Pedestrian Detection using YOLOv8 on the IDD Road Object Detection using Deep Learning

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***Abstract*—This technical report outlines the implementation of a pedestrian detection system using the YOLOv8 algorithm. The system is trained on the IDD Dataset and focuses explicitly on detecting pedestrians who are in high danger while crossing the roads. This report outlines the development and evaluation of a training model, named YOLOv8, designed to detect pedestrians who are at increased risk while crossing roads.**

We describe the methodology used to train the YOLOv8 model, including dataset collection, annotation process, and model configuration. We elaborate on the choice of YOLOv8 architecture due to its high detection accuracy and real-time processing capabilities for reducing pedestrian accidents and better traffic management ensuring road safety for all.

I. Introduction

Pedestrian safety is a critical concern in today's fast-paced and urbanized world. With the increasing number of road accidents involving pedestrians, it is imperative to develop advanced computer vision systems that can accurately detect high-risk crossings and alert drivers in real-time and deploying cameras equipped with this model, cities can collect data on pedestrian movement patterns, identify high-risk areas, and implement measures to improve safety, such as adjusting infrastructure, adding traffic calming measures, or enhancing street lighting. In this report, we present the development and evaluation of YOLOv8 model, specifically designed for detecting pedestrians who are at high risk while crossing roads. With the help of YOLOv8's advanced architecture, we aim to enhance pedestrian safety by enabling proactive measures to mitigate potential accidents.

II. Problem Definition

Detecting pedestrians crossing roads poses several challenges due to various factors such as varying lighting conditions(shadows,glare,reflection..etc),complex backgrounds and partial or complete occlusion of pedestrians by objects like vehicles,poles or trees which can affect the visibility of pedestrians, making it difficult for computer vision systems to detect them accurately.Only by implementing a specialised system for pedestrian detection can be crucial for timely detection and alerting drivers of potential risks.

III. Proposed Solutions

To address the challenges of detecting pedestrians crossing roads, we have developed a solution using the YOLOv8 model. Instead of training the model with the entire dataset, we carefully select a smaller set of images that represent different scenarios. This helps us train the model more efficiently. By gradually increasing the number of annotated images, we improve the accuracy of the model's predictions. Once trained, we can use the YOLOv8 model to detect pedestrians in other images and videos, even in challenging situations like low light or obstructed views. This approach enables us to identify pedestrians in real-time and provide timely alerts to drivers, ultimately making roads safer for everyone.

IV. Criteria for Assessing Solutions

The evaluation criteria for pedestrian detection are designed to identify pedestrians who are at a higher risk of accidents. When a pedestrian starts crossing the road from a nearby lane, they are labeled in the "high" region during the annotation process. This classification indicates that they have a greater chance of being involved in an accident compared to pedestrians walking on the lane when vehicles pass by. By classifying pedestrians in this way, it helps to collect data on pedestrian movement patterns, identify high-risk areas, and implement measures to improve safety, and potentially alert drivers

V. Research Methodology

A thorough analysis of the problem was conducted to understand the requirements, challenges, and potential impact of the project. This involved reviewing relevant literature, studying existing pedestrian detection methods, and identifying the key factors contributing to pedestrian risk. e system's capability to assess pedestrian risk levels based on contextual information was evaluated. It measured the accuracy of risk classification, considering factors such as proximity to vehicles, traffic conditions, and pedestrian behavior.

Dataset Collection: A diverse and representative dataset was collected from IDD dataset, consisting of annotated images depicting pedestrians in various scenarios. Special attention was given to including challenging situations such as low light conditions

Preprocessing and Annotation: The collected dataset underwent preprocessing to ensure data quality, consistency, and compatibility. Annotations were created to label the pedestrian regions of interest (ROIs) and define their associated risk levels based on contextual information.

Model Selection and Training: The YOLOv8 model was chosen as the base model for pedestrian detection due to its real-time performance and accuracy. The model was trained using the annotated dataset, gradually increasing the number of images to improve its performance. *Do not include your findings in this section.*

VI. Analysis and Interpretation

In the analysis and interpretation of the project we evaluated the viability of the proposed solution for pedestrian detection using YOLOv8 here are some the key findings

cost effectiveness: Although the cost required for setting up this model may be high depending upon the scale the societal and economic impact of reducing pedestrian accidents and their associated costs, including medical expenses and property damage, can be substantial.

Environmental acceptability : this project requires large data centers and hardware resources The environmental acceptability of the project can be enhanced if the developed system prioritizes energy efficiency. This includes optimizing the algorithms, hardware, and software implementation to minimize power consumption and reduce the carbon footprint associated with the system's operation. Technical feasibility : Based on these factors, the project exhibits strong technical feasibility. The utilization of an established model, the practical approach to data collection and annotation, the rigorous training and evaluation processes, the robustness to challenging scenarios, and the emphasis on real-time performance collectively support the technical feasibility of the project

Our analysis seems to point to the fact that the model is can an be deployed in traffic management systems to monitor pedestrian activity at intersections, zebra crossings, or busy streets. This information can be utilized to optimize traffic flow, adjust signal timings or it can be used in smart city Initiatives By deploying cameras equipped with your model, cities can collect data on pedestrian movement patterns and implement measures to improve safety, such as adjusting infrastructure, adding traffic calming measures, or enhancing street lighting. But it appears that when it comes to autonomous vehicles and alerting drivers of potential risk this model lacks as more constraints come into the picture such as speed of vehicle proximity to the person etc

VII. Conclusions and Recommendations

In conclusion this, project focused on developing a pedestrian safety model using YOLOv8, through analysis and interpretation of the research findings, the following conclusions can be drawn

The proposed solution in efficient in detecting pedestrians at high risk of potential accidents and can find patterns this data can be used for better town planning, real time traffic management which will be really helpful in a country like India but when it comes to autonomous cars and driver alert system we need to interpret the semantic meaning of the detected objects. This includes understanding traffic rules, road signs, and the intentions of other road users. The pedestrian detection model alone may lack the semantic understanding necessary for autonomous vehicles to make informed decisions in complex traffic situations. Having a large and very complex dataset and by combining multiple object prediction models along with behavior prediction this can be a major game changer when it comes to pedestrian safety.

Appendix A

The Appendix A of the report consists of annotated images showing pedestrians crossing roads. To detect and identify these pedestrians, the deployed model uses the YOLOv8 algorithm. When an image is provided, the model applies bounding boxes to highlight the positions of the pedestrians it detects.The class of prediction used for pedestrian detection is labelling them as "high" indicating higher risks of accidents.

Fig. 1. Pedestrian Detection-Image 1

Fig. 2. Pedestrian Detection-Image 2

A screenshot demonstrates the model's effectiveness in accurately identifying and locating pedestrians on the road. This user-friendly interface makes it easy to recognize pedestrians crossing the road, ensuring their safety. By using this model, we can quickly and efficiently identify pedestrians, allowing for timely actions like alerting drivers or activating automated systems to keep pedestrians safe.

Appendix B

In Appendix B of the report, you will find a collection of performance graphs that offer a detailed evaluation of the pedestrian detection model. These graphs provide valuable insights into how well the model performs across different evaluation metrics. By analyzing these graphs, we gain a deeper understanding of the model's effectiveness.For this purpose,the following graphs are used:

1.Confusion matrix:

The confusion matrix, shown in Figure 3, is a valuable tool for evaluating the accuracy of the model. It provides the number of true positives, true negatives, false positives, and false negatives for each class. By analyzing the confusion matrix, we can know about the model's performance, including its ability to correctly classify instances and identify any areas of misclassification.

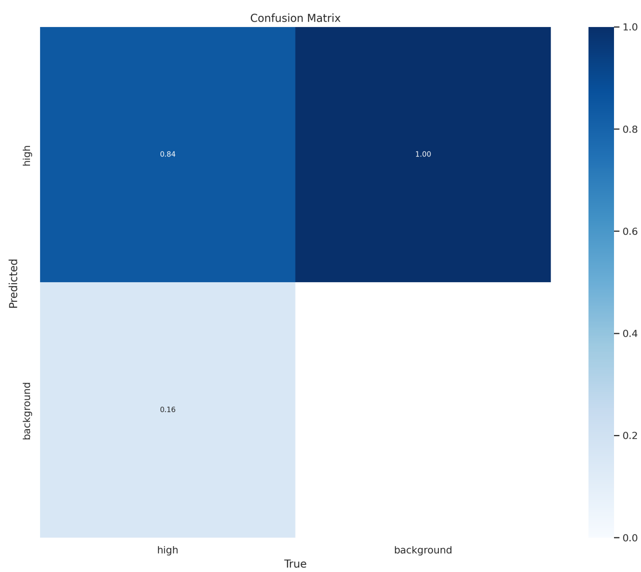

Fig. 3. Confusion Matrix

2.Model Output Graph:

Figure 4 shows the graph generated as the output of the model's predictions.The model output graph of a pedestrian detection model based on YOLOv8 shows the confidence scores and bounding box coordinates for each detected pedestrian in an image. It provides visual representations of the detected pedestrians by overlaying bounding boxes around their locations. The graph displays the confidence score, indicating the model's confidence in classifying the detected object as a pedestrian. Additionally, the bounding box coordinates define the precise location and size of each pedestrian in the image. By examining this graph, we can quickly assess the number of pedestrians detected, their locations, and the model's confidence in those detections, enabling further analysis and decision-making based on the model's output.

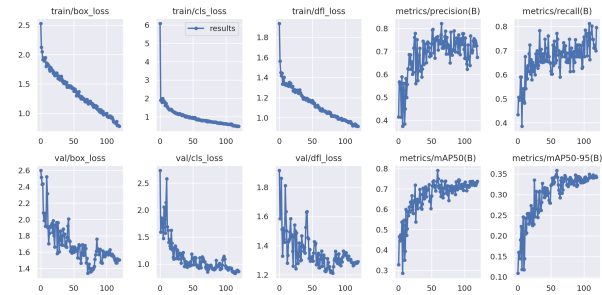

Fig. 4. Model Output Graph

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