OPEN ACCESS
International Journal of Engineering Innovations in Advanced Technology
ISSN: 2582-1431 (Online), Volume-6 Issue-2, June 2024

Real-Time Accident Detection in Traffic Surveillance Using Deep Learning

Patan Suraj Khan
M.Tech Scholor, Department of CSE, GVR&S College of Engineering & Technology,Guntur, India.
Email: surajpatan549@gmail.com

Ch Papa Rao
Associate Professor, Department of CSE, GVR&S College of Engineering & Technology,Guntur, India.
Email: paparao.challagundla@gmail.com

***Abstract*- Extensive research is now underway in the field of traffic monitoring systems, particularly focusing on the automated detection of traffic accidents. Surveillance cameras that are connected to traffic control systems are being installed at a growing number of urban intersections. Computer vision approaches have the potential to be very valuable tools for automatically detecting accidents. This study aims to provide an innovative and efficient framework for traffic monitoring applications, specifically focusing on detecting accidents occurring at crossings. The proposed framework starts with the first hierarchical phase, which involves the use of a Kalman filter and the Hungarian algorithm for object tracking and association. The second phase is referred to as trajectory conflict analysis, the third step is known as the advanced YOLOv4 technique, and the final stage is named efficient and accurate object detection. Subsequently, the procedure is completed. During the object tracking stage, the presence of obstructions, overlapping objects, and changes in shape are all carefully considered. This is achieved by using a distinct cost function. Analyzing object trajectories involves considering characteristics such as speed, angle, and distance in order to identify various forms of trajectory conflicts. Examples of these disputes include those pertaining to autos, individuals, and bicycles. These examples represent just a small fraction of the many forms of trajectory conflicts that may be detected. The experiment's results, based on video footage obtained from genuine traffic scenarios, indicate that the recommended approach has potential for use in real-time traffic monitoring technologies. Two key attributes that enhance the accuracy of defining trajectory conflicts are a low false alarm rate and a high detection rate. This category include contentious occurrences, including as collisions and close calls, that occur at heavily trafficked intersections in urban or suburban regions. Prior to implementation, the proposed framework undergoes a battery of tests to verify its durability and longevity. The tests include evaluating various lighting conditions and video sequences that are imported from YouTube.**

***Keywords:* YOLOv4, Kalman filter, framework, and Youtube.**

I. INTRODUCTION

When we talk about building a transportation infrastructure that includes consumer-oriented telecommunications, road networks, and cars, we're talking about Intelligent Transport Systems (ITS).

The majority of its applications are in the field of Intelligent Transportation Systems (ITS), where detection plays a pivotal role. Vehicle detection and tracking in moving films is complicated by the fact that backdrop pictures may vary greatly depending on factors like lighting, shadows, and environmental factors.

Consequently, recognizing moving automobiles is rather difficult due to factors such as changing background objects, brightness changes, and autos' desire to stick to their environment. As a solution to this issue, this thesis investigates the possibility of autonomous moving vehicle detection. The evolution of the Intelligent Transportation System (ITS), its components, and their uses are detailed in this chapter. Following an explanation of the car-detecting system, the purpose of the research and the structure of the thesis are detailed.

A new transportation design that incorporates a sophisticated data and communications network for users, roadways, and automobiles is called an intelligent transport system (ITS).

In their description of advanced technology, Guerrero-Ibafiez et al. (2015) outlined the coordinated employment of sophisticated sensors, hardware, computers, and communication systems. In addition to giving passengers vital information, these apps make the transportation system more efficient and secure. The postal code for Anna University in Chennai is 600 025. A number of communication technologies are shown to be interdependent in Figure 1.1 of an Intelligent Transportation System (ITS).

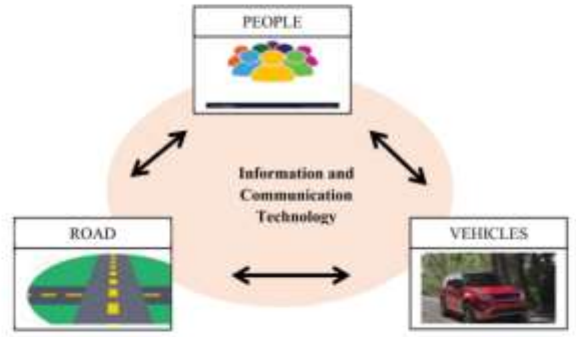

Figure 1.1 Relationship between an ITS and Communication Technology

Cities, states, and federal agencies can now meet the growing need for transportation networks with the help of intelligent transportation systems (ITS) technology. Improvements in public safety and reductions in traffic congestion are the primary goals of ITS.

Lessen negative effects on the environment, speed up data transfer, pay engine operators and crisis managers right away, etc. As the demand on transportation networks continues to rise, this organization's suggestions assist state and local governments as well as metropolitan regions in meeting this challenge. The efficiency and comprehensiveness of the moving vehicle detection system largely dictate its productivity. The effective operation of Intelligent Transportation Systems (ITS) relies heavily on vehicle identification and tracking systems, which gather and organize data on transportation vehicles. Research conducted by Sun et al. in 2006. More and more apps and dynamic vehicles are relying on Intelligent Transportation Systems (ITS) to track and analyze traffic trends in real time.

Among Chennai's most esteemed educational institutions is Anna University, which can be found at 600 025 postal code. Research in the area of congestion marvels is substantial because it modifies the requirements of an ITS application and a dynamic traffic task model based on traffic conditions (Mimbela et al., 2000).

To address transportation-related problems, the Intelligent Transportation System (ITS) integrates various communication methods, detection systems, state-of-the-art vision technologies, and complex software algorithms. The traffic discovery zone has long been relied upon by public offices and counseling organizations as a visually attractive circular place embedded in the roadway surface (Grant et al. 2000). Nevertheless, this approach could come with hefty startup costs, be impractical in most cases, and only work for certain types of testing

II LITERARURE SURVEY

In the last few decades, deep learning has been a hot subject. By learning features and classifications directly from the input picture, deep learning aims to achieve end-to-end learning.

Image. Here we take a closer look at how moving vehicle detection using deep learning techniques works.

To enable the tracking and classification of a large number of cars, Kim et al. (2019) developed a system based on CNN classifiers. Training efficiency and the precision of vehicle categorization predictions are both enhanced as a result. The initial set of findings shows that it was feasible to track and classify a large number of vehicles while also determining their speeds. An integrated machine learning mechanism had to be designed into the digital video camera system so that it could watch and distinguish between many lanes of vehicles at the same time.

Separating the exciting zone (the moving vehicle) from the boring district (the rest of the region) is the goal of Muchtar et al.'s (2019) attention-based approach. In the end, the arrangement's execution is substantially improved thanks to the deep CNN's enthralling reference point. Using their own dataset and a few of external tests from the 2014 CDNET, they test their hypothesis.

A technique for identifying license plates, known as Region-Based CNN, was presented by Rafique et al. (2018). The following issues are addressed by the system: (1) LP recognition in every frame of the video display; (2) incomplete LP detection for Anna University, Chennai - 600 025 18; and (3) incomplete LP detection with moving cameras and vehicles. This method successfully identified the license plate, allowing for the security-related disclosure or concealment of a vehicle's identity.

Using aerial images, Koga et al. (2018) presented a Convolutional Neural Network (CNN)–based vehicle identification method. Nevertheless, the CNN classifier was instructed to employ the Hard Example Mining (HEM) method, which included training it using radar or aerial photos. Each batch's loss values were calculated, and the instances with the largest losses were chosen. Next, Stochastic Gradient Descent (SGD) was used with the HEM approach to choose the most relevant training data.

An new traffic monitoring system that uses text and symbols for the autonomous driving assistance program was created by Hengliang Luo et al. (2017). The system is data-driven. After processing, the system extracts regions of interest for traffic signs, and then refines and categorizes these regions of interest.

Using a built-in camera in a car, we were able to record video footage and then use CNN technology to find ROI and get the best possible outcome with little effort and cost. Using a deep Convolutional Neural Network, Jiyong Chung and colleagues created a technique for measuring traffic density in 2017. This counting method uses roadside observations and machine learning to alleviate traffic congestion. However, the lack of CNN's hyperparameter might be the reason for this system's inefficiency. Hence, a sophisticated counting technique is required for vehicle data identification.

To precisely recognize the region of a vehicle and locate its license plate position, Kim et al. (2017) presented a two-step method that utilizes deep learning. This method provides details about the size of the license plate region and narrows the search area to find it. At ANNA UNIVERSITY (600 025, Chennai, India), we apply the Convolutional Neural Network (CNN) Algorithm to detect and understand the vehicle's region and its hierarchical structure. For every spot that has been located, nineteen different license plate examples are generated. By using pedestrian identification algorithms to assess the removal of non-plate regions using a deep Convolutional Neural Network (CNN), we can prove that this strategy is better than previous approaches.In their 2017 publication, Liu et al. detailed a deep learning-based vehicle categorization system. Many videos are used in the categorization process in this context. Interference caused the wrong classification.

Improving the effectiveness of photos acquired by a multi-view security camera, Kim and Lim (2017) introduced a novel program for vehicle type classification based on four separate principles. Accurate tracking and recognition of moving vehicles is a key component of image processing and AI research. One common approach was to use computer vision methods; in this case, a Convolutional Neural Network (CNN) was trained to improve the accuracy of route violation detection.

The suggested approach for classifying vehicle types by Dong et al. (2015) makes use of a typical neural network that is semi-supervised. Vehicle frontal-view images are the primary focus of this system. Though helpful, the computer can only assess the car right in front of it, which limits its usefulness.

Automated traffic system monitoring was the subject of research by Dipti Srinivasan et al. (2004). Developed and tested in a real-world traffic environment were the multilayer FFNN, fundamental PNN, and constructive PNN.

An update rule was used to modify the BPNN variables. While the Multi-Layer Feedforward Neural Network (FFNN) demonstrated strong performance in auto recognition, its flexibility was severely lacking. But, the Counterpropagation Neural Network (CPNN) demonstrated remarkable flexibility for tiny networks and was straightforward to set up.

III MOVING VEHICLE DETECTION SYSTEM USING OPTIMAL PROBABILISTIC NEURAL NETWORKS

Smart reconnaissance is receiving increased attention as a result of the growing concern for the safety and security of transportation networks. Event detection, object identification and categorization, tracking, motion segmentation, object recognition in motion, and behavior interpretation and representation are all tasks performed by automatic monitoring systems. Despite object tracking's critical role in computer vision, developing an algorithm to accomplish this feat is no easy feat. A wide variety of results have been made possible by recent significant developments. However, elements like partial occlusion, changes in illumination, variations in position, rapid motions, and backdrop clutter further challenge the creation of a tracking system. Many different fields may benefit from video-based object monitoring, including navigation, computer-human interaction, video surveillance, motion analysis, and video surveillance. For applications like surveillance, HCI, and image interpretation, it integrates sophisticated picture analysis with fundamental video processing in order to comprehend image behavior. One common way to keep tabs on things is to employ vehicle detection on roads. To avoid traffic jams, it is crucial to be able to identify moving vehicles. A method for identifying moving autonomous cars is introduced in this thesis. Chennai is home to Anna University, which can be found in 600 025 37 postal code. Accurate and trustworthy vehicle identification is a crucial part of traffic monitoring. The use of Intelligent Transportation Systems (ITSs) to track vehicles is not without its difficulties. The ever-changing shapes and whereabouts of vehicles make it challenging to create a tailored detection model. The capacity to distinguish between things would be significantly impaired in challenging environments such as those with extreme weather, varying levels of light, and constantly shifting lighting conditions. Many cars may merge into one larger vehicle in order to avoid the glare of traffic jams. It is critical to make the necessary modifications to the learning parameter for vehicle detection. Detection systems with intricate parameters are seldom used. The parameters are trained using cutting-edge machine learning techniques. Using the cars' visual characteristics, object detection can assess the image's key components. In order to identify moving vehicles accurately, this chapter presents a novel method that makes use of optimum probabilistic neural networks. To maximize the weight value of the PNN (Probabilistic Neural Network) model and enhance the performance of Moving Vehicle Detection, this technique integrates the ideas of CS (Compressive Sensing) and OLB (Online Boosting). There are two parts to the suggested OCS-PNN based moving vehicle detection system: one is making the background, and the other is detecting moving vehicles using the OCS-PNN model. Presented below is an explanation of the primary goal of the suggested approach: Using the OCS algorithm, we improved the PNN weight approach and got more accurate results. Chennai is home to Anna University, which can be found in 600 025 38 postal code. A method that efficiently chooses the opposite answer in an OBL situation. Using this method, we can get closer to the ideal answer in our data. To accurately and thoroughly identify moving objects, one method is to line up incoming pixels with a basic backdrop model. The implementation of a background updating system and block estimates allows for this to be accomplished. We compare and evaluate the outcomes with the results of the current approaches by replicating the suggested methodology.

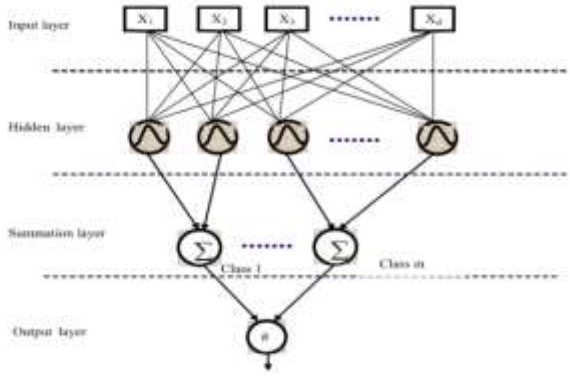

Figure 3.1 Block diagram of PNN

In order to generate a sample that faithfully depicts the source-to-training-data distance, the hidden layer determines how close the input is to the training vector. The output layer takes into account all of the individual's contributions. All of the parameters that went into the probability function that produced the yield vector after all net.

Finally, to find the best classification for a given class, a competitive transfer function is calculated halfway between the first and third layers. Instead of using an iterative learning method, probabilistic neural networks (PNNs) may handle large amounts of training data more effectively than classic neural networks.The technical behavior of Bayes is credited with the PNN functionality.

IV REAL-TIME ACCIDENT DETECTION IN TRAFFIC SURVEILLANCE USING DEEP LEARNING

In urban areas, the management of traffic is heavily influenced by conflicts and accidents that occur at intersections. It is possible that drivers who are in the dilemma zone may opt to speed when the traffic light changes from green to yellow. This will increase the chance of rear-end and angle accidents occurring for those vehicles. People have a tendency to disrespect traffic signals, especially red lights, despite the fact that there have been substantial attempts made to reduce dangerous driving habits. Additional potentially hazardous behaviors, such as rapid lane changes and unexpected movements of pedestrians and cyclists, may also take place as a result of the arrangement of crossings or the application of traffic control systems. In order to lessen the impact of these trajectory conflicts, it is very necessary for us to gather information about them as soon as possible.

At the moment, the majority of traffic management systems rely on human review of recorded video in order to monitor motion captured by traffic surveillance cameras. Taking into consideration the ubiquitous availability of surveillance cameras at junctions, the performance of traffic monitoring systems would be considerably improved by the use of computer vision technology for the purpose of automating accident detection. It has been established in a variety of research publications [1]-[10] that computer vision algorithms have been used extensively in traffic surveillance systems for a variety of purposes. Through the use of spontaneous input, automatic traffic incident detection not only reduces the amount of human engagement that is required, but it also makes it possible to deploy emergency ambulances and paramedics in a timely manner. By permitting alterations to junction lights and adjusting the architecture of junctions, an automated accident detection system may be used to reduce the severity of traffic accidents. This might be accomplished by having the system identify accidents automatically. In order to detect objects, we make use of the YOLOv4 [11] approach, which is well-known for its efficiency and precision. This technique is an excellent fit for the real-time edge computing devices that we implement. Following that, it is essential to keep a close eye on the environment for any fascinating items and to carefully follow their motions. A unique set of dissimilarity measures is developed and used by merging the object association approach of the Hungarian algorithm [12] with the trajectory smoothing and missing object prediction capabilities of the Kalman filter method [13]. This results in the generation and utilization of a novel set of differences. In addition to this, the framework makes use of motion analysis and heuristics in order to identify various kinds of collisions between trajectories that have the potential to result in accidents. We hunt for anomalies in the paths that these road-user pairs are taking by analyzing the speed and direction of movement of surrounding road-user pairs. These irregularities have the potential to result in collisions. A representation of the system architecture of the accident detection framework that we have presented may be seen in the figure.

This section offers a description of the three key components that make up the accident detection system that is being under consideration. Two of the procedures that are involved in this process are as follows: first, the identification of potential road users through the utilization of a pre-trained model that is based on deep convolutional neural networks and the advanced YOLOv4 [11] method; second, the tracking of the identified road users through the utilization of a Kalman filter approach; and third, the analysis of their trajectories to identify hazardous abnormalities that have the potential to cause minor or major accidents. The architecture that has been developed for real-time traffic monitoring systems is purposefully constructed using algorithms that were supposed to be efficient.

A. Road-User Detection

Identifying the items in the scene that are relevant to the analysis is the first stage in the majority of video and image analytics systems. Due to the fact that we are particularly interested in the object category, we make use of a sophisticated object identification approach known as YOLOv4 [11] in order to identify and categorize the individuals who are using the roads in each video frame. When it comes to object detectors, the YOLO-based deep learning technique family comes out on top with the most advantageous balance between efficiency and performance. 2015 was the year that saw the introduction of the first iteration of the You Only Look Once (YOLO) deep learning technology [14]. For the purpose of dividing the input picture, this method makes use of an S-S grid, with each grid cell serving either as a background or an object detector. Each cell receives a collection of bounding boxes that have confidence ratings attached to them. This collection is comprised of a predetermined number (B) of boxes. Multiplying the intersection over union (IOU) of the ground truth and predicted boxes with the probability of each item is the method that is used to arrive at the confidence scores. Subsequent generations of YOLO have been subjected to a significant amount of work in order to improve their detection capabilities and reduce the complexity of their computational processes [15], [16]. Previous approaches have been surpassed in terms of speed as well as mean average accuracy (mAP) by the most recent official iteration of the YOLO lineage, which is YOLOv4 [11]. However, there are also alternative versions that may be found online, such as YOLOX [17]. A representation of the YOLO implementation's design may be seen in Figure 2. The process begins with a CSPDarknet53 model, which serves as the structural backbone of the network for the purpose of feature extraction. The components of the head and neck are the next ones to be examined. In contrast, the neck is made up of the path aggregation network (PANet) and the spatial attention module. The dense prediction block is in charge of managing bounding box localization and classification respectively. Methods that are referred to as "bag of specials" and "bag of freebies" are other strategies that further enrich this design. For the purpose of this item identification challenge, we made use of the YOLOv4 [11] model, which has been trained on the MS COCO dataset [18] in the past. YOLOv4 displayed great performance when applied to aerial pictures, despite the fact that it was trained on a dataset that included objects of varying sizes and that were seen from a variety of perspectives. The study of trajectory conflicts that take place at typical urban crossings between the three most popular types of road users—cars, pedestrians, and bicycles—is something that especially piques our curiosity.

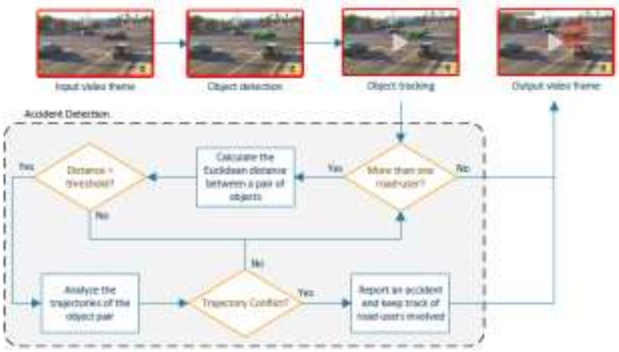

Figure 4.1. The system architecture of our proposed accident detection framework

Multiple object tracking (MOT) has been the subject of a significant amount of research over the last several decades [19], mostly because of its significance in the context of video analytics applications. Following the example set by SORT, we make use of a tracking technique that is both straightforward and efficient, and it has shown to be beneficial in past situations [20]. The Hungarian method is used in order to establish a connection between the bounding boxes that have been identified from one frame to the next [12]. Because the estimating model uses the Kalman filter technique [13] to forecast the future positions of each detected item based on their present location, it is able to improve association, give continuous trajectories, and anticipate the absence of tracks. These are all goals that are accomplished via the use of this approach. In order to determine the inter-frame displacement of each item that has been identified, a linear velocity model is often used. An explanation of the objective states that are included in the Kalman filter tracking approach is provided after this:

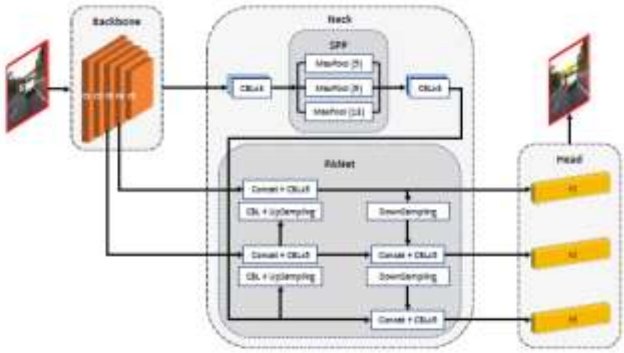

Figure 4.2. Architecture of the YOLOv4 model with three major component

$$o_i^t = [x_i, y_i, s_i, r_i, \dot{x}_i, \dot{y}_i, \dot{s}_i] \qquad (1)$$

The bounding box scale (si) and aspect ratio (ri) are two of the factors that are associated with object oi at frame t. Additionally, the horizontal and vertical coordinates of the center of the bounding box are xi and yi, respectively. Furthermore, the velocities of the object oi in each of these three parameters (xi, yi, and si) are also taken into consideration. Following the establishment of a connection between a target and a detection, the velocity components are rapidly updated. To make a prediction about the state, the linear velocity model is used in the event that there is no relationship. We are going to identify two groups of objects at each frame by taking into consideration two video frames that are next to one another, t and t+1.

$$\begin{aligned} O^t &= \{o_1^t, o_2^t, \ldots, o_n^t\} \\ O^{t+1} &= \{o_1^{t+1}, o_2^{t+1}, \ldots, o_m^{t+1}\} \end{aligned} \qquad (2)$$

There is an element oj in set Ot+1 that may decrease the cost function C(oi; oj) to the greatest extent that is conceivable for each and every item oi that is included within set Ot. The index i ∈ [N] = {1, 2,..., N} is used to represent the things that were identified in the previous frame. On the other hand, the index j ∈ [M] = {1, 2,..., M} is used to represent the objects that have been detected in the current frame. We have developed a dissimilarity cost function in order to successfully manage tough circumstances such as occlusion, inaccurate item identification results, object overlap, and shape alterations. This was done in order to allow us to properly handle these scenarios. In order to tackle the issue of data association, this function takes into account a number of

International Journal of Engineering Innovations in Advanced Technology
ISSN: 2582-1431 (Online), Volume-6 Issue-2, June 2024

different heuristic signals, such as size, location, intersection over union (IOU), and appearance. It is the histogram correlation that serves as the foundation for the formula that is used to compute the appearance distance between an item oi and a detection oj.

$$C_{i,j}^{A} = 1 - \frac{\sum_b \left(H_b(o_i) - \bar{H}(o_i)\right)\left(H_b(o_j) - \bar{H}(o_j)\right.}{\sqrt{\sum_b \left(H_b(o_i) - \bar{H}(o_i)\right)^2 \sum_b \left(H_b(o_j) - \bar{H}(\right.}}$$

In the aforementioned scenario, CA i;j is a variable that may take on values ranging from 0 to 1. There is a bin index that is represented by the variable b, and the histogram of the item in the RGB color space is represented by the variable Hb. The following procedure is used in order to do the computation of H:

$$\bar{H}(o_k) = \frac{1}{B}\sum_b H_b(o_k) \qquad (4)$$

This item's histogram has a total of B bins in its distribution. To determine the difference in size between the two things, the dimensions of the objects are used:

$$C_{i,j}^{S} = \frac{1}{2}\left(\frac{|h_i - h_j|}{h_i + h_j} + \frac{|w_i - w_j|}{w_i + w_j}\right) \qquad (5)$$

Consider the width of the object's surrounding box to be denoted by w, and the height of the box to be denoted by h. The more different the bounding boxes of object oi and detection oj are in size, the more Ci;jS approaches one. Similar steps are used in the calculation of the position dissimilarity, which are as follows:

$$C_{i,j}^{P} = \frac{1}{2}\left(\frac{|x_i - x_j|}{x_i + x_j} + \frac{|y_i - y_j|}{y_i + y_j}\right) \qquad (6)$$

When the distance between object oi and detection oj increases, the value of CP i;j is a decimal that ranges from 0 to 1, with a tendency to become closer to 1 as the distance increases. A good illustration of how the IOU value may be used to compute the Jaccard distance by making use of the dissimilarity measures that were discussed before is as follows:

$$C_{i,j}^{K} = 1 - \frac{Box(o_i) \cap Box(o_j)}{Box(o_i) \cup Box(o_j)} \qquad (7)$$

Box(ok) is the representation of the collection of pixels that work together to produce the bounding box of object k.

Figure 4.4. Vehicle-to-Vehicle (V2V) traffic accidents at intersections detected by our proposed framework. The red circles indicate the location of the incidents.

The framework that was proposed obtained a Detection Rate of 93.10% and a False Alarm Rate of 6.89%, which is evidence that it is effective. A comparison of the results with those obtained via other typical approaches is shown in Table I. It is necessary to utilize the object tracking and object identification modules in an asynchronous fashion in order to reduce the amount of time that is spent on computations. The quick reporting of trajectory discrepancies with just two false alarms is considered satisfactory when taking into consideration the limitations of the methods used for detection and tracking.

CONCLUSION

With the help of this study, a novel framework has been developed for automatically recognizing accidents and near-accidents that occur at traffic crossings. The framework is made up of three primary modules: one for object recognition that makes use of the YOLOv4 method, another for tracking that makes use of the Kalman filter and the Hungarian algorithm with a unique cost function, and a third module for accident detection that makes use of the obtained trajectories for the purpose of analyzing and detecting anomalies. During the process of capturing the movements of objects of interest, the robust tracking approach takes into account difficult circumstances such as occlusion, objects that overlap, and changes in form. Next, we conduct an analysis of the routes in order to keep track of the travel patterns of the individuals who have been recognized as users of the road in relation to their position, velocity, and movement direction. The motion analysis takes into account a number of heuristic signals in order to identify irregularities that might potentially result in traffic accidents. To determine whether or not the suggested framework is successful, a collection of different traffic recordings that show accidents or occurrences that are dangerously near to becoming accidents is compiled. Our system has been found to be successful in real-time traffic control applications, as shown by the experimental assessments.

REFERENCES

[1]. Zhang, Y., Li, P., & Wang, X. (2019). Intrusion detection for IoT based on improved genetic algorithm and deep belief network. IEEE Access, 7, 31711-31722.

[2]. Elmasry, W., Akbulut, A., & Zaim, A. H. (2020). Comparative evaluation of different classification techniques for masquerade attack detection. International Journal of Information and Computer Security, 13(2), 187-209.

[3]. Shelke, M. P. K., Sontakke, M. S., & Gawande, A. D. (2012). Intrusion detection system for cloud computing. International Journal of Scientific & Technology Research, 1(4), 67-71.

[4]. Rajput, D., & Thakkar, A. (2019). A survey on different network intrusion detection systems and countermeasure. In Emerging Research in Computing,Information, Communication and Applications: ERCICA 2018, Volume 2 (pp.497-506). Springer Singapore.

[5]. Wang, C., Zhao, T., & Liu, Z. (2020). An activity theory model for dynamic evolution of attack graph based on improved least square genetic algorithm. International Journal of Information and Computer Security, 12(4),
397-415.

[6]. Larson, D. (2016). Distributed denial of service attacks–holding back the flood. Network Security, 2016(3), 5-7.

[7]. Vijayakumar, D. S., & Ganapathy, S. (2022). Multistage ensembled classifier for wireless intrusion detection system. Wireless Personal Communications, 122(1),645-668.

[8]. Alkasassbeh, M. (2017). An empirical evaluation for the intrusion detection
features based on machine learning and feature selection methods. arXiv preprint arXiv:1712.09623.

[9]. Gu, S., Cheng, R., & Jin, Y. (2018). Feature selection for high-dimensional classification using a competitive swarm optimizer. Soft Computing, 22, 811-822.

[10]. Rao, H., Shi, X., Rodrigue, A. K., Feng, J., Xia, Y., Elhoseny, M., ... & Gu, L.(2019). Feature selection based on artificial bee colony and gradient boosting decision tree. Applied Soft Computing, 74, 634-642.

[11]. Mafarja, M., Aljarah, I., Faris, H., Hammouri, A. I., Ala"M, A. Z., & Mirjalili, S.(2019). Binary grasshopper optimisation algorithm approaches for feature selection problems. Expert Systems with Applications, 117, 267-286.

[12]. Thanh, H., & Lang, T. (2019). An approach to reduce data dimension in building effective network intrusion detection systems. EAI Endorsed Transactions on Context-aware Systems and Applications, 6(18).