# BLINDSPOT MONITORING SYSTEM

**A MINOR PROJECT REPORT**

*Submitted by*

**LALITH SURYA G [RA2211032010009]**
**SHABARINATHAN K R V[RA2211032010011]**
**AMAL R[RA2211032010015]**

*Under the Guidance of*

**Dr. S. USHASUKHANYA**

Assistant Professor, Department of Networking and Communication
*in partial fulfillment of the requirementsfor the degree of*

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**SIGNATURE**

**Dr. S. USHASUKHANYA**
**SUPERVISOR**
Assistant Professor,
Department of Networking Communication

**SIGNATURE**

**Dr. ANNAPURANI**
**HEAD OF THE DEPARTMENT**
Department of Networking and Communication

Department of Computational Intelligence
**SRM Institute of Science & Technology**
**Own Work Declaration Form**

**Degree/ Course** : **B. TECH/CSE - IOT**

**Student Name** : **LALITH SURYA G**
**SHABARINATHAN K R V**
**AMAL R**

**Registration Number** : **RA2211032010009**
**RA2211032010011**
**RA2211032010015**

**Title of Work** : **BLINDSPOT MONITORING SYSTEM**

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LALITH SURYA[RA2211032010009]

AMAL R [RA2211032010015]

SHABARINATHAN K R V [RA2211032010011]

# ABSTRACT

Blind-spot detection is a crucial feature in Advanced Driver Assistance Systems (ADAS) that can significantly improve the safety of vehicles on the road. Blind spots are areas around a vehicle that are not visible to the driver, even with the use of mirrors, and can pose a significant risk when changing lanes or merging onto a highway. ADAS blind-spot detection systems use sensors such as cameras or radar to detect other vehicles in the driver's blind spot. The system then alerts the driver through visual or auditory cues if there is a vehicle in the blind spot, allowing the driver to avoid a potential collision. Blind-spot detection systems can also complement other ADAS features such as lane departure warning systems, forward collision warning systems, and automatic emergency braking systems. By working together, these features can provide drivers with a more comprehensive safety net on the road, reducing the risk of accidents caused by human error. In addition to improving safety, blind spot detection can also enhance the driving experience by reducing driver stress and increasing confidence on the road. With blind-spot detection, drivers can be more aware of their surroundings and make better-informed decisions, leading to a more comfortable and enjoyable driving experience. According to the National Highway Traffic Safety Administration (NHTSA), blind-spot monitoring systems can reduce the number of lane-change crashes by up to 14%. This statistic alone highlights the importance of blind-spot detection systems in reducing the number of accidents on the road. However, blind-spot detection systems are not foolproof and should not be relied upon solely. Drivers should always check their mirrors and look over their shoulders before changing lanes, even if the blind spot detection system does not alert them to a vehicle in their blind spot. Blind-spot detection is just one of many ADAS features that can improve the safety and comfort of vehicles on the road. As technology continues to advance, we can expect to see more innovative features added to ADAS systems, making driving safer and more enjoyable for everyone.

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# ABBREVIATIONS

| | |
|---|---|
| **YOLO** | You Only Look Once |

# CHAPTER 1

# INTRODUCTION

Blind-spot detection is a critical safety feature in Advanced Driver Assistance Systems (ADAS) that can significantly reduce the risk of accidents caused by human error. With the increasing popularity of ADAS systems, there is a growing need for reliable and accurate blind-spot detection systems that can work in various driving conditions.

This report presents a blind-spot detection model using the YOLOv8 algorithm from Ultralytics. The model can identify safe and unsafe lane-changing conditions and notify the user via function calls and warning alarms if an "unsafe" class is detected. The model's ability to detect objects and classify them into "safe" and "unsafe" classes can help autonomous vehicles determine when it is safe to change lanes while avoiding accidents.

We trained our model on an annotated dataset obtained from Roboflow and evaluated its performance using various metrics such as confusion matrix, F1 curve, P curve, PR curve, and R curve. Additionally, we present the results of the model's performance on sample videos, including our own and those available on the internet.

The report is structured as follows. The next section discusses the related work on blind-spot detection using computer vision. We then describe our methodology for developing the blind-spot detection model using the YOLOv8 algorithm. In the subsequent sections, we present our results and evaluate the model's performance using various metrics. Finally, we conclude the report with a discussion of the findings and suggestions for future work.

## 1.1 PROBLEM STATEMENT

The blind spot is a critical safety concern for drivers, as it refers to an area of the road that is not visible through the side mirrors or rearview mirror. Changing lanes without checking the blind spot can lead to collisions and accidents, which can be severe and even fatal in some cases. Therefore, it is important to develop effective and reliable blind-spot detection systems that can assist drivers in making safe lane changes.

In this context, the problem statement is to develop an Advanced Driver Assistance System (ADAS) that uses computer vision to detect vehicles in the driver's blind spot and alerts the driver when it is not safe to change lanes. The system should be able to accurately and reliably detect objects in the blind spot and classify them as "safe" or "unsafe" based on their relative position and speed to the driver's vehicle. The system should also be able to provide real-time alerts to the driver in case an unsafe lane change is attempted.

To solve this problem, we propose using the YOLOv8 algorithm, which is a state-of-the-art object detection algorithm that can detect objects with high accuracy and speed. By training the YOLOv8 algorithm on a dataset of annotated images of vehicles in the blind spot, we can develop a blindspot detection model that can accurately detect and classify vehicles in real time. The model can then be integrated into an ADAS system to provide real-time alerts to the driver when it is not safe to change lanes.

Overall, the problem statement addresses a critical safety concern in driving and presents a viable solution using computer vision and machine learning techniques.

## 1.2 SOFTWARE AND HARDWARE REQUIREMENT

**SOFTWARE REQUIREMENT:**

The following modules need to be installed in the system to run the project:

- ultralytics==8.0.20 - This module provides the YOLOv8 algorithm, which is used to detect objects in the images or videos.
- roboflow - This module is used to access annotated datasets from Roboflow.
- pycuda - This module is required to run the YOLOv8 algorithm on GPU for faster computation.
- opencv-python - This module is used for image processing tasks such as loading, displaying, and saving images.
- tensorflow - This module is used for machine learning tasks, particularly for neural network models.
- pygame - This module is used to play audio alerts.

**HARDWARE REQUIREMENTS:**

The project's performance is greatly affected by the system's hardware configuration. The following hardware requirements are recommended for optimal performance:

- CPU - Intel Core i5 8th Gen or higher
- GPU - NVIDIA RTX 2060 or higher with 4 GB or more memory. The higher the GPU memory, the better the performance.
- RAM - 8 GB or more
- Storage - 50 GB of free storage space to store the datasets, model weights, and other related files.
- Display - A monitor with at least a 1920x1080 resolution for better visualization. It should be noted that these requirements are estimated and may vary depending on the size and complexity of the dataset and the number of iterations needed for training the model. Therefore, it is recommended to have a system that meets the above requirements or higher to ensure the smooth execution of the project.

## 1.3 OBJECTIVES

- Enhanced Safety: The foremost objective is to improve safety by reducing the risk of collisions caused by vehicles entering or exiting the driver's blind spots. By providing visual or audible alerts, these systems help drivers become aware of vehicles that may not be visible in their side or rearview mirrors.

- Accident Prevention: Blind spot monitoring systems aim to prevent accidents and potential collisions, particularly during lane changes or merging maneuvers on highways or multi-lane roads. By detecting vehicles in blind spots, they give drivers more comprehensive awareness of their surroundings, reducing the likelihood of accidents.

- Increased Awareness: These systems contribute to enhancing driver awareness and attentiveness by providing additional information about the vehicle's surroundings. By alerting drivers to the presence of vehicles in their blind spots, they encourage more cautious and informed driving behavior.

- Improved Driving Experience: Blind spot monitoring systems aim to enhance the overall driving experience by reducing stress and uncertainty associated with lane changes and merging. Drivers can feel more confident and secure knowing that their vehicle is equipped with technology that helps them navigate traffic more safely.

- Support for Driver Assistance Systems: Blind spot monitoring systems often complement other advanced driver assistance systems (ADAS), such as adaptive cruise control and lane-keeping assist. By integrating with these systems, they contribute to the overall goal of improving vehicle safety and reducing the likelihood of accidents caused by human error.

  Overall, blind spot monitoring systems play a crucial role in modern vehicle safety technology, helping to mitigate the risks associated with blind spots and improving overall road safety for drivers and passengers alike.

## 1.4 CHALLENGES

Blind spot monitoring systems face several challenges, including ensuring accuracy and reliability in detecting objects, particularly in adverse weather conditions, such as heavy rain or fog. Calibration and maintenance of sensors are essential to mitigate errors that could compromise system performance. Integrating the system with driver behavior poses another challenge, as some drivers may become overly reliant on it, leading to complacency or a lack of vigilance in checking blind spots manually. Cost can also hinder widespread adoption, especially in markets where advanced safety features are not yet standard, necessitating efforts to balance affordability with effectiveness. Educating drivers about system capabilities and limitations is crucial to ensure proper usage and interpretation of alerts. Meeting regulatory standards and compliance requirements across different regions adds complexity to development and deployment efforts. Addressing these challenges requires ongoing research, collaboration between manufacturers and regulatory bodies, and effective driver education initiatives to maximize the safety benefits of blind spot monitoring systems.

# CHAPTER 2

## LITERATURE SURVEY

This study has submitted by the authors of Guiru Liua, Mingzheng Zhoua, Lulin Wang b, Hai Wang b, Xiansheng Guo. A blind spot detection system called BSDW is proposed for day and night driving conditions. Using millimeter-wave radar sensors mounted on the rear bumper, the system effectively detects moving targets within the blind spot area of the vehicle. The study highlights the system's architecture, radar hardware structure, signal processing methods, detection algorithms, calibration techniques, and integration strategies. Results from testing on the Chery Arrizo7 vehicle showed early warning rates of up to 98.20% during the day and 98.21% at night. Compared to other sensor-based systems like cameras and Lidar, millimeter-wave radar proved more suitable for achieving higher alarm rates, thus enhancing driver safety by providing timely warnings and preventing collision accidents.

This study has submitted by the authors of Bing-Fei Wu a , Hao-Yu Huang a , Chao-Jung Chen b , Ying-Han Chen a , Chia-Wei Chang a , Yen-Lin Chen c introducing an effective blind spot warning system (BSWS) designed for both daytime and nighttime driving conditions. The BSWS utilizes camera models with dynamic calibration and blind spot detection algorithms. For daytime operations, it employs the Horizontal Edge and Shadow Composite Region (HESCR) method to detect vehicles based on shadow locations and lane markings. At night, the system extracts bright objects and identifies paired headlights to detect vehicles. Implemented on a DSP-based embedded platform, the BSWS achieves promising results in practical experiments conducted on a highway in Taiwan. The system exhibits high accuracy in vehicle detection, with rates reaching 97.22% for daytime and 91.11% for nighttime conditions. Additionally, the BSWS incorporates vehicle distance estimation to provide early warnings to drivers. Comparative performance evaluations with existing research show the proposed system's robustness, computational efficiency, and effectiveness in driver assistance and collision warning applications. Operating at 600 MHz with 32 MB DRAM, the BSWS achieves an average of 20 and 50 frames per second under daytime and nighttime conditions, respectively, highlighting its suitability for real-world road environments.

This study has submitted by the authors of Burak Çayır , Tankut Acarman , Emrah Yürüklü a study addresses the limitations of existing Advanced Driver Assistance Systems (ADAS), focusing on "blind spot," "lane departure," and "safe following distance" monitoring. A vision-based active safety system is developed to prevent traffic accidents during lane changes and following tasks, considering the driver's involvement. The system generates visual and audio warnings if unintentional lane departures or lane changes into oncoming traffic occur. Design and implementation issues of the developed system are discussed. In freeway traffic testing, successful detection of lane markers and computation of the vehicle's position relative to lane borders is achieved. Real-time performance is demonstrated on standard computer hardware. Preliminary results of the monitoring and warning system are presented, along with ongoing work on system configuration, integration of warning interfaces, driver acceptability, and false alarm reduction. The study suggests promising and cost-effective methods for future ADAS development, including blind spot detection and collision warning using simple web cameras and single-camera systems.

This study has submitted by the authors of Guiru Liu , Lulin Wang , Shan Zou  introducing a blind spot detection and warning system (BSDWS) designed for both daytime and nighttime driving conditions. The system encompasses various components such as system architecture, radar structure, signal processing algorithms, and calibration methods. Utilizing a line frequency modulated continuous wave (LFMCW) millimeter-wave radar, the BSDWS effectively monitors moving targets within the vehicle's blind spot warning area. Employing a clutter distribution model, a cell greatest, smallest, and averaging constant false-alarm rate (CGSA-CFAR) detector ensures high detection rates with low false alarms. Implemented on an ADI DSP-based embedded platform, the system demonstrates promising early warning rates of up to 98.38% and 98.34% under daytime and nighttime conditions, respectively, when tested on the Chery Arrizo7 car. Comparative analysis suggests that the proposed radar-based system outperforms visual-based systems in real-world scenarios, exhibiting higher warning rates and target detection accuracy. Overall, the study highlights the effectiveness of the BSDWS in providing early warnings to drivers and enhancing road safety in various driving environments.

This study has submitted by the authors of Emilia Magdalena Szumska, Paweł Tomasz Grabski emphasizes the critical role of the driver's visual field in ensuring road safety and identifies blind spots as areas around the vehicle invisible to the driver. It discusses how blind spots can impede maneuvers and contribute to collisions and accidents. Automotive manufacturers offer solutions to mitigate blind spots, enhancing safety by alerting drivers to nearby road users. The study presents findings on the percentage of blind spots for drivers of different heights and explores the impact of seat height adjustment on these blind spots. It concludes that seat height adjustment influences the size and range of blind spots, particularly affecting maneuvers at low speeds. Additionally, it notes that accessories added by vehicle users can further limit the driver's field of vision. Overall, the study underscores the importance of addressing blind spots to improve road safety.

This study has submitted by the authors of Darren Aquilina , Thomas Gatt discusses the increasing number of traffic accidents involving motorcycles due to unsafe lane changes, prompting the proposal of a real-time blind spot detection system. The system aims to accurately detect vehicles in a motorcycle's blind spot to improve road safety without distracting the rider. Addressing limitations of existing models, the study implements a custom dataset to enhance vehicle detection, particularly during nighttime. Experimental results show significant improvements in precision and recall with the custom model compared to pre-trained models. The conclusion highlights the effectiveness of using a helmet-mounted camera and YOLOv5 algorithm for blind spot detection, outlining the research steps and suggesting areas for further improvement, such as dataset augmentation and exploring alternative camera solutions. Despite limitations, the study demonstrates the feasibility of using computer vision for blind spot detection and suggests potential enhancements to reduce motorcycle accidents in the future.

This study has submitted by the authors of M. Nor, Mz Hassan, N. Ab Wahab, S. M. Najib, Khairil Anwar Abu Kassim addresses the growing concern over road safety and the increasing number of accidents each year. It highlights various safety systems, from basic installations like seat belts and airbags to more advanced technologies such as braking assist and blind spot monitoring. The study proposes a Smart Vehicle Blind Spot Detection System (VBDS) equipped with radar sensors to detect vehicles in blind spot regions, providing audible and visual alerts to drivers. Tests conducted under different conditions assess the system's accuracy in detecting vehicles within blind spots. The conclusion showcases the successful design and implementation of the VBDS, demonstrating its effectiveness in urban areas during peak traffic hours. Future work is suggested to enhance recognition accuracy and speed up detection time for multiple vehicles simultaneously. Overall, the study presents a promising solution to enhance road safety through advanced detection systems.

This study has submitted by the authors of Seunghwan Baek , Heungseob Kim and Kwangsuck Boo introduces a method for detecting vehicles from the side and rear using a vision system for Blind Spot Detection Systems (BSDS). The complexity of real-time image processing during driving, including background noise and lighting variations, poses challenges for isolating target vehicles. The proposed approach utilizes repetitive image processing techniques like Sobel and morphological operations, along with a Kalman filter to eliminate background noise and accurately identify target vehicles. Experimental evaluations conducted on highway driving scenarios demonstrate the algorithm's improved speed and robustness compared to previous methods. In conclusion, this paper presents an algorithm for detecting and tracking rear-side vehicles on highways, employing simple image processing and signal-level vehicle detection techniques. The integration of a Kalman filter facilitates accurate vehicle tracking and is adaptable to computational boards with simplified model equations. Overall, the study contributes to enhancing vehicle detection systems' efficiency and reliability for road safety applications.

This study has submitted by the authors of Phat Nguyen Huu, Phuong Nguyen Quynh, Minh Hoang Nhat Detecting people in a vehicle's blind spot is crucial for preventing accidents, especially in areas like parking lots where hazards are common. This article proposes a solution combining image processing algorithms with microwave radar sensors to detect individuals entering a car's blind spot. By leveraging the Yolo-fastest module to extract human features and using microwave radar sensors to detect moving objects, the system achieves an accuracy of 91.63% on cars. This technology holds promise for applications in self-driving cars and advanced driver assistance systems. Additionally, our study emphasizes the significance of incorporating microwave sensors into fusion models to enhance detection accuracy, particularly in scenarios involving children. This innovative approach has practical implications for improving safety in family vehicles and children's transportation services.

# CHAPTER 3

## SYSTEM ARCHITECTURE

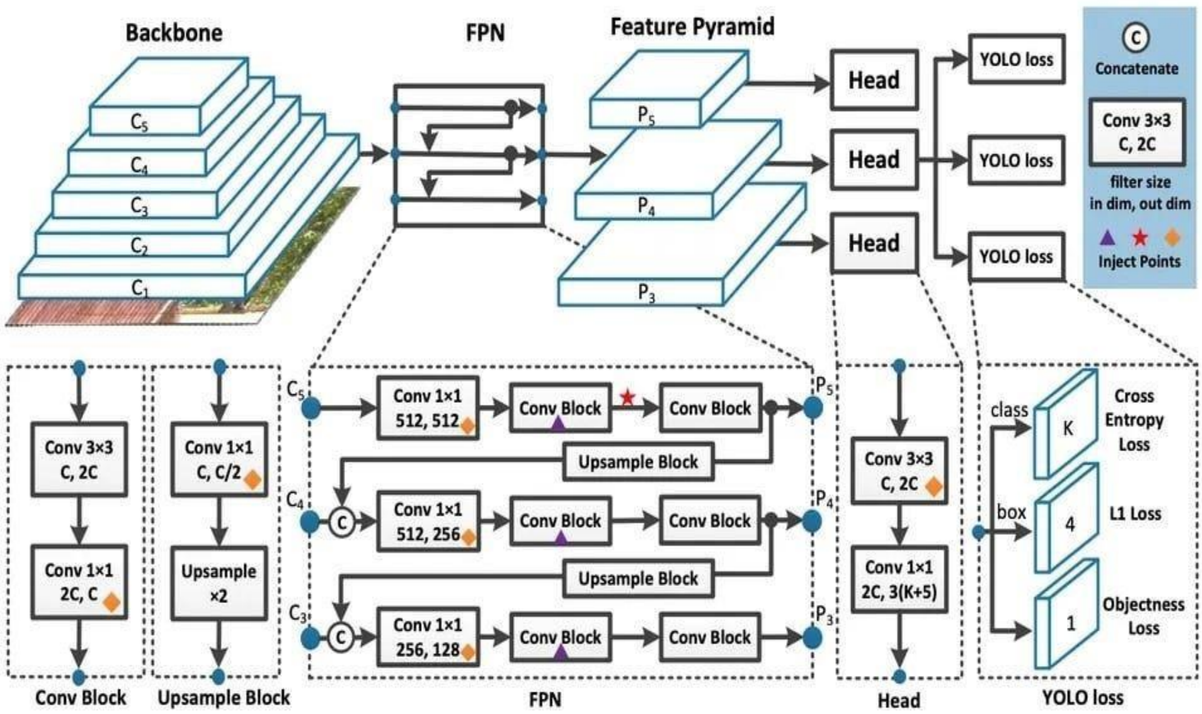


Fig 3.1 YOLOv8 architecture diagram

YOLOv8, an evolution of the YOLO (You Only Look Once) object detection architecture, builds upon previous versions to improve accuracy and speed. It employs a single neural network to predict bounding boxes and class probabilities directly from full images in one evaluation. The architecture typically consists of a backbone network, such as Darknet, followed by multiple detection layers responsible for detecting objects at different scales. YOLOv8 integrates various optimization techniques, including advanced anchor box clustering, feature pyramid networks (FPN), and multi-scale prediction to enhance detection performance across different object sizes and aspect ratios. Additionally, it incorporates improvements in network architecture, training strategies, and loss functions to enhance detection accuracy and robustness. YOLOv8 architecture strives to strike a balance between accuracy and speed, making it suitable for real-time object detection applications in diverse environments.

YOLOv8 is the latest version of YOLO family of object detection algorithm.YOLOv8 is mainly divided into 3 parts

**Backbone**

This is the foundation of the model which is based on modified CSPDarknet53 [1,5] (a pre-trained convolution neural network) and it is mainly used to extracts from the input image at various levels of details (low , medium , and high).

**Neck (Path Aggregation)**

This section utilizes the techniques like the Feature Pyramid Network (FPN) to combine coarse (spatial) and fine-grained(semantic) information. It merges the feature maps which we get form the backbone.

**Head (Object Detection)**

This Section consists of many convolution layers followed by fully connected layers which uses the processed features to predict bounding boxes and class probabilities for objects in image.

Blind Spot Detection System Architecture:

Now let us see the whole working system architecture:

**1. Sensors:** Utilizes a combination of radar, ultrasonic sensors, or cameras mounted on the vehicle to monitor the surrounding areas.

**2. Sensor Data Processing:** The data from sensors are processed to identify potential objects or vehicles in blind spots.

**3. Object Detection:** Utilizes computer vision algorithms to detect and classify objects in the sensor data, such as vehicles, pedestrians, or cyclists.

**4. Blind Spot Analysis:** Analyzes the detected objects to determine if they are within the blind spot zones of the vehicle.

**5. Decision Making:** Based on the analysis, the system decides whether to trigger an alert to the driver.

**6. Alert Generation:** Generates alerts using visual indicators (e.g., LED lights on side mirrors) and/or auditory signals (e.g., warning sounds).

**7. Driver Interface:** Interfaces with the vehicle's dashboard or infotainment system to display alerts and provide feedback to the driver.

**8. Calibration and Maintenance:** Includes mechanisms for sensor calibration and regular maintenance to ensure the accuracy and reliability of the system.

**9. Integration with Vehicle Systems:** Integrates with other vehicle systems, such as the vehicle's CAN bus, to access additional data and enhance functionality.

**10. Data Logging and Analysis:** Optionally, logs data for analysis and feedback to improve the system's performance over time.

# CHAPTER 4

# METHODOLOGY

## 4.1 DATA COLLECTION:

Data collection for a blind spot monitoring system involves identifying driving scenarios such as highway driving, urban driving, parking lots, and intersections, and selecting appropriate equipment like dashboard cameras or smartphones to capture clear and high-quality images or videos. Annotating blind spot regions in the captured data is crucial, marking areas where objects may not be visible to the driver due to vehicle structure or obstructions. Diverse data collection is necessary, encompassing various lighting and weather conditions, road types, traffic densities, and vehicle types to ensure system robustness. Adherence to privacy regulations and obtaining consent for data collection are paramount. Organizing the collected data into labeled datasets with annotations specifying blind spot regions in standardized formats like COCO or PASCAL VOC is essential. Verifying annotation quality and potentially augmenting the data with transformations such as rotation or scaling further enhance the dataset's quality and diversity. Splitting the dataset into training, validation, and test sets facilitates model training and evaluation, while documenting metadata such as camera parameters and environmental conditions provides additional context for analysis and troubleshooting. Through these steps, a comprehensive dataset can be compiled to train and evaluate machine learning models for blind spot detection effectively.

## 4.2 DATA ANALYSIS:

### 4.1.1 DATASET DESCRIPTION:

The dataset used in this project contains gradient images from the front, left, right, and rear cameras of a moving vehicle. Each object in the images has its colour, making it easier to identify and track different objects in the scene. The dataset is annotated with bounding boxes around each object of interest, such as other vehicles, pedestrians, and obstacles, which are labelled as either "safe" or "unsafe" for lane changing. The images are captured from different angles and distances, simulating real-world driving conditions.

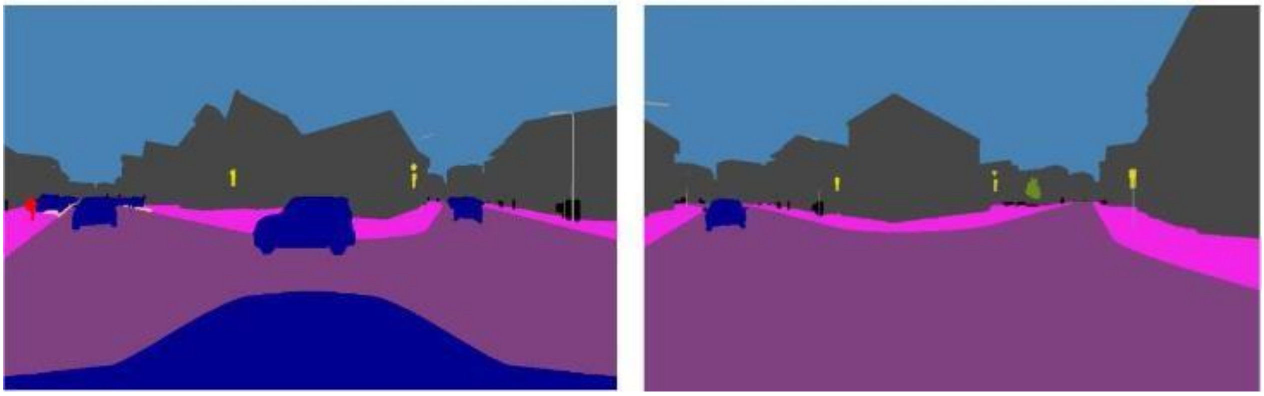

Fig 4.1 Sample Dataset

The dataset provides a diverse set of scenarios, such as highway driving and city driving, making it suitable for training a robust and accurate blind spot detection model. The dataset is split into a training set, a validation set, and a testing set. The training set comprises 70% of the total data, with 627 images, while the validation set and testing set make up 20% and 10% of the data, respectively, with 179 and 91 images each.To enhance the accuracy of the model, the dataset is pre-processed using techniques such as data augmentation, normalization, and scaling. These techniques help in improving the model's generalization ability and reducing overfitting on the training data. The images are auto-oriented and resized to a standard size of 640x640. However, no augmentations were applied to the dataset.

Overall, this dataset provides a valuable resource for training and evaluating blind spot detection models, helping to improve the safety of vehicles on the road. With annotated bounding boxes and images captured from different angles and distances, it provides an excellent opportunity to train a model that can detect vehicles in the driver's blind spot accurately.

## 4.3DATA VISUALIZATION:

In the "ADAS Blind Spot Detection using YOLOv8" project, data visualization plays an important role in understanding the performance of the model and the results of the object detection. The following visualizations are available in the project:

```
#CONFUSION MATRIX
Image(filename=f'{HOME}/runs/detect/train/confusion_matrix.png', width=600)
```

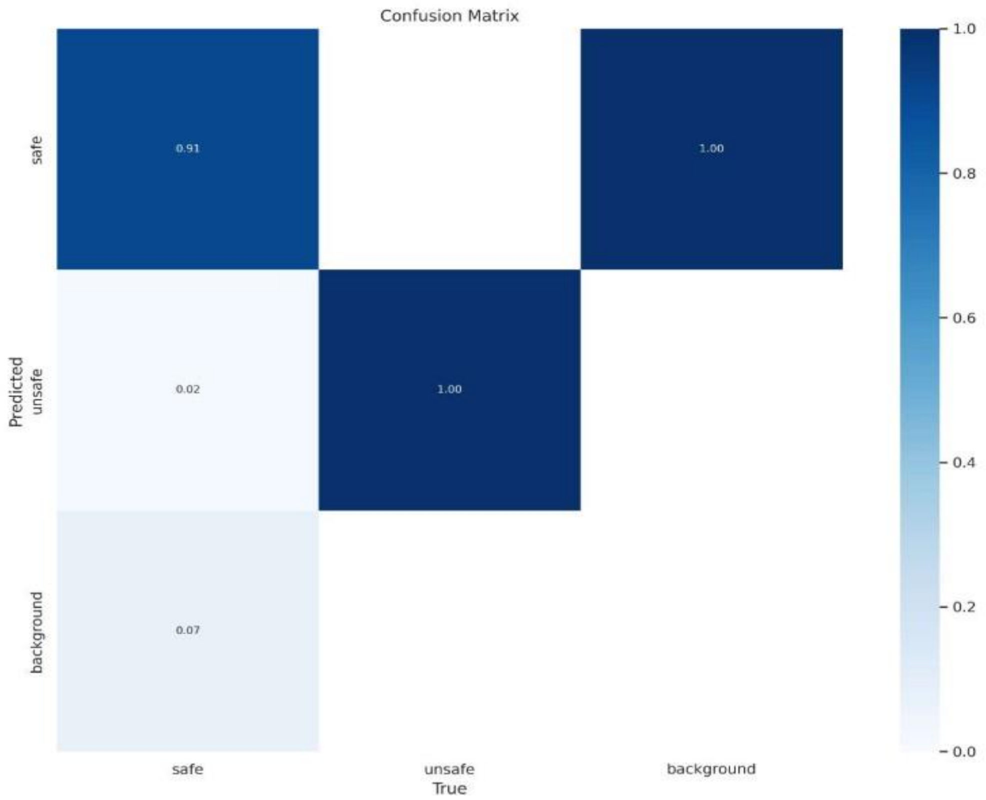


Fig 4.2 Confusion Matrix

- **Confusion Matrix:** The confusion matrix is a table that shows the number of true positives, false positives, true negatives, and false negatives for each class in the dataset. This allows for an easy evaluation of the model's performance in terms of precision, recall, and accuracy.

## 4.4 MODEL TRAINING:

The YOLOv8 model training stands as a pivotal phase in our project, demanding significant time investment in configuring essential modules. Leveraging the YOLOv8 architecture, we've embarked on blind spot detection within Deep Learning frameworks like Darknet or PyTorch. Through meticulous training over 300 epochs on annotated datasets, we fine-tune hyperparameters for optimal performance. Continuous monitoring of model performance using accuracy, precision, recall, and F1-score ensures iterative refinement. Adjusting training parameters and employing data augmentation techniques, we aim to surpass a 96% accuracy threshold on the validation set. Currently, we've initiated the evaluation of the trained model on separate video and image datasets to ensure consistent detection proficiency. The model's performance is being assessed using classification metrics such as average precision (mAP), ensuring robustness across varied scenarios.

## 4.5 EVALUVATION:

The project's requirements and performance metrics are aligned to ensure optimal execution and reliable results. By meeting or exceeding the specified software and hardware requirements, the project can effectively utilize the YOLOv8 algorithm for blind spot detection. The choice of modules facilitates seamless data handling, efficient computation, and enhanced user interaction.
Moreover, adherence to the recommended hardware configuration ensures smooth execution of the project, with sufficient resources allocated for data processing, model training, and visualization tasks. These requirements are tailored to accommodate the project's complexity and ensure consistent performance across different datasets and training iterations.
Overall, the project's adherence to specified requirements and performance benchmarks underscores its robustness and suitability for blind spot detection applications, demonstrating its potential to enhance safety measures in relevant environments.

# CHAPTER 5

# CODING AND TESTING

## 5.1 LEARNING AND PREDICTION:

In the "ADAS Blind Spot Detection Using YOLOv8" project, training, validation, and prediction are the three main stages of the model development and deployment process.

### 5.1.1 TRAINING

The training stage involves using a dataset of annotated images to train the YOLOv8 algorithm. The objective of the training process is to teach the algorithm to accurately detect and classify objects in an image. During training, the algorithm adjusts its weights and biases based on the error between its predicted output and the ground truth labels. It is set to run 25 epochs. This process is repeated multiple times until the algorithm reaches an acceptable level of accuracy.

```
#TRAINING
%cd {HOME}
!yolo task=detect mode=train model=yolov8s.pt data={dataset.location}/data.yaml epochs=25
imgsz=800 plots=True
```

### 5.1.2 VALIDATION

After training, the model is validated using a separate dataset to evaluate its performance. The validation set is used to measure the accuracy, precision, and recall of the model. This helps ensure that the model is not overfitting to the training data and can generalize well to new data.

```
#VALIDATION
!yolo task=detect mode=val model={HOME}/runs/detect/train/weights/best.pt
data={dataset.location}/data.yaml
```

### 5.1.3 PREDICTION

Once the model is trained and validated, it can be used to make predictions on new data. In the case of the "ADAS Blind Spot Detection Using YOLOv8" project, the model can detect objects in the driver's blind spot and classify them as safe or unsafe. When an unsafe object is detected, the model alerts the driver via function calls and warning alarms.

```
#PREDICTION
!yolo task=detect mode=predict model={HOME}/runs/detect/train/weights/best.pt conf=0.25
source={dataset.location}/test/images save=True
```

Overall, the training, validation, and prediction stages are crucial for the development and deployment of the model. Through iterative training and validation, the model can achieve high accuracy and reliability in real-world scenarios.

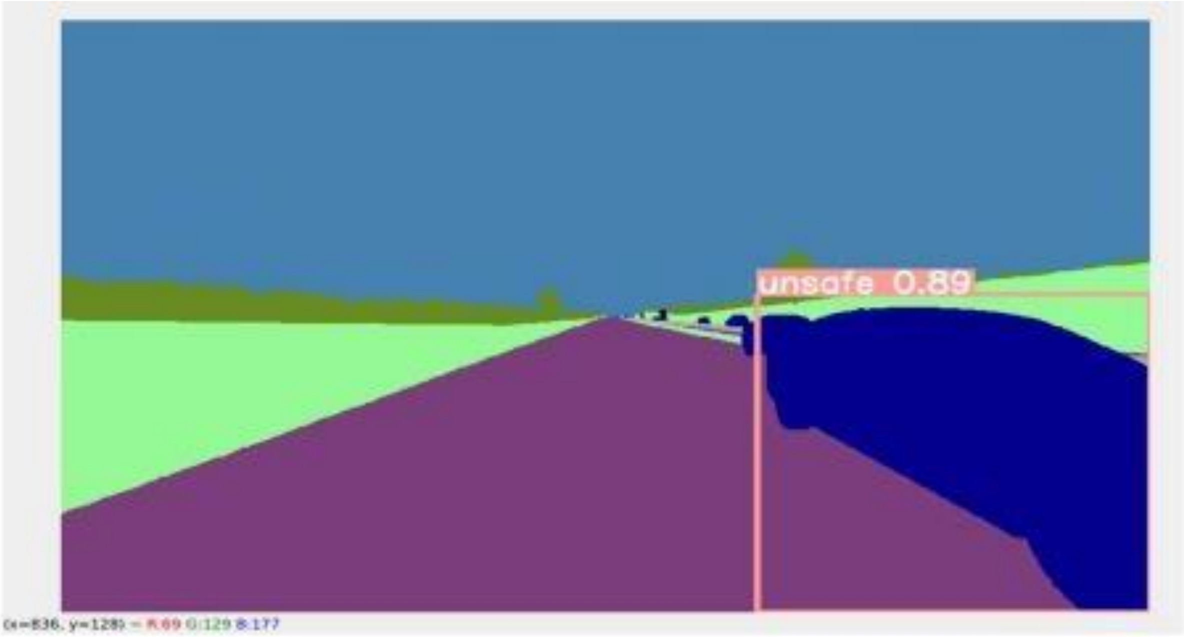


Fig 5.1 Dataset For Prediction

In the YOLOv8 car image detection workflow, the training stage involves feeding the model with annotated car images, enabling it to iteratively learn to detect cars by adjusting parameters based on input data and annotations through forward and backward passes, minimizing loss via optimization algorithms across multiple epochs. The validation stage assesses model performance using a separate validation set, comparing predictions to ground truth annotations to fine-tune hyperparameters such as learning rate and augmentation techniques. Finally, in the prediction stage, the trained model is deployed to detect cars in new, unseen images or videos, applying learned detection algorithms to identify and localize cars, with optional post-processing techniques like non-maximum suppression applied to filter detections. Through this iterative process, the YOLOv8 model is refined and deployed effectively for accurate and reliable car image detection tasks.

**5.2 USING THE MODEL:**

Defining the model:

```
import ultralytics
ultralytics.checks()
from ultralytics import YOLO
model = YOLO("runs/detect/train/weights/best.pt")
```

Using the model on an input video:

```
import cv2
from pygame import mixer

#Change 'fr' to change playback speed. Lower fr -> Greater playback speed
fr=50
# Open video file using OpenCV
video_path = "SampleVideos/short_rear.mp4" #EDIT INPUT FILE
cap = cv2.VideoCapture(video_path)
mixer.init()
mixer.music.load('warning.mp3')
i=0
# Define alert function to display a message when "unsafe" is detected
def show_alert(i):
   print("ALERT{0}!!!INCOMING VEHICLE".format(int(i)))
   mixer.music.play()

# Loop over frames in the video
while cap.isOpened():
   # Read next frame from video
   ret, frame = cap.read()
   if not ret:
      break

   # Perform object detection inference on frame using the trained YOLOv8 model
   response = model.predict(source=frame, classes=[1], conf=0.8, show=True)

   if response[0].boxes.cls.shape[0] > 0:
      show_alert(i)
      i=i+1
   else:
      mixer.music.stop()

   cv2.waitKey(fr)
   if cv2.waitKey(fr) & 0xFF == ord('q'):
      break

# Release video capture and close window
cap.release()
cv2.destroyAllWindows()
```

When the user runs the `main.ipynb` Jupyter notebook and selects the source video directory, the YOLOv8 model is used to predict the positions of vehicles in the video frames. If a vehicle is detected in the driver's blind spot, an alert warning is generated to notify the driver that it's not safe to change lanes. Additionally, a beep sound is played to capture the driver's attention and encourage them to take appropriate action.

This is an important feature because blind spot accidents can be very dangerous, and they are unfortunately quite common. By using an ADAS system with blind spot detection, drivers can be alerted to the presence of other vehicles in their blind spots, which can help them avoid accidents and stay safe on the road. The use of a beep sound can be particularly effective because it can quickly capture the driver's attention and encourage them to take action, which can be especially important in situations where there is limited time to react.

Overall, the blind spot detection feature of this project can be a valuable addition to any ADAS system, as it can help drivers stay safe on the road and avoid accidents.

# CHAPTER 6

## RESULT AND DISCUSSION

## RESULTS:

The results section provides a visual representation of object detection on sample images or videos. The detected objects are labelled with their class and a bounding box. This allows for a quick evaluation of the model's performance in real-world scenarios.

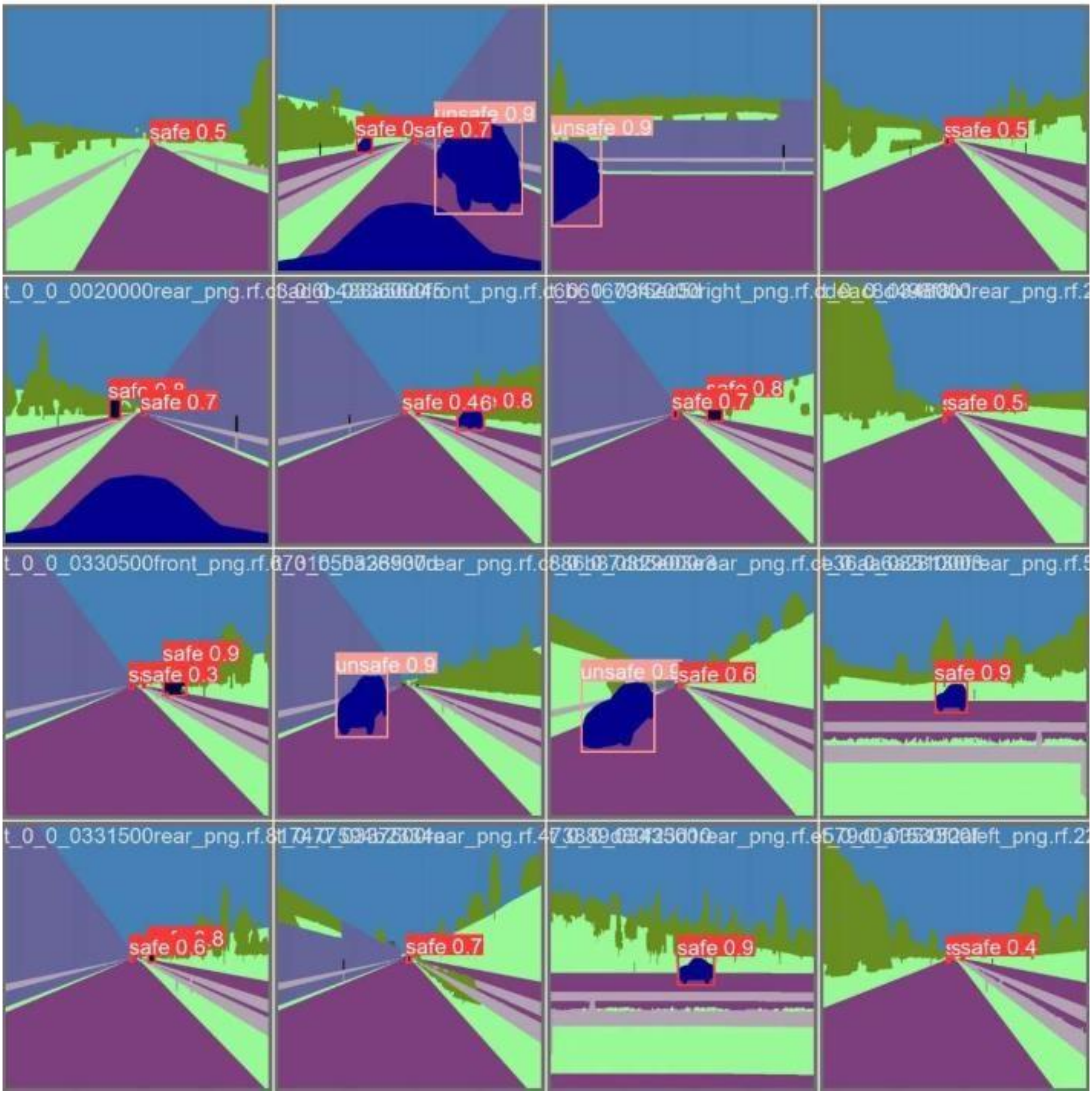


Fig 6.1 Result Dataset

- **Training Losses at each Epoch:**

| epoch | train/box_loss | train/cls_loss | train/dfl_loss |
|---|---|---|---|
| 1 | 1.4902 | 3.7832 | 1.3224 |
| 2 | 1.2416 | 1.1627 | 1.1013 |
| 3 | 1.2505 | 1.0882 | 1.0925 |
| 4 | 1.2209 | 1.0255 | 1.0851 |
| 5 | 1.274 | 0.94847 | 1.0871 |
| 6 | 1.2935 | 0.87873 | 1.0958 |
| 7 | 1.2765 | 0.86245 | 1.1015 |
| 8 | 1.2828 | 0.85627 | 1.1006 |
| 9 | 1.2599 | 0.81715 | 1.1001 |
| 10 | 1.1889 | 0.77299 | 1.0763 |
| 11 | 1.1998 | 0.76919 | 1.0742 |
| 12 | 1.2079 | 0.76201 | 1.0719 |
| 13 | 1.2262 | 0.76672 | 1.089 |
| 14 | 1.1606 | 0.72792 | 1.0546 |
| 15 | 1.2094 | 0.72129 | 1.0716 |
| 16 | 1.2535 | 0.72184 | 1.1198 |
| 17 | 1.2164 | 0.66475 | 1.079 |
| 18 | 1.2211 | 0.6644 | 1.0819 |
| 19 | 1.1893 | 0.64519 | 1.0776 |
| 20 | 1.1654 | 0.61235 | 1.0579 |
| 21 | 1.1769 | 0.61889 | 1.0691 |
| 22 | 1.1715 | 0.61625 | 1.0431 |
| 23 | 1.138 | 0.59027 | 1.0367 |
| 24 | 1.1148 | 0.56405 | 1.027 |
| 25 | 1.1099 | 0.54767 | 1.0278 |

- **Validation Losses at each Epoch:**

| epoch | val/box_loss | val/cls_loss | val/dfl_loss |
|---|---|---|---|
| 1 | 1.2961 | 1.164 | 1.1204 |
| 2 | 1.2552 | 0.93645 | 1.0219 |
| 3 | 1.2027 | 0.97677 | 1.0214 |
| 4 | 1.3351 | 0.84611 | 1.0927 |
| 5 | 1.2778 | 1.1547 | 1.0612 |
| 6 | 1.3459 | 0.89431 | 1.1249 |
| 7 | 1.2902 | 0.84282 | 1.0904 |
| 8 | 1.2741 | 0.78178 | 1.0711 |
| 9 | 1.2032 | 0.8086 | 1.0315 |
| 10 | 1.2586 | 1.0372 | 1.0421 |
| 11 | 1.2201 | 0.76799 | 1.0356 |
| 12 | 1.2468 | 0.78801 | 1.0525 |
| 13 | 1.2118 | 0.79099 | 1.0489 |
| 14 | 1.1867 | 0.69816 | 1.0327 |
| 15 | 1.2764 | 0.72414 | 1.054 |
| 16 | 1.195 | 0.68522 | 1.0267 |
| 17 | 1.2135 | 0.66731 | 1.0455 |
| 18 | 1.2098 | 0.65597 | 1.0378 |
| 19 | 1.2015 | 0.65553 | 1.0412 |
| 20 | 1.2295 | 0.65493 | 1.0496 |
| 21 | 1.1808 | 0.64221 | 1.0223 |
| 22 | 1.1592 | 0.62223 | 1.0158 |
| 23 | 1.1628 | 0.62952 | 1.0172 |
| 24 | 1.1579 | 0.59383 | 1.0153 |
| 25 | 1.1631 | 0.59267 | 1.0179 |

- **Learning Rate for each Parameter group at each epoch:**

| epoch | lr/pg0 | lr/pg1 | lr/pg2 |
|---|---|---|---|
| 1 | 0.07075 | 0.00325 | 0.00325 |
| 2 | 0.040489 | 0.0063226 | 0.0063226 |
| 3 | 0.0099646 | 0.0091313 | 0.0091313 |
| 4 | 0.008812 | 0.008812 | 0.008812 |
| 5 | 0.008812 | 0.008812 | 0.008812 |
| 6 | 0.008416 | 0.008416 | 0.008416 |
| 7 | 0.00802 | 0.00802 | 0.00802 |
| 8 | 0.007624 | 0.007624 | 0.007624 |
| 9 | 0.007228 | 0.007228 | 0.007228 |
| 10 | 0.006832 | 0.006832 | 0.006832 |
| 11 | 0.006436 | 0.006436 | 0.006436 |
| 12 | 0.00604 | 0.00604 | 0.00604 |
| 13 | 0.005644 | 0.005644 | 0.005644 |
| 14 | 0.005248 | 0.005248 | 0.005248 |
| 15 | 0.004852 | 0.004852 | 0.004852 |
| 16 | 0.004456 | 0.004456 | 0.004456 |
| 17 | 0.00406 | 0.00406 | 0.00406 |
| 18 | 0.003664 | 0.003664 | 0.003664 |
| 19 | 0.003268 | 0.003268 | 0.003268 |
| 20 | 0.002872 | 0.002872 | 0.002872 |
| 21 | 0.002476 | 0.002476 | 0.002476 |
| 22 | 0.00208 | 0.00208 | 0.00208 |
| 23 | 0.001684 | 0.001684 | 0.001684 |
| 24 | 0.001288 | 0.001288 | 0.001288 |
| 25 | 0.000892 | 0.000892 | 0.000892 |

- **Metrics at each Epoch:**

| epoch | metrics/precision(B) | metrics/recall(B) | metrics/mAP50(B) | metrics/mAP50-95(B) |
|---|---|---|---|---|
| 1 | 0.69128 | 0.75729 | 0.79229 | 0.54721 |
| 2 | 0.81508 | 0.80481 | 0.86567 | 0.63558 |
| 3 | 0.78592 | 0.7753 | 0.85137 | 0.60829 |
| 4 | 0.84566 | 0.82947 | 0.90594 | 0.62254 |
| 5 | 0.787 | 0.87066 | 0.8773 | 0.62183 |
| 6 | 0.68298 | 0.90963 | 0.82158 | 0.55363 |
| 7 | 0.7398 | 0.66283 | 0.77618 | 0.51108 |
| 8 | 0.78106 | 0.86152 | 0.81763 | 0.55923 |
| 9 | 0.7794 | 0.7763 | 0.86216 | 0.61565 |
| 10 | 0.63274 | 0.74028 | 0.74717 | 0.52253 |
| 11 | 0.83472 | 0.81731 | 0.89446 | 0.65424 |
| 12 | 0.81813 | 0.78669 | 0.89585 | 0.63013 |
| 13 | 0.80897 | 0.86005 | 0.92806 | 0.66652 |
| 14 | 0.84181 | 0.84419 | 0.93567 | 0.68569 |
| 15 | 0.80385 | 0.91942 | 0.91691 | 0.65681 |
| 16 | 0.84501 | 0.91736 | 0.94602 | 0.7073 |
| 17 | 0.80378 | 0.93182 | 0.94766 | 0.69547 |
| 18 | 0.83165 | 0.94215 | 0.95145 | 0.70216 |
| 19 | 0.87263 | 0.90299 | 0.93791 | 0.68467 |
| 20 | 0.87418 | 0.8688 | 0.94084 | 0.69795 |
| 21 | 0.8393 | 0.93388 | 0.94404 | 0.71726 |
| 22 | 0.86447 | 0.91663 | 0.9468 | 0.72047 |
| 23 | 0.8393 | 0.94905 | 0.94655 | 0.71183 |
| 24 | 0.84577 | 0.9364 | 0.94872 | 0.714 |
| 25 | 0.85263 | 0.93444 | 0.9609 | 0.73924 |

## GRAPHICAL REPRESENTATION:

The results of the Blind Spot Detection project include several graphs that provide insight into the model's performance during training and evaluation. These graphs include:

- Train/Box_loss, Train/Cls_loss, Train/Dfl_loss: These graphs show the loss values for the bounding box regression, classification, and deformable convolutional layers during the training process. Lower values indicate better performance, indicating that the model is learning to detect objects more accurately.
- Val/Box_loss, Val/Cls_loss, Val/Dfl_loss: These graphs show the same loss values as the training graphs but for the validation set. This helps to determine if the model is overfitting to the training data and if it can generalize to new data.
- Precision, mAP50(B), Recall: These metrics are used to evaluate the model's performance on the validation set. Precision measures the ratio of true positive predictions to the total number of positive predictions, while recall measures the ratio of true positive predictions to the total number of actual positive instances in the data. mAP50(B) is a commonly used metric in object detection that measures the mean average precision of the model at 50% intersection over the union (IoU) threshold.

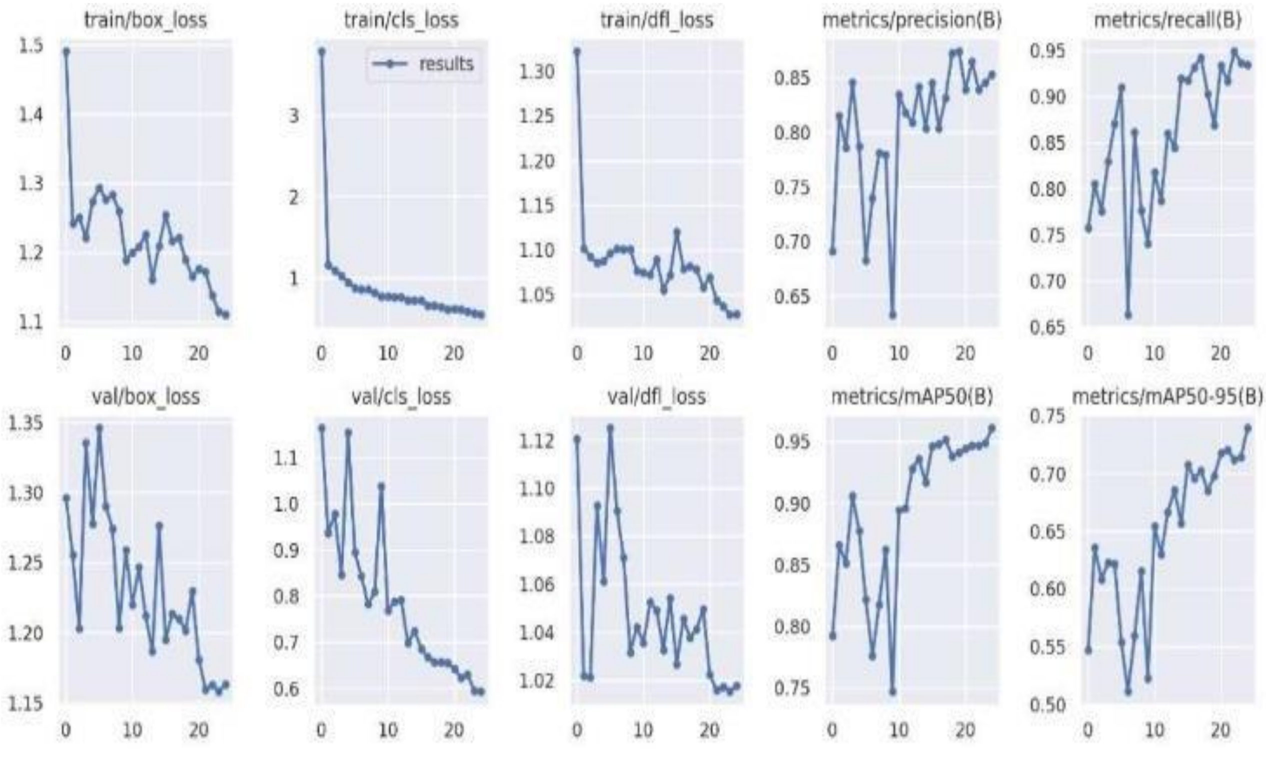


Fig 6.2 Graphical representation

- **F1 Curve:** The F1 curve is a plot that shows the F1 score for each class at different levels of confidence intervals. This curve provides insight into how well the model can balance confidence intervals for each class.

```
#F1-CURVE
Image(filename=f'{HOME}/runs/detect/train/F1_curve.png', width=600)
```

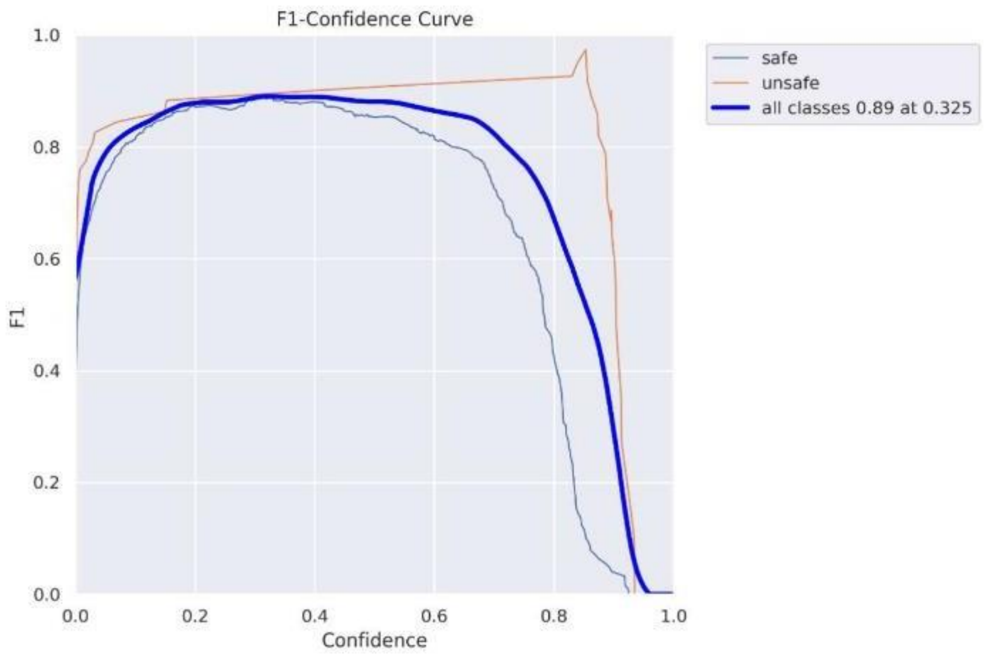


Fig 6.3 F1 curve

- **P Curve:** The P curve is a plot that shows the precision for each class at different levels of confidence. This curve provides insight into how well the model can correctly identify objects of each class for a confidence interval.

```
#P-CURVE
Image(filename=f'{HOME}/runs/detect/train/P_curve.png', width=600)
```

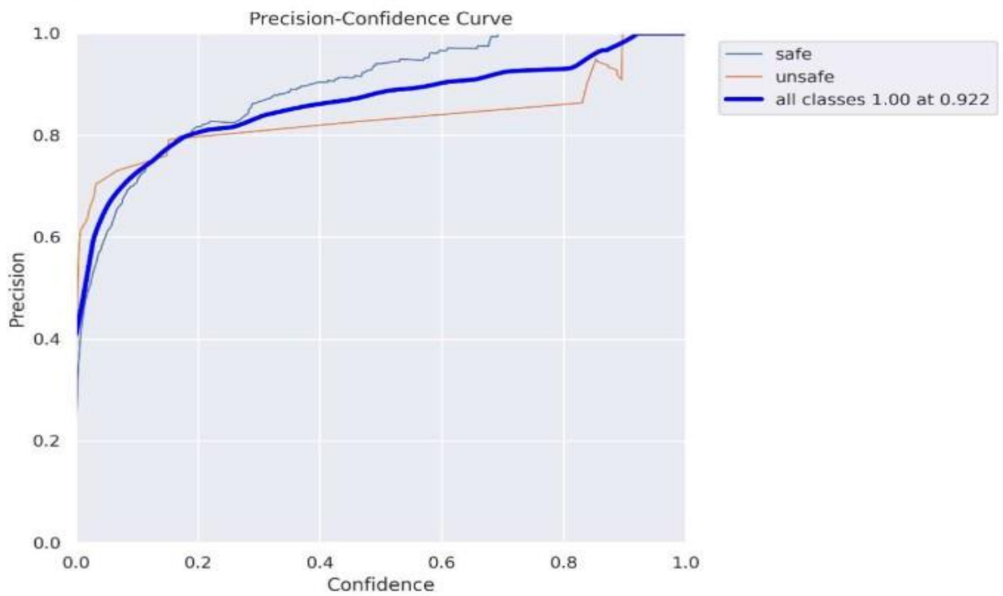


Fig 6.4 P curve

- **PR Curve:** The PR curve is a plot that shows the precision and recall for each class. This curve provides insight into how well the model can balance precision and recall for each class.

```
#PR-CURVE
Image(filename=f'{HOME}/runs/detect/train/PR_curve.png', width=600)
```

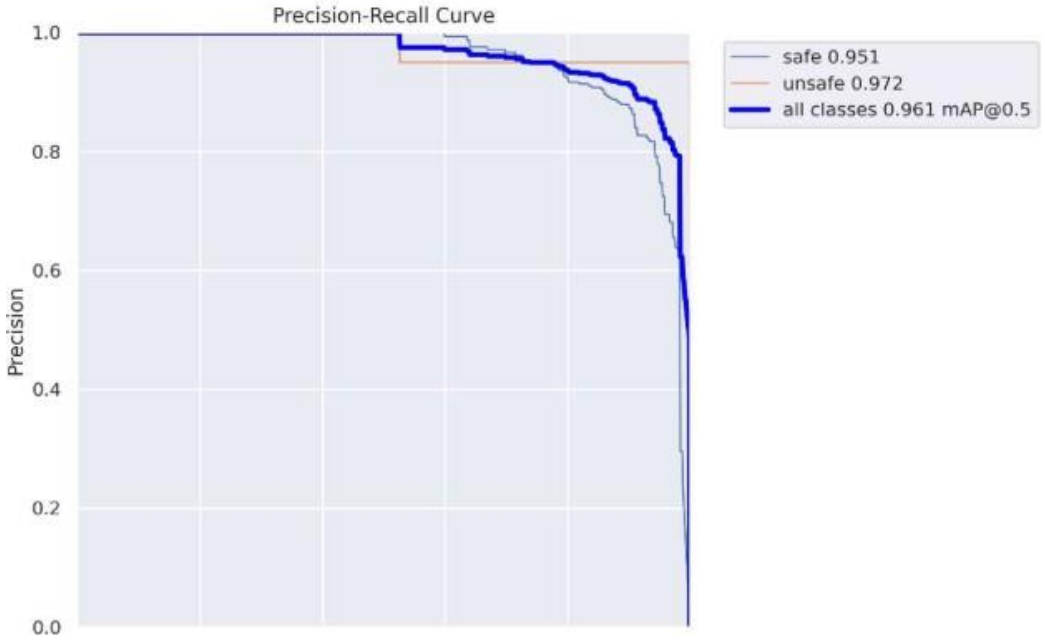


Fig 6.5 PR Curve

- **R Curve:** The R curve is a plot that shows the recall for each class at different levels of confidence intervals. This curve provides insight into how well the model can identify all objects of each class.

```
#R-CURVE
Image(filename=f'{HOME}/runs/detect/train/R_curve.png', width=600)
```

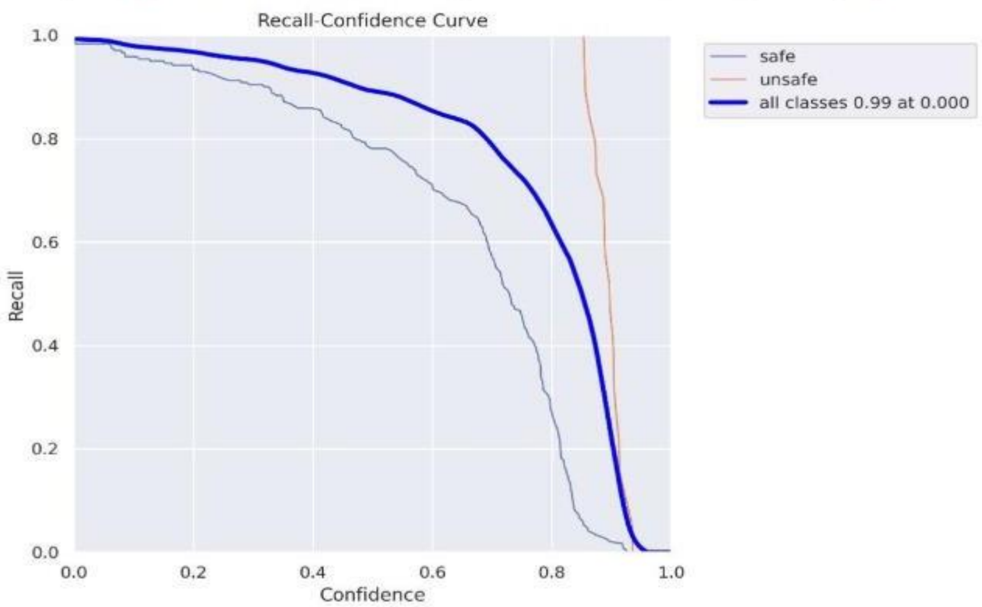


Fig 6.6 R curve

These graphs and metrics are useful for evaluating the performance of the model and determining if further adjustments are necessary. For example, if the loss values for the validation set are consistently higher than those for the training set, it may indicate that the model is overfitting and requires more regularization techniques. On the other hand, if the precision and recall values are low, it may indicate that the model needs to be trained on more data or that the data needs to be preprocessed to improve object detection accuracy.

Overall, data visualization is an important aspect of the "ADAS Blind Spot Detection using YOLOv8" project, as it allows for a better understanding of the model's performance and its ability to detect objects of different classes.

# CHAPTER 7

## CONCLUSION

The project aimed to address the critical safety issue of blind spots in vehicles by developing a robust blind-spot detection system using YOLOv8, a state-of-the-art object detection algorithm. By leveraging a dataset comprising feeds from multiple cameras positioned around the vehicle, including front, left, right, and rear cameras, the model was trained to accurately identify vehicles present in the driver's blind spots. This training data was meticulously preprocessed and augmented using Roboflow, ensuring the model's robustness and generalizability. The training process itself utilized Ultralytics YOLOv8, a powerful framework known for its efficiency and accuracy in object detection tasks. As a result, the developed model successfully achieved the desired outcome of accurately detecting vehicles in blind spots and alerting the driver when it was unsafe to change lanes, thus significantly enhancing overall road safety.

Looking ahead, the project holds promising avenues for further development and enhancement. One potential direction is to extend the system's capabilities to encompass other types of vulnerable road users, such as motorcycles, bicycles, and pedestrians. By expanding the model's object recognition capabilities, the system can provide even more comprehensive protection for all road users. Moreover, the integration of advanced algorithms, such as deep reinforcement learning, offers the potential for the model to adapt dynamically to diverse driving scenarios, further refining its performance and responsiveness.

Furthermore, the blind-spot detection system can be integrated with existing Advanced Driver Assistance Systems (ADAS) to create a more holistic vehicle safety solution. Features such as lane departure warning, automatic emergency braking, and adaptive cruise control can synergize with the blind-spot detection system to provide drivers with comprehensive support in navigating challenging driving conditions, reducing the risk of accidents and enhancing overall road safety standards.

Exploring alternative object detection algorithms, such as Faster R-CNN, RetinaNet, and SSD, presents another avenue for future investigation. By comparing and evaluating the performance of these different algorithms against the specific requirements and characteristics of the dataset and application, researchers can gain valuable insights into their respective strengths and weaknesses, enabling informed decisions regarding algorithm selection for similar projects in the future.

In summary, the successful development of a blind-spot detection system using YOLOv8 represents a significant advancement in vehicle safety technology. With opportunities for future expansion and enhancement, including the incorporation of additional features, integration with existing ADAS functionalities, and exploration of alternative algorithms, the project lays a solid foundation for further innovation in the pursuit of safer and more reliable transportation systems.

## FUTURE ENHANCEMENT

Explore YOLOv8x or YOLOv8n for faster inference while maintaining good accuracy. Integrate multiple sensors like radar, lidar, and ultrasonic sensors along with cameras for more comprehensive coverage and redundancy. Implement machine learning algorithms to improve object detection and classification accuracy, especially in challenging scenarios like adverse weather conditions or complex road environments. Enable vehicle-to-vehicle (V2V) communication to exchange blind spot information between nearby vehicles, enhancing overall safety and awareness on the road.

In future enhancements of blind-spot monitoring systems, integration of multi-modal sensor fusion, including LiDAR and radar, can improve object detection accuracy across various environmental conditions. Implementing semantic segmentation offers detailed object classification, aiding in nuanced decision-making. Real-time object tracking enhances collision risk prediction, while driver behavior analysis ensures adaptive alerts based on attentiveness. Leveraging V2X communication facilitates real-time data exchange for proactive collision avoidance. Machine learning model compression optimizes performance for edge devices, and adaptive alerting mechanisms tailor warnings to driving context. Providing driver feedback and personalization options encourages safe usage, while continuous performance monitoring allows iterative refinement based on real-world feedback.

# CHAPTER 8

## 8. REFERENCE

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