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Original Article

Design Study of Smart Robotic Framework for Sewer Conservation

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Abstract *- Technology has revolutionized different human endeavors to take advantage of a clean, comfortable, safe life. In this paper, the proposed work introduces a robotic system that can navigate through buried sewers to detect isolated blockages using camera sensors and embedded vision. AI detection algorithms YOLOv3 and YOLOv4 have been trained with newly created imagery datasets and are a major aspect of this development. This robotic system will also solve the problem of human hygiene by removing the obstructions in the sewer in real-time with the help of a newly developed cutter. The linkage mechanism, cutting tools, the central frame and three separate crawler modules developed in Catia V5 R21 ED2 are also crucial parts of the proposed robotic system. The system provided is one of the best achievements in the field of sewer robotics that works to detect and remove barriers for real-world application. The methodologies in the presented system are revealed to specify the concepts and advantages.*

Keywords *- Sewer robotics, Central frame, Linkage mechanism, Computer vision, Embedded system, Artificial intelligence.*

1. Introduction

The underground drainage system is essential to modern development to maintain a safe and clean environment. However, despite many benefits, underground systems have several problems such as blockages, corrosion and cracks in pipes causing leaks and tree roots intrusions. Periodic maintenance is required to keep sewers in good condition.

Government authorities maintain the sewerage system in India, and the Government of India has presented standard operating procedures (SOP) for maintaining sewerage systems [1], [22]. The practice of manual scavenging continues in some places in India, although the government banned manual scavenging in 2013. Technological solutions, including robotics and remote-controlled devices, should be used to avoid this practice permanently.

In this regard, mechanical methods and sewer robotic systems are available and reviewed in earlier work [2]. The KARO [19], PIRAT [21], KANTARO [16], SIAR [17], KURT [18], MAKRO [20] are some instances in the sewer robotic field. The previous survey details were also analysed based on computer vision methodologies for the assessment of sewerage systems [23], [24], [25]. The mechanical systems are also used for water quality monitoring [26][28]. These robotic systems used sensors, computer vision, onboard remote control processing unit, and navigation assembly. Many existing systems are operated to solve distinct sewer defects to maintain sewerage [12]. In contrast, blockage is the most common concern in the real-world scenario in underground sewers [3]. There is not much information on detecting various sewer blockages, so necessary remedial actions are selected.

This paper collected a set of sewer blockage images, and the dataset is used to train YOLOv3 and YOLOv4 detection models on the darknet to detect sewer blockages. The linkage mechanism, cutting tools, the central frame and three separate crawler modules of the robotic framework are also presented for modelling purposes and highlighting the features required to work in underground infrastructure.

This paper describes the proposed methodology of dataset formation, training outcomes for YOLOv3 and YOLOv4, and hardware modelling in the proposed system.

2. Methodology

The block diagram shown in figure 1 details the assembly of the proposed sewer robotic system. The key aspects of the systems are a new imagery dataset for training detection models and computer vision algorithms with an embedded platform for identifying gutter blockages. The central frame, linkage mechanism, cutting tool and three separate crawlers are the main components for system navigation and sewer blockages removing tasks. The embedded vision is the significant platform for developing the real-world visual application system [27], [28].

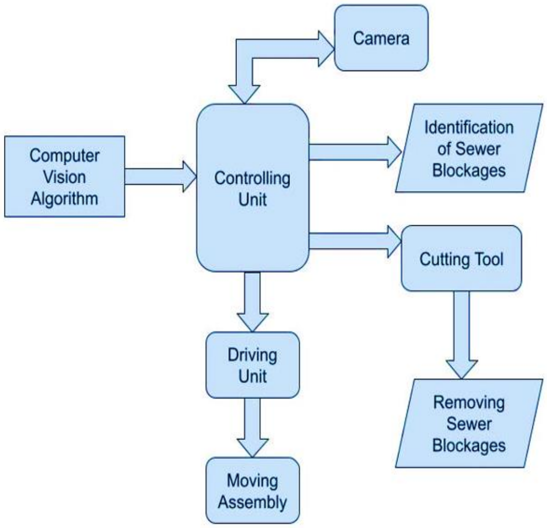


Fig. 1 Block Diagram of Proposed Sewer Robotic System

3. Collection of Sewer Blockages Frames

A typical sewer line of 12-inch diameter was built in the research laboratory (DYPSOE, Pune) shown in figure 2. Various common sewer blockages were replicated in the sewer pipe setup, and images of these simulated blockages were captured to build an "image dataset".

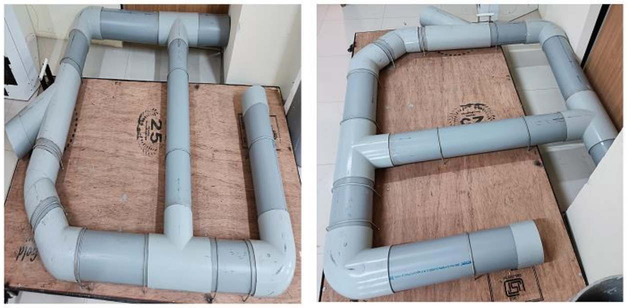


Fig. 2 Lab set for sewer line

The new dataset S-BIRD (Sewer-Blockage Imagery Recognition Dataset) of sewer blockages images was used to train detection models (E.G. Yolov3 and Yolov4) to enable these models to detect isolated sewer blockages. A total of 7040 images of sewer blockage were captured, out of which 5984 images were used as a training set, and 1056 images were utilized as a testing set.

Figure 3 shows a few of these captured images of common blockages in sewer lines, such as tree roots, plastic and grease.

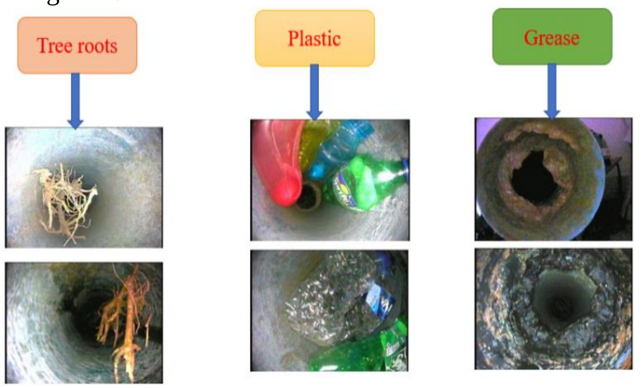


Fig. 3 Sewer blockages frames

4. Training of Object detectors

Many object detectors are available and classified as single-stage and two-stage object detectors. One-stage detectors like YOLO (You Only Look Once) were introduced first by Joseph Redmon [4], SSD, etc. These one-stage detectors are faster than the two-stage and are commonly used for real-time applications.

YOLO has been modified a few times, and we used the third-generation model YOLOv3 presented in 2018. YOLOv3 is three times faster than SSD detector [5], [13] and Retinanet detector, but as accurate as SSD and has the same functionality as Retinanet.

The YOLOv4 has also been used, a one-stage object detector introduced by Alexey Bochkovskiy with novel features such as WRC, CSP, CmBN, SAT, Mish activation, Mosaic data augmentation, CmBN, DropBlock regularization, and CIoU loss and achieved advanced results [6].

YOLOv3 and YOLOv4 use DarkNet 53 Neural Network Framework that supports both CPU and GPU execution and being a one-stage detection, the device's architecture is good for real-time detection. YOLOv4 has better mean average precision (mAP) by about 10% and an improvement in the number of frames per second by 12% compared to Yolov3.

4.1. Setting up Training Parameters

The annotations for each object were done with higher precision to locate objects exactly in the images for respective computations. The annotation of a frame consists of the information shown in figure 4 about the object:

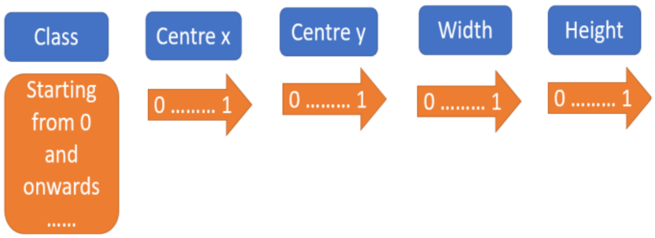


Fig. 4 Annotation details for each object

All these parameters are normalized by original frame width and height, and all values must range from 0 to 1. In classes, 0 represents Tree roots, whereas 1 for Plastic and 2 for Grease.

For the presented dataset, the customization has been done in the respective network for the three classes mentioned above. The training parameters are defined as max_batches, and filters are calculated by equations (1) and (2), respectively.

$$max\_batches = classes * 2000 \quad (1)$$

$$Filters = (Classes + Coordinates + 1) * Masks \quad (2)$$

$$Steps = 80\%\ max\_batches,\ 90\%\ of\ max\_batches \quad (3)$$

In our case, max_batches (total no. iterations) are 6000 for three classes; filters are 24, and steps are 4800 and 5400 computed from equations (1), (2) and (3), respectively.

Table 1 shows the training parameters with their values for key referencing.

Table 1. Training Parameters

Parameters	Values
Batch	64
Subdivisions	16
Width	416
Height	416
Channels	3
Decay	0.0005
Angle	0
Exposure	1.5
Hue	.1
Learning Rate	0.001

4.2. Training outcomes of YOLOv3

Tesla V100-DGXS workstation with 32 GB of GPU was used for training the YOLOv3 detection model. Tables 2 and 3 give the outcomes of trained model at a particular iteration. It was noticed that the precision rate was increasing as the iteration increased, so the iteration doubled, i.e., 12000 iterations. However, the accuracy rate was saturated while achieving 12000 repetitions, so training was stopped. The best-trained model gave 89.59 % of the mean average precision for the overall mentioned classes for real-time detection application in robotic sewer systems.

The training progress charts have been given for 6000 iterations in figure 5 (a) and from 6000 to 12000 iterations in figure 5 (b).

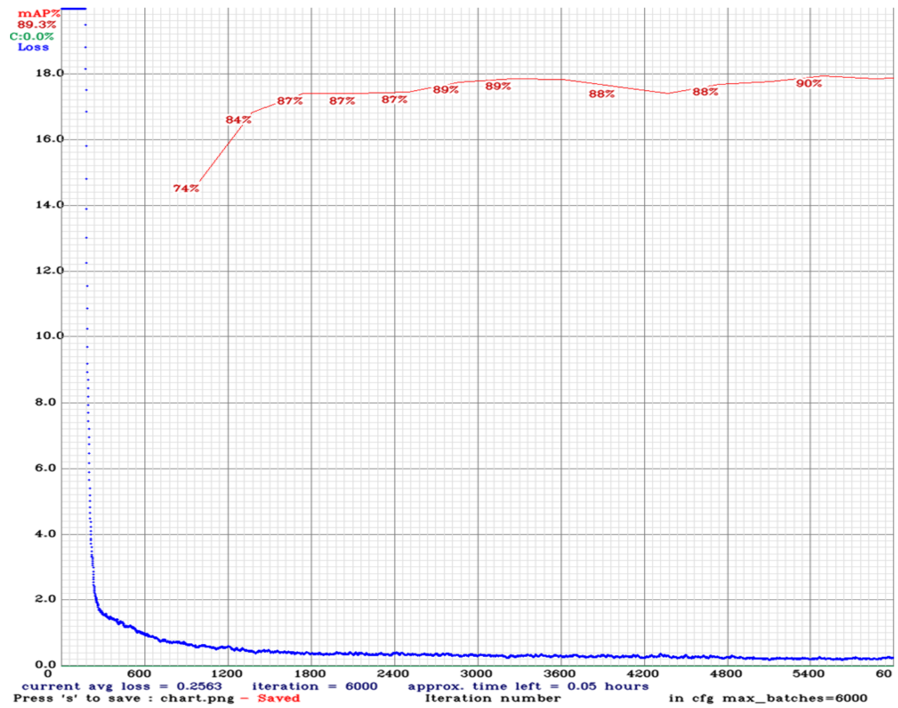
Table 2. Outcomes of the trained model at a particular iteration

Trained model at a particular iteration	Average precision in %			True Positive (TP)	False Positive (FP)	False Negative (FN)
	Tree-roots	Plastic	Grease			
1000	64.85	87.67	68.56	854	63	686
2000	75.62	93.10	89.24	1083	44	457
3000	78.99	93.88	91.77	1247	166	293
4000	76.81	93.06	91.95	1235	194	305
5000	81.03	93.97	91.67	1269	128	271
6000	81.52	93.53	92.94	1289	110	251
10000	80.39	91.53	92.16	1294	167	246
12000	80.04	92.53	92.85	1299	116	241
Best-Model	**82.08**	**93.80**	**92.87**	**1309**	**131**	**231**

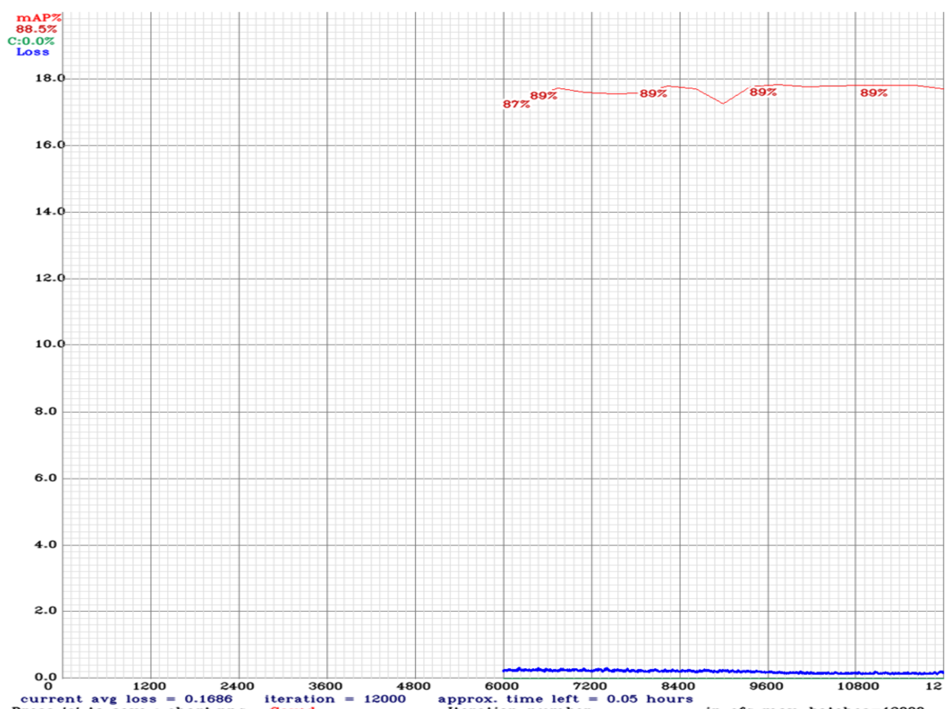
Table 3. Outcomes of the trained model at a particular iteration

Trained model at a particular iteration	Mean Average Precision in %	F1-score	Aver. IoU in %	recall	Precision	Detection Time in seconds
1000	73.70	0.70	69.87	0.55	0.93	9
2000	85.99	0.81	77.70	0.70	0.96	9
3000	88.21	0.84	72.38	0.81	0.88	9
4000	87.27	0.83	70.83	0.80	0.86	10

5000	88.89	0.86	73.05	0.82	0.91	10
6000	89.33	0.88	78.18	0.84	0.92	9
10000	88.02	0.86	73.33	0.84	0.89	10
12000	88.47	0.88	78.77	0.84	0.92	10
Best-Model	**89.59**	**0.88**	**77.62**	**0.85**	**0.91**	**9**



(a)



(b)

Fig. 5 Training progress charts for YOLOv3

Figure 6 illustrates the precision versus recall curve of the obtained values for the trained YOLOv3 detection model.

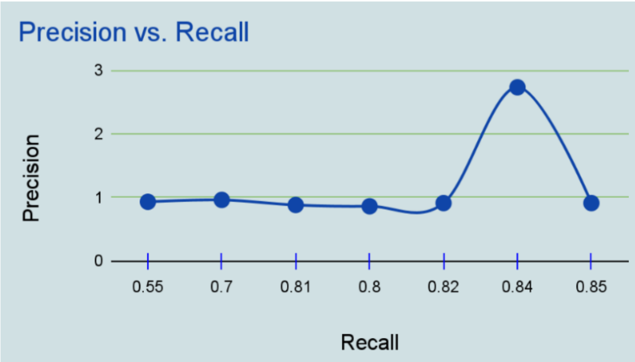


Fig. 6 Precision versus Recall curve

4.3. Training outcome of YOLOv4

The training parameters were customized exactly in the same way as for YOLOv3 for the new dataset.

Tables 4 and 5 give the trained model outcomes at a particular iteration. In this, iterations have also been increased up to 12000 to get the best-performing model.

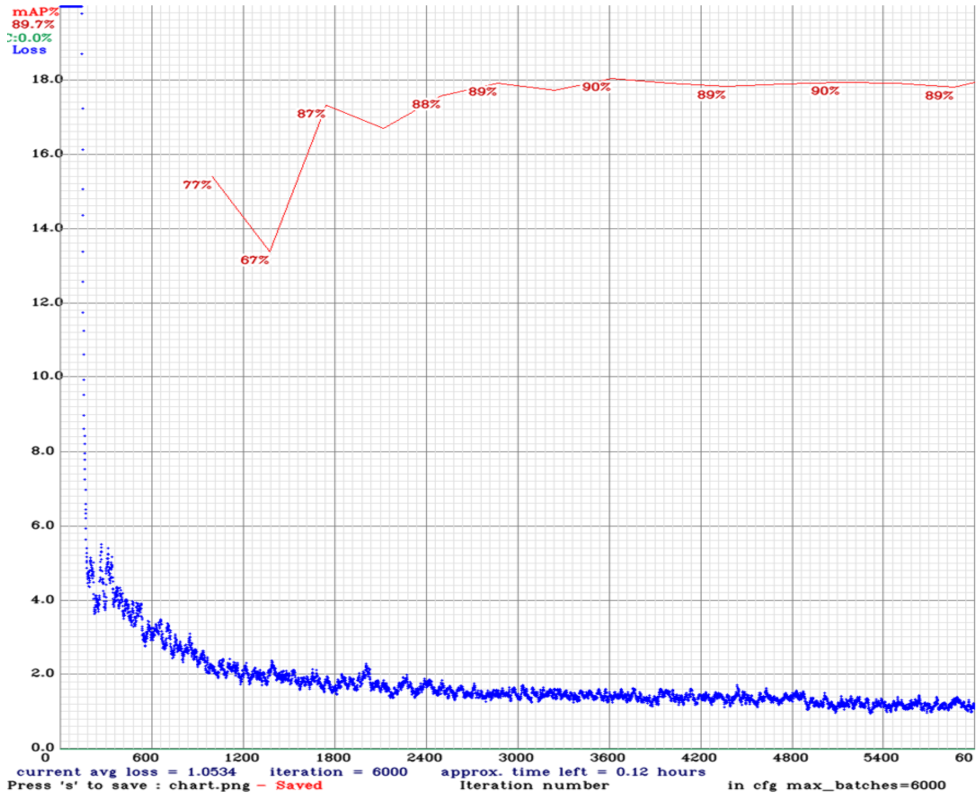
Figure 7 (a) displays a training progress chart for 6000 iterations, whereas figure 7 (b) gives a training progress chart for 6000 to 12000 iterations.

Table 4. Trained model outcomes at a particular iteration

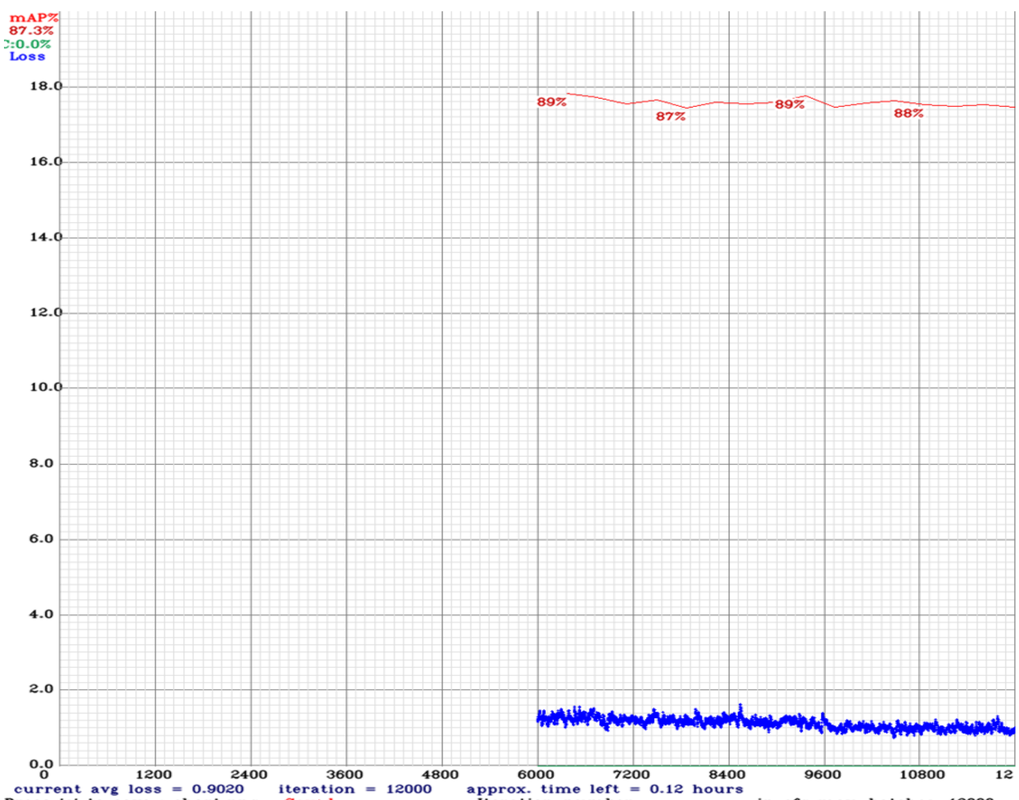
Trained model at a particular iteration	Average precision in %			True Positive (TP)	False Positive (FP)	False Negative (FN)
	Tree-roots	Plastic	Grease			
1000	70.27	89.18	71.55	1004	134	536
2000	77.16	93.13	88.28	1156	74	384
3000	79.49	95.53	92.79	1244	118	296
4000	80.33	94.23	94.15	1270	124	270
5000	79.59	95.34	94.32	1283	131	257
6000	79.25	95.34	94.38	1283	127	257
10000	75.65	93.73	92.37	1284	139	256
12000	75.73	93.72	92.46	1299	126	241
Best-Model	**81.55**	**95.39**	**93.44**	**1267**	**110**	**273**

Table 5. Trained model outcomes at a particular iteration

Trained model at a particular iteration	Mean Average Precision in %	F1-score	Aver. IoU in %	recall	Precision	Detection Time in seconds
1000	77.00	0.75	66.41	0.65	0.88	18
2000	86.19	0.83	74.25	0.75	0.94	18
3000	89.27	0.86	76.67	0.81	0.91	18
4000	89.57	0.87	75.82	0.82	0.91	18
5000	89.75	0.87	77.78	0.83	0.91	18
6000	89.66	0.87	78.24	0.83	0.91	18
10000	87.25	0.87	77.54	0.83	0.90	18
12000	87.30	0.88	79.30	0.84	0.91	18
Best-Model	**90.13**	**0.87**	**76.80**	**0.82**	**0.92**	**18**



(a)



(b)

Fig. 7 Training progress charts for YOLOv4

The precision versus recall curve of obtained resulting values for the trained YOLOv4 detection model has been revealed in figure 8.

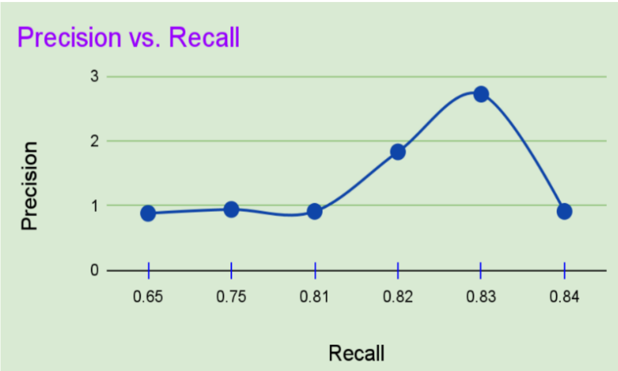


Fig. 8 Precision versus Recall curve

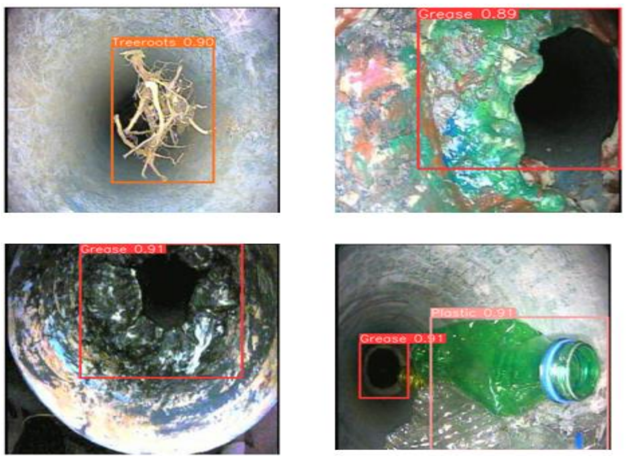


Fig. 9 Detection Results for mentioned sewer blockages types

Figure 9 shows the imagistic detection results for mentioned classes of sewer blockages in real-time states.

5. Hardware Design

5.1. Central Frame

The central frame is a major part of any navigation system. The central frame carries the automotive system's external load, including its weight. The central frames have been modelled in Catia V5 R21 ED2 version. A semi-integral frame involves a half-frame fixed in the front end, and the front suspension is mounted. It is used due to its flexibility in replacing damaged sections without requiring complete robotic disassembly [7]. Three crawlers in 120-degree angle configuration have been attached to the central frame.

5.2. Revolute joint mechanism for Left-Right Rotation

Revolute joint rotating in single axis consists of one degree of freedom kinematic pair and utilized repeatedly in devices and automotives [8]. It is applied in a semi-integral frame, as shown in figure 10. The revolute joint mechanism uses a 60 kg cm metal gear servo motor.

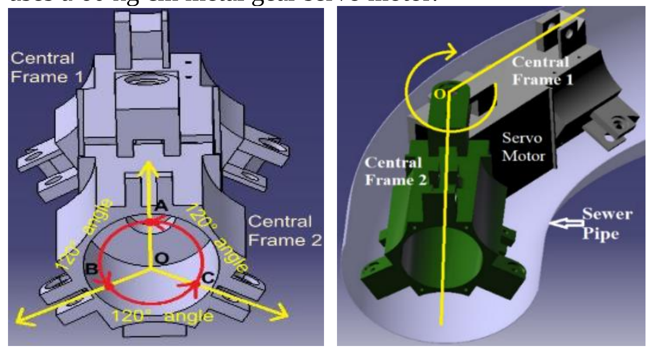


Fig. 10 Up-view CAD Model of Central frame and Rendering view in Sewer pipe

5.3. Parallel linkage mechanism

A four-bar linkage mechanism is used in the proposed system to transmit motion. The parallel motion linkage is a four-bar linkage mechanism in which opposite sides of the parallelogram ensure that input and output motions remain parallel [9], [15].

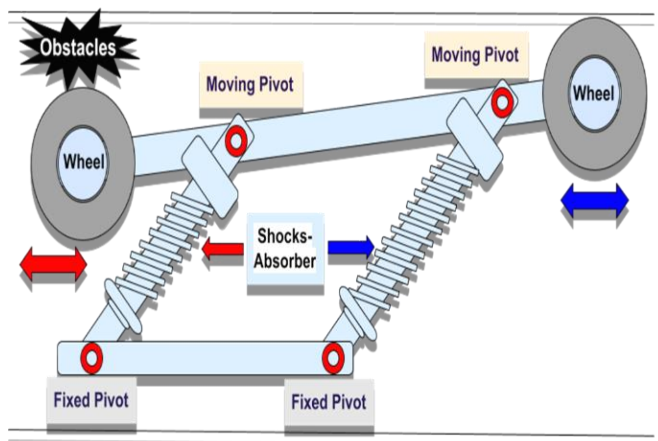


Fig. 11 Four bar parallel linkage mechanism with movement

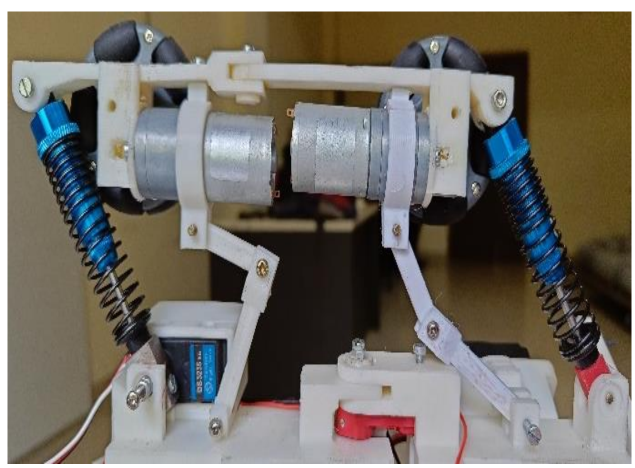


Fig. 12 Implemented four-bar parallel linkage mechanism

The parallel linkage mechanism helps the system to navigate with wall press type in the slippery surrounding. The proposed prototype has three independent crawlers moving with the help of servo motors and a pair of six wheels.

5.4. Gear Box

It has a single start worm of 20-degree pressure angle and an axial pitch of 4mm, whereas the worm wheel comprises 10 mm wide 13 helix teeth [10], [14]. Here, a radial ball bearing is used to reduce friction and maintain the rotating shaft's correct position.

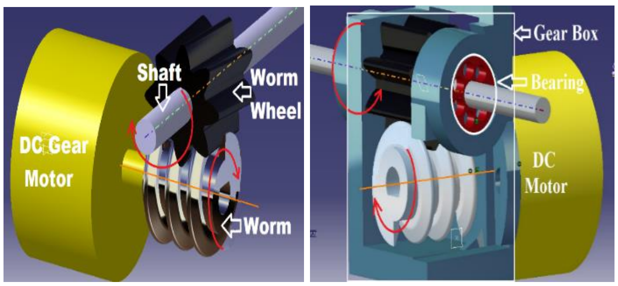


Fig. 13 CAD model and Rendering image of worm wheel gearbox

5.5. Cutter

The double-sided serrated flat root saw blade and round wire corkscrew are made of alloy steel, which have been employed for cutting obstructions after detection [11].

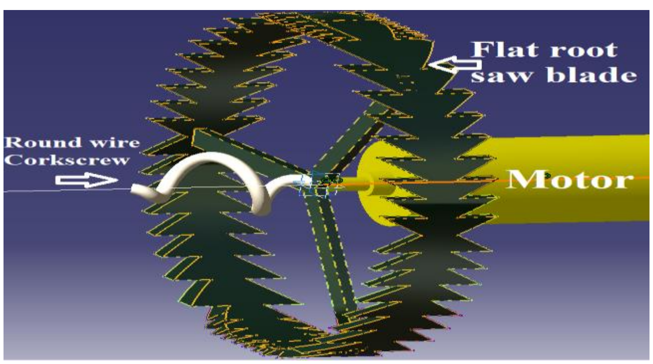


Fig. 14 Cutting Tool

6. Conclusion

This paper presents a robotic platform for identifying and removing common obstructions such as tree roots, plastics and grease in buried sewers.

A newly created S-BIRD dataset was used to train AI detection models, which delivered 89.59% AP (Average Precision), 0.85 recall, and 77.62% Ave. IoU for YOLOv3 while 90.13% AP, 0.82 recall, 76.80% Ave. IoU for YOLOv4 in the task of detecting sewer blockages. It is noticed that the detection time of YOLOv3 is less, i.e., half that of YOLOv4.

The cutting tool, central frame, parallel linkage mechanism, and crawler modules were designed to function in the robotic sewer framework based on their needs.

The developed robotic system will be a significant addition to the robotic sewer field due to the ability to detect the major sewer blockages mentioned by a trained detector using a new training dataset and remove sewer blockages by cutting tools without employing water pressure like Jetting machines.

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