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A Comprehensive Review of Obstacle Detection and Distance Measurement Techniques in Rail Transport

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***Abstract*— Railway transportation is the most used means of travel of the people. In India around 2.4 crore people travel by train on daily basis. As train network is expanding, accidents on railroad are also increasing. Most of the accidents happen because of the drivers lack of attention. The aim of this paper is to study the various approaches use to detect the objects on the track. More research is yet to be done in this area. To detect the obstacle on the railway, track many researchers used various techniques to detect and classify the objects (obstacles). Small number of them worked on obstacle detection as well as distance estimation between the obstacle and train car. Initially work done on, to find the cracks on railway track by using hardware device like sensors. Later research expanded by using supervised learning and unsupervised learning. Earlier both the approaches have been joined. i.e. a system made using software and hardware (like sensors, camera, radar etc.). Therefore, this study going to explore the techniques used by various researchers to detect the obstacles on the railroad and estimate the distance between obstacle and loco Pilot.**

***Index Terms*— Supervised Learning, Unsupervised Learning, Sensor, Radar, Obstacle Detection.**

I. INTRODUCTION

As Indian Railways are growing rapidly, the accidents also increasing consequently. Indian railways stretching across with running track length of 99235 Kms and serving 23 crores passengers on daily basis [2]. Increasing demand of fast transportation resulted growth of railway track network countrywide. According to NCRB (National Crime Records Bureau) report state that more than 1 lakh train related deaths were reported between 2017 to 2021.Reason behind the majority of the accidents is inappropriate monitoring of railway tracks resulted collision between trail and obstacle like human, animals and vehicles on the railway track as well as on level crossing. Appropriate monitoring may result in labour, which in turns means an incredible increase in maintenance expenses for the government. Many experiments have been conducted on using a deep learning approach [11]. To monitor train track in order to reduce the amount of human interaction. In this paper, we categorize the study in aspects like only obstacle detection and obstacle detection with distance estimation. As research has been taken place to reduce the accidents on railway tracks but in our perspective that not done up to that context. Hence, we elaborating the study taken place for this purpose. In earlier studies various techniques were used such as computer vision by using camera, Sensors, Radars, LiDAR's, Unmanned vehicles, IoT etc. Every technique has its own advantages and disadvantages. In order to stop the train a safe distance needed and weight of the train also matters.In recent years, the researchers focused on to use supervised AI based technique.

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Supervised learning utilizes a machine learning procedures to learns from labeled data [6]. Unsupervised learning uses machine learning to learn from unlabeled data [12]. Intension of this work is to analyzed the various approaches used in their proposed work, what are the advantages and what are the limitations. Furthermore, our objective to categorize the study according to techniques (device) they have used, functions they incorporate etc.In this study, we give an overview of the most advanced use of autonomous railway infrastructure surveillance and how it could be used in self-governing smart railways. We anticipate that this survey will yield significant perception for analyst in the domains of computer science and transit.

II. EXISTING SECURITY METHODS

A. KAVACH

KAVACH is an autonomous train protection (ATP) system developed by Indian railways (IR) to enhance railway safety by preventing train collisions, over speeding and human errors. It assists loco pilot driver by displaying real-time signaling information and ensures safety in high-speed train operations.

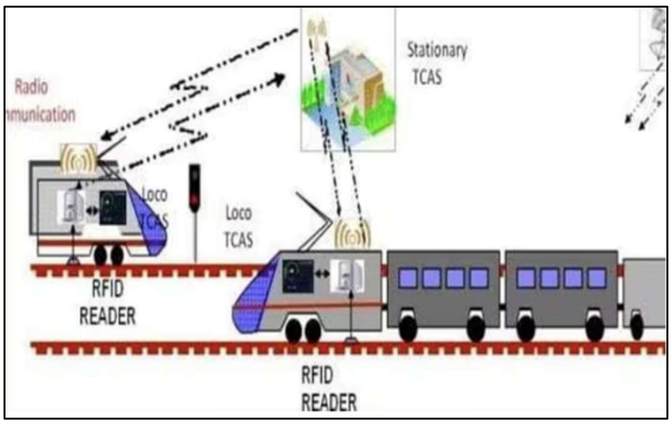

Figure 1. KAVACH system

KAVACH uses radio communication between station interlocking system and locomotive via RFID tags on the track. The system continuously monitors train movements, applies brake when necessary and sends data to a centralized monitoring system.

Applications of KAVACH system
Prevention of SPAD (Signal passing at Danger)
KAVACH continuously monitors the trains movement and compares it with signal aspects and permissible speed limit. If loco pilot fails to acknowledge a danger signal, the system automatically applies brakes to bring the train to a half.
Train Collision Avoidance Mechanism
KAVACH detects the positions of other trains on same track using RFID (Radio Frequency Identification) tags place along the railway trains. Automatic Speed Control and Breaking The system continuously supervises the trains speed profile, checking against pre-programmed gradient, curves and track. If the loco-Pilot exceeds the speed limit, KAVACH applies automatic braking gradually to bring the train back to a safe speed.KAVACH system is unable to detect the intruder on railroad it only detects weather the train is coming on the same track. Another limitation is its deployment cost. To deploy KAVACH 50 Lakhs required per kilometer which is very huge like country India.

B. Practical use-case

To detect animals on railway track AI-based camera were used. One of the examples is, in Odisha, Rourkela Forest division is famous for elephant, but lots of accidents happened in this forest division. To avoid the mishap with animals AI-based (Thermal image enabled) camera have been deployed. In this system AI- camera detected the movement of some elephants on the track. The system alerted the forest department control room and the same conveyed to the railway department. Resulted a cargo train made halt for 30 minutes allowed them pass track.

Figure 2. Elephants detected in railway track

II. LITERATURE REVIEW

This section provides comprehensive study or methodology used in respective research papers

A. Vision-based obstacle detection method

As Artificial Neural Networks evolved, researchers have looking into deep learning- based perimeter intrusion detection techniques. In [1] used YOLOv3 to detect obstacles on railway track. Authors have compared and showed how YOLOv3 is better than YOLOv2. The authors of [2] proposed FR-NETS, a kind of neural network in order to to detect obstacles in real-time. By calculating dimensions, system classify then as an obstacle or not. In [3] authors proposed an active long-range intrusion observation system with a adjustable high focal length camera. Instead of training the model with a dataset, it learns to recognize the railway environment and ignores everything else. The authors in [4] introduced, a memory mechanism-based multi-domain few-shot continual learning algorithm. This method combines few-shot learning with continual adaptation to varying obstacles, reducing catastrophic forgetting and enhancing model generalization. The Authors in [5] presents background subtraction approach tailored for moving cameras.

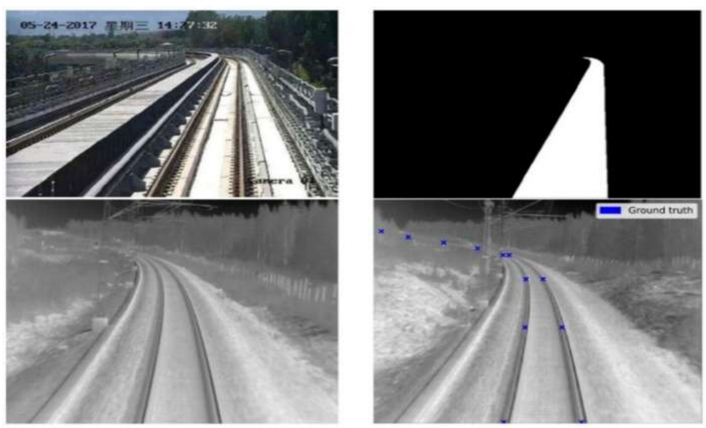

Figure3. AI based rail track detection

Above diagram shows raw captured image segmented mask, processed and prediction of track image. To detect obstacle, temporal alignment used in which frame-by-frame correspondent between current and reference image sequence are between present and source image sequences are established. Next spatial alignment is used, and at last Image subtraction is used in which normalized vector distance and radial reach filter subtraction techniques are integrated to detect object. The authors of [6] implemented Convolutional Neural Network (CNN) model called MobileNetv2 which achieved a 97% accuracy rate in detecting obstacles.

After training of the model, they have given result of MobileNetv2 outperforms other methods. The authors in [8] presented 2-D singular spectrum Analysis (SSA) to decompose images into useful components which are then applied to a deep classifier Network for obstacle recognition.The study presented in [10] done specially for passenger detection on or near the track. The authors evaluated several object detection algorithms and found that YOLOv5 showed the best result. The authors in [11] proposed a Single Shot Multibox Detection (SSD)

MobileNet Model Implemented on a Raspberry Pi to recognize and categorize objects in real-time video feeds. The authors of [14] authors have imported a real-time track area detection method using deep learning called semantic segmentation. Also does track line continuity analysis to identify the object. Edge detection algorithm is used by the authors in [15], by segmenting the railroad section and detecting edges within each, the algorithm models the tarin area effectively. The authors of [16] proposed feature extraction with attention mechanism using spatial pyramid pooling (SPP) and customized residual blocks to detect the object.

Figure 4. windows-based structured search for obstacle through the discovered railway tracks and digitally added static item and its spotting.

In the above image green bounding boxes shows railway track at left image and at right image one obstacle is marked with the red bounding box. and The authors of [17] presented two stage object detection on railway track. In stage one model takes railway images and in second stage if an image is classified as intruded. It is passed to the foreign object detection network (YOLOv3) to identify and locate objects. The study evaluates various deep neural networks models for recognizing obstacles on railway tracks using ariel images captured by Unmanned Areial Vehicles (UAV). Authors proved SSD MobileNet and faster RCNN models have the highest accuracy as compared to others in [18]. the authors of [19] discusses a method for improving the localization of railway vehicles using mono focal video camera. The algorithm estimates the track geometry and detects turnouts by tracking the rails in camera images using Kalman Filter. The authors of [20] provided a method for determining the danger zone based on the train's current speed, and the system notifies the driver if an obstruction is detected. The authors of [23] proposed the system which detects, separate and track moving objects in the level crossing using video analysis. The system uses a hidden Markov model to estimate ideal trajectories to avoid the dangerous situations and the dempster-Shafer data fusion techniques is used to evaluate the level of risk. The authors of [24] used two-fold process in which stage one does binary semantic segmentation to extract rail tracks from the background. Where as in stage two self-supervised learning techniques is used to detect anomalies. The authors of [25] proposed a method for generating high-quality and realistic images of intruding objects in high-speed railway scenes using Improve Conditional Convolutional Generative Advercial Network (C-DCGAN). In [26] authors Introduced anti-collision system for light rail vehicles. The system consists of three cameras, a Synch Box for synchronization and a controller. It processes images to identify tracks, compute future trajectories, detect obstacles and estimate collision risk. The authors of [27] presented a method to enhance human detection accuracy using histogram of Orient Gradient (HoG) features combine with optical flow estimation. The authors of [28] presented FB-Net which consist of Depth-wise point wise convolution, priory module and feature fusion module to object detection in railway traffic scenarios. The study presented in [29] [30] used faster RCNN framework which integrates region proposal generation into a deep learning model. YOLO formulations are given below.
YOLO formulates object detection as a single regression problem:

$$\hat{y} = f_\theta(I)$$

Where:

I= input image
f_θ= CNN with parameters θ
$\hat{y}$= predicted bounding boxes, objectness, and class probabilities
The input image is divided into an $S \times S$grid:

$$I \to \{G_{ij} \mid i, j \in [1, S]\}$$

Each grid cell predicts:
B bounding boxes
Objectness score
Class probabilities

B.Methods Based on obstacle Detection and estimation

Most of the researchers have done work on obstacles detection, few of them worked on distance estimation while considering the safety of the train, distance is a crucial factor. it not only estimates the distance but the safe distance should be there so that locomotive driver will able to apply the brake. It depends on the weight of the train and the distance between intruder and locomotive. For estimating the distance, a separate new method has to be combined with the object detection method.

Figure 5. DisNet approximate of distances to obstacle in a railroad site from the RGB camera image

As shown in the above figure objects like car, persone 1, person 2 and person 3 are detected on or near railway track in the left image and in right image person detected as obstacle on railway track. The authors of [37] proposed two approaches, first for segmenting the railroad and another to detect the object and estimate the risk (distance). To achieve the result camera images used as a input to a model. D-LinkNet model is used to segment the rail track area. For detecting obstacle semantic segmentation network used to segment track by using Mobilenetv3 in [39]. Also, if pedestrian invading the track Resnet50 based regression network to forecast the distance is used. In [40] ultrasonic sensors, ESP32 camera, Arduino board, and YOLOv3 CNN pre-trained on COCO dataset used by the authors. Combination of them used detect the obstacle and estimate the distance between them. The authors of [4] introduced Rayleigh wave sensing with a laser vibrometer to detect obstacle on railway track. The study shows if rocks and timbers dropped on track a laser vibrometer (sensors) detects dropped obstacles distances up to 2 Km. The authors of [42] proposed a system that integrates on-board object localization. To cover curve used UAV. The on-board system uses thermal cameras and deep learning models like CenterNet for object detection and DisNet for distance estimation.The study presented in [43] applications Regression network based on ResNet18 calculates the gap between the train and detected intrusion. In [53] authors proposed instance segmentation by using YOLOv8 to detect object and use pinhole camera model to predict the distance between target and train. Basically, system is made for turnout areas using monocular vision. In [54], authors presented DisNet method. DisNet is trained on 2000 features with ground truth distance from LiDAR. The System uses single camera for railway based on machine learning application. Distance estimation done by using normalized bounding box dimension and average dimension of the object class. The authors in [55] proposed DistFormer method which uses local and global features for accurate distance estimation. The model combines CNNs and transformer layers to blalnce local and global information.the authors of [56] presented vision-based method for detecting and tracking a moving fixed-wing UAV using monocular camera. YOLO (You Only Look Once) is used to detect object and Kalman filter is used to minimize the distance error. The authors of [57] introduced pose estimation DNN to estimate object orientation to improve distance estimation using object detection output (Bounding Boxes).

Stereo Vision–Based Distance Estimation

The most classical and accurate vision-based method when two cameras are available.

$$Z = \frac{f \cdot B}{d}$$

Where:

Z: Distance to obstacle (meters)

f: Camera focal length (pixels)
B: Baseline distance between cameras (meters)
$d = x_L - x_R$: Disparity between left and right images

C. IOT Based Obstacle Detection

The authors of [44] presented a microcontroller to integrate an LCD, buzzer and ultrasonic and integrated (IR) sensors to detect obstacles and estimate distance. In [45] authors presented 2D and 3D object detections. The 2D branch extract texture features while 3D branches capture spatial structure. Distance estimation using a 3D monocular detection algorithm done. In [46] authors proposed the system uses ultrasonic sensors to detect obstacles on railway track. the authors of [47] presented a system to detect obstacles on railway track using IoT and machine learning. The authors in [48] introduced the system fuses transformation between Lidar and cameras. A modified SSD network is trained to detect potential obstacle and Lidar is used to distance estimation.

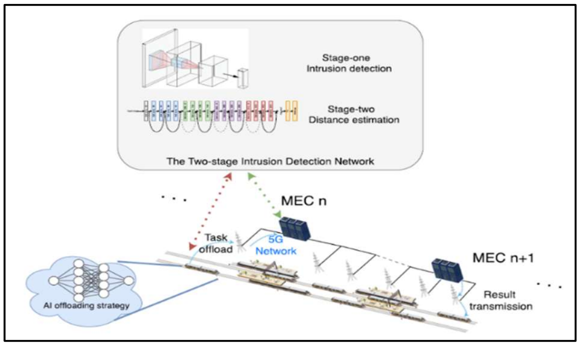

Figure 7. AI and IoT based obstacle intrusion detection system

In the above figure use of IoT is given where MECs are used through out the track connected using 5G network. In this architecture two stages are used. In first stage intrusion is detected and in second stage the distance is calculated between train and the intrusion. Below the formula for data acquisition for sensor is given.

Sensor Data Acquisition
Visual data captured by IoT camera:

$$I_t = \Phi(D_s, t)$$

Where:
I_t: Image/frame at time t
$\Phi(\cdot)$: Sensor acquisition function
In [49], the authors used various sensors like vibration sensors, IR sensors, Load sensors. PIC microcontroller to detect obstacle on railroad and estimate the distance between obstacle and locomotive. The authors of [50] proposed 4D radar, DBSCAN clustering algorithm for range detection and CBAM to enhance obstacle recognition. The authors of [51] combines GNSS with odometers, Inertial Measurement Unit (IMNs) and RFID balises to enhance localization. The authors of [52] presented methods based on wild life safety. System uses ultrasonic and proximity sensors connected to Arduino board. The sensors detect the presence of animals and activate buzzer to scare them away.

TABLE I. COMPARATIVE ANALYSIS OF OBJECT DETECTION TECHNIQUES

Technique	Working Principle	Accuracy	Speed (FPS)	Suitability for Railway Obstacle Detection
R-CNN	Region proposals and CNN	High	Very Low	No
Fast R-CNN	Shared CNN features	High	Low	Limited
Faster R-CNN	RPN and CNN	Very High	Medium	Offline analysis
SSD	Multi-scale feature maps	Medium–High	High	Moderate
YOLOv8	Anchor-free detection	Very High	Very High	Highly suitable
YOLOv8-seg	Detection and pixel-level masks	Very High	High	Highly suitable
Vision Transformer (ViT)	Global attention	High	Low	Limited
Hybrid (YOLO and LSTM)	Spatial and temporal learning	Very High	High	Highly suitable
Fusion-Based DL	Camera and depth and tracking	Very High	Medium	Highly suitable

III. Discussion

This literature review explains the various implementation of railroad monitoring systems like vision- based obstacle detection, sensor-based obstacle detection, IoT Based obstacle detection as well as distance estimation. The review of current literature on railway track obstacle detection and distance estimation discloses considerable progress in applying advanced technologies such as computer vision, deep learning, LiDAR, and sensor fusion. These systems aim to tackle critical safety challenges faced by modern railways due to the presence of unexpected obstacles on the tracks. Various studies have investigated object detection methods using convolutional neural networks (CNNs), particularly YOLO, SSD, and Faster R-CNN, which have exhibited strong performance in identifying track intrusions. While high detection accuracy is feasible under controlled conditions, challenges remain in ensuring consistent performance across diverse environmental scenarios—such as low lighting, occlusion, fog, and rain. This highlights the importance of comprising multi-modal sensing (e.g., infrared cameras or radar) to improve robustness. Distance estimation techniques reviewed in the literature especially include stereo vision, time-of-flight (ToF) sensors, and ultrasonic sensors. Stereo vision is worthwhile for real-time distance measurement but is limited by depth propose accuracy at longer ranges. LiDAR offers high precision and reliability, but at a higher cost, which may hinder widespread implementation in resource-constrained settings. Several papers highlight the importance of real-time processing capabilities, especially for incorporation with autonomous or semi-autonomous train control systems. However, computational complexity and power consumption present practical limitations for edge deployment. Research is taking place into lightweight models and embedded AI solutions to address these limitations. Another crucial observation is the lack of large-scale, annotated datasets specific to railway environments, which alter the generalizability and training of AI models. Future research should prioritize dataset development and standardization for evaluating. In summary, while promising solutions have been proposed and authenticated in experimental settings, real-world deployment demands greater robustness, lower latency, and cost-effective scalability. The blending of multiple sensing technologies, model optimization, and collaboration between academia and industry will be critical for advancing this domain.

IV. Conclusion

This review has surveyed the state of research in railway track obstacle detection and distance estimation, highlighting the remarkable development and ongoing challenges in the field. The integration of computer vision, machine learning, and sensor technologies has opened new possibilities for enhancing railway safety by enabling real-time monitoring and early warning systems. While deep learning-based object detection approaches such as YOLO, SSD, and Faster R-CNN show high potential in accurately identifying track obstacles, their reliability is still affected by environmental conditions and the need for domain-specific training data. Similarly, distance estimation methods like stereo vision, LiDAR, and ultrasonic sensors offer different degrees of accuracy, cost, and implementation complexity. In spite of the progress, real-world deployment remains bounded due to challenges in model robustness, computational requirements, sensor fusion, and the lack of standardized datasets. Future research should concentrate on developing lightweight, efficient models, improving detection under adverse conditions, and promoting the creation of large, annotated railway datasets. In conclusion, railway obstacle detection and distance estimation technologies are advancing rapidly, and with continued interdisciplinary association and technological refinement, they have the capability to remarkably improve railway safety and operational efficiency in the near future.

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