AN APPLICATION OF SPOTTING OF UNEXPECTED ACCIDENT UNDER BAD CCTV MONITORING CONDITIONS IN DANGEROUS AREAS USING DEEP LEARNING CONVOLUTIONAL NUERAL NETWORK ALEX NET

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ABSTRACT- As the urban population rises and the number of motor vehicles increases, traffic pollution is becoming a major concern in the twenty-first century. Accidents are a major cause of traffic delays since they not only result in injuries and losses for those involved, but also in lost and squandered time for others who are stuck behind the wheel. The proposed Object Detection and Tracking Technology (ODTS) would be used and expanded to automatically identify and control irregular events on CCTVs in tunnels in conjunction with a well-known deep learning network, Faster Regional Convolution Neural (Faster R- CNN), for Object Detection and Traditional Object Tracking. It enables the detection of a moving target in real time, which is typically not possible in standard object tracking systems. The proposed method takes a time frame as input for Object Detection Bounding Box discoveries, comparing current and preceding picture bounding boxes to provide a unique ID number to each moving and detecting object. [3] A video clip is the suggested system. It enables the detection of a moving target in real time, which is typically not possible in standard object tracking systems. As a result, the computer will identify any and all injuries. More specifically, because the training data set is large, it is possible to automatically improve the ODTS capabilities without modifying the programme codes. **KEYWORDS-** R-Convolutional Neural Network, Object Detection, Tunnel accident detection.

INTRODUCTION Accidents have been one of the leading causes of death all over the world. It is difficult to track an isolated tunnel [1]. If cars outside the tunnel are not aware of the crash, it can cause further harm. It is usually difficult for policymakers to understand the complexities of the problem and obtain the desired assistance. In this paper, we will present an automated accident warning system. Object recognition technology has been used effectively to determine the size and location of target points in photographs or videos. Several technologies have emerged, primarily in automotive self-driving, CCTV tracking and surveillance systems, cancer detection, and so on. [5] Formal paraphrase Object detection is another field of image processing where unique recognition and tracking the location of known objects over time can be accomplished. To monitor objects, however, it is important to first identify the object type and location in a static image using object detection. As a result, the effects of object monitoring can be heavily reliant on the efficiency of the object detection involved. [3] This object detection system has been successfully used for tracing targeted pedestrians and moving cars, crash surveillance in traffic cameras, crime and security monitoring in specific local areas of concern, among other applications. In a cave, CCTV surveillance is completely ineffective. [6] Because the tunnel footage has a poor IL luminance, the video is heavily affected by the moving vehicle's tail light or the warning light of the car in service. The tone of the tunnel video is dark and distinct from the color of the road outside the tunnel. [2] Formalized paraphrase for the reasons mentioned above, the video surveillance device installed on the roads outside the tunnels was likely to fail to function properly inside the tunnel. [1] Formalized paraphrase. As a result, an attempt is made in this paper to create an accident detection method that can acquire moving details of target objects by integrating an object tracking algorithm with a deep learning-based object detection mechanism. [5] Formal paraphrase in the following part, the complete object detection and tracking system (ODTS) procedures will be outlined in detail. In addition, the tunnel accident warning method within the scope of ODTS would be considered. This device detects collisions or unusual occurrences occurring on moving structures and targets geographic areas on CCTV.

LITERATURE SURVEY On-road vehicle identification is critical for perceiving driving settings, and localising the observed vehicle assists drivers in anticipating potential hazards and avoiding collisions. However, there has been no research on vehicle identification with partial appearance, and the process for partially visible vehicle localization has not been investigated. Using stereo vision and geometry, this paper proposes a novel paradigm for vehicle identification and localization with partial presence. The initial images from the stereo camera are then analyzed to create a v-disparity diagram. Vehicle candidates are created with prior knowledge of potential vehicle positions on the image after object detection using v-disparity. Vehicle identification is completed through deep learning-based verification. A new partly transparent vehicle tracking algorithm is implemented for each identified vehicle. This algorithm senses the vehicle edge on the earth, known as the grounded edge, and then selects a reference point for Kalman filter tracking to map partially visible vehicles. [1] Author Propose a clear and accurate vehicle identification system focused on texture and presence histograms of local vehicles fed into clustering woods. Local binary pattern-like descriptors are used to remove texture properties. The align collection of histograms developed by LBPs spatial for randomly sampled local regions is used to calculate the dissimilarity between regions of all training photos. Clustering forests are used to evaluate the match of histograms. The effectiveness of the proposed approach is tested on numerous car datasets under various imaging conditions, and the findings demonstrate that the method achieves substantial advances over previously reported approaches. [2] Smart traffic and information systems necessitate the processing of traffic data from various sensors in order to regulate traffic. In this respect, security cameras have been installed in traffic management and control in recent years. Several experiments on video surveillance applications using image recognition methods for traffic control are being conducted. Video processing of traffic data collected from surveillance cameras is an example of an application for advance warning or data extraction for realtime vehicle analysis. This paper provides a thorough analysis of vehicle identification and recognition procedures, as well as discussion of various methods for identifying vehicles in inclement weather. It also addresses the datasets used in different experiments to evaluate the proposed techniques. [3] The Object Detection and Tracking System (ODTS) will be implemented and used in conjunction with a wellknown deep learning network, Faster Regional Convolution Neural Network (Faster R-CNN), for Object Detection and Conventional Object Tracking, for automated detection and control of unusual events on CCTVs in tunnels, which are likely to (1) Wrong-Way Driving (WWD), (2) Stop, (3) Person out of vehicle in tunnel (4) Fire. This technology allows you to trace a moving target in real time, which is unusual in traditional object tracking frameworks. As a result, the device is capable of detecting all injuries in less than 10 seconds. The more interesting argument is that as the training dataset grows in size, the detection capability of ODTS can be automatically improved without any modifications to the software code. [4] To hypothesise object positions, cutting-edge object detection networks depend on area proposal algorithms. SPPnet [1] and Quick R-CNN [2] advancements have shortened the running time of these detection networks, exposing region proposal computation as a bottleneck. We present a Region Proposal Network (RPN) that shares fullimage convolutional features with the detection network, allowing for nearly cost-free region proposals. An RPN is a completely convolutional network that predicts object bounds and objectless scores at each location at the same time. The RPN is trained from start to finish to produce highquality area proposals, which Quick R-CNN uses for identification. [5] The author accomplished the goal in two aspects in the article. In terms of data processing, we investigated how to process tracking data effectively by using the parallel characteristics of iDMA (integrated direct memory access) and a DSP core; and in terms of data storage, we suggested a time-sharing approach to address the DSP local memory (data RAM) usage problem for multiple tracking properties. In addition, we suggest a new approach for software architecture that involves two stages of parallel computations: frame-level parallel computations and monitoring object-level parallel computations. [6] Owing to the limited visibility of vehicles in road tunnels, an accidental crash could quickly be accompanied by a major secondary accident. As a result, a number of automatic event monitoring systems have been put in place, but they have very poor detection rates due to the low image quality on CCTVs in tunnels. To address this limitation, a deep learning-based tunnel incident detection system was developed, which demonstrated high detection rates in November 2017. However, since the object detection mechanism was limited to still photographs, the movement path and speed of moving vehicles could not be determined. [7] In addition to the RCNNs discussed in this thesis, there are several other methods for using Convolutional networks. The identification of model artefacts was presented as a regression problem. They use a CNN in a picture window to predict foreground pixels over a coarse grid for the whole object as well as the top, bottom, left, and right halves. The projected masks are then converted into sensed bounding boxes by a grouping mechanism. Szegedy et al. train their model on PASCAL visual object classes (VOC) 2012 training and evaluation from a random initialization and achieve a mean average precision (mAP) of 30.5 percent on the VOC 2007 test. In contrast, an R-CNN of the same network configuration achieves a mAP of 58.5 percent, but it is pre-trained with supervised ImageNet. [8] In addition to accuracy, object detection systems must scale well as the number of object categories increases. Discriminatively trained component based models (DPM) [8] are capable of handling thousands of object categories. In DPM, for example, hash table lookups are used in place of exact filter convolutions. Their findings indicate that this technique can operate 10k DPM detectors in around 5 minutes per picture on a desktop workstation. However, there is a cost. When a large number of DPM detectors compete, the approximate hashing method results in a significant loss of detection precision. R-CNNs, on the other hand, scale very well with the amount of object classes to detect and almost all processing is spread across all object groups. [9] Regardless of scaling actions, an R-CNN on a GPU will take between 10 and 45 seconds per picture, based on the network used, since each area is passed across the network independently. Recent efforts have been made to minimize preparation and identification time while increasing accuracy and simplifying the training process. One of them is Fast RCNN [10], which has better detection efficiency (mAP) than R-CNN and the other is SPPnet, which is trained in a single stage using a multi-task failure. SPPnet training will refresh all network layers, and function caching requires no disc capacity. Another strategy is Faster RCNN. In this paper, a Region Proposal Network (RPN) is implemented that shares full-image convolutional features with the detection network, allowing for virtually cost-free region proposals. An RPN is a completely convolutional network that predicts object bounds and objectless scores at each location at the same time. [10]

GAP ANALYSIS

- As there are very few videos of fire in tunnel accidents. So, the detection of fire is not up to the mark and requires furthermore learning.
- New models of vehicles sometimes are not properly understood so the learning-based algorithm will need to be made familiar with all newly-launched vehicles from time to time.
- For processing such unclear and noisy images various enhancement techniques need to apply

PROPOSED SYSTEM APPROACH

The process of defining the architecture, components, modules, interfaces, and data for a system to meet specified criteria is known as systems design. Systems design may be defined as the application of systems theory to the creation of products. The areas of systems analysis, systems architecture, and systems engineering have some overlap. The goal of this system is to provide the user with an interactive interface that may be used in office settings. The system architecture encompasses the modules used in the project as well as the interactions between them based on data flow and processing. The System is made up of the following parts:

1. Video Camera
2. Connecting Wire
3. Required Software
4. Fire Brigade

WORKING The system leverages an application to notify local authorities of any unexpected problems in noisy tunnels. The raw footage will be captured from the tunnel and supplied to our system via this approach. The video will have some frame rate, mostly the frame rate of CCTV cameras and regular cameras, which is 25 frames per second. After achieving the frame rate, it is split up to acquire the frame rate for 1 second; after obtaining the frame rate for 1 second, the lighting must be adjusted to extract the colour feature. It should be noted that the image's input size is around 800*800. Once the colour feature has been extracted and the lighting has been modified, the retrieved frame will be presented to a classifier that has been trained for fire detection. Whatever colour characteristic we acquire, we must do a colour transformation. Normally, the picture we get is RGB, and the colour of the fire in a regular RGB image is yellow. However, if a yellow cloth or car is already there, identifying fire will be difficult. To solve this problem, we'll utilise a colour modification known as YCbCr to extract the Mean, Median, and Standard Deviation, which will then be used to identify fire. The illumination-adjusted picture will then be processed by a faster CNN. The suggested network will provide a quicker CNN, which will turn the picture into a block and passthrough layer and identify the presence of the vehicle. We'll put the car detection model through its paces. After detecting the vehicle, a square or rectangular bounding box and its centroid are obtained. From then, we'll break it down, which means that the time x and y-direction, as well as the centroid, will be recorded. For this, the picture output size is roughly 300*800. Because our pictures are two-dimensional, the X-axis will represent velocity and the Y-axis will represent the vehicles up and down movement. If the vehicle changes direction, it will travel uphill or downward. If the two-y vehicle's axis connects and the colour feature matches fire, a message will be sent to the fire department and the nearby hospital. We are using the FRCNN technique for object detection; it contains two fully connected layers, one after the convolutional layer and the other after the ROI pooling layer, so we have two dense layers in total

Faster RCNN

Faster R-CNN is a single, unified network for object detection. The RPN module serves as the ‘attention’ of this unified network. The R-CNN system trains CNNs from start to finish to identify the proposal regions as object or context. R-CNN is mostly used as a classifier and does not estimate object bounds (except for refining by bounding box regression). Its precision is determined by the efficiency of the area proposal module. Several papers have suggested methods for predicting object bounding boxes using deep networks. A fully-connected layer is trained in the Over Feat method to predict the box coordinates for the localization task that assumes a single entity. The fully-connected layer is then converted into a convolutional layer for detecting multiple objects of the same class. The Multi Box methods produce area proposals from a network in which the last fully-connected layer predicts several class-agnostic boxes at the same time, generalising Over Feat's "single-box" fashion. These class-agnostic boxes are used as R-CNN proposals. In comparison to our totally convolutional system, the MultiBox proposal network is extended to a single image crop or several big image crops (e.g., 224224). The functionality of the proposal and detection networks are not shared by MultiBox. We go over Feat and MultiBox in greater detail later in the sense of our process

CONCLUSION We will propose a new ODTS process that combines a deep learning-based object recognition network and an object tracking algorithm, and it will demonstrate how complex knowledge of an object for a particular object type can be accessed and used. Deep learning training secured the object detection efficiency of a stable Car object, while Person demonstrated relatively poor object detection performance. However, in the case of fire, there is a high likelihood of false identification in untrained videos due to a lack of Fire artefacts. Nonetheless, by concurrently practising No Fire artefacts, it is possible to reduce the frequency of false detections. The deep learning object detection network's fire object detection efficiency should be improved later by securing the Fire image

FUTURE WORK This application is simple to build in a variety of settings, and we may add additional functionality as needed. Because all of the modules are flexible, reusability is available as and when needed in this application. Software scope extensibility: This software improves on extensible ideas such as concealing data structures, avoiding numerous links or methods, avoiding case statements on object type, and distinguishing between public and private actions. Reuse usability: It is easy to upgrade this programme to the next version as and when needed. Reusable software lowers design, coding, and testing costs by spreading work across several designs and lowering the amount of code. We can add a feature to the system that scans the licence plates of vehicles that are still on the road or have been damaged, and then searches the database server for the specific automobile details. A phone or text message would be sent to the registered owner of the vehicle.

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