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Vehicle Detection for Accident Prevention

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Abstract: One of the key components of the smart traffic concept is vehicle detection and tracking. Modern city planning and development is impossible to achieve without a thorough understanding of the city's existing traffic flows. Surveillance video is an underutilized source of traffic data that can be discovered using a wide range of information technology tools and solutions, including machine learning techniques. A critical step in these systems is robust and reliable vehicle detection. It employs an object detection model to locate vehicles in images captured by an outdoor surveillance camera. A review of recent vision-based on-road vehicle detection systems is presented in this paper. YOLO generates a region proposal network and classifies these region proposals at the same time. The purpose of this paper is to address the issues raised above. This model has good performance in object detection.
Keywords: Traffic management, Vehicle detection, Tracking, Deep Neural Networks, Image processing, YOLOv3

I. INTRODUCTION

Traffic congestion at railway crossings is the most serious problem that people face nowadays, especially when an overbridge is not built or is difficult to build.

Traffic congestion occurs as a result of increased vehicle use, increased vehicular queueing, longer time railway gates are closed, and improper vehicle queueing near railway crossings. The safety and smooth flow of traffic are critical. Traffic management not only makes people feel safe, but it also keeps them safe. The goal of this study is to create and demonstrate the use of a machine learning framework for real-time traffic monitoring based on publicly available video streams, as the authors address the underutilized availability of video data on urban roads, which can undoubtedly be used for traffic flow monitoring. Different techniques and approaches, such as pressure sensors, inductive loops (Bhaskar et al., 2015), and magnetoresistive sensors, can be used to recognize vehicles[1]. The authors address the underutilized availability of video data on urban roads, which can undoubtedly be used for traffic flow monitoring, by developing and demonstrating the use of a machine learning framework for real-time traffic monitoring based on publicly available video streams. It is difficult to develop effective and efficient models for vehicle detection and classification in surveillance videos due to factors such as visual occlusion, illumination change, and pose variation. Despite the fact that numerous existing related models have been proposed, many issues remain unresolved.

Deep neural networks (DNNs) have demonstrated outstanding performance in object detection. However, because DNNs typically run on powerful devices with high computational capability and sufficient memory, their deployment in constrained environments such as embedded devices has been severely limited[11]. A deep convolutional neural network (CNN) model is built to capture high-level image features for vehicle classification. In addition, to pre-train CNNs, a new pre-training strategy based on sparse coding and auto-encoder is developed.

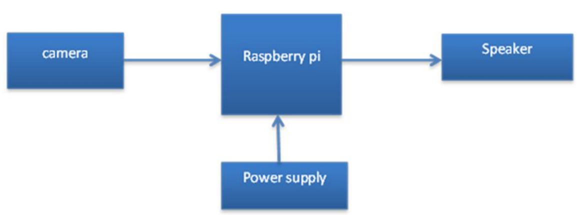

Fig. 1 Main flow of the proposed framework includes four steps, i.e., foreground extraction, object segmentation, feature learning, and vehicle classification.

Vehicle detection and statistics in highway monitoring video scenes are critical to intelligent traffic management and highway control. With the widespread use of traffic surveillance cameras, a massive database of traffic video footage has been amassed for analysis.

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II. METHODOLOGY

The classic older detectors were based on a detailed analysis of image features and produced very good results. The Viola and Jones detector was one of the first widely used algorithms. Originally, this detector was used to detect human faces in images. It applied the sliding window method to the image, analyzing individual features before classifying the object. These traditional detectors served as the foundation for today's advanced detectors based on deep learning techniques [2].

Modern techniques are complex techniques that enable object detection in images. These deep learning techniques are classified into two types: one-stage and two-stage methods. RCNN, Fast-RCNN, and Faster-RCNN are two-stage techniques. These methods generate suggestions for object occurrence areas and then classify these areas. Their main advantage is detection and classification accuracy, but they have considerably higher computational requirements than one-stage algorithms. SSD and YOLO are examples of the second type of algorithm. As the name implies, these methods predict object detection regions while also classifying these regions. These algorithms rely on object regression detection.

Systems monitoring the traffic of railroad level crossings need real-time status evaluation. Two-stage algorithms are a bad choice if we only take into account deployment on a single computing machine and ignore computing clusters. As a result, we selected the one-stage network YOLOv3, which requires less computing and can operate in real-time. Its innovative architecture lowers computational requirements without significantly affecting the resulting detection accuracy. The current version three of the YOLO network is the most accurate of all the existing versions.

The images in the YOLO network are subdivided into SS grids. On both the X-axis and the Y-axis, there are an equal number of candidate boxes. The candidate boxes can detect objects and estimate the probability that an object is present in each candidate box. Whether the object is visible in the photos and how precisely it is positioned are both indicators of confidence [9].

There are different methodologies suggested to date. For example, the detection model was trained using a relatively small training set and personnel hours and was bound to peculiarities of particular locations, camera view angles, color modes, and other parameters, which is a simple process and takes a relatively small amount of time and could be repeated for each needed location separately. Another method proposed considered deployment on a single computing machine ignoring cluster computing, and chose a one-stage network YOLOv3, reducing computational demands without a significant impact on the resulting detection accuracy. The output of this work was a detector, which could detect and then classify the current state of traffic lights, train traffic lights, and railway-level crossing barriers with a high detection rate.

Apart from this the robustness of the RECIFE-MILP real-time traffic management solutions in relation to the uncertainty of train entrance times in the considered infrastructure. The microscopic railway simulator OpenTrack was used and the same procedure was repeated while varying the buffer time to assess the impact of this factor on the robustness.

The majority of methods followed two basic steps: HG, in which possible vehicle locations in an image are hypothesized, and HV, in which tests are performed to confirm the presence of vehicles in an image.

PLC and IoT-based railway track monitoring and control systems had been designed using LOGO and Visual Basic software. However, the system was designed with cable and if its connection failed then the sensors would not work.

One amongst these was demonstrating using a multi-camera vehicle detection system with an MLP/CNN pipeline. The pre-trained fine-tuned CNN was used to remove false positive predictions by projecting all cells on the ground plane that could be occupied by a vehicle back to each side view and inferring whether the cell was occupied by a vehicle or not.

To tackle the occlusion problem, an efficient model based on the techniques of Recursive Segmentation and Convex Hull (RSCH) was developed which treats the connected regions as sets and utilizes a subset decomposition optimization for dealing with multiple occluded vehicles.

DL techniques for image processing and object recognition in autonomous detection and monitoring systems deployed at railway crossings using collections of sensors.

The YOLOv3 tiny model was chosen as the most suitable model for the detection subsystem.

The YOLO network model for object detection. The degenerative model which is fed with the degraded image was trained with the degraded images and it learned more features and that the model could cope with more complex scenes which improved the average precision of the object detection and had better generalizing ability and higher robustness.

The superior feature extraction method was used before vehicle detection classification and the accuracy rate of vehicle detection classification increased. S-shaped functions were selected to be activation functions in hidden layers, while the famous back-propagation algorithm was adopted in the training process. The test results showed that the deep neural network sufficiently approximated some specific functions with a given precision.

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Tinier-YOLO is proposed to reduce the model size while achieving improved detection accuracy and real-time performance. The computational cost of the network was reduced by removing the batch normalization from the fire modules of Tinier-YOLO.

An automatic railway object detection system was designed using a graphics processing unit (GPU) and convolution neural networks. The author proposed an FE-SSD based on a PDM, an FTB, and an RFEM for railway object detection.

YOLO with Faster RCNN to detect and classify the vehicles was carried out. The method could distinguish intra-class objects, identifying appropriate region size, and lacked efficiency for not identifying occluded objects. Filtering out frames that show little to no activity, this way reducing the amount of data to be processed by the later extremely compute-intensive stage and adopting a model based on CNN to ensure effective detection of trespassing activity.

An efficient railway system technique framework based on CNN and DL algorithms to foster the detection of unwanted events in railway stations was proposed and applied respectively.

Fig. 2 Traffic congestion at railway gate

Performance of several ML-based prediction models used in short-term traffic flow prediction and studied the scalability for different models and provided an off-line optimization method, i.e., desensitization, that could highly improve the adaptability of a prediction model.

The paper reviewed two levels of probability for the collision which was a high probability of probable collision and another, an imminent collision. The use of Bayesian Network was built for two speeds, one for host automobiles and another for fast approaching automobiles.

These systems were not effective in meeting all the scenarios of security as some installed sensors got affected due to bad weather and so on. But, the proposed system maintained a high level of accuracy by detecting trains, even in noisy environments.

III. DISCUSSION

For this proposed system we need a camera to capture vehicles that are on the wrong side of the road blocking the path of vehicles on the other side. So, we select a spot and install the camera. The area that we are going to monitor for vehicle detection is called the region of interest. This area is on both sides of the track. This image is then processed in the raspberry pi processor which is a small computer. YOLO, a real-time object detection method for constrained environments, is proposed in this paper. YOLO's method uses DenseNet's dense connections. Dense YOLO's connections aided in improving detection accuracy and real-time performance by strengthening feature propagation and ensuring maximum information flow in the network.

Detection and identification of vehicles are done in the controller and depending upon the result controller gives a command to the speaker to generate an audio signal. The audio signal will carry the message that they are on the wrong side and they should move their vehicles backward and make that area clear for the vehicles on the other side. There are several drawbacks of using a sliding window for object localization such as selecting appropriate kernel size, stride etc. which leads to high computational cost.

The YOLO object detection is often cited as being one of the fastest deep learning-based object detectors, achieving a higher FPS rate than computationally expensive two-stage detectors (ex. Faster R-CNN) and some single-stage detectors (ex. RetinaNet and some, but not all, variations of SSDs). However, even with all that speed, YOLO still needs to be faster to run on embedded devices such as the Raspberry Pi. To help make YOLO even faster, a variation of the YOLO architecture called Tiny-YOLO was defined. The Tiny-YOLO architecture is approximately 442% faster than its larger big brothers, achieving upwards of 244 FPS on a single GPU. The small model size (< 50MB) and fast inference speed make the Tiny-YOLO object detection naturally suited for embedded computer vision/deep learning devices such as the Raspberry Pi.

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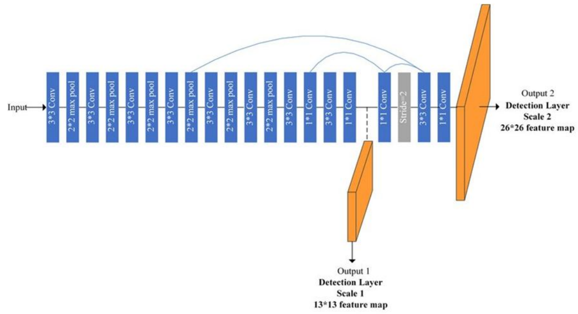

Fig. 3 The network structure of Tiny-YOLO-V3.

The approach of our method is to frame object detection as a regression problem and pass it to a fully connected neural network. The system divides the input image into an S×S grid and each grid cell predicts bounding boxes, confidence for those boxes, class probabilities. For uninterrupted operation, we need a power backup or battery. For experimental purposes, a number of videos are recorded from the aforementioned outdoor camera.

IV. RESULT

In this paper, we have proposed a method that detects a vehicle whenever it is out of the region of interest. Basically, it finds the centroid of the object (vehicle) and then checks whether it lies within ROI or not. If the vehicle lies out of ROI then as a result a sound warning will be generated so that the vehicle follows the lane. This is how not only the traffic congestion will be managed but also accidents will be prevented near the railway gateway.

Fig. 4 Vehicles detected in ROI

The boom barrier (railway crossing gate) will remain closed until vehicles clear the ROI area. As soon as the vehicles clear the ROI area, the red light will turn off and green light will glow to indicate the path is clear to go. As soon as the green light turns ON, the gate will open for vehicles to cross the railway track. If there is no vehicle to detect on the ROI area, the green light will turn ON after the train passes and the gate will directly open without any audio indication.

V. CONCLUSION

The proposed system is a design of an autonomous system to fix the railroad crossing traffic, which monitors violation of traffic rules at railroad crossings. It also gives audio warning to those vehicles that are in the wrong lane. To convey opening and closing signals to the gate controller. It will eventually avoid traffic on railway crossings and maintain traffic rules and discipline. Application of YOLO model for domain specific object detection results in a much faster training process and robust results.

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