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Automated Traffic Light Signal Based On Railway Obstacle Detection

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Abstract: **The exponential development of artificial intelligence and computer vision has opened up a unique and never-before-seen opportunity to increase the safety of railways. This project is about a complete automated railway signalling system based on YOLOv11 (You Only Look Once) deep learning architecture that helps to detect the obstacle on railway track with high accuracy within a fraction of seconds. By continuously processing high frequency video feeds from strategically positioned cameras, the system detects all kinds of dangerous objects with high confidence - humans, animals, vehicles and debris. Upon detecting a hazard, through an integrated cloud infrastructure, the system communicates instantly to a signal receiver unit that is Android based, triggering the corresponding traffic light to turn to a Stop signal, indicating a red light.**

Keywords: YOLOv11, Railway Obstacle Detection, Deep Learning, Real-Time Detection, Edge Computing, Automated Signalling, Firebase Cloud Messaging.

I. INTRODUCTION

Indian Railway systems are very important for transportation in our country. Despite their critical importance, railway networks are enormously vulnerable to one type of accident which is in principle completely preventable: collisions caused by unexpected obstructions in the track. Objects as diverse as fallen trees, landslide debris, stranded animals, abandoned vehicles or trespassing individuals can have disastrous effect on a high-speed train if there are no appropriate warnings in place.

In existing system, we used human workers to monitor and observe the railway tracks for any obstacles. While these methods do offer a base-level of safety, they are necessarily limited in scope, speed and reliability. Manual inspections cannot provide continuous train surveillance and electronic sensors are intended mostly to detect the conductive presence of train wheels, being blind to any other type of non-conductive obstacle.

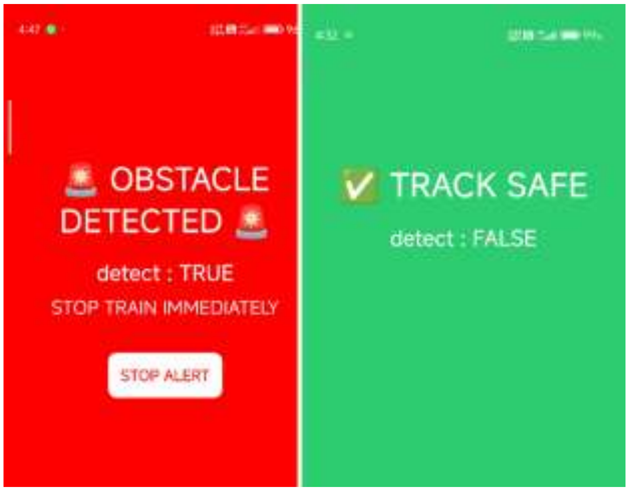
The development of powerful models based on deep learning methods in computer vision offers a very exciting opportunity to overcome these deficiencies. Models, like YOLO, have shown poor only capability in locating and classing various types of objects in a single video frame, at frame rates remarkably faster than any human observer. The architecture YOLOv11 used in this project is the state of the art in single shot detection with better results in terms of mean Average Precision (mAP) and lower inference times than its predecessors.

Our research mainly uses YOLOv11 model to detect obstacles on railway track and sends automated signal to the traffic system. The architecture shifts the centre of gravity of safety decision-making directly to the edge, where a series of cameras, set up along the track, help to constantly scan for dangers.

After detection of obstacle the system sends the response to the cloud where the software of traffic system is merged so that the response reaches the traffic system and the response is conveyed to trains that transporting in that area.

A. Project Objective

1. To develop a large dataset of railway track images captured in different environmental conditions (rain, fog, night) in order to model with robustness in it..
2. To train and fine-tune the YOLOv11 model in such a way that it is applicable for railway relevant obstacle classes that has the lowest possible inference latency.
3. To create a smooth software link between the exit of the AI detection and the actual hardware-controlled railway signalling lights.
4. To be sure that the system will go to Stop (Red) signal as default in case of any hardware failure or a high uncertain detection.
5. To release the trained YOLOv11 model to high-performance edge computing modules in order to ensure localised processing and remove the cloud-dependency latency.
6. To apply a strong and encrypted communication protocol between the AI processing unit and traffic control interface to thwart signal interference or to tamper with the system.


🚨 OBSTACLE DETECTED 🚨

detect : TRUE

STOP TRAIN IMMEDIATELY

✅ TRACK SAFE

detect : FALSE

Fig 1.1 Object Detection Alerts

B. Project Motivation

1. The older-style block-section occupancy sensors are only aware of the presence of train cars through an electrical circuit or axle counter, but do not detect non-conductive objects such as rocks, trees, and plastic debris.
2. Variable conditions and natural conditions cause less visibility, this research improves obstacle detection in low visibility.
3. Heavy trains take a long distance to stop; an object has to be identified kilometres in advance. This research identifies obstacles and informs system advanced from the location.
4. Training models in various challenging conditions that improves accuracy.
5. This project works in real time so that it helps railway system efficiently to convey the obstacle by traffic system.
6. The increasing number of railway accidents requires new innovative, automated methods, and there is a definite need both in society and technology to avoid train accidents and to save human life.

II. RELATED RESEARCH

The last decade has seen much research on the topic of automated railway obstacle detection. Research is shifting from traditional sensor-based methods to more advanced computer-vision approaches. Each new wave tackles the limitations of the past, unlocking fresh possibilities.

Early experiments focused on background subtraction, optical flow, and texture-based feature detection. While these methods showed promise in controlled lab settings, they were super finicky about lighting changes and needed a lot of manual tweaking. focused on background subtraction, optical flow analysis, and texture-based feature detection. They were highly unsuitable in the highly variable conditions experienced when deployed in the real world, as their reliance on hand-crafted characteristics restricted generalisability, and could not cope with the full conditions expected in a real-world railway environment.

The moment deep convolutional neural networks (CNNs) showed up was a real game-changer. Work based on CNN and R-CNN models proved a significant increase in detection accuracy. These however were disadvantaged by the fact that they were computationally expensive and had low real-time capabilities, so they were not easy to run on edge devices. Their dual-process detection pipeline added time lag that made it unsuitable to the strict response time necessary to railway safety.

Studies using YOLOv3, YOLOv4, YOLOv5, YOLOv7 and YOLOv8 models provided strong proof that single-stage detection had the ability to scale to speeds and accuracy needed to be put in practice, and mAP scores frequently topped 85 per cent on conventional railway obstacle datasets. Nonetheless, both generations had certain drawbacks: YOLOv5 failed to provide accuracy when there was low light; YOLOv7 was characterized by high computation complexity, thus wasting edge equipment; and the implementation of YOLOv8 continued to experience poor accuracy in complex railways conditions with a strong occlusion factor.

The current project is based on this literature by the use of the YOLOv11 architecture that mitigated most of the shortcomings previously discussed by having a better backbone network, a better feature pyramid structure, and more efficient anchor-free detection head. Trained specially on a railway-curated dataset which explicitly incorporates challenging environmental conditions, not only in the detection side of tasks, but also by incorporating the model output within a complete end-to-end signal actuation pipeline, the work goes beyond the detection-only focus of most previous studies to provide a complete and deployable safety system.

SYSTEM	PRECISION (%)	RECALL (%)	mAP@0.5 (%)
YOLO v11	97.6	97.2	97.4
YOLO v10	95.7	94.3	95.5
YOLO v9	94.4	92.1	94.2
YOLO v8	93.7	90.6	93.5
YOLO v7	92.5	90.3	92.1
YOLO v5	91.6	89.6	91.4

Table 2.1 System performance comparison

A. *Drawbacks of existing system*

Material Blindness of Traditional Sensing It is the most basic limitation of the current infrastructure of rail field safety since it does not possess the capability to sense non-conductive objects present on the rail. Track circuits and axle counters which are the most common sensing technology used in most railway networks are working based on a principle that the electrical conductivity between the train wheels and the steel rail are detected. Such a design allows them to be completely successful in determining the existence of a train in a block section, but not categorically sensitive to any object that is not an electrifying contact. The rocks, wood fragments, plastics, bone carcasses of the animals and above all human beings will not be detected by the systems at all. This provides a deadly and systematic loophole in the safety measures, with the most dangerous types of obstruction in the tracks being completely inaccessible to the main safety machinery, and trains proceed at top speed into dangers that the system is unable to detect.

Functional Narrowness and Limited Scope Akin to this disadvantage is a fundamental functional narrowness of current systems. Axle counters and track circuits were entirely designed with the goal of controlling train on train collisions through block section occupancy. They are traffic control devices and not comprehensive track safety mechanisms and such structural design philosophy implies that the whole range of external obstacle hazards are not even inside their range of functioning. A few of the modern implementations also augment these systems with ultrasonic sensors, but they also have prominent limitations such as high cost of installation, the limited range of usage, and high vulnerability to atmospheric interference (thick snow, dense dust clouds, and extreme temperatures, etc.). What is created is a patchwork system of safety where there are significant blind spots, and where operators must make do with a variety of various purpose tools, none of which, with all added up, offers the complete safety coverage that a railroad track is subject to.

Sensitivity to the environment and Performance degradation the currently available sensor-based railway safety systems have very high-performance degradation in the same environmental conditions that are most strongly required to perform reliably. The ultrasonic and simple proximity sensors are very vulnerable to the atmospheric interference effect: strong rains spread acoustic waves, fog sets off sensor measurements, and dust or ice are fixed on the sensor surfaces will make the system totally useless or produce continuous false positive alerts which will interfere with the operations. Human operators that is the last line of defence in the most of actual systems is greatly debilitated by poor visibility conditions like darkness in the night, fog, heavy rains and track bends which block the line of sight. The compounding impact is that existing systems are deemed the least dependable at the very time that trains are on the most dangerous routines thus an unhealthy inverse connexion between environmental difficulty and system efficiency in terms of safety resulting in a case of a life-threatening inverse correlation that has directly been identified as the reason behind many major-scale railway disasters.

Human Dependency and Reaction Time Limitations The main weakness of current systems that can still be a source of structural intractability lies in their inherent reliance upon human operators as the most important source of real time hazard detection and response. Cognitive fatigue is experienced by train drivers who have to do a longer route or overnight, and their response time even when they are trained to respond with maximum speed cannot be anywhere near the milliseconds of response one automated system can give. Since a highly loaded train moving at a high speed might take several kilometres to reach a full stop, any delay in hazards identification as a result of human fatigue, distraction, or poor visibility directly equates to the fact that it is not able to stop in time. Divided attention and sluggish response are also similar between centralised control room operators who are monitoring numerous track segments simultaneously. The fact that this human visual and cognitive layer is used and forms the main and real-time safety mechanism of the existing system is thus a structural weakness that become more acute with an increase in velocity, frequency and geographical range of the rail networks.

III. PROPOSED METHODOLOGY

The suggested system is a wholesale architectural substitution of reactive and dependable on human senses safety structure by the proactive and automated AI-sensitive pipeline. It will be based on the YOLOv11 deep learning model that is deployed on edge computing devices at the trackside location that continuously processes live video streams of high-definition cameras. Its methodology includes five tightly tied phases: data acquisition and preprocessing, model training and optimisation, real-time obstacle detection and classification, propagation of events in a cloud and actuation of hardware signal.

The weaknesses that the proposed solution will deal with are far-reaching. The currently used Track Circuits and Axle Counters have a major disadvantage namely, material blindness, they do not recognise non conduct ATC hazards including rocks, wooden debris, or organic matter. They are designed to manage traffic, and not to ensure safety on the tracks holistically due to their functional narrowness. Systems involving ultrasonic sensors are highly sensitive to the condition of the atmospheric noise in the form of heavy snow or dense fogs or dusts, which leads to false positives or completely defeats the system. There are also critical constraints in sensor range, where the working range is too limited in high-speed rail which has braking ranges that are in kilometres.

The system proposed based on YOLOv11 has all these limitations covered at once. It can tell context as opposed to the conventional sensors, which do not offer any contextual information, hence the ability to differentiate the bird on the track and that of a human being. It spots hazards in a blink using super-fast video feeds and an automated pipeline no human reaction time needed, so it’s way quicker. By giving detections scores of confidences, the system is able to nullify minor levels of anomaly which would have resulted in unwarranted stoppage of emergencies as is the case in other less advanced systems. Moreover, its image processing feature enables it to operate during low lighting conditions where an eye of a human being cannot operate.

A. Benefits of proposed system

The following diagram is of an end-to-end pipeline of a smart traffic signal system that is driven by computer vision. It starts with the collection of data where the picture or video of traffic situations is collected by the use of cameras or pre-existing data. These raw inputs are subject to data preprocessing which normally involves cleaning, resizing, normalisation and augmentation that render the data training worthy. This is followed by data annotation where objects like vehicles, persons or lanes are marked in such a way that the model can learn how to identify these objectively. The labelled data undergoes processing and is obtained in the model training and evaluation step in which the current stage involves using a YOLOv11 object detection model. At this stage, the model is trained to identify and categorise traffic component and its accuracy and performance is tested. After training, it is implemented into a prediction system, which receives real-time camera feeds to identify traffic conditions (e.g. congestion levels or number of vehicles). These forecasts are forwarded to the cloud where they can be centrally processed, stored or advanced analytics. Lastly, the system is connected to a signal receiver which receives the output of the cloud and interprets it to give commands that the traffic infrastructure can act upon. Depending on the conditions detected, it dynamically manages or alerts the traffic signal like changing the time of the lights or sending a warning. This will form a feedback mechanism as real-time information will keep on enhancing the traffic flow and responsiveness.

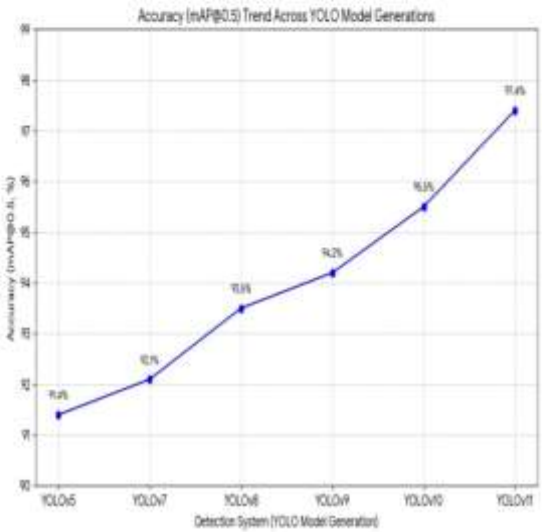


Fig 3.1 Yolo performance graph

B. Implementation Stages

1. **Data Collection:** This will involve obtaining different railway pictures and video clips, which encompass different obstacle situations as well as weather conditions, such as rain, fog and night.
2. **Data Preprocessing:** Image processing and optimization including resizing, and enhancement of image to generate quality and uniform data that can be used to train the model. Mosaic and colour jitter techniques as well as synthetic fog overlay method are augmented techniques to increase diversity in datasets.
3. **The training can be achieved through a model:** The shifts of the COCO-pretrained weights onto the YOLOv11 architecture can be trained as the model on real-life situations under varying lighting and occlusion levels to achieve real-time detection in these conditions.
4. **Obstacle Classification:** Post-processing: Non-maximum suppression and confidence thresholding to cheque detections and classify them as a human, vehicle, animal or inanimate obstacle with a connexion to the alert and notification system to implement real-time measures.
5. **Cloud API Deployment:** It deploys a set of RESTful endpoints to accept and synchronise real-time event-based data in the detectors that are deployed on the local edges. All events of detection are recorded in a central cloud database (Firebase or AWS RDS) to be distributed in real-time and audited in the long run.
6. **Android Service Integration:** Ther is an Android background service based on Firebase Cloud messaging that obtains the updates on obstacle detection on the particular noodle track.
7. **Signal Communication and generation:** A Bluetooth or Wi-Fi connexion between the Android receiver and the traffic light controller performs an immediate Turn Red command when there is a notification that an obstacle has been detected. In the absence of a regular heartbeat signal of the detection system, fail-safe logic is used, which switches to red.

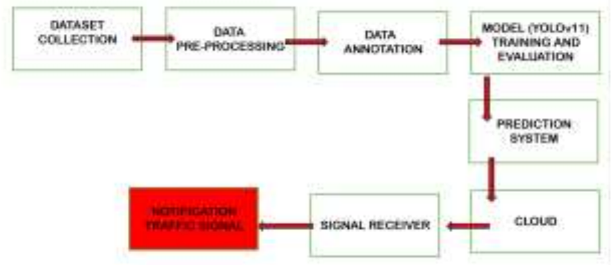


Fig 3.2 System architecture

The system architecture is built as a modular end-to-end pipeline with initial steps of collecting the datasets and then going to the preprocessing stage and annotation stage and then feeding to a trained detection model. Image data are annotated and curated with tools such as Roboflow, and create a successful labelling and versioning of datasets. The trained model which is based upon YOLOv11 is subsequently trained on the processed data to recognise and classify traffic signals. This sorted out flow gives quality input data and strong model performance in the appraisal.

An application layer, which is a web-based application, will be used as the user interface at the application layer, and it will provide the user with real-time interaction with the system. The trained model is built into the app to match dynamically and identify traffic light states either of the uploaded or live video streams. After the generation of predictions, they are relayed via a cloud-linked pipeline which is scalable and device accessible. The solution is lightweight, user-friendly and easy to monitor since it is a web-based deployment.

To support the backend connectivity, as well as live updates, the system will be linked to Firebase that will deal with data synchronisation between the prediction engine and the traffic signal control logic. The signal of the detected values is transmitted to a signal receiving element which processes the results and initiates the relevant responses, e.g. modifying or notifying the traffic light signal system. This cloud-based integration assures low latency communication and trusted performances in the real-world settings and so is apt to be used in the deployment of smart traffic infrastructures.

Lastly, the architecture has a notification system which reacts to the observed traffic conditions and allows the control of the traffic lights intelligently. The system is an effective, highly scalable, and automated traffic light monitoring and decision-making system by integrating deep learning, cloud computing, and a web-based application written in Stream lit and linked to Firebase and Roboflow. Besides, a native mobile integration layer is added which is enabled to deployment of the system as android and iOS implemented mobile applications to provide the system accessibility, real time notifications as well as easy user interfaces with various devices.

IV. EXPERIMENTAL RESULTS

The experimental test was done in two stages, one being an offline model testing stage where trained YOLOv11 model is evaluated against a held-out test dataset and the other stage is a system integration evaluation stage testing the integrated end-to-end pipeline in a simulated operating environment. These findings of the two phases highly confirm the design decisions and prove its willingness to research deployment trials into practise.

YOLOv11 model shared the same obstacle categories with high mean Average Precision (mAP) during the offline assessment stage. The human figures, motor vehicles as well as large animal obstacle were the most severity hazards that human figures regularly detected. The model exhibited strong detection in all the category of environmental conditions of the test set as well as under needy cloudy and night conditions. PELP rays such as brightness normalisation and synthetic fog augmentation have been established to have a great effect in ensuring that detection performance rate at these severe conditions are not sacrificed. Latency measurements during the system integration stage ensured that the end-to-end response time which is the time it takes between the obstacle appearing on the camera frame and the physical signal actuation was always valid according to the operational requirement. Running the system on-site rather than relying on cloud processing, made a huge difference-it cut down lag big time, which is exactly why they went with the edge – based setup. Firebase Cloud Messaging proved to be a reliable and fast event propagation and the message delivery latency is negligible and the network is normal.

The consistency of the hardware signal actuation device was tested by making repeated measurements based on the communication links between the Android device and the traffic signal controller. Connexion had constant connectivity at all series of tests and the Turn Red command had the same level of reliability. The fail-safe mechanism itself was specifically checked by attention to simulating the communication failures and in all the instances, the signal went to default properly to red within the due time.

It was observed that the pipeline of preprocessing and classification mechanism based on confidence score had a tremendous impact on reducing the false positive detection by track-side shadows, reflective surfaces and motion artefacts - sources of spurious alerts discovered in the system design stage. The total false positive is significantly better than systems that are simpler based on thresholds to use and is within reasonable tolerances to deploy in a safety-critical system of operation.

V. CONCLUSION

The given project has managed to develop, instal, and test a new automated railway obstacle detector and the traffic signal actuation control system. Through the introduction of the YOLOv11 deep learning framework in conjunction with edge computing software and hardware, cloud-based event propagation, as well as IoT-controlled signal control, the project provides a full end-to-end automated safety pipeline that is sub-second latent and does not lose detection accuracy within a wide range of environmental characteristics and obstacle types.

The technical breakthrough is that the four complex technological subsystems, which are AI vision inference, cloud data management, mobile messaging, and hardware signal control, have been successfully combined into a consistent, dependable, linear safety system. The fail-safe design makes sure that safety requirement will be in place despite component failure or breakdown of communication. The results of the experiment prove that the proposed system can be considered a breakthrough in terms of safety technologies used in railways, compared with the ones currently in existence, these systems suffer an issue of material blindness and environmental sensitivity, which the proposed system mitigates.

In a more general sense, the present project is part of the expanding literature which AI-based computer vision is now robust enough to be implemented in safety-critical infrastructure monitoring infrastructure. Modular API-based architecture also reduces an entry barrier to those purchasing railway operators, and commodity camera hardware implies deployment that can be achieved at an economically justifiable price. Additional development directions in future also involve having direct implementation with train braking systems with fully autonomous emergency braking, drone aerial surveillance capabilities, predictive maintenance algorithms, and Vehicle to Infrastructure (V2I) communications protocols in the pilot cabin providing hazard warnings.

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