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Tracking of Intruder using Video Analytics

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Abstract:- Video analytics is a technology that processes a digital video signal using a special algorithm to perform a security- related function [12]. There is a need to design an automated trespass detection and early warning prediction tool leveraging state-of-the-art machine learning techniques. Leveraging video surveillance through security cameras [3]. In particular, they adopt a CNN-based deep learning architecture (Faster-RCNN) as the core component of solution. However, these deep learning-based methods, while effective, are known to be computationally expensive and time consuming, especially when applied to a large amount of surveillance data [3]. Given the sparsity of railroad trespassing activity, design a dual-stage deep learning architecture composed of an inexpensive prefiltering stage for activity detection followed by a high fidelity trespass detection stage for robust classification. The former is responsible for filtering out frames that show little to no activity, this way reducing the amount of data to be processed by the later more compute-intensive stage which adopts state-of-the-art Faster- RCNN to ensure effective classification of trespassing activity [3]. no vehicle entry zone, no parking zone, smart home security [14], etc.

***Keywords**:- Intruder Tracking, Trespass Detection, Video Analytics, Security.*

I. INTRODUCTION

The fundamental objective of computer vision is to em- power computers to reproduce the essential elements of human vision, for example, movement recognition and scene under- standing [2]. To accomplish the objective of quick motion observation, effective work has been done on visual object tracking. In visual object tracking, the object of interest is sur- rounded with the bounding rectangular box and the constraints of this box are then estimated for each incoming video frame [2]. Intelligent security systems focused on video surveillance are commonly used to identify suspected crimes at an early level. This allows real-time sending of intimations and Enables users to take preventive action to minimize the damage. Malicious entry into vulnerable areas, such as restricted areas, unattended places and in inflated possibility security areas [19]. This is an offence, in the event of Intrusion Identification system, "watching is trusting", that is visual perception and Intrusion detection are favor at the same time. In addition, an advantage over further devices like microwave Doppler detector provided by the video-based intrusion detection system, infrared detector, magnetic wall, vibration detector and etc, considering the growing illegal activity rate and the availability of powerful general purpose processors and security cameras [14]at reasonable rates.

Video digital surveillance intelligent protection that can be used as a multi-purpose security device because systems are economical, that is the video-based intrusion detection (IDS) system used [5]. This research and product development work is funded financially by an IMPRINT (Grant No.-7794/2016) initiative of the Ministry of Human Resource Development. Government of India, Secretariat for Housing and Urban Affairs, Government of India. The same platform that is used for security for other applications. For different applications, different versions of the IDS were suggested. However, these systems lack optimum online performance, such as fast , low execution memory, processing speed and high accuracy [5].

The goal of this paper is to describe an AI framework which can analyze live video feeds in real time to gather useful information for safety purposes [1]. Specifically, this study aims to yield the following deliverable:

1) To Design and Implement an object tracking system using Artificial intelligence algorithms [1].
2) Applying algorithm on various data sets to analyze the behavior and performance [1].
3) Identifying and detecting intruders and producing video alarm. Figure 1 shows a conceptual view of the system, in which an AI algorithm can send live alerts to designated personnel by analyzing and identifying trespassing events in live CCTV feeds. In addition, trespassing events are also recorded in a trespass event database containing video and associated metadata [1].

II. LITERATURE REVIEW

Major factors affecting video analytics are mentioned below

- Lighting issues [7]. Not enough light causes poor camera quality; light in the wrong places can produce shadows, glare and dark spots.
- Detection ranges. Know how many pixels on target the system requires, and design the camera coverage accordingly [7].
- High false alarm rates. Wind in many regions can cause false alarms, as can sun glare, shadows and the presence of other nuisances.
- Transmission issues. Weak networks, wireless links and improperly terminated video cable can create headaches [7].

In this paper LiDAR Point Cloud Classification for Visual Object Detection. Neural Network-based approach to object detection and tracking is considered for visual detection to aid the processing of the LiDAR point cloud, visual-LiDAR calibration Not to fully assess the efficiency of this approach in publicly available data.

The Industrial Surveillance Systems Improved Unsupervised Shift Detector [17]. A crucial role of intelligent surveillance systems is to identify an intruder that is entering a prohibited area [11]. This work involves a detector shift to segment the trespasser from the background (foreground object). Due to the dual camera sensor like color or IR, light shifts, night, static, and camouflaged foreground artifacts, the role suffers from the inherent disadvantages of change detectors. Gaussian Mixture Models model the history (GMM). To overcome the different challenges raised by the areas and object, like static foreground object, the adaptive context model update scheme is suggested. The comparison is done on three databases algorithms for the detection of unsupervised transition.

Curb Detection and Tracking Based on Optimization Frame- work [18] in Low-Resolution 3D Point Clouds. Curb detection and tracking in urban environments for autonomous vehicle operation. Detecting curbs in different weather conditions because of their robustness and can provide reliable distance measurement Indicates low performance in intersection areas and can not differentiate between occlusion situation and intersection areas.

An Approach using Context Subtraction for Unattended Object Detection by Contour Formation [21]. In public areas, any unattended object is usually known as a suspicious object. One of the demanding tasks of computer vision is the recognition of certain items in public places. Robust object detection system that detects safety violations promptly and reliably improves safety measurements Public locations, Shopping centers, malls, train stations, etc., for example. They are further classified into static objects by these foreground objects. In consecutive frames, and by the moving object by weigh up their respective centroid coordinate. The foreground objects are known as an unknowing objects if that objects are static for a predefined period of time and its size is within the predefined align [15].

Video analytics focused on Deep Learning for individual tracking [22]. As people's assets are growing, security and surveillance have become a matter of great concern today. Surveillance cameras are common and identifying criminals from a vast number of surveillance video frames is a repetitive technique. A new intelligent approach using deep learning was suggested in order to simplify the search process [9]. This technique takes gender, shirt pattern, and spectacle status as input to figure out the entity as a person from the video log. The efficiency of this approach achieves an accuracy of 87 percent in identifying the person in the video frame.

Real Time Object Detection and Video Monitoring System Tracking System [23]. This presents a device capacity of real- time video surveillance by integrating the algorithm of object detection tracking in a low end edge computing environment. One stage detection algorithms such as a single shot detector have been developed and you only look once (YOLO) at the expense of some precision and can be used for real- time systems. However, high performance hardware such as a general-purpose graphics processing unit is needed to achieve excellent object detection efficiency and speed [4]. A system that can guarantee success in real time by adjusting to managing the cycle of object detection and tracking in different edge computing environments has been proposed.

Cloud-based environment intrusion detection systems (IDS) and future challenges. Crucial applications for cost-effectiveness and quantifiable reasons are being additionally connected to the network. Due to various problems, most IDS structures are incorrect for cloud conditions. Intrusion Detection Systems and also the various related threat problems that are present in this paper are discussed in supplies direction.

A deep learning method of approach to identification of trespassing of object using data from video captured surveillance [24]. Railroad trespassing is a hazardous practice with serious risks to safety and security. Due to exceptionally high levels of patrolling, constant patrolling of suspected trespassing areas is, however, infeasible. Elevated demands for services and staffing expenses. This raises the need to use state of the art machine learning to Creation of automatic intruder detection and prediction of warning technique. To meet this need, For the Automated Railroad Trespassing Detection System, we suggest a new architecture uses video surveillance information known as ARTS. The basis of this approach, we are implementing a CNN based deep learning architecture caliber of video processing [6]. However, these deep learning based technique, while successful, are called

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computationally high and time taking, specially when apply to the high volume of surveillance information. Leveraging the sparsity of Intruder activities on railway tracks, ARTS corresponds to a dual- stage deep learning architecture consisting of an inexpensive behavior detection pre-filtering stage followed by a deep neural network classification stage of high fidelity trespass. The resulting dual stage ARTS architecture is a flexible method capable of trading off accuracy with calculation time [6]. We show the effectiveness of our public domain surveillance data strategy, achieving a 0.87 f1 score when Keeping up with the massive volume of video, maintaining a reasonable time and precision trade off.

The fundamental objective of computer vision is to em- power computers to reproduce the essential elements of human vision, for example, movement recognition and scene under- standing. To accomplish the objective of quick motion observation, effective work has been done on visual object tracking. In visual object tracking, the object of interest is surrounded with the bounding rectangular box and the constraints of this box are then estimated for each incoming video frame [2].

A number of research works have been attempted to improve the performance of the video-based intrusion detection system to make it more suitable for real-time applications [5].Video surveillance is among the most evolved applications of object tracking. It can be defined as process of monitoring the area with the help of camera network employed such that entire area is covered. Any unethical activity can be observed inside the control room and accordingly action can be taken. There are enough scopes to improve it with respect to the accuracy [5], processing speed and time latency. Most of the proposed techniques for object detection rely on tracking information to detect drop-off events [10]. these methods are not well suited in complex scenes involving crowds and large amount of occlusions [2]. They have used alarm system to provide alert against any motion detected. Include sensors for recognition of body temperature for distinguishing between humans and animals.

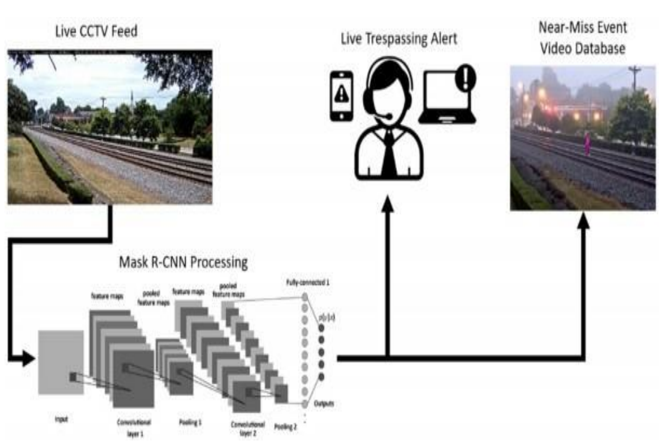

Fig. 1. Conceptual trespasser detection alert system using artificial intelligence

III. SYSTEM DESIGN

Detection of trespassing events in video feeds has many challenges. There are a wide variety of configurations, environmental variables, and technical features of live data streams watching railroads [1]. An AI built for trespass detection must have several fundamental performance qualities. It must accurately identify pedestrians and vehicles within the frame, unhindered by video artifacts, shadows, and other distortions. Secondly, the AI must maintain accuracy in diverse environmental conditions (e.g., rain, snow, day, night, and fog). Finally, when analyzing a live video stream, the AI must be able to process the frames with enough speed to maintain a fast response time to possible trespassing events [1].

To address these challenges a generalized AI framework for trespass detection which utilizes the combined techniques of ROI and Mask R-CNN is proposed (Figure 2). After defining the ROI, the Mask R-CNN analyzes frames of the live video feed. If an unauthorized person or vehicle enters the ROI an alert would be sounded, and relevant trespass data would be recorded to a database for later review and analysis [1]. A key part of Mask R-CNN performance is the training data- set, which allows it to recognize objects. The COCO data-set, consisting of many labeled images of everyday scenes built for use in object-recognition research, was utilized for this purpose. It was selected because of its depth (330,000 Images), diversity (80 object categories), and timeliness through its continual growth and refinement. In addition, the COCO data-set includes pre-generated boundaries around recognized images allowing for better object recognition. By providing the Mask R-CNN with this data-set it can recognize people, cars, trains, and other objects within the ROI. If an illegal object is detected within the ROI a subroutine of the AI will execute two simultaneous commands. First, an alert SMS text or email is relayed to a pre-determined user [1]. This can be a railroad safety official who can decide of possible respiratory actions. Second, a clip of the trespass incident is recorded and metadata, for example object detected, time, location, video file name, and so forth, are stored in a trespass event database. These metadata are automatically generated by the AI, demonstrating that context of the image can be extracted and interpreted. Trespass data can provide valuable information about hazardous environments and behaviors that lead to trespassing events, which can inform education, enforcement, and engineering strategies for trespass prevention. In addition, the aggregation of these trespass events has the potential to enhance railroad risk analyses in the future. The AI frame- work should be trained to verify its accuracy by having the algorithm analyze a video data-set with established results [1]. Comparing the results of the data- set to the known number of trespasses verifies the AI algorithm’s performance. Additional data-sets, including varying environmental conditions, should be tested with the algorithm to verify its performance under diverse circumstances.

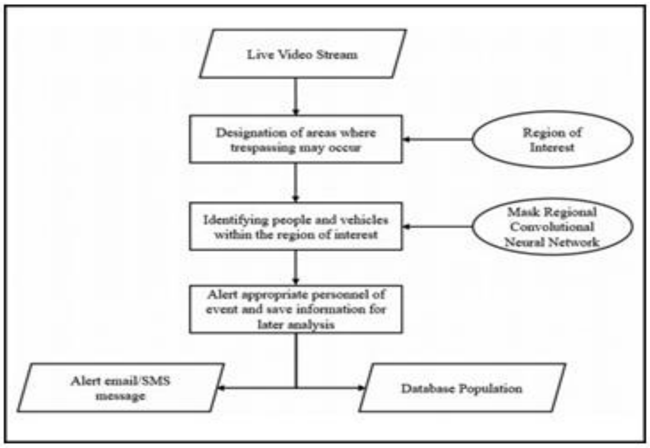

Fig. 2. General AI framework for trespass detection.

In Fig.3, the background subtractor module is needed by all the parallel threads except object detection and tracking. Hence background subtraction is done first through a synchronized thread and then the 3 modules commence. Multiple object tracking with detection, anomaly detection, trespass detection and tampering detection are parallelly executed in the second level thread. Meanwhile the user interface (UI) undertakes communication between these threads as well. Final thread level combines these results 17 and video output is rendered in the Graphical User Interface (GUI). GPU acceleration is utilized for anomaly detection and object tracking to speed up the process.

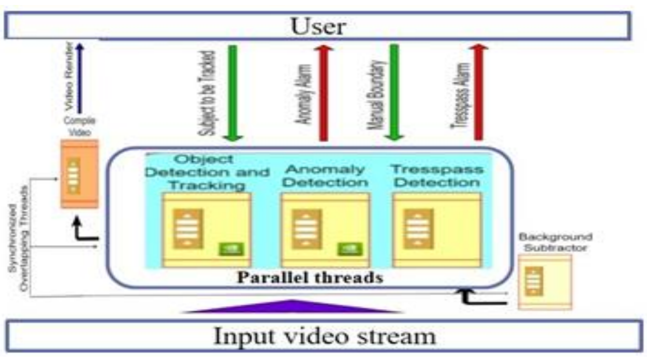

Fig. 3. Surveillance system architecture

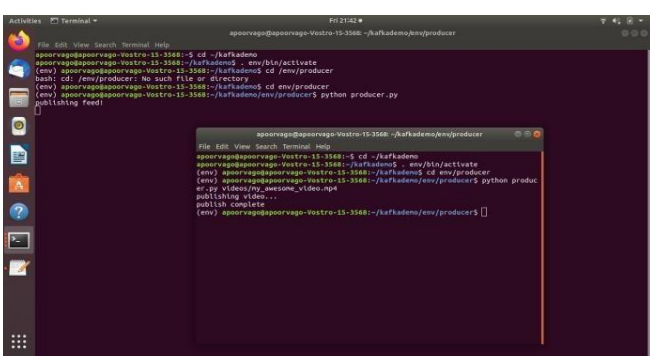

Fig. 4. shows the publishing of live video using Kafka video streaming .

IV. IMPLEMENTATION

To ensure that the AI algorithm achieved maximum accuracy a several-step validation plan was enacted [1]. Four results of the analysis were possible: an illegal trespass occurs, and a detection is recorded (true positives); no illegal trespass occurs but a detection is recorded (false positive); a trespass occurs, and no detection is recorded (false negative); and no trespass occurs, and no detection is recorded (true negative).

In the training section, the AI analyzed 129 h of live video data and reported a conglomeration of correct and incorrect trespassing identification as compared with ground truth data acquired by manual review of archival footage [1]. These mistakes were corrected by improving the algorithm, and a recording of the live feed was reprocessed with the updated algorithm to ensure that the false positives and false negatives would not occur again, resulting in the algorithm achieving 100 percentage accuracy at this point. In the testing phase, two right-of-ways were analyzed with no intermittent program modifications. Over 100 live hours of combined right-of-way footage was manually reviewed and compared with the results generated by the algorithm. To date, the program was 100 percent accurate (no false negative or false positive) [1].

V. RESULTS AND DISCUSSION

To evaluate the performance of the detection and tracking system. Here we show limited results for the sake of brevity. The total number of frames present in the video are 430. Some example frames are shown as follows in order to prove the efficacy [8].It explains that even if a new intruder enters or old intruder leaves the restricted zone, the tracking and association of each detection with the corresponding tracking does not disturb.

In our work, loss functions provide a static representation of how our model is performing. Our proposed algorithm use loss function for optimization; thus, finding the best parameters (weights) for our data. YOLO optimizes a multi-part loss function that is composed of four parts during training the model [4].

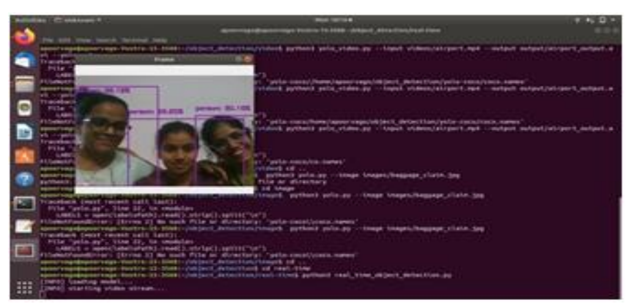

Fig. 5. shows the detection of object in live video streaming with accuracy in percentage.

Fig. 6. Restricted zone is selected.

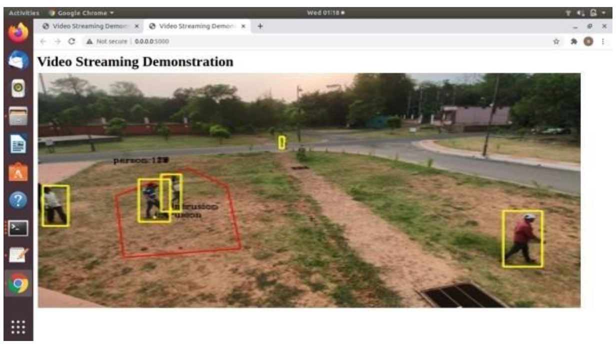

Fig. 7. shows the Intruder detected in the ROI and classify the object.

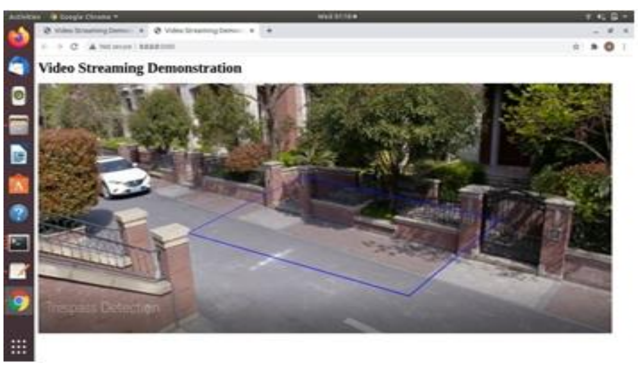

Fig. 8. shows the region which we are selected.

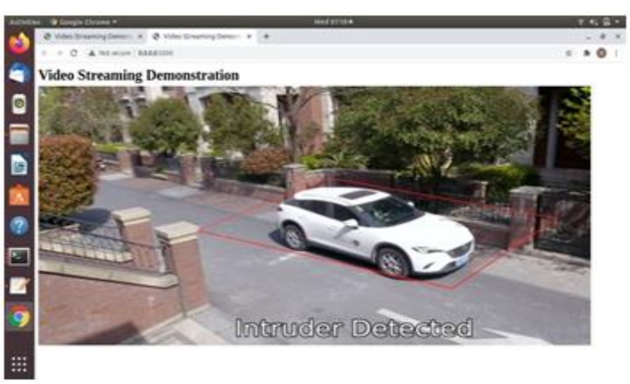

Fig. 9. shows the Intruder detection of object in restricted area

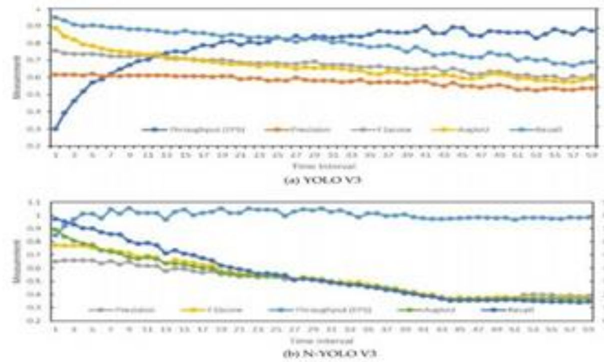

Fig. 10. Graph of YOLO and N-YOLO accuracy according to tracking intervals

VI. CONCLUSION

The including of Artificial Intelligence to find an answer to the Computer vision function has out performing the image processing approach of handling the functions. The selection of suitable algorithm for a particular task is always a trade-off between speed and accuracy. For real time application, a generic, but successful video-based Intrusion Detection System with a new intrusion detection mechanism are Identified where the users can pick the possible intruders from the classes of list for which the model is being educated. In addition, inside the camera view, the client can draw the ROI using reference frame of any size and shape. A modern intrusion detection low-computational algorithm. A real-time notification is sent to the users via registered email ID when the intrusion event is occur.

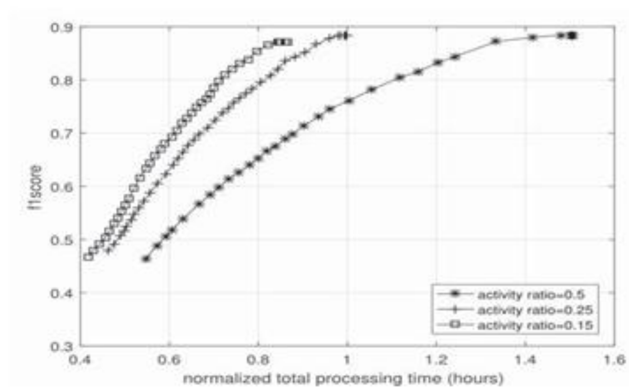

Fig. 11. Time-accuracy trade-off for varying AR

FUTURE WORK

To further validate this framework, the amount of data reviewed will be increased. This will allow the AI algorithm to experience more environmental conditions and possibly more trespassing events [1]. A limitation of the current AI is the inability to differentiate between authorized personnel and trespassers. Future research will apply transfer learning techniques to update the AI's library to recognize authorized personnel through the identification of their personal protective equipment and other unique features. These techniques will also be used for future research into the recognition of debris and non moving objects.

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