Automated Level Crossing System: A Computer Vision Based Approach with Raspberry Pi Microprocessor

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***Abstract*—In a rapidly flourishing country like Bangladesh, accidents in the unmanned level crossings are increasing day by day. In this study, we present a deep learning-based approach for automating level crossing junctions ensuring maximum safety. Here, we develop a fully automated technique using computer vision on a micro-controller that may reduce and eliminate level crossing deaths and accidents. A Raspberry Pi micro-controller detects impending trains using computer vision on live video and the intersection is closed until the incoming train passes unimpeded. Live video activity recognition and object detection algorithms scan the junction 24/7. Self-regulating micro-controllers control the entire process. When persistent unauthorized activity is identified, authorities (police, fire-brigade, etc.) are notified via automated messages and notifications. The micro-controller evaluates live rail-track data, arrival and departure times to anticipate ETAs, train position-velocity, and track problems to avoid head-on collisions. This proposed scheme reduces level crossing accidents and fatalities at a lower cost than current market solutions.**

***Index Terms*—Deep Learning, Micro-controller, Object Detection, Railway Crossing, Raspberry Pi**

I. Introduction

Bangladesh Railway (BR) is a government-owned and operated transportation agency in Bangladesh that covers 2,955.53 route kilometers and employs 25,822 regular employees [1]. According to Bangladesh Railway data, the country has 1,468 authorized and 1,321 unauthorised level crossings. What's more concerning is that all of the illicit level crossings are unattended, and only 32% of the authorised level crossings are [2]. Level crossings which are supposed to ensure safe passage of trains are currently managed manually. This is understandably unreliable as many accidents happen due to negligence. Train accidents are nothing new; accidents led to 1,546 recorded casualties over the span of 10 years from July 2007 to June 2017, including 365 deaths and 1,181 cases of injury, according to BR [3].

As of now, there has not been many attempts to automate the process. Currently in all parts of Bangladesh, the system is managed manually by a gate-man who is after all a human and humans make mistakes. This project work is conducted to propose a futuristic solution to the ever increasing problems associated with level crossing junctions; to improve the performance and lessen the casualties across the board.

II. Literature Review

Many approaches have been taken to solve railway crossing accidents with mixed success. Stereo vision sensor system known as the Ubiquitous Stereo Vision (USV) method have been tried using stereo cameras which capture 3D images of railway crossing to detect people [4]. By focusing solely on people, it ignores other vehicles that may cross the railway crossing and since it was tested in Japan, the same rules and conditions don't apply to Bangladesh. Also, the equipment is expensive. Automated video surveillance through object detection and classification using smart background subtraction and Parzen technique [5] considering occlusion of objects, inter-camera travel time etc have been tested [6] [7]. In [6] and [7], KNIGHT, a Windows-based standalone object detection, tracking and classification software has been tested but it only works during the day and no testing was done under rain or other adverse weather conditions. Studies on vehicle detection at level crossings by Histogram of Oriented gradient (HOG) method and the Support Vector Machine (SVM) classifier have carried out [8], but data sets with cars on track, empty track and trains on track were tested separately. Deep learning has been used to first estimate the time of train passing and estimated number of vehicles at normal traffic conditions in the level crossing and then use those as input to estimate the time of decongestion once the train passes through [9]. This study narrowly focuses on one criteria that concerns safety of level crossing but doesn't address the bigger picture. It is no doubt that deep learning algorithms are adept at objection classification tasks but the challenge is to do so at high accuracy in real time on a mobile device. Exactly this challenge was tackled using deep learning models such as MobileNetSSDLite, Tiny YOLO etc. with the objective of counting vehicles and classifying them(ATTC) in [10]. As we can see a lot of techniques have been tried to solve railway crossing problems or other adjacent problems but to the best of our knowledge, no study adequately tries to detect incoming train and controls the movement of the level crossing barrier accordingly while simultaneously raising an alarm to alert nearby vehicles, humans etc. This is attempted in our study.

III. Methodology

A brief summary of the main tasks completed by system is shown in fig. 1. Briefly, a train is detected and the junction is closed for safety. Then while the train passes through, the junction is monitored. Finally, the junction is closed after the safe passage of the train.

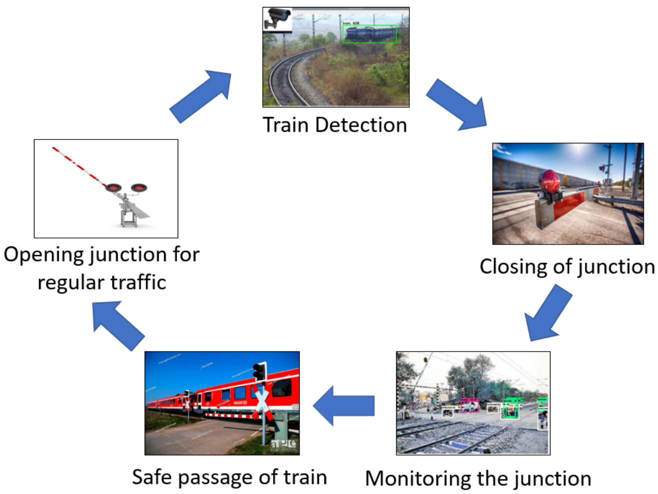


Fig. 1: Summary of methodology

A. Train Detection and Junction Closing

The main goal of any automated level crossing system is to detect the presence of an oncoming train. Without that knowledge, no suitable action can be taken. To detect the presence of a train we rely on several different technologies here. First, we use object detection on a video feed from a camera 2-3km from the junction as our point of detection. If necessary, this input is prepossessed for object detection. A live video feed is used for object detection. SSD mobilenet v1 [11] was trained on the COCO 2017 dataset containing 80 classes and quantized and translated to tflite format for faster inference. This model provides fast inference and low memory needs. Larger and more accurate models can be used based on specific requirements and available computational resources. Upon receiving the camera feed, the raspberry pi recognizes the presence of a train and sends a control signal to the peripheral actuators to close the barrier and sound an alarm to inform surrounding pedestrians and traffic. The train's arrival is displayed on a screen or indicator. The junction barrier closes when the pi sends a control signal, immobilizing nearby vehicles. This is a fully automated process requiring no human input. A CNN-based classification model is also developed for ensuring maximum safety and redundancy. Some examples of successful detection are shown in figures 2 and 3.

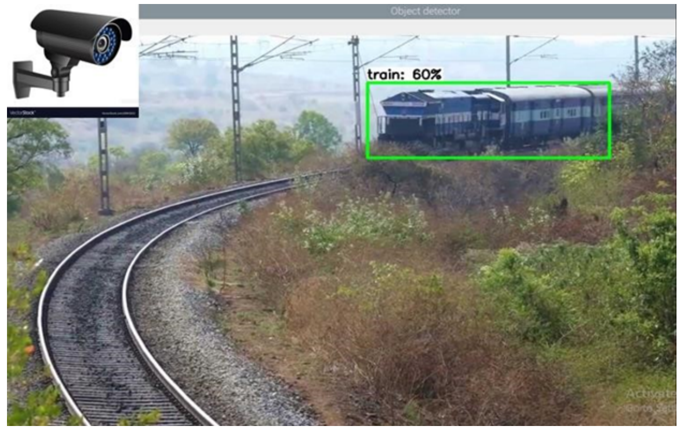
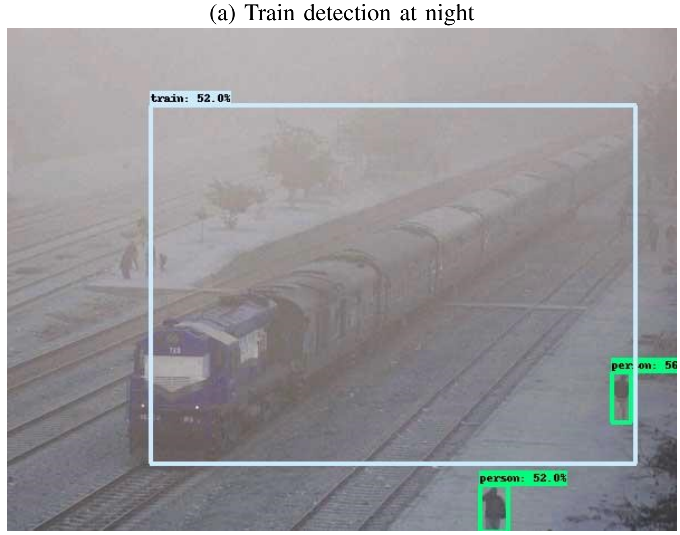


Fig. 2: Train detection in normal conditions

(a) Train detection at night



(b) Train detection in foggy condition

Fig. 3

B. Activity Monitoring and Alarms

No vehicle or pedestrian should cross the intersection once the barrier is closed. A camera at the junction will give live video feed to the micro-controller and the object detection model will detect trespassers. If trespassing is detected, the pi sounds a pre-recorded voice alert and an emergency siren. If the junction isn't cleared after the warnings, the pi sends a distress signal to neighboring emergency services (police, fire brigade, etc.) for a rescue effort. Also, an emergency signal shall be sent to the incoming train to alert it about any possible fatal collisions. Furthermore, an activity identification program may be added into the system to detect any abnormal or unusual behavior in the junction zone. Multiple suicides by railway jumping have occurred in Bangladesh in recent decades. To prevent such deplorable acts and mishaps, the junction activity will be constantly monitored by an activity recognition model trained to identify suspicious or unusual behavior. After the train passes, the raspberry pi sends a signal to the actuators and motors to open the junction. Traffic then resumes normally. An example of successful object detection is shown in fig. 4.

Fig. 4: Object detection for activity monitoring

IV. Experimental Setup and Results

The goal was to simulate a real life level crossing scenario as accurately as possible. The first objective was to detect an incoming train (using a first camera) and bring down a level crossing barrier (blocking traffic flow) while simultaneously raising an alarm. Once the train leaves, another camera detects that and raises the level crossing barrier once again to allow traffic to pass through. While traffic is blocked, the train track is checked for human/vehicle activity (object detection) using a third camera.

A. Components

The main components used for the demonstration as shown in fig. 5 are Raspberry Pi 4 Model B (4GB RAM), a servo motor (to simulate a larger motor that will lift the level crossing barrier), a speaker (to simulate buzzer system), a monitor/laptop to view the micro-controller's desktop and a mini level crossing barrier (to simulate a real barrier).

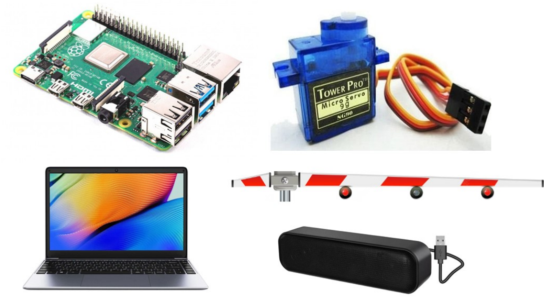


Fig. 5: Components used for demonstration

B. Setup & Data Collection

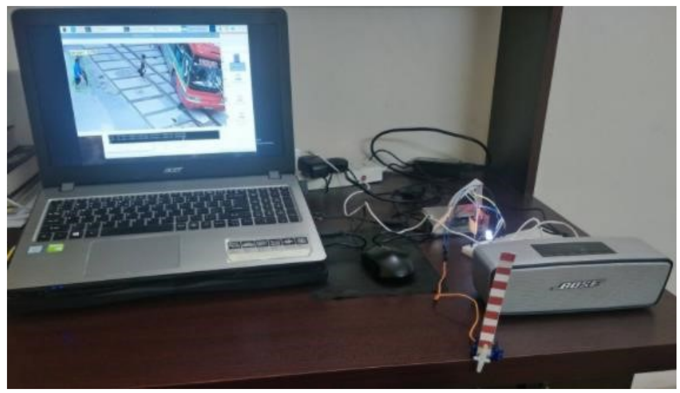


Fig. 6: Setup for demonstration

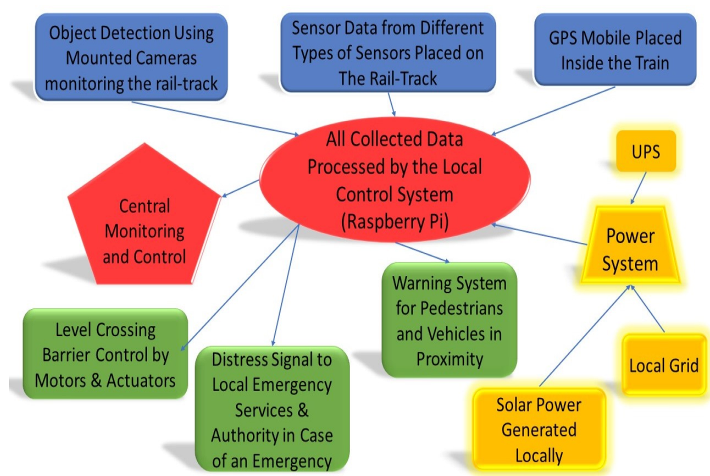


Fig. 7: Automated Level Crossing Flowchart

For training and validating our proposed models, data is collected from various well-known computer vision datasets such as the Image-net dataset as well YouTube and other online platforms. A prototype hardware implementation using a servo motor connected to a Raspberry Pi for demonstration purposes is developed as shown in Fig. 6. When a video file containing

TABLE I: Classification Model Output

Categories	No. of Images Analyzed	True Positive	True Negative	False Negative	False Positive	Detection Accuracy
Daytime	8540	4582	3826	93	39	98.45%
Night Time	3750	2124	1247	319	60	89.89%
Bad Weather	770	329	294	96	51	80.91%

TABLE II: Object Detection Model Output

Detection Categories	Number of Frames Analyzed	Detection Accuracy (Per frame)	False Negatives	Detection Accuracy (Ten Consecutive Frames)	False Negatives (Ten Consecutive Frames)
Train (Day)	4533	95.6%	195	100%	0
Train (Night)	2158	84.3%	337	99.9%	1
Train (Bad-Weather)	1326	82.7%	222	99.9%	1
Trespasser (Day)	3783	91.7%	306	100%	0
Trespasser (Night)	2078	87.5%	269	99.9%	2
Trespasser (Bad-Weather)	1129	77.8%	234	99.7%	3

an event of train arrival at a level crossing junction is run on the raspberry pi for train detection, the train is first detected by the object detection model. Then the Raspberry Pi signals the servo motor to lower the miniature junction barrier and alarm is sounded through the connected speaker. Once the train passes by, the junction barrier is again lifted. Although only a few components are used here for demonstration purposes, the proposed real life system will have a structure similar to the one shown in fig. 7.

C. *Detection Result*

In order to verify the performance and robustness of our model, we have tested it with various images ranging from images of trains, humans, cats , dogs, cars. buses. trucks etc. Fig. 3 shows some of the extremely challenging images classified and localized perfectly by our model which shows almost human level performance. The summarized results of the classification model is shown in Table I. As we can see the detection accuracy is excellent considering the diverse conditions tested. The summarized results of the object detection model is also shown in Table II and again the amount of false negatives is negligible.

V. Conclusion and Future Work

Unmanned level crossing accidents are rising in a growing country like ours. Our paper is about Automatic Level Crossing System, which replaces gatekeepers with automatic junction barrier control. It deals with two things, firstly it detects the impending train by a camera module positioned at a certain distance. Second, it provides safety by automatically closing and opening the junction barrier. We worked on a foolproof warning system and plan to add more. Our method proposed a cost-effective way to mitigate a fatal flaw in our railroad transport system and reduce casualties. Very large-scale implementation is possible within a very short time due to the wide availability and low-cost of the required materials. A pilot project can be conducted with the help of government agencies with very little effort to prove the effectiveness of the proposed system. If proper support and finance is made available, our proposed method can pave the way for a revolutionary and essential advancement in transport systems safety in developing countries like ours.

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