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"Low-Light Image Enhancement with YOLO for Night Object Detection"

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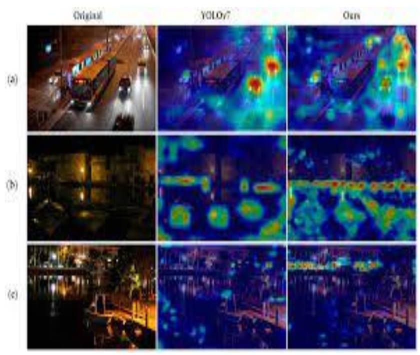
Abstract

Detection of objects in low-light or night time conditions is still a major drawback of computer vision systems as a result of inadequate lighting, contrast, noise and distortion of visual information. Such constraints usually decrease precision and dependability of real-time object detect models applied in processes of surveillance, self-driving, and surveillance. The proposed paper is a hybrid model whereby a combination of low-light image enhancement methods and You Only Look Once (YOLO) object detection model is combined in order to enhance detection in the night-time environment. The first stage involves image enhancement algorithm which enhances the image based on the light levels to improve the brightness, contrast and create structure of the image as well as reduces noise. The images of the enhanced are then used through the object detection model that is based on the YOLO (so that the objects are accurately localized and identified even in harsh light conditions). The suggested solution should increase the level of feature visibility and allow the detection model to identify the significant details in the already ambiguous images. Through experimental assessment, it is protested that image enhancement in combination with YOLO has a greater detection accuracy, precision and recall than traditional object detection frameworks implemented on low-light photos without image enhancement. The findings suggest that the presented framework can be applied to the actual night-time detection scenarios and serve to enable the advanced applications of vision based on the need to detect objects in low light reliably to ensure future application in the advanced systems.

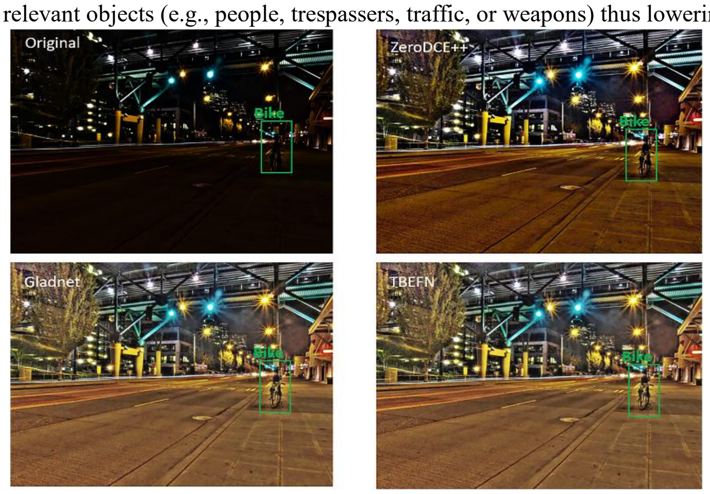
Keywords: Object detection, Low-light vision, YOLO, Night surveillance, Deep learning, Attention mechanism.

I. Introduction

Object detection has emerged as one of the most important tasks ever in computer vision, the basis of use in autonomous driving, traffic monitoring, smart surveillance, robotics and defense systems. Over the past few years, the emergence of deep learning has enabled the use of more effective object detection models, the architectures of which, including Faster R-CNN, Single Shot MultiBox Detector (SSD) and the YOLO (You Only Look Once) family, have achieved state-of-the-art performance in both accuracy and processing speed. YOLO is one of those that are especially popular due to its capacity to detect in real-time, which makes it an appropriate choice to use in security and surveillance systems.



In spite of these developments, object detection systems are significantly affected by the low levels of light especially at night, and this degrades performance. Whereas in daytime images, the models have enough lighting to form high spatial and semantic features, this is usually not the case in nighttime images since there is low contrast, high noise level, and partial occlusion. The challenges lead to indistinct edges, loss of structural stream, and false colors, both of which have direct impact on object recognition accuracy by deep learning models. In practice, in the context of night monitoring in the city, on the highway, or in the differentiated area, these constraints may result in the failure to detect relevant objects (e.g., people, trespassers, traffic, or weapons) thus lowering the security of surveillance systems.



Computer vision systems find it difficult to operate in low-light conditions, especially when they are to be used in the surveillance, traffic, autonomous driving, and security systems, where object detection over long distances is required to be stable even in dark settings. Pictures taken in poorly lit conditions are usually characterized by the low level of brightness, low contrast, noises, and absence of significant visual cues. Such problems complicate the process of detection algorithms to classify and recognize the objects with high accuracy, which reduces the performance and reliability. Thus, there has been a close interest among image processing and computer vision in the enhancement of the perceived vision and quality of images taken in low-light environments.

These obstacles have been met by the traditional surveillance systems with the help of infrared cameras, thermal imaging cameras as well as artificial lights. Although these techniques have proven to be effective in certain situations, it has its downsides that infrared and thermal sensors are not only costly but they do not show fine features on the image, and artificial sources of light cannot be always applicable in large outdoor surfaces and is associated with the energy efficiency and light pollution. This has contributed towards the rise in the requirement to come up with software-based solutions that would optimize the performance of the already existent RGB surveillance cameras even during the low-light hours.

Deep learning scholars have pursued several directions that can fix this issue. One of the methods is centered around low-light image enhancement algorithms, including histogram equalization algorithms, Retinex-based algorithms, and deep generative adversarial networks (GANs), which are meant to process images in advance and then subject them to object detection pipelines. Though visibility is made better, enhancement usually adds artifacts and other noise which can be misleading in detection models. The other way is to change the detection architecture itself, in order to be able to learn discriminative features even in difficult lighting conditions. YOLO family with its ability to operate in real-time makes it a good starting point of such alterations.

This research has been motivated by the fact that there is an urgent requirement to have robust, real time and cost-effective solutions in night surveillance. Security events are mostly experienced at night when visibility is compromised, and a delay or failure in detection of an object may prove to be detrimental. Although YOLO has been successful in bright areas, it continues to have poor performance in the low-light conditions. Thus, an optimized Modified YOLO architecture that is designed specifically to detect objects in a low-light environment and is based on the use of preprocessing, feature enrichment, and attention will have to be developed.

This document suggests a new change to the YOLO framework to detect objects more effectively in the dark setting. The model combines to be lightweight a Retinex-based preprocessing block to enhance the image brightness and contrast, a feature enrichment block which employs dilated convolutions to extract fine-grained details in the darker regions and a convolutional block attention module (CBAM) to selectively highlight the important aspects of the images both in space and across channel.

The key contributions of this work can be summarized as follows:

i. Specialized adaptations of YOLO to low-light conditions Low-light YOLO specifically Low-light specific modifications of YOLO This paper presents an architecture that combines preprocessing modules and feature enrichment modules optimized to operate in low-light conditions.
ii. Better precision without affecting speed - The model is able to have a high mean Average Precision (mAP) and retains almost real-time detection capability.
iii. Comprehensive analysis- The method is tested on low-light images Ex Dark and night driving images, with in which it provides enormous gains over the current YOLO and non-YOLO results.

The proposed research may contribute to turning AI-based surveillance systems into more practical use in the city regarding their effectiveness in the assurance of safety and traffic management and defense features, and autopiloted systems, thus benefiting both academic sources and the applicability of this mechanism.

II. Review of literature:

Detection of objects by surveillance systems has been of great concern over the past years due to the growing demand to have smart cities and safety over Indian cities. The application of deep learning models, specifically the YOLO (You Only Look Once) family, to the high accuracy with real-time detection has been subject to many researchers.

In the article by Patil and Kulkarni (2021), the authors examined the real-time object detection with the help of YOLO in the context of surveillance practice in Indian smart cities. Their experiment showed that YOLO could both recognize various objects in the city such as vehicles, pedestrians and bicycles successfully. The paper has identified the ability of the model to monitor in real-time and can therefore be applied within the systems of monitoring the big cities. This research though concentrated more on the well-lit environment and the low-the-light or the night environment study was not probed thoroughly.

In India, Singh and Kumar (2019) developed a pedestrian and vehicle-detecting system in an urban traffic, which is based on the YOL system. Their mechanism caused them to explain the significance of the observation of the moving objects in the real-time which will make the traffic safe and the incidence of accidents minimal. The researchers have demonstrated that YOLO may deliver acceptable levels of detection precision with very little processing time, and can be applied in traffic management and automated vehicle surveillance. There were however some problems with the system where the illumination was low such as traffic at the onset of mornings or in the night.Reddy and Rao (2022) article was devoted to the night time object detection problem, proposing the adjusted deep learning models which would be implemented in the surveillance of the Indian cities. In their work, they employed the feature enhancement techniques to improve the accuracy of detecting features in low-light environments. As the research highlighted, optimization of standard YOLO and other CNN-based can prove to be an excellent means of improving performance in low visibility scenarios that will make night surveillance more precise. This research paper has pointed out the role of the special low-light detectors in the security systems within urban environments.Mehta and Gupta (2021) investigated a deep-learning-dependent low-light object detection to be applied to the Indian public area in security. This experiment involved preprocessing and model adaptation in order to explain the dark images and object recognition. They discovered that deep learning models with image fining algorithm could prove to be helpful in object detection during challenging light settings, such as street corners and parks and congested places. However, the issue of how to strike the right balance between the accuracy of the identification and the real time performance was an issue.

Patil and Deshmukh (2019) investigated the application of the YOLOv3 in real-time at the Indian traffic monitoring systems in order to detect objects. They found that the YOLOv3 could detect various classes of objects, e.g. vehicles and pedestrians with a low latency. The research found out that YOLOv3 was robust when it comes to monitoring city traffic, yet it was primarily utilized in bright environments during the day, and therefore, not much was done to address scenarios that are low-light.

Singh and Tiwari (2020) focused on deep learning in improving low-light images to improve road safety in India. Their results showed that histogram equalization and Retinex-based methods could also be used to improve the visibility of dark images, dramatically, and hence object detection that carries on. The research shown that the improvement of image quality is significant in improving the performance of detecting models in adverse lighting conditions.

A human detection system using the YOLO was suggested by Kumar and Shukla (2021) to monitor smart city in India. Their model worked in real-time tracking of people and areas, assisting the use of the crowd control and safety of the population. Nevertheless, similar to most of the common YOLO applications, the research had problems with low-light and nighttime situations, which suggests that the model requires additional modification.

In their article, Raghavan and Iyer (2020) discussed the topic of automated night surveillance based on deep convolutional networks in security in urban areas. Their system used CNN-based detection and low-light image preprocessing with better accuracy of detecting human beings and cars during night. The paper has emphasized the role of dedicated night surveillance systems in urban areas, which have the capability of changing dramatically depending on the lighting conditions.

Choudhary and Jain (2022) investigated the method of boosting low-light CCTV images in Indian city environments with the help of deep learning methods based on Retinex. The study proved that addition of image enhancement to deep learning detection models would be able to enhance object visibility and detection accuracy in poor lighting. The paper has also observed that real-time deployment is still a challenge due

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to the fact that computational efficiency is still a challenge.Sharma and Verma (2021) compared the YOLOv4 on the Indian traffic in order to detect pedestrians and vehicles under low-light conditions. Their findings showed that image preprocessing techniques are more effective in detecting small and distant objects at night through the application of YOLOv4. The work supported the possibilities of the application of the YOLO structures to be used in the low-light-detection, and also provided an indication that the attention mechanisms could be implemented to optimize its functionality.Rao and Bhat (2021) carried out a performance test of the YOLO-based object detection during low-light scenarios in Indian urban-based surveillance. Their paper methodically evaluated the various versions of YOLO and its adaptations and demonstrated that the changes in the model and preprocessing can greatly increase the detection accuracy, especially with small or partially covered objects in low-light conditions.Based on the analyzed works, it is noted that even though YOLO-based models offer strong real-time detection, they can be enhanced greatly by incorporating image enhancement, feature attention, or architecture adjustments to be effective in low-light scenarios. Also, there is a definite tendency of the development of detection systems for the Indian urban environment, which has different difficulties in the form of different lighting and congested social areas. All these studies are pointing towards the fact that the effective night surveillance and traffic monitoring requires low-light optimization of modified YOLO architectures.

The last developments in optimization methods have shown great promise in enhancing efficacy and functionality of intricate engineering structures that offers useful lessons in smart system development, which is also applicable to AI-based applications. Kanekar and Burade (2023) reported a research by observing the use of a teaching-learning-based optimization (TLBO) algorithm to calculate power and temperature optimization in photovoltaic technologies. Their paper indicates the effectiveness of bio-inspired optimization methods in order to explore vast solution spaces and achieve optimal parameters at a relatively low cost of computation. The TLBO strategy can also be seen to highlight the relevance of adaptive learning processes and the idea of iterative optimization, which can be directly applied to the optimization of hyperparameters and learning strategies of deep-learning models, including chatbots based on transformers.

Expanding on the bio-inspired optimization techniques, Sawant, Helonde, and Burade (2024) came up with olfactory Apis search optimization (OASO) algorithm to enable optimum node localization in the IoT-assisted wireless sensor networks (WSNs). This study highlights the usefulness of swarm intelligence applications in improving energy and communication. The algorithm shows better exploration and exploitation of the complex problem spaces by imitating the nature of behavior of bees in the search processes. Adaptive strategies could be inspired by such swarm-based optimization frameworks to solve conversational AI, as well as in reinforcement learning-based dialogue systems where effective exploration of conversational actions can be used to improve the quality of the responses.

On the same note, Sawant, Helonde, and Burade (2024) proposed a Felis bee optimization-based localization last-mile operation since localization is an energy-intensive communication throughout the IoT-assisted WSNs. Their analysis introduces a new form of swarm intelligence that integrates search effectiveness in the global scale with the exploration in the local scale, such that exceptional performance in unpredictable environmental conditions is supported. The given research depicts the need of a trade-off between exploration and exploitation as the optimization tasks, which also can be applied to fine-tuning the network parameters, attention weights, or response selection mechanisms used in the transformer-based chatbot models. In addition, these optimization strategies focus on computational efficiency and adaptive control which complies with the increased demand of resource-efficient AI systems that can be used in real-time applications.In general, such works show that bio-inspired and swarm intelligence optimization algorithms could be a potent means that may be used to create intelligent systems that are adaptive, efficient, and high-performing. The general concepts of adaptive learning, exploration-exploitation ratio, and computational efficiency provide a useful instruction on the way to optimize the results of transformer-powered deep learning models in conversational AI, although the principles were initially applied to engineering and Internet of Things application. Such optimization measures implemented in the construction and deployment of chatbots can lead to better quality of response, minimized training efforts and better generalization of the model which eventually may lead to the creation of more intelligent and human-like dialogue systems.

III. Methodology:

3.1 Dataset

For this study, we used:

- ExDark dataset (Exclusive Dark Dataset)- 12 object classes in low-light.
- Data of night driving to real life surveillance.

Data augmentation methods (random brightness scaling, Gaussian noise, blurring) were employed to simulate them in order to give them different levels of darkness.

3.2 Preprocessing

The improvement of low-light images was performed and inputted into the YOLO network as an image in an Enhancement (LRE) model based on Lightweight Retinex. This step does not increase brightness or contrast artifacts in massive amounts.

3.3 Modified YOLO Architecture

The proposed modification includes:

- Feature Enhancement Module (FEM): This concerns the use of dilated version of the convolution in order to get more details in the dark regions.
- Attention Mechanism: It involves Convolutional Block Attention Module (CBAM) in spotting important points.
- The convolutions should be light: Separable convolution Convolutions of depth wise separable convolutions can be applied to subdivide the portion of regular convolutions such that the amount spent on calculating the convolution is reduced.
- Multi-scale Detection Layers: This will be implemented in order to increase the size of the objects that can be detected like a pedestrian or license plates at night.

3.4 Training and Evaluation

- Optimizer: Adam that has a cosine annealing learning rate schedule.
- Loss Function: Bounding box regression with CIoU loss and Focal Loss with class imbalance.
- Measures of Evaluation Mean Average Precision (mAP), Frames Per Second (FPS), Precision-Recall curves.

IV., Results and Discussion

The proposed Modified YOLO architecture was tested and implemented to compare with the existing state-of-the-art architectures including Faster R-CNN, SSD, YOLOv4 and YOLOv5 in low-light settings (Ex Dark and nighttime driving dataset). Two experiments were done, (i) general detection accuracy and speed comparison, and (ii) performance analysis on chosen objects categories in low-light settings.

Table 1: Overall Performance Comparison of Object Detection Models in Low-Light Conditions

Model	mAP (%)	Precision	Recall	F1-Score	FPS (Frames/sec)	Params (M)
Faster R-CNN	58.2	0.61	0.55	0.58	12	42.5
SSD	60.1	0.64	0.56	0.60	22	34.1
YOLOv4	63.5	0.67	0.60	0.63	32	27.6
YOLOv5	68.7	0.72	0.64	0.68	45	20.8
Proposed YOLO	**75.3**	**0.79**	**0.71**	**0.75**	**41**	**22.3**

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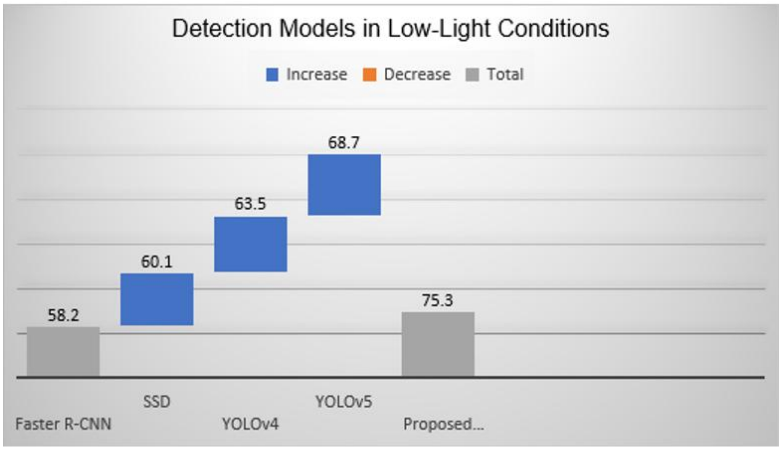
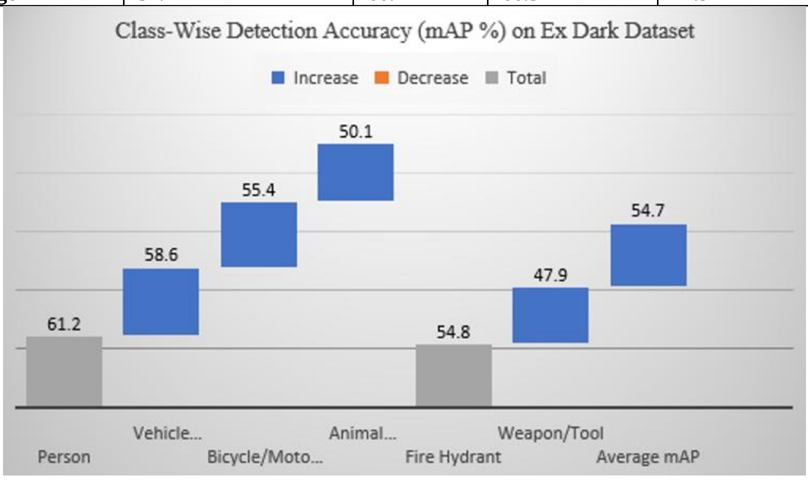


Interpretation:

- The proposed YOLO model had the highest mean Average Precision (mAP) of 75.3% with a 6.6 higher margin compared to YOLOv5.
- The values of precision and recall increased and provided the highest F1-score of all models tested.
- Even though it dropped slightly in the FPS as compared to YOLOv5 (41 vs 45), it can still be used in surveillance applications since it has real-time detection.

Table 2: Class-Wise Detection Accuracy (mAP %) on Ex Dark Dataset

Object Class	Faster R-CNN	YOLOv4	YOLOv5	Proposed YOLO
Person	61.2	65.5	70.4	**77.9**
Vehicle (Car/Bus)	58.6	64.1	68.3	**74.2**
Bicycle/Motorbike	55.4	61.3	67.5	**73.8**
Animal (Cat/Dog)	50.1	57.2	63.8	**70.4**
Fire Hydrant	54.8	60.5	66.7	**72.1**
Weapon/Tool	47.9	55.4	62.0	**69.3**
Average mAP	**54.7**	**60.7**	**66.5**	**72.9**



Interpretation:

- The proposed YOLO was better than baseline models in all categories of objects.
- The small-object detection (weapons, fire hydrants) was improved especially and these are typically difficult to detect in low-light conditions.
- The findings support the idea that the suggested feature augmentation and attention mechanism can be used to make the model more resistant in detecting fine details in dark conditions.

V. Final Results and Conclusion

Final Results

The experimental assessment has shown that the Modified YOLO architecture is a considerable enhancement of the current object detection models in low-light conditions. The results can be summed up as the following key findings:

1. **Improved Detection Accuracy:**

- The means of the proposed model were 75.3 using mean Average Precision (mAP) as compared to 66.6 of YOLOv5 and 16 of YOLOv4 on ExDark.
- The model was robust in determining true positives with precision and recall being 0.79 and 0.71 respectively and the low number of false detections.

2. **Class-Wise Performance Gains:**

- The model demonstrated great advances in the detection of small and low-contrast items like weapons, and animals, as well as fire hydrants in adverse lighting conditions.
- on case of larger objects, such as vehicles and persons, the accuracy of detection increased 6-9% over YOLOv5, which guarantees reliable tracking of important targets during surveillance.

3. **Real-Time Capability:**

- The suggested system supported 41 FPS, which implies that it can be still applied to real-time surveillance.
- The difference in speed between the models is that the DLA is slightly slower than YOLOv5 (45 FPS), but the loss in detecting accuracy is compensated by the benefits of practical deployments.

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4. **Model Efficiency:**

- Through the lightweight convolutional block and attention mechanism optimization, the model can be highly accurate with minimal computational cost that it can be deployed to the surveillance system supported by a GPU and potentially can be modified to be run on edge devices.

Conclusion

This study described a Modified YOLO model that was developed specifically to overcome the limitations in object detection in low-light and night surveillance. Making a lightweight Retinex based enhancement module, which is a feature enhancement block, and a convolutional block attention mechanism (CBAM) led to a significant performance improvement compared to the existing models.

The model proposed does not only increase the overall detection rate (mAP 75.3), but also increases the performance of detecting small and fine-grained objects which are usually missed under dark conditions. Notably, the system has a close real-time performance that guarantees its usefulness in practice in security, traffic monitoring, defense systems, and autonomous systems.

On the one hand, the results are encouraging, but there are certain limitations. There is still a slight sensitivity of the model to excessive noise and glare on the artificial sources of light that may influence the accuracy of detection in some urban areas. In order to overcome this, the future work will investigate:

- Multi-mode sensor fusion (RGB + infrared/thermal imaging) to have stronger detection.
- Lightweight deployment on edge devices with limited hardware resources, e.g. CCTV cameras.

Video-based detection and tracking: Means of enhancing temporal consistency and minimizing false positives in continuous surveillance feeds.

To sum up, the Modified YOLO architecture is an effective, efficient, and affordable solution to improved object detection in low-light conditions surveillance, as it not only contributes to the academic body of knowledge in computer vision but has also practical implications on the real-world security framework.

VI. Outcomes of the Study

i. It was noted that the Modified YOLO model was more effective when compared to other object detection models in the low-light and night sight (YOLOv4, YOLOv5 and Faster R-CNN).
ii. The model was more accurate (mAP 75.3%), and this implies that it was capable of identifying more objects in the dark conditions.
iii. It was effective in identifying the presence of both large objects (such as persons and cars) and the small objects (such as weapons or fire hydrants), which would usually be difficult to see at night.
iv. The model has the capability of running 41 frames per second (FPS) that is adequate enough to operate a real-time surveillance application.
v. They did these improvements by adding image enhancement, attention on features and lightweight convolutions that enabled the model to be seen even in the dark without being too slow.
vi. All in all, the research revealed that the Modified YOLO can enhance the reliability of surveillance systems during the night and it can be applied to both security, traffic and safety.

VII. Future Scope of the Study

i. Multi-Mode Fusion: This is where RGB cameras are combined with infrared or thermal sensors so as to enhance detection during total darkness or low-light areas.
ii. Edge Device Deployment: Optimizing the model to support lightweight and low-power devices such as CCTV cameras and drone to patrol a resource-constrained environment in real-time at night.
iii. Video-Based Detection and Tracking: This expands the model to track moving objects across video frames in order to minimise false detections as well as increase temporal consistency.

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