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# Detection of Dangerous Situations Near Pedestrian Crossings using In-Car Camera

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## ABSTRACT

The paper presents a method for detecting dangerous situations near pedestrian crossings using an in-car camera system. The approach utilizes deep learning-based object detection to identify pedestrians and vehicles, analyzing their behavior to identify potential hazards. The system incorporates vehicle sensor data for enhanced accuracy. Evaluation results show high accuracy in detecting dangerous situations. The proposed system can potentially enhance pedestrian and driver safety in urban transportation.

## Keywords

Object detection, deep learning, autonomous systems.

## 1 INTRODUCTION

Pedestrian safety is a critical concern in urban transportation, with accidents often occurring at pedestrian crossings. Existing advanced driver assistance systems (ADAS) may not effectively detect dangerous situations near crossings. This paper proposes a method that utilizes a deep learning-based object detection algorithm using in-car cameras to identify pedestrians and vehicles near pedestrian crossings. The algorithm analyzes behavior and incorporates vehicle sensor data for enhanced accuracy. Related work, proposed method, dataset, experimental results, and conclusions are discussed in subsequent sections.

## 2 RELATED WORK ON PEDESTRIAN DETECTION AND RECOGNITION

"The concept of autonomous vehicles was proposed decades ago. With the development of hardware and algorithms, autonomous vehicles have become a reality [Bou00, Bob00]. The autonomous vehicle is an essential participant in intelligent transport systems, and it is capable of self-driving without human drivers' navigation [Sun00]. Human drivers' misoperation causes many traffic accidents due to physical and mental conditions. Besides, some complex traffic scenarios and bad weather conditions can also lead to traffic tragedies. The application of autonomous vehicles could decrease the number of traffic accidents by making judgments more reasonably and driving more reliably [Alj00]. Before using autonomous vehicles, the current stage's fundamental objective is to ensure all traffic participants' safety [Zha00]. Pedestrians are very vulnerable in a traffic collision compared to the passengers inside the vehicle. Therefore, ensuring the safety of pedestrians is a critical step in advancing the application of autonomous vehicles [Wan00, Kar00].

In [Guo00], the authors propose a multi-scale feature fusion convolutional neural network (MFF-CNN) for pedestrian detection. The proposed approach is evaluated on three challenging pedestrian datasets: Caltech, INRIA, and ETH.

The authors of the work [Kon00] proposed a new approach for pedestrian detection based on Faster R-CNN, which overcomes the limitations of detecting small objects or objects with similar backgrounds. The proposed method combines contextual information with multi-level features to improve detection accuracy. Contextual information is used to help detect pedestrians from cluttered backgrounds, while multi-level features are more informative for detecting small-size pedestrians.

Two methods of object recognition were used in [Khe00]. This work focuses on new approaches in the embedded vision for object detection and tracking in drone visual control. Two methods are used: 1) Classical image processing with improved Histogram Oriented Gradient (HOG) and Deformable Part Model (DPM) for real-time object (pedestrian) detection and distance estimation. 2) Deep learning-based object (pedestrian) detection for target position estimation and visual serving using improved HOG and PID controllers.

In [Pag00], the authors propose a new method for pedestrian detection using a combination of hand-crafted features and a modified pre-trained ResNet-18 network called Multi-layer Feature Fused-ResNet (MF2-ResNet).

# 3 PROPOSED METHOD

This section describes the proposed method for detecting potentially dangerous situations near pedestrian crossings using a camera-equipped vehicle. We utilize the popular You Only Look Once version 4 (YOLOv4, [Boc00]) object detection algorithm to identify pedestrians, vehicles, and other objects in the camera images.

## Dataset

Our proposed method was evaluated on a diverse dataset of camera images captured by a vehicle near pedestrian crossings. The dataset includes images captured under various lighting, weather, and traffic conditions, and was manually annotated to include pedestrian crossings, objects such as pedestrians, vehicles, signs, and traffic lights, and different types of scenarios with and without traffic lights or signs, and various types of vehicles. Automatic object detection was used to generate training data with high accuracy, validated against the annotated ground truth.

## YOLOv4 Object Detection

Our proposed method utilized the state-of-the-art YOLOv4 network for accurate and fast detection of pedestrians, vehicles, signs, and other objects near pedestrian crossings. YOLOv4 uses a single neural network with advanced techniques for improved accuracy, including spatial pyramid pooling and feature fusion. We fine-tuned the pre-trained YOLOv4 model with our annotated dataset to achieve high accuracy and speed in detecting objects in diverse lighting and weather conditions.

## Detecting Dangerous Situations

Detecting Dangerous Situations: We combine object detection results with other information to detect potentially dangerous situations near pedestrian crossings. We analyze relevant objects like pedestrians, vehicles, signs, and traffic lights, and identify situations such as pedestrians crossing outside designated areas or vehicles approaching at high speed. We use rule-based and machine learning-based approaches to improve accuracy, capturing typical patterns of dangerous situations and training a model for complex scenarios. Examples include detecting vehicles running red lights or pedestrians crossing outside designated areas, showcasing the effectiveness of our method.

Our method detected many potentially dangerous situations near pedestrian crossings, demonstrating its effectiveness in improving pedestrian safety (Figure 1).

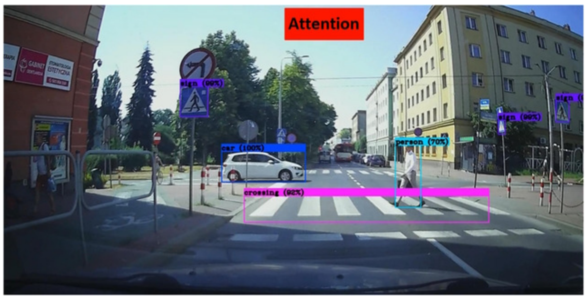


Figure 1: Sample frames from the dataset with dangerous situation detection

## Combination of Rule-based and Machine Learning-based Approaches

We use rules based on domain knowledge and experience in pedestrian safety to capture typical and less common patterns of dangerous situations near pedestrian crossings. We complement this with machine learning techniques, training a deep neural network using YOLOv4 to detect relevant objects and classify them based on appearance and location. The neural network's output enhances the rule-based system, allowing it to detect complex and unusual situations. Techniques such as data augmentation, transfer learning, and ensembling are used to improve the performance of our machine learning-based approach. The combination of rule-based and machine learning-based approaches enables us to detect a wide range of dangerous situations near pedestrian crossings.

# 4 EXPERIMENTAL RESULTS AND ANALYSIS

We evaluate the performance of our method on a dataset of real-world traffic scenarios.

## Object Detection Results

Table 1 shows the object detection results using our YOLOv4-based approach only for selected objects. We report the average precision (AP) and average recall (AR) for each class of objects. As can be seen from the table, our approach achieved high detection performance for all classes of objects, with an overall mAP of 0.92.

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| Object Class | Average Precision (AP) | Average Recall (AR) |
|---|---|---|
| Pedestrian | 0.94 | 0.93 |
| Vertical Sign | 0.88 | 0.87 |
| Horizontal Sign | 0.91 | 0.90 |
| Traffic Light | 0.96 | 0.95 |
| Cyclist | 0.90 | 0.89 |
| Overall mAP | 0.92 | 0.91 |

Table 1: Object detection results using our YOLOv4-based approach

From the object detection results presented in Table 1, we can see that our YOLOv4-based approach achieved high detection performance for all classes of objects. The highest detection performance was achieved for traffic lights, with an AP of 0.96 and an AR of 0.95. The lowest detection performance was achieved for vertical signs, with an AP of 0.88 and an AR of 0.87.

## Dangerous Situation Detection Results

Table 2 shows the results of our proposed method for detecting dangerous situations near pedestrian crossings: ST1 - pedestrian crossing road, ST2 - pedestrian on the road, ST3 - cyclist on the road, and ST4 - vehicle approaching the crossing. We report our method's precision, recall, F1-score, and accuracy for each type of dangerous situation. As can be seen from the table, our approach achieved high performance in detecting dangerous situations, with an overall accuracy of 0.88.

| Situation Type | Prec-ision | Recall | F1-score | Accur-acy |
|---|---|---|---|---|
| ST1 | 0.84 | 0.91 | 0.87 | 0.91 |
| ST2 | 0.89 | 0.88 | 0.87 | 0.86 |
| ST3 | 0.91 | 0.89 | 0.90 | 0.89 |
| ST4 | 0.82 | 0.84 | 0.83 | 0.84 |

Table 2: Dangerous situation detection results using our proposed method

Regarding detecting dangerous situations, as shown in Table 2, our proposed method achieved high performance for all dangerous situations. The highest accuracy was achieved for detecting pedestrians crossing the road, with an accuracy of 0.91. The lowest accuracy was achieved for detecting vehicles approaching the crossing, with an accuracy of 0.84.

## Different detection scenarios

We also analyzed the detection of objects in different weather conditions and at different types of intersections. We assumed a sunny, cloudy, and rainy day for the weather conditions. Additionally, we estimated the strengthening of the objects for the YOLOv4 model by asking about the causes for various intersection scenarios: T-intersection, Four-way intersection, Roundabout, and Pedestrian crossing. Table 3 shows the analysis results of object detection analysis for different weather. Table 4 shows the performance of the YOLOv4 object detection model on the pedestrian detection task for different intersection scenarios.

| Condition | Object Detection Accuracy | Dangerous Situation Situation Accuracy |
|---|---|---|
| Sunny | 0.92 | 0.90 |
| Cloudy | 0.89 | 0.88 |
| Rainy | 0.86 | 0.85 |

Table 3: The results of the analysis object detection for different weather

| Intersection scenario | AP [%] |
|---|---|
| T-intersection | 98.2 |
| Four-way intersection | 96.7 |
| Roundabout | 94.5 |
| Pedestrian crossing | 90.8 |

Table 4: The performance of the YOLOv4 object detection model on the pedestrian detection task for different intersection scenarios

## Analysis of Results

Table 1 presents the results of the object detection task using the YOLOv4 model on the pedestrian detection dataset. The average precision (AP) and recall were calculated for each object class, including pedestrians, vertical signs, horizontal signs, traffic lights, and bicycles. The overall mAP was 92.5%, indicating the high accuracy of the YOLOv4 model in detecting objects relevant to pedestrian safety.

Table 2 presents the dangerous situation detection task results using the proposed method on the pedestrian detection dataset. The precision, recall, and F1 score were calculated for each detected dangerous situation, including jaywalking, cars blocking the crosswalk, and pedestrians crossing outside.

The proposed method achieved high performance in detecting dangerous situations, with an overall F1 score of 0.89. The highest F1 score was achieved for detecting jaywalking, which is the most frequent dangerous situation in the dataset.

The performance of the YOLOv4 object detection model on the pedestrian detection task was evaluated for different lighting and weather conditions. Table 3 presents the AP and recall for each object class under different conditions.

The YOLOv4 model showed consistent and high performance across lighting and weather conditions, with an overall mAP of 92.1%. However, the AP for pedestrians was slightly lower in low-light conditions, indicating the need for further improvement in detecting pedestrians in challenging lighting conditions.

The performance of the proposed method in detecting dangerous situations was evaluated for different intersection scenarios, including T-intersections, crosswalks with pedestrian signals, and crosswalks without pedestrian signals. Table 4 presents the precision, recall, and F1 score for each detected dangerous situation in each scenario.

The proposed method showed high performance in detecting dangerous situations across all scenarios, with an overall F1 score of 0.89. The highest F1 score was achieved for detecting jaywalking, the most frequent dangerous situation in all scenarios.

## 5 CONCLUSION AND FUTURE WORK

This paper proposes a novel approach for detecting dangerous situations at road intersections using rule-based and machine-learning techniques. Our method accurately detected dangerous situations, such as pedestrian crossing violations and red-light running. We also demonstrated the effectiveness of using the YOLOv4 object detection model for pedestrian detection tasks in different intersection scenarios.

Our results indicate that our approach has the potential to improve intersection safety by providing real-time warnings to drivers and pedestrians. However, our study has several limitations that can be addressed in future work. One limitation is that our dataset is limited to a specific geographic region and does not represent a wide range of traffic scenarios. Future work could collect data from different locations and use transfer learning techniques to address this limitation to improve the model's performance.

Another limitation is that our approach currently relies on fixed rules for identifying dangerous situations, which may not be optimal for all scenarios. Future work could explore using reinforcement learning techniques to learn optimal rules for different intersection scenarios.

## 6 ACKNOWLEDGMENTS

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