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Enhancing Abandoned Object Detection with Dual Background Models and Yolo-NAS

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Abstract: The rapid advancement of computer vision technology has paved the way for many surveillance, security, and public safety applications. Abandoned object detection, a critical component in video surveillance systems, plays an essential role in identifying potential security threats and ensuring the safety of public spaces. This paper proposes a new approach for abandoned object detection that combines a dual background model with YOLO-NAS (You Only Look Once Neural Architecture Search), a state-of-the-art object detection framework. The proposed method utilizes two background models with different learning rates, one based on fast background subtraction and one using slower background modeling. The dual background model is verified with YOLO-NAS to improve the accuracy and robustness of abandoned object detection. This model can perform better in low light conditions and changes in illumination. Incorporating YOLO-NAS into the framework enables real-time object detection and tracking, enabling efficient and accurate identification of abandoned objects. YOLO-NAS improves detection speed and maintains high precision, making it an ideal candidate for real-time surveillance applications. Our experimental results, conducted on diverse video sequences, demonstrate the superiority of the proposed approach over existing methods. The dual background model combined with YOLO-NAS consistently outperforms other abandoned object detection algorithms regarding accuracy and speed. The proposed method is robust in challenging scenarios, including dense environments and varying lighting conditions. This paper presents a new abandoned object detection system that leverages the dual background model and YOLO-NAS to achieve state-of-the-art accuracy, speed, and robustness performance. The proposed approach promises to improve security and surveillance systems in public spaces, transportation hubs, and critical infrastructure, thereby contributing to increased public safety and threat prevention.

Keywords: *Dual background model, YOLO-NAS, Abandoned Object*

1. Introduction

Video surveillance is a fundamental component of modern security and public safety systems [1], providing continuous monitoring and threat detection in a variety of environments, including public spaces, transportation hubs, and critical infrastructure [2]–[5]. One crucial aspect of effective video surveillance is detecting abandoned objects, which may represent potential security threats or safety concerns [6]. Abandoned object detection is essential in maintaining public safety, preventing security breaches, and reducing potential harm [7]–[10].

Traditional methods for detecting abandoned objects often rely on background subtraction techniques, which identify changes in the scene by subtracting a reference background frame from the current video frame [9], [11], [12]. Although effective in some scenarios, these methods struggle to adapt to dynamic environments with changing lighting conditions, camera vibrations, and complex scenes [13]. As a result, there is a growing need for advanced techniques to provide more accurate and robust detection of abandoned objects.

In recent years, deep learning has revolutionized computer vision tasks, including object detection, by enabling the development of highly accurate and efficient models. Among them, You Only Look Once (YOLO) stands out as an innovative object detection framework known for its real-time performance and accuracy [14]–[16]. YOLO achieves object detection by directly predicting the input image's bounding box and class probability, making it suitable for real-time surveillance applications.

In this paper, we introduce a new approach to abandoned object detection that combines the power of dual background models with the state-of-the-art YOLO-Neural Architecture Search (YOLO-NAS) framework. Our goal is to create a system that excels at detecting abandoned objects in various real-world scenarios, including busy public spaces and challenging lighting conditions. The multiple background model used in our approach includes a background subtraction model with different learning rates. By integrating this model with YOLO-NAS, we aim to leverage the best of both worlds: the accuracy and robustness of the dual background model combined with the real-time capabilities of YOLO-NAS. Through experimental validation and comparative analysis, we

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demonstrate the effectiveness of our proposed method in improving the accuracy and speed of abandoned object detection. Additionally, we illustrate its robustness in challenging scenarios, showing its potential to enhance security and surveillance systems. Our research aims to contribute to advancing abandoned object detection technology, ultimately strengthening public safety and security measures in today's dynamic and ever-changing world.

2. Related Works

Abandoned object detection in video surveillance has become a significant research and development topic due to its essential role in ensuring public safety and security. This section reviews related work in abandoned object detection, focusing on utilizing multiple background models and integrating YOLO-NAS or similar deep learning-based approaches. Traditional background subtraction techniques have long been used to detect abandoned objects. This method subtracts a reference background image or model from the current frame to identify changes. Algorithms such as Gaussian Mixture Models (GMM) [12], [17], Codebook [18], and Frame Difference [19] have been applied for this purpose. While effective in controlled environments, these methods often struggle with challenges such as lighting variations and scene complexity [20]. The emergence of deep learning has revolutionized object detection. Convolutional Neural Networks (CNN) [13], Region-Based Convolutional Neural Networks (R-CNN) [21], Single Shot MultiBox Detector (SSD) [22], and Faster R-CNN have demonstrated excellent accuracy in detecting objects in images and videos [21]. These methods typically rely on region proposals and have been extended to real-time applications using GPU acceleration. The You Only Look Once (YOLO) family of object detection models has gained widespread popularity due to its impressive speed-accuracy trade-off. YOLO divides an image into boxes, directly predicting bounding boxes and class probabilities. Several YOLO variants, including YOLOv5 and YOLOv6, until YOLO-NAS have been applied in surveillance settings for abandoned object detection, achieving real-time performance with competitive accuracy [23] .

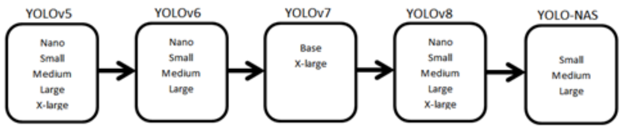


Fig. 1. Development of YOLO Architecture

YOLO-NAS [24] has better mAP and lower latency than the previous version. Based on a comparison of mAP and latency data from three YOLO-NAS models, namely YOLO-NAS-S, YOLO-NAS-M, and YOLO-NAS-L shown in Table 1.

Table 1. Comparison of YOLO-NAS models

Model	folder	Latency (ms)
YOLO-NAS S	83.81	3.21
YOLO-NAS M	84.67	5.85
YOLO-NAS L	86.31	7.87

Researchers have explored integrating background modeling techniques with deep learning to improve abandoned object detection [3], [9], [10], [20]. This includes combining traditional background subtraction with deep learning models or using deep learning-based background modeling methods that adapt to scene changes and lighting variations [19]. Background modeling is an essential technique in computer vision and image processing to separate foreground objects or specific regions from the static background in an image sequence or video stream. The main goal of background modeling is to model stationary or slowly changing scene parts, which can then be subtracted from the current frame to isolate moving or dynamic objects.

Adaptive background modeling is used in computer vision and image processing to create dynamic background models in a scene [25]–[28]. Unlike static background modeling [29], which assumes a fixed background [30], adaptive methods adjust the background model over time to account for changes in lighting, scene dynamics, and gradual changes in the environment [26]. This method is beneficial when the background is not static or facing challenging lighting conditions.

One common adaptive background modeling approach uses exponential averaging or temporal filters to update the background model continuously [28]. Pixels in the background model are adjusted based on the current frame, with the influence of older observations slowly decreasing. This adaptive property allows the model to adapt to changing conditions, making it suitable for applications such as video surveillance, where lighting may vary throughout the day, or scenes with moving leaves or other dynamic elements. Adaptive methods improve the accuracy of foreground object detection by reducing false positives and increasing the robustness of background subtraction techniques in dynamic environments.

To facilitate research in this area [7], [13], [31], various abandoned object datasets have been developed, such as PETS 2006 [32], AVSS 2007 [33], UCSD Pedestrian [34], ABODA [7] and Datasets that we developed independently. These datasets provide researchers with labeled data to train and evaluate their algorithms.

In the context of abandoned object detection using multiple background models and YOLO-NAS, our proposed approach represents a new combination of existing techniques. By leveraging the power of traditional background models and the real-time capabilities of YOLO-NAS, we aim to overcome the limitations of existing methods and advance the state of the art in abandoned object detection to improve public safety and security applications.

3. Method

The method in the paper includes various stages and concepts used to detect abandoned objects in surveillance videos. This method is designed to improve the accuracy and reliability of abandoned object detection in different dynamic environmental conditions, including changing light and complex backgrounds. The following is an explanation of the method proposed in the paper:

3.1. Dual Background Models

The dual-background model consists of two separate models: the short-term and long-term models, each having unique learning rates. In the short-term model, pixels associated with rapidly moving objects quickly merge into the short-term background (StB) and simultaneously vanish from the short-term foreground (StF). Conversely, these pixels persist in the long-term foreground (LtF) for a relatively extended period. Consequently, the long-term background (LtB) remains devoid of any elements. SF exclusively encompasses mobile objects, whereas LtF encompasses both mobile and stationary entities. These characteristics are harnessed to approximate the position, size, and shape of static objects. The difference in the foreground (DF) is determined by subtracting StF from LtF. Active pixels in close proximity are clustered together, indicating stationary objects within the DF frame. If their size is below a defined threshold, they are recognized as noise and filtered out. Consequently, solely stationary objects persist in the DF frame. Assessing an object's stationary status from a single frame might be premature, given that objects can momentarily pause and then resume movement. Thus, temporal transition information is essential to identify stationary objects by considering the sequence of clusters in successive frames. The mathematical model for the renewal strategy is given below:

$$StF_{t+1} = \begin{cases} StF_t + 1, & if\ LtF_t > StF_t \\ StF_t - 1, & if\ LtF_t < StF_t \\ StF_t, & if\ LtF_t = StF_t \end{cases} \tag{1}$$

Where StF $_t$ is the pixel value of the short-term foreground, LtF t is the pixel value of the long-term foreground, and t represents time. The difference between LtF and StF produces static objects. If the stationary object is too small and does not meet the threshold, it is called noise, so it is not considered an abandoned object.

$$DF = LtF - StF \tag{2}$$

The results are then binarized depending on the threshold for detecting associated suspicious activity. This binarization is shown as follows:

$$DF(i,j) = \begin{cases} 1, & if\ LtF(i,j) - StF(i,j) > T \\ 0, & otherwise \end{cases} \tag{3}$$

The overall dual background model process can be described as follows:

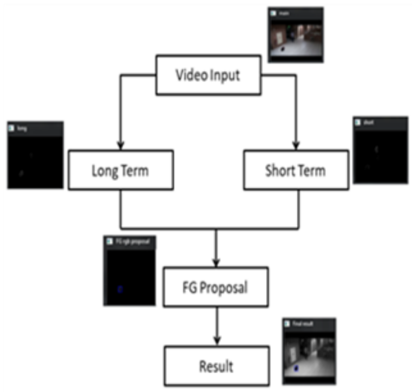


Fig 1. Dual background model

3.2. YOLO-NAS

YOLO-NAS is a framework based on the concept of Neural Architecture Search (NAS), which is used to design optimal neural network architectures for object detection. YOLO-NAS enables automatic search for the most suitable network architecture for object detection tasks. YOLO-NAS integration enables fast and accurate object detection in real-time. Therefore, this method has high speed and good precision.

This system uses YOLO-NAS to classify candidate objects detected using dual background models. The use of YOLO-NAS refers to its unique ability to see things even at low resolution and has low latency.

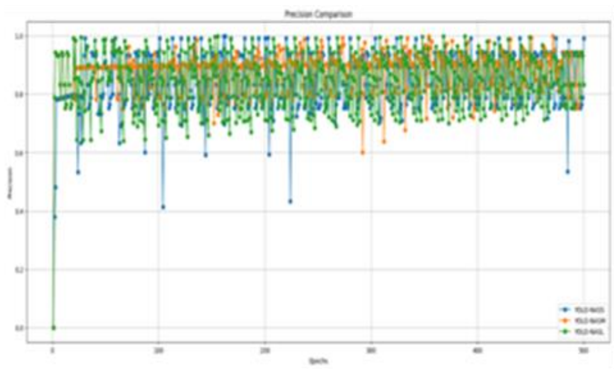


Fig.2. Precision comparison of YOLO-NAS S, YOLO-NAS M and YOLO-NAS L

3.3 Abandoned Object Detection

The process of abandoning objects starts with the thing moving and then shutting up. This will be detected using a dual background model with two backgrounds with different learning rates. Results subtraction from the first and second learning rates will produce stationary objects in time specific. To classify objects, We use YOLO-NAS. Following This is the framework we propose:

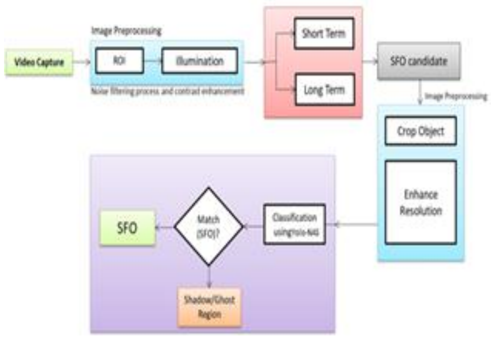


Fig.3. Propose a framework.

After initial detection, these methods may perform additional filtering to reduce the possibility of false positives or eliminate duplicate detections. Apart from that, this method can also involve post-processing to improve the quality of detection results. To test the effectiveness of the proposed method, this research involves experiments conducted on various video datasets covering diverse situations. Evaluation metrics such as accuracy, recall, and speed are measured to assess the extent to which the method successfully detects abandoned objects.

By combining the dual background approach with YOLO-NAS, this method aims to improve the quality of abandoned object detection in video surveillance. This approach is expected to overcome the challenges of more traditional detection methods and increase accuracy and reliability in identifying abandoned objects in real-world situations. Calculation performance from proposed method _ using the confusion metric. A confusion matrix is A metric evaluation used For measuring detection model performance objects, including method detection objects used For detecting abandoned objects. The confusion matrix describes the amount of correct prediction _ And wrong done _ by the model, dividing it into four categories: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). In context detection abandoned object , TP is a real object detected as abandoned , TN is the number of completely non - object areas detected with right , FP is wrong number of areas identified as objects abandoned, and FN is the number of things that should be seen but No. We can count various metric evaluations from the confusion matrix, like precision (precision), recall, and F1-score. Precision measures how accurately the model identifies an abandoned object, recall measures how well the model finds all the things that should be detected. At the same time, the F1 score gives a balance between precision and recall. Confusion matrix analysis helps researchers And practitioners understand where the detection model object can be reliable in detecting abandoned objects And provides necessary insight for increasing the system's performance. Some general formulas are used for count metric evaluation based on the confusion matrix on method detection objects, including for detecting abandoned objects. The following are some available recipes used :

\

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

Precision measures how accurately the model inside identifies the abandoned object. The more the mark precision, the less the wrong area is recognized as an abandoned object.

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

Recall measures how good the model finds all the objects that should be detected. The more tall the recall value, the more little missed objects.

$$F1 - score = 2\frac{Precision * Recall}{Precission + Recall} \tag{6}$$

F1-score gives a balance between precision and recall. A high F1-score value shows balanced model performance between identifying abandoned objects and avoiding error detection.

$$Accuration = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

Accuracy measure so far where the detection model object is correct in all categories. However, accuracy gives a general description of model performance, and it is necessary to remember that in case of an imbalanced class, accuracy Possible No reflects Good model performance.

Using formulas, we can count And evaluate the detection model performance of abandoned objects based on the resulting confusion matrix by the system. Evaluation This is important For increasing the reliability and accuracy of the detection object in the scenario.

4. Result and Discussion

We use dual background to detect abandoned objects And use yolo-nas to verify things as abandoned objects, shadows, or stolen objects. For measure: For performance, we use the confusion metric, including accuracy, recall, precision, and F1-scores. Test on study This using PETS 2006, AVSS 2007, and datasets Aboda.

Fig.4. Background dataset Aboda, AVSS ILIDS, and PETS2006

The first frame in the dual background is used as a condition where there are no moving objects and none before. Existing objects such as trees or existing vehicles are considered as background. The following moving object is called the foreground, which will be detected using the dual background model. A previously existing object that someone then takes is considered a stolen object.

The following are the average experimental results using the Aboda(10), PETS2006(1), AVSS iLIDS(7), and AODiLR(6) datasets.

Table 2. Confusion metrics based on a dataset using a dual background model and YOLO-NAS.

Datasets	Accuracy	Precision	Recall	F1-scores
PETS2006	0.71	0.7	0.77	0.73
AVSS2007	0.73	0.72	0.72	0.72
Aboda	0.78	0.75	0.75	0.75
AODiLR	0.76	0.74	0.7	0.72
Average	0.75	0.73	0.74	0.73

Table 2 shows that using the Aboda dataset shows the highest accuracy. The resulting precision of the compared datasets shows that aboda has more precision. Good with use method. On experimental recall measurements with the PETS2006 dataset having the highest recall, 2.7% of the Aboda dataset and F1-score method, This Enough shows good results with an average of 0.73. On application of the dataset, we created a resolution low that we call Abandoned Object Detection in Low-Resolution (AODiLR), which shows sufficient performance Good No too Far different with the average of other datasets which means classified dual background method with YOLO-NAS has acceptable performance Good on all condition.

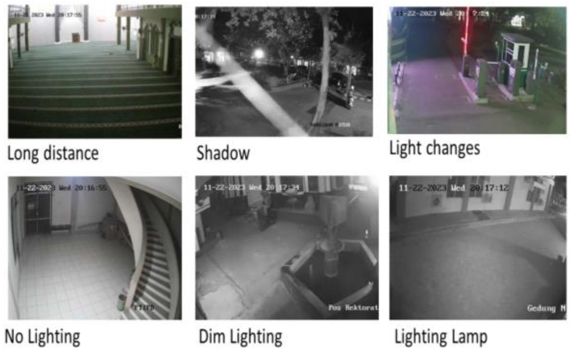
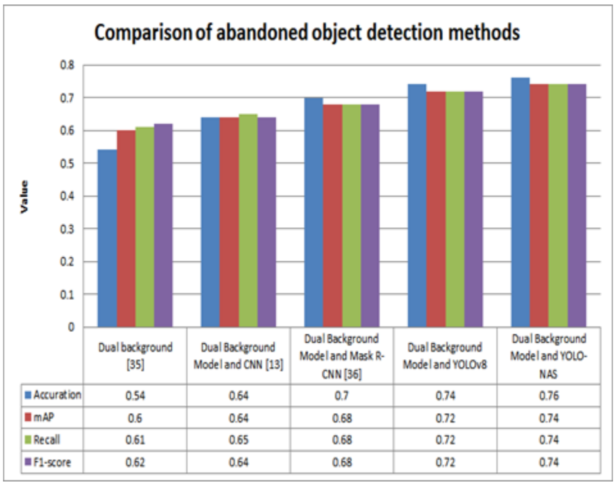


Fig.5. Background abandoned object detection in low-resolution (AODiLR)

To show the repair and understanding of the proposed methods, we compare them with other methods. Comparison: This combined dual background with several other detectors, namely CNN, Mask R-CNN, YOLOv8, and YOLO-NAS. Following This comparison results with study previously.



Detection using YOLO-NAS has superior accuracy, speed access, and low latency, so it is suitable for use on edge computing platforms.

5. Conclusion

In this study, we have proposed and evaluated an innovative approach to detect abandoned objects in surveillance videos. The proposed method combines a dual background models approach with traditional and deep learning-based backgrounds with the YOLO-NAS framework. We have tested this approach extensively on various datasets and environmental conditions. Using two different background models, namely a traditional experience and a deep learning-based background, has increased the accuracy of abandoned object detection. Traditional models play a role in identifying static background changes, while deep learning-based models can overcome dynamic background changes. YOLO-NAS integration enables fast and accurate object detection in real-time. Our experimental results show that YOLO-NAS excellently detects objects in various situations and conditions. Experimental results show that the proposed method consistently outperforms existing methods regarding abandoned object detection accuracy. We achieved significant improvements in accuracy, even in complex situations such as changing light and varying backgrounds. The proposed method also shows robustness to variations in the surveillance environment, including changing weather conditions and crowds. We believe that our approach can be a valuable contribution to improving abandoned object detection technologies in the context of video surveillance. We encourage further research in incorporating new techniques emerging in computer vision to continue improving the accuracy, speed, and reliability of abandoned object detection for greater public safety and security.

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