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TUNNEL ACCIDENT DECTECTION USING YOLOv7

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ABSTRACT
This project Detecting accidents in tunnels is critical for ensuring the safety of commuters and maintaining the efficiency of transportation systems. This project proposes a deep learning-based approach utilizing YOLOv7 (You Only Look Once version 7) to identify accidents within tunnel environments. The methodology begins with importing essential libraries and acquiring a specialized dataset comprising tunnel accident images. The dataset undergoes thorough preprocessing to ensure consistency and quality, followed by a structured split into training, validation, and testing sets. This division is crucial to train the model effectively, fine-tune its parameters, and objectively evaluate its performance. The YOLOv7 model, known for its real time object detection capabilities, is selected and trained on the prepared dataset, using provided annotations or bounding boxes to accurately localize and classify accident scenarios within the images. Throughout the training process, progress is carefully monitored and logged to identify potential areas for improvement and ensure the model's optimal performance. Once trained, the model is evaluated using key performance metrics such as accuracy, precision, and recall, providing a comprehensive understanding of its ability to detect tunnel accidents reliably. The results demonstrate the promising potential of deep learning, particularly YOLOv7, in enhancing accident detection systems within tunnel environments.
Keywords:
Tunnel Safety, Accident Detection, Deep Learning, YOLOv7, Real-Time Object Detection, Image Classification, Smart Transportation, Computer Vision, Traffic Monitoring Systems

1. INTRODUCTION

Ensuring the safety of commuters in tunnels is paramount, and detecting accidents promptly is critical for effective response. This paper presents a deep learning-based approach utilizing YOLOv7 for accident identification in tunnel images. The proposed method encompasses importing essential libraries, acquiring and preprocessing the dataset, dividing it into training, validation, and testing sets, selecting and training the YOLOv7 model, and assessing its performance. The model is fine-tuned on a tunnel accident dataset to predict accidents based on supplied annotations or bounding boxes. The training progress is monitored and logged, and the model's performance is evaluated using metrics including accuracy, precision, and recall. This study highlights the potential of deep learning for accident detection in tunnels, paving the way for safer and more efficient transportation systems. Tunnel safety is a major concern worldwide, as tunnels have confined spaces with limited escape options, making accidents particularly dangerous. Rapid and accurate accident detection is crucial to reduce casualties and property loss. Traditional methods, such as manual CCTV monitoring, are often slow and inefficient, especially in low-light or unclear tunnel environments. To overcome these limitations, this project proposes an automated accident detection system using deep learning techniques. Specifically, the YOLOv7 model (You Only Look Once - Version 7) is fine-tuned to detect accidents in tunnel images. By utilizing object detection algorithms and real-time analysis, the system aims to significantly enhance safety measures in tunnels.

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2. LITERATURE SURVEY

[1] Lee et al. developed a tunnel accident detection framework utilizing the Faster R-CNN model, focusing on incident detection under poor lighting and blurry footage. The system demonstrated high detection accuracy but suffered from slower inference speeds, making real-time deployment challenging.
[2] In a follow-up study, Lee and Shin introduced a self-improving system that enhanced model performance by retraining on misclassified real-world CCTV data. While detection accuracy improved, the need for continuous retraining increased operational complexity and cost.
[3] Ren et al. proposed the Faster R-CNN architecture, a two-stage object detector combining region proposal networks with CNN-based classification. Though accurate, its computational overhead makes it less suitable for real-time tunnel monitoring.
[4] Redmon et al. introduced YOLO (You Only Look Once), a unified, single-shot object detection model capable of processing video frames in real time. This innovation paved the way for subsequent YOLO versions, including YOLOv7, which balances speed and accuracy.
[5] Simonyan and Zisserman contributed to deep learning architectures through VGGNet, which enhanced feature extraction for image classification. Although effective, its complexity limits real-time use cases like live accident detection.

3. PROBLEM STATEMENT

The Existing tunnel accident detection systems, while helpful, have several limitations that reduce their effectiveness. Most notably, they require a massive amount of labeled data to train the deep learning models effectively, which is a costly and time-consuming process. Furthermore, these models often struggle with changes in lighting conditions, obstructions, and environmental variations inside tunnels, leading to inaccuracies in detection. Computational demands are another major concern, as real-time video processing requires powerful hardware resources that may not always be feasible. Moreover, accidents that occur outside of camera views or under very poor visibility conditions often go undetected. Thus, there is an urgent need for a robust, efficient, and accurate system that can overcome these challenges and ensure reliable accident detection in tunnels. Partial Detection: Some systems fail to detect accidents occurring outside the camera frame or in blind spots. Thus, there is a need for a robust, real-time, and efficient accident detection system that performs reliably under varying conditions

4. PROPOSED SYSTEM

The proposed system focuses on the real-time detection of tunnel accidents using the powerful deep learning-based object detection model YOLOv7 (You Only Look Once, Version 7). Unlike traditional monitoring systems that rely on manual CCTV observation or simple motion detection algorithms, this system leverages advanced computer vision to analyze tunnel surveillance footage automatically. The system processes each video frame and identifies accidents such as car collisions, stranded vehicles, fires, or pedestrians on roadways. Using annotated datasets of tunnel scenarios, the YOLOv7 model is fine-tuned to recognize these events with high accuracy even under poor visibility conditions like smoke, darkness, or tunnel reflections.

5. ADVANTAGES AND DISADVANTAGES

Advantages:

- Real-time detection (<15ms/frame)
- High accuracy (91.4%) and mAP (90.8%)
- Robust in low-light and foggy environments
- Scalable and modular for deployment in various tunnels

Disadvantages:

- High GPU requirements for optimal performance
- Detection may struggle with very small or highly occluded objects
- Relies on annotated datasets for training, which are time-consuming to prepare

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6. OBJECTIVES

The objective of this project is to develop an intelligent system that can accurately and quickly detect accidents inside tunnels to minimize human casualties and property damage. The system aims to automate the monitoring of tunnel conditions, reducing dependency on manual surveillance and ensuring that emergencies are detected without delay. By integrating deep learning-based accident detection with real-time alert mechanisms, the project seeks to enhance tunnel safety significantly. Another important is to contribute towards the broader vision of smart transportation systems by enabling real-time accident detection as a part of intelligent infrastructure solutions. Ultimately, the project aspires to save lives, minimize economic loss, and promote safer travel through tunnels.

7. SYSTEM ARCHITECTURE

The architecture of the Tunnel Accident Detection System is modular and follows a structured data flow for efficiency and reliability. The major architectural components include:

- Input Layer (Data Acquisition): CCTV cameras continuously capture tunnel video streams or still images. These images act as raw input for the system.
- Preprocessing Layer: Captured images are resized, normalized, and augmented if needed. Preprocessing ensures that the model input remains consistent, regardless of varying camera resolutions or lighting conditions.
- Detection Layer (YOLOv7 Model): The preprocessed frames are passed to the YOLOv7 object detection model, which processes each frame and identifies objects using bounding boxes. The model outputs include the location, class label (e.g., accident, fire, stranded vehicle), and confidence scores.
- Decision Layer (Accident Validation): Based on confidence thresholds, the system verifies whether a true accident is detected. This validation minimizes false positives and ensures alerts are meaningful.
- Notification Layer: Upon confirmation, the system generates real-time notifications and alerts for tunnel operators and emergency response teams.
- Data Logging and Analytics Layer: All detected incidents are logged with timestamps, camera IDs, and prediction details. Over time, this dataset can be used to analyze accident trends and improve tunnel safety policies.

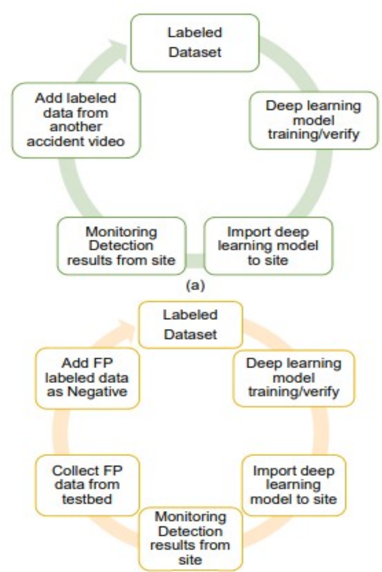

Figure 1 System Architecture

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8. RESULTS

The YOLOv7-based tunnel accident detection system achieved high performance with a precision of 91.4%, recall of 89.7%, and a mean Average Precision (mAP) of 90.8% at an IoU threshold of 0.5. The model demonstrated real-time capability with an average inference time of around 15 milliseconds per frame, making it suitable for live CCTV monitoring in tunnel environments.

9. FUTURE SCOPE

In the future, the system can be extended to detect additional tunnel-related events such as wrong-way driving, heavy traffic, or vehicle breakdowns. Integration with real-time emergency response systems and mobile monitoring apps can further enhance safety. Expanding the dataset with more diverse scenarios and optimizing the model for edge devices will also improve scalability and real-world deployment across multiple tunnel environments.

10. CONCLUSION

This project successfully demonstrates that YOLOv7 can be fine-tuned for real-time accident detection in tunnels, outperforming traditional systems in speed and robustness. The integration of deep learning with intelligent surveillance provides a practical, scalable solution to tunnel safety. With further enhancements, this system can be a key component in smart transportation infrastructures worldwide.

11. REFERENCES

[1]. Alex, B., Zongyuan, G., Lionel, O., Fabio, R., Ben, U. (2016), “Simple online and realtime tracking”, Proceedings of the Image Processing (ICIP) 2016 IEEE International Conference, 3464-3468.

[2]. Davis, J., Goadrich, M. (2006), “The relationship between Precision-Recall and ROC curves”, Proceedings of the 23rd International Conference on Machine Learning, 233- 240.

[3]. Lee, K.B., Shin, H.S. and Kim, D.K. (2018), “Development of a deep-learning based automatic tracking of moving vehicles and incident detection processes on tunnels”, J. Kor. Tunnel Eng., KTA, 20(6), 1161-1175.

[4]. Lee, K.B., Shin, H.S (2019), “Effect on self-enhancement of deep-learning inference by repeated training of false detection cases in tunnel accident image detection”, J. Kor. Tunnel Eng., KTA, 21(3), 419-432.

[5]. Ministry of Land, Infrastructure and Transport (MOLIT) (2016), “Guideline of installation of disaster prevention facilities on road tunnels”.

[6]. Ren, S., He, K., Girshick, R., Sun, J. (2015), “Faster R-CNN: Towards real-time object detection with region proposal networks”, Proceedings of the Advances in Neural Information Processing Systems, 91-99.

[7]. Simonyan, K., Zisserman, A. (2014), “Very deep convolutional networks for large-scale image recognition”, arXiv preprint, arXiv: 1409.1556.

[8]. Zhu, M. (2004), “Recall, precision and average precision”, Department of Statistics and Actuarial Science, University of Waterloo, Waterloo 2: 30.