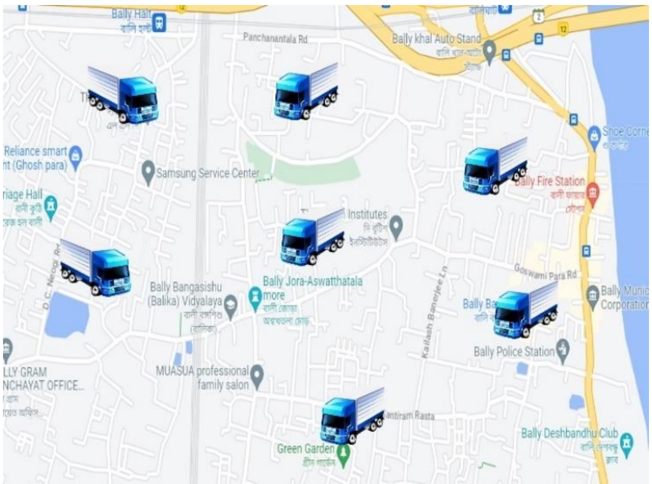

Fig 8: Garbage Collector truck attached in map

Architecture for shortest path plaining and monitoring on vehicle system is shown in figure 9, in this figure the shortest path of different vehicle for different location is shown. The architecture defined as GPS satellites provide position data (GPS points) to GPS tracking systems enabled in vehicles. These locations are broadcast to GGNS servers via BTS and GSM towers using GSM and 4G networks. The GGNS server, on the other hand, stores the location of all GPS devices and stores the same information in its database. When requesting GPS coordinates or proper Google Maps, the app device sends a request to his GGNS server or app server. The app server then forwards this request to the Google Maps servers. On the Google Maps server, the results are merged with the GPS points obtained from her GGNS server and delivered to the end user (system user). To go from one stoppage to another in minimal time and the shortest route, the Floyd-Warshall shortest path algorithm is implemented in the program, allowing the user of the system to find the shortest path from the app (a digital map containing GPS coordinates) to the vehicle.

Fig 9: Google map with shortest path

6. VEHICLE SOFTWARE

For discussing about the hardware parts of garbage collector, the process of locating the bin and holding them then lifting it to the bin is done in fully automatic. This helps to keep the workers safe from the health issues. No man is needed to collect garbage, instead of that the vehicle automatically come and collect garbage and return back to dispose area. As recently fuel shortage is shown and due to usage of fuel creates pollution in environment. So, in this paper the proposed vehicle runs on battery. This battery can charge both through solar charge and also by electric charging station. For on-board solar charging photovoltaic cell is used which help to reduce the drain time of battery on long distance route. The Polycrystalline solar cell, shown in figure 10 is installed in electric vehicle which convert most of the sunlight they receive into usable electricity. It is less expensive and produce comparatively low energy than Monocrystalline solar cells.

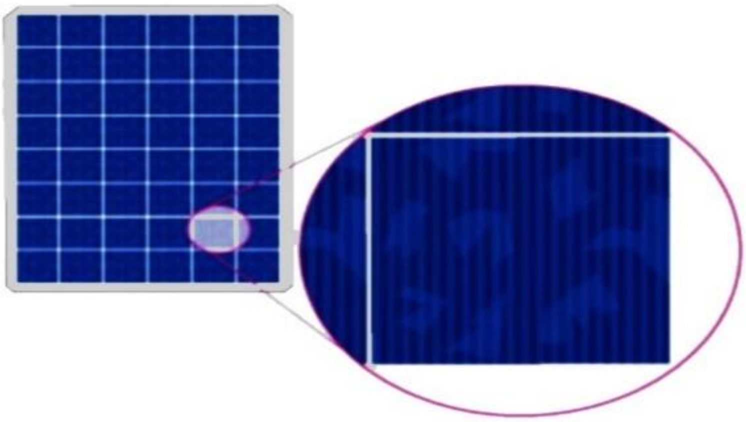

Fig 10: Poly-Crystalline Solar Cell

To Store the solar charge Lithium-Ion batteries is used. This battery is having high energy density, low self-discharging, having long life as compared to other batteries, and fast charging which is important for EVs, where fast charging is necessary to enable long-distance travel and reduce downtime for commercial vehicles.

For motor which are used in electric vehicles typically have a single-speed transmission, which means that the motor can deliver the maximum amount of torque to the wheels at all speeds. This makes electric vehicles feel very responsive and powerful when accelerating, even at low speeds. Thus, AC induction motor is used. A common AC induction motor used in medium to heavy-duty electric trucks can deliver torque in the range of 1500 Nm (1106 lb-ft) to 2500 Nm (1844 lb-ft).

Figure 11 illustrate the mechanical model of garbage bin, which is externally fitted on automated truck. This bin is having two side compressors to reduce the occupying space of garbage in bin and one slider to push the garbage inside the bin. The lifting arm is fitted on left side of the vehicle which lift the garbage bin automatically by identifying the bin.

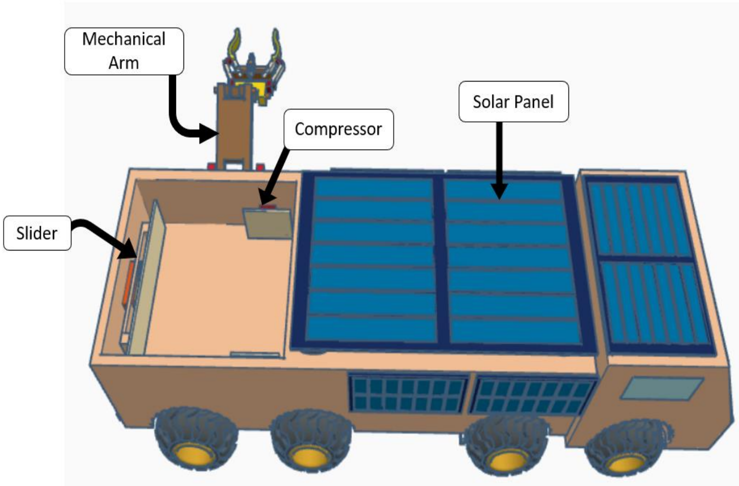

Fig 11: Proposed model of Automated Garbage collector Truck

7. CONCLUSION AND FUTURE SCOPE

This paper has created an autonomous vehicle and its self-driving system for garbage collection in residential and industrial areas. We infer from previous research that this medium is directly related to society. This is a step forward in "Swatch Bharat Abhiyan" when this medium is not only useful for society but also environmentally friendly. Designing and building an automated garbage collection vehicle is a daunting challenge and this paper provides a clear understanding of our vehicle design and analysis. For futuristic scope this vehicle running algorithm can be changed accordingly with new and high accuracy algorithm for better result. Any changes on the design is also being accepted as in this paper a normal design is implemented.

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Appendix

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