BLIND SPOT DETECTION IN VEHICLES TO ENHANCE ROAD SAFETY

A project report submitted in partial fulfillment
of the requirements for the degree of

Bachelor of Technology
in
Electronics & Communication Engineering
by

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Declaration

We hereby declare that the report titled "***Blind Spot Detection in Vehicles to Enhance Road Safety"*** submitted by me to the School of Electronics Engineering, Vellore Institute of Technology, Chennai in partial fulfillment of the requirements for the award of **Bachelor of Technology** in **Electronics and Communication Engineering** is a bona-fide record of the work carried out by me under the supervision of
Dr. Sivasubramanian A.
I further declare that the work reported in this report, has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma of this institute or of any other institute or University.

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Signature:	....	Signature:	....
Name:	....	Name:	....
Date:		Date:	

Examiner

Signature: ....

Name: ....

Date:

(Seal of the School)

Abstract

Blind spot detection in vehicles is one of the most important innovations aimed at increasing road safety given the increasing number of vehicles on the roads. Blind zones are regions around a vehicle that are obscured from the driver's view, thus posing risks to both drivers and occupants of other road user. Previous methods to reduce blind areas have included observation and mirrors, which are not effective especially in dynamic or poor visibility situations.

Here in this paper, we introduce an intelligent real time blind spot detection system to detect the nearby objects or other vehicles, which are present in blind area. This system combines information feed from cameras, ultrasonic sensors to give a complete picture of the environment around the vehicle. As a result of the near real-time analysis of data and the application of sophisticated algorithms, our concept promises to minimize the response time frequently characteristic of typical sensor-based solutions. Besides, this solution helps to reduce the possibility of the accident and improve the driving experience, as it takes care of the most important and dangerous tasks and assists the drivers in making right decision on the road.

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Contents

List of Figures

Chapter 1

Introduction

Today's vehicles are equipped with sophisticated safety systems, but blind zones remain dangerous, and vehicle owners experience accidents that could have been avoided. This is a challenge that the blind spot detection (BSD) technology seeks to overcome by giving drivers real time information on the objects they cannot see. In conventional configurations, the BSD process is based on separate elements like camera to obtain the data; this information is processed within the vehicle's system. But this method has some drawbacks, namely, the speed of data processing and the response time, which may deteriorate with increasing traffic and the complexity of the driving environment.

The proposed system also uses multiple sensors, including cameras, ultrasonic sensors to observe the environment of the vehicle. Information from these sources is in most cases either unstructured or semi-structured and are processed through an in-vehicle optimized analytics unit that aggregates, processes and refines the information into actionable alarms. Although this approach may contain duplicative data from different sources, the presence of a filtering system guarantees that only important data is passed through to the driver, thereby reducing false alarms and increasing the driver's alertness. Last of all, an easily understandable display interface translates these insights into real-time and provides a clear view of the risks. This layered approach ensures a more responsive, accurate and reliable blind spot detection solution that would improve road safety, and in extension, the driving experience.

Chapter 2

Literature Survey

2.1 Lane Detection in Autonomous Vehicles

The ADAS is essential for safety in self-driving vehicles and self-sufficient operating components, which include ACC, Auto-Brake, and LKAS. Lane detection which is an important part assists the vehicle in identifying the lane markings and therefore effectively enabling a safe drive. This paper provides a systematic literature review (SLR) of lane detection techniques in self-driving vehicles. The study involves both conventional approaches, such as geometric modelling and recent advances in artificial intelligence such as deep learning and machine learning. It shows that deep learning is gradually adopted in the field, and there are some studies employing deep learning with other approaches. Another approach that people incorporate together with deep learning is the attention mechanisms. The review focuses on characteristics of existing techniques, instruments applied for dataset acquisition, and such issues as training and testing. It points out that there is a need for advanced research in order to enhance the efficiency and effectiveness of lane detection in adverse situations. In this research, the findings can be used as reference for future research work in the automation field.

2.2 Developing Vehicles Blind Spot Sensors Using Arduino to Avoid Parking Accidents

As the number of vehicles on the road rises, parking area accidents caused by blind areas, the portions that are not visible to the driver are on the rise. The objectives of this paper are to design an economical yet effective blind spot detection system employing Arduino microcontroller. The system employs ultrasonic and infrared sensors for obstacle detection, and applies the threshold-based logic to minimize false alarm. It uses a Bluetooth module for the data to be transmitted in order to monitor the situation as it unfolds. The system was tested in different parking scenarios and proved to reliably detect and inform about nearby objects to improve parking safety. The proposed system using Arduino platform is economical, scalable and useful in enhancing parking safety. It can be fully compatible with other automotive technologies, which can be further developed by DIY enthusiasts, which will lead to improved traffic safety.

2.3 Surrounding Vehicle Motion Prediction in Non-Lane-Based Environments for ADAS Enhancement

Predicting the road agents' behaviour is also becoming crucial, especially for improving the Advanced Driver Assistance Systems (ADAS) and self-driving vehicles. This research is aimed at estimating the motion of vehicles in non-lane environments, which are typical in urban areas and in unstructured environments. The research sought to establish the vehicles' intention to use narrow side spaces from the evaluation of lateral descriptor values. It introduces a hybrid model integrating a hybrid network, which consists of a modified Long Short-Term Memory (LSTM) with a lateral descriptor-based estimation of uncertainty, based on the existing detection and tracking techniques. This model enhances knowledge of spatial attributes and traffic conflict parameters. The methodology was assessed using two datasets; one was the simulation of urban roads and settings, and the other was a representation of non-structured environments. The findings presented in the paper show that the prediction accuracy is improved by 24.69% improvement over baseline models for the 5 seconds ahead prediction horizon, displaying the validity of the approach in the prediction of vehicles' actions.

2.4 Roadmap for Measurement and Applications: Supporting Safe Driving for Older Adults — at a Crossroads with ADAS

In many countries of the West, an automobile is crucial for the elderly to remain productive and functional mobility, to facilitate work, social and physical activities, for independent living. As people will age and some will get ill and as such may not be safe to drive at certain ages, meaning that there will always be a problem in making sure that people drive safely at their certain age. In this paper, the author puts forward the idea of a new application of ADAS for older drivers. ADAS technologies can serve two purposes: improving the safety and practicality for routine everyday driving and also as indicators of the decline in driving performance due to age. Thus, these systems can assist in the prolongation of relevant driving abilities in elderly people and guarantee their safety on the roads.

2.5 Radar-Camera Fusion for Object Detection and Semantic Segmentation in Autonomous Driving: A Comprehensive Review

New developments in deep learning have boosted the perception technology in autonomous driving, that would allow the vehicle to identify the environment and navigate it safely. For better and reliable perception, the autonomous vehicles rely on multiple sensors, radar, and cameras as a solution that provides complementary coverage at lower cost. Functioning of environmental sensing in different lighting and weather conditions. This review provides the radar-camera integration literature, specifically for object detection and semantic segmentation tasks. It discusses principles of radar and camera sensors, data acquisition, and data analysis and fusion techniques. To answer questions like “why,” “what,” “where,” “when,” “how,” and emerging issues and prospects of integrating radar and camera data are also discussed. Some of the research directions in this area.

2.6 Driving Behaviour Analysis of Intelligent Vehicle System for Lane Detection Using Vision-Sensor

Lane detection is one of the essential sub-tasks in the ADAS application that enables vehicles to maintain the marked lanes to prevent an accident. In the past, lane markings are based on speeds and are driving areas. Although the Intelligent Vehicle Systems (IVS) employs sensor-based systems such as radar, LiDAR and GPS, the associated costs of operation are high. While vision-based detection methods are being developed they are becoming more popular for the following reasons: The costs involved are low and the scene understanding is good. The main focus of this work is the application of computer vision and image processing to determine lane features. Intelligent lane line detection is achieved on a vehicle prototype through the implementation of the proposed Lane Detection Model (LDM) on Raspberry Pi. The system is inexpensive, energy efficient and performs well under different conditions, thus making it feasible to be used in real life situations.

2.7 Lane Change Intention Classification of Surrounding Vehicles Utilizing Open Set Recognition

In this paper, we present a classification algorithm of open set recognition to identify the lane change intentions of surrounding vehicles to improve the ACC and avoid accidents. Conventional approaches of machine learning may be wrong when exposed to data not in the training dataset or when data is noisy. To overcome this, the proposed algorithm employs a multi-class support vector machine integrated with open set recognition for the purpose of estimating the lane change intention of vehicles. The algorithm builds feature vectors from lateral data derived from a Kalman filter with radar and in-vehicle data acquisition.
This is achieved through Meta-Recognition with binary classifier results as the inputs to the open set recognition system. The system conservatively manages incorrect decisions and identifies lane change, inhibiting the identification of the closest in-path vehicle (CIPV) ahead of time. The experimental results reveal that this approach can detect a lane change 1.4 sec and 0.4 sec prior to a commercial radar system, enhancing the system's reaction time and reliability.

Chapter 3

Methodology

3.1 Blind Spot Detection Overview

The ***Blind spot detection BSD System*** is aimed at increasing road safety since the most crucial issue of the blind spot remains a significant problem for drivers. A blind spot is an area around the vehicle that the driver cannot see by looking in the side or rearview mirror. These areas are rather dangerous, particularly when changing lanes or overtaking, or turning at intersections. Basic techniques like the elongated mirrors or basic ultrasonic sensors provide comparatively poor effectiveness because of the inability to recognize and classify an object in real time.

In this project, there is a new strategy of using cameras and image processing algorithms in combination with real time alerting systems. In the proposed system, a trained object detection model is used alongside an ***ESP32 microcontroller*** so that the blind spot is identified promptly and accurately. The entire setup works in real time and gives feedback to the driver in real time; thereby minimizing probable incidences of road accidents due to objects within blind zones.

3.2 System Architecture

The system architecture of the blind spot detection solution is structured into three distinct layers: There are three layers; ***Data Acquisition Layer, Processing Layer and Feedback Layer***. Each of these layers has a critical role of enabling the functionality of the system; they include data capture from the environment, processing of input data, and giving of feedback to the driver.

3.2.1 Data Acquisition Layer

The ***Data Acquisition Layer*** is to be charged with the task of acquiring visual data in real-time from the vehicle’s environment. This layer mainly includes the camera module and the interaction with the hardware part.

a. **Placement and Coverage**:

The camera is placed to get the best view of blind zones of the vehicle which is usually located near side mirror or the rear end of a vehicle. The positioning avoids blind zones resulting from the physical structure of vehicles and allows the system to monitor the vicinity of the surrounding vehicles.

b. **Real-Time Streaming**:

The captured video feed is then sent in real time to the processing unit using either a wired link or even wireless link using USB or SPI respectively; or Wi-fi or Bluetooth. A buffer mechanism is incorporated to deal with occasional frame loss so that data transmission is not interrupted.

3.2.2 Processing Layer

The ***Processing Layer*** comprises the most critical part of the system as it is tasked with identifying vehicles in the blind spot from the visual data. It involves several subcomponents and functionalities:

a. Edge Computing with ESP32:

The ESP32 is used as the main microcontroller for edge computing and another microcontroller is used for routing. Fig.3.1 illustrates the architecture of ESP32. They decode video frames locally thus reducing on cloud processing and managing to work with lower latency. The 8nm process technology and support for TensorFlow Lite mean it can run light object detection models with a dual-core processor.

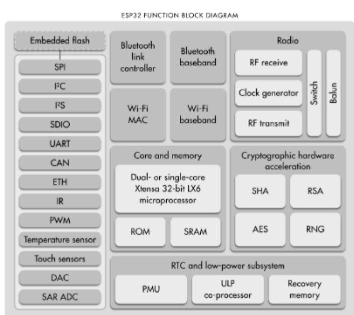


Fig.3.1: ESP 32 architecture

b. Preprocessing of Frames:

The frames of the video are then resized, normalized and if required, converted to grayscale and then are used as input to the object detection model. Some work done in denoising algorithms is used in enhancing the quality of the frames captured in the noisy conditions like high traffic or unfavorable weather conditions.

c. Object Detection:

For vehicle detection, the MobileNet model is employed with pretraining. Fig.3.2 Depicts the object detection method. The model does object detection through segmenting areas in each frame, and then labels the regions with rectangles and a probability of correct recognition.

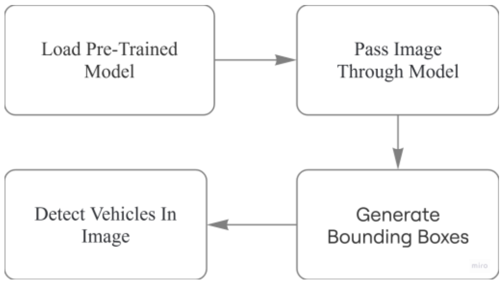


Fig.3.2: object detection

d. Real-Time Processing and Decision Making:

Every frame of the video is analyzed within milliseconds so that the feedback given to the driver is almost instant. There is a detection threshold to eliminate false positives, only objects with a score higher than this threshold will raise an alarm.

e. Expandable Framework:

The most important feature of the video processing layer is that it is scalable and it is planned to incorporate more sensors in the subsequent versions of the system. This framework can accommodate multiple cameras for larger coverage as indicated earlier.

3.2.3 Feedback Layer

The ***Feedback Layer*** is to inform the driver in a natural manner and without interrupting with the other functions. This layer comprises the hardware and software elements for presenting alerts in visual and auditory form.

a. Visual Alerts:

Displays in the vehicles are used to inform the driver about the device's status. In sophisticated systems, the feedback can be displayed on a screen within the vehicle's dashboard.

b. Auditory Alerts:

A buzzer produces signals in form of sound to alert the driver of impending danger. Depending on the size and the distance of the object calculated using ultrasonic sensors, the loudness as well as the pitch of the alert might be completely different. For instance, a steady sound would mean that the object is nearer while beep, beep sound would mean that the object is at a safer distance.

c. Driver Customization:

You can have the feedback mechanism in any way that you prefer as a driver. For instance, the users can set the intensity of the visual cues or put off the sound signals at certain circumstances. The ability to control feedback settings with the vehicle's infotainment system means that all feedback can be controlled from one location.

d. Redundancy for Safety:

To make the feedback layer reliable, it has spare parts which help when there is a failure. For example, if the visual alert system is not working the auditory system can still operate on its own.

e. Ergonomics and Placement:

Visual alerts are placed at the driver's field of vision at the side mirror so the driver is not easily distracted while driving. Visual alarms are set to emit sound at the proximity of the blind area to allow the driver to determine the threat.

3.2.4 System Workflow

The interaction between the layers can be summarized as follows:

I. The ***Data Acquisition Layer*** records and broadcasts video data to the Processing Layer of the system.

II. The ***Processing Layer*** tends to analyze the video stream to identify vehicles in the blind zone and sends the detection report to the Feedback Layer.

III. The ***Feedback Layer*** of the system then maps these results into alert messages that the driver can act on.

3.3 Image Processing and Object Detection

Image Preprocessing

The video feed from the camera is subjected to several preprocessing steps to enhance detection accuracy.

Object Detection Model

Vehicle detection in the project uses a pre-trained mobile model from TensorFlow Lite known as MobileNet. It detects vehicles in the blind spot and its parameters are adjusted to classify them using labelled data. Key aspects of the detection model include:
The model annotates ***bounding boxes*** around the detected vehicles and each bounding box is associated with a probability score of the object being a vehicle. Finally, there is classification, where each bounding box is labelled depending on the model prediction as either a vehicle or not a vehicle. This process enables the system to be able to differentiate between different objects in the field of view of the camera with a view of making appropriate decisions for blind spot detection.

3.4 Real-Time Feedback Mechanism

3.4.1 Alert System Design

Upon detecting a vehicle in the blind spot, the system provides alerts to the driver.
Whenever a vehicle is detected, the ***visual indicator*** the infotainment display in vehicles.
Buzzer an ***auditory alert*** is an alarm that makes use of sound to inform the driver.
These alerts are set to be activated when the model detection is done by the ESP32.

3.4.2 Human-Machine Interaction

Placing of the visual and auditory alarm makes sure they interfere with the driver instead. There are no false alarms to consider as alerts are made easily recognizable and easily interpretable according to current ergonomic principles applied to in-vehicle systems.

3.5 Hardware Components and Setup

The equipment connection is most important for attaining good real-time performance in the current blind spot detection system. The components used include ESP32 microcontroller that is the processing hub for the image data used to enable particular alerts.

A camera module is used to stream video frames from the vehicle environment to furnish the system with visual data. This keeps the voltage steady to keep both the ESP32 and the camera smooth while it operates.

The ultrasonic sensor is used to measure the distance of objects in the blind zone of the vehicle at a continuous manner. In the case of an object within the blind spot, the sensor raises an alert if the object's distance is below the threshold distance. The buzzer is used as an auditory warning that provides sound signals when the object is closer to the device, and its frequency rises. At the same time, the infotainment display serves as the video output display. This setup makes it possible to measure distance accurately and give timely alerts thus reducing the probability of an accident. Fig.3.3 illustrates the overall flow of the system.

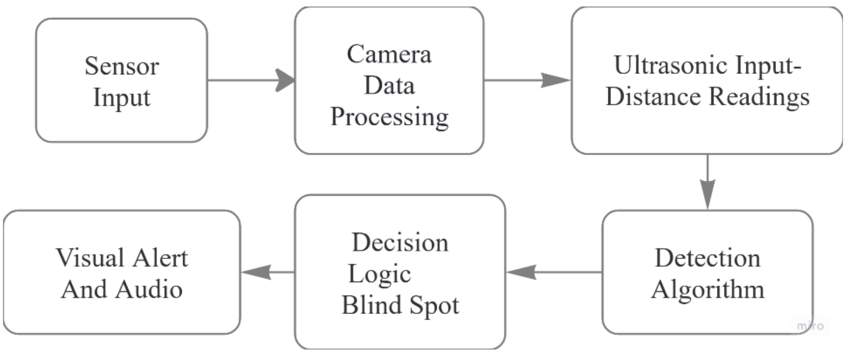


Fig.3.3: overall system setup

The hardware setup consists of a ESP32 microcontroller as the main board along with two ultrasonic sensors, two LEDs, two cameras, a buzzer and a toggle switch. The ultrasonic sensors are used to calculate the distance of obstacles and the data is fed back to ESP32 for further analysis. The LEDs are arranged in such a way that they will show which of the two sensors; left or right is currently in operation. The two cameras are positioned to capture video footage, serving a dual purpose: capturing videos for future analysis and enabling a streaming of the videos for real-time prediction. The toggle switch is designed to be multifunctional and serves as a vehicle indication switch, and for switching between the two cameras. Fig.3.3 and Fig.3.4 illustrates the overall Hardware setup of the system. Such a configuration integrates obstacle identification, videography, and live stream, making it a versatile and powerful tool for increased security and future trajectory analysis in vehicular settings.

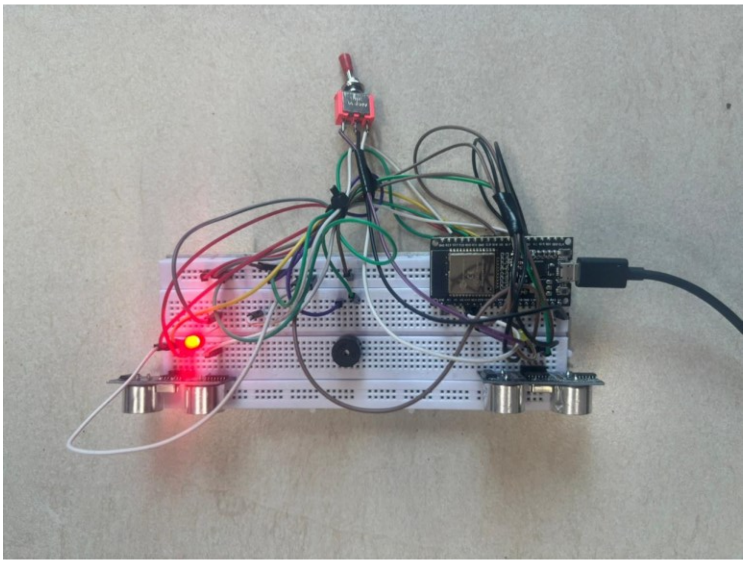


Fig.3.3 illustrates the setup where left indicator is turned on.

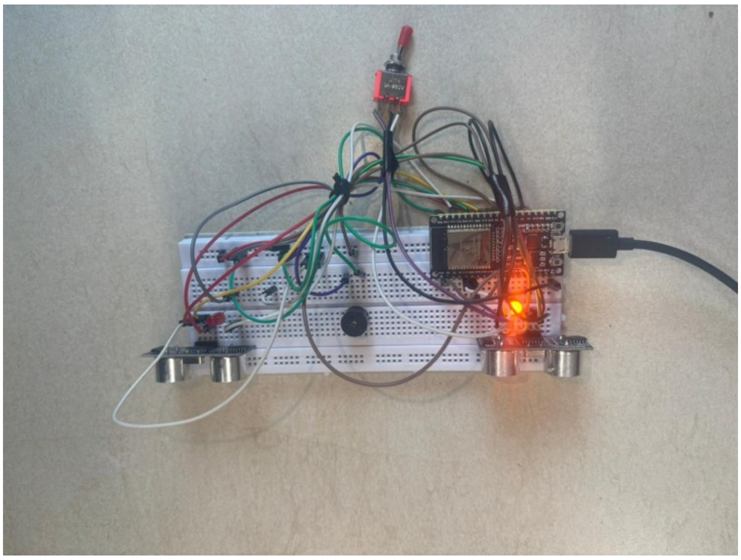


Fig.3.4 illustrates the setup where right indicator is turned on.

3.6 Model Training and Optimization

For the training of the MobileNet model, a large dataset of blind spot images of vehicles is used. This dataset is collected very carefully and extended to include different levels of illumination, different climatic conditions and different types of vehicles. A transfer learning approach is employed to fine-tune the MobileNet model using this dataset, leveraging its pre-trained weights for faster convergence and improved performance. Therefore, the augmentation of the model increases its accuracy and ensures that it can be used in real road conditions. Then the model is converted to TensorFlow Lite to make it run on the ESP32 microcontroller.

In this conversion, quantization techniques are employed to minimize the size of the model while at the same time maintaining its efficiency for low power devices such as ESP32. The last TensorFlow Lite model is then run on the ESP32. It handles model prediction well and provides immediate results for the inclusion of the blind spot detection system.

MobileNet model applied in this project is a thin deep convolutional neural network model optimized for running on devices with limited computational power. The network uses depthwise separable convolutions, which greatly decreases the computational load in comparison with the basic convolution layers. In this case, transfer learning is employed whereby the MobileNet model is trained with a new dataset of blind spot images. This approach builds upon the model where the feature extraction layers are frozen and the final layers are trained specifically for blind spot detection. In this way, the model successfully extracts necessary features including vehicles, changes in lighting and weather conditions. Due to its portable nature and flexibility it can be deployed in embedded systems like ESP32, where it will provide real-time predictions to support blind spot detection in dynamic systems. Fig.3.5 illustrates the model architecture.

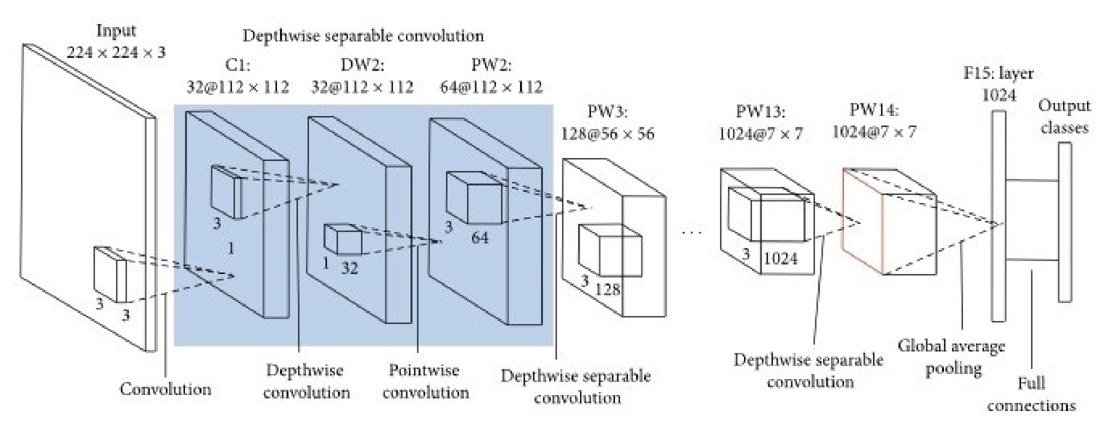


Fig.3.5 model architecture.

3.7 Challenges and Mitigation Strategies

Real-Time Processing
Challenge: The need to process video feeds with low latency.
Mitigation: It is fast and does not have to utilize the cloud for inference through TensorFlow Lite and edge computing.

Environmental Factors
Challenge: Cameras may be obscured by adverse conditions such as rain or fog.
Mitigation: These impacts are minimized by adaptive preprocessing techniques and robust mounting.

Power Management
Challenge: To maintain continuity of operations in vehicles.
Mitigation: Having a good supply voltage and using low power devices such as the ESP32.

3.8 Testing and Validation

This makes the system to be tested at various conditions in order to confirm its effectiveness and stability. Such scenarios include moving through traffic congested areas where several objects move erratically and present a major threat to the accuracy of detection. It is also evaluated in a highway environment where automobiles move at high velocities and where early and accurate identification is crucial for safety purposes.

Furthermore, the system is tested on low light and different adverse weather conditions like rainfall or fog to check its functionality in suboptimal conditions. It also guarantees that the system works in different conditions as it would be implemented in the real world.

3.8.1 Performance Metrics

Detection Accuracy: The accuracy of the system in identifying vehicles in the blind spot percentage.
Latency: The amount of time it takes from the moment the image is captured to the time the alert is produced.
Driver Feedback: Surveys to determine the level of satisfaction of the drivers with the alert system.

3.9 Future Enhancements

Despite the fact that the current system effectively delivers the project's goals and objectives, there are many prospects for future advancement. One idea is to utilize more than one camera to be able to capture as many blind zones as possible around the automobile. The second area for improvement is the application of better deep learning algorithms, to provide higher detection performance and shorter time. Moreover, the application of V2V could easily increase safety by making the vehicles themselves to share blind spot information in real time and making traffic smart. Most of these enhancements would not only enhance the functionality of the system but also make it conform to current trends in intelligent transportation systems.

Chapter 4

Results and Discussions

4.1 Objective

The purpose of this project was to design and test a blind spot detection system for vehicles that works in real time using camera vision and image processing. This system was designed to identify vehicles that were approaching the blind spots of the driver and inform the driver about them to improve road safety. The success of the project depended on achieving accurate and reliable detection and at the same time, integrating the hardware and software. Some of the major issues were the speed of the ESP32 microcontroller, the stability of the trained MobileNet model, and how to keep the system efficient in real-time. The system was tested in simulation and real traffic environment and the results were measured in terms of detection rate, response time and robustness.

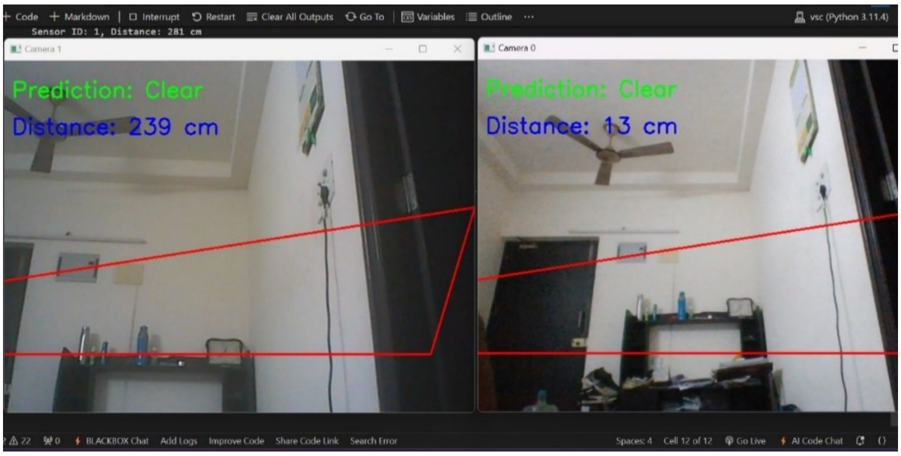
4.2 **Results**

a. ***Detection Accuracy:*** In the case of the MobileNet model trained on an augmented dataset, the accuracy of the model was 91% in detecting vehicles entering the blind spot. The quantized TensorFlow Lite model was able to retain an 88% accuracy after being deployed on the ESP32, which shows that there was very little drop in accuracy even after the model was compressed. Fig.4.1: illustrates the output screen

b. ***Real-Time Responsiveness:*** The ESP32 microcontroller was able to process frames from the camera at an average latency of 150 ms per frame. This low latency made it possible for the driver to receive alerts on time.

c. ***Scalability:*** The system currently only monitors a single blind spot but the design of the system can be expanded to multiple cameras for full blind spot coverage.

Fig.4.1: Output screen



4.2.1 Discussion

The findings show that the proposed system solves the blind spot issue in vehicles. The choice of MobileNet is the best because it offers a good trade-off between the computational load and the detection performance, which makes it possible to deploy the solution on resource-limited microcontrollers, such as ESP32. The performance of the system in different traffic conditions shows the feasibility of the proposed system for practical use. Future enhancements could be to use more sophisticated deep learning algorithms such as YOLO to increase the detection rate and to add V2V for better performance. In conclusion, the system offers a great advancement in enhancing road safety and minimizing the occurrence of accidents due to blind zones.

4.2.2 Performance Under Traffic Scenarios

The system was tested under urban, highway, and low-light conditions. The results highlighted consistent performance across scenarios:

a. ***Urban Traffic****:* Accurate identification of vehicles amidst congestion with minimal false positives.
b. ***Highway Conditions***: Reliable performance at high vehicle speeds, maintaining detection accuracy of above 85%.
c. ***Low-Light Conditions***: Slight performance dropped, attributable to lighting variations but still significantly better than manual observation.

4.2.3 Comparison – Traditional vs. Proposed

The box plot below compares the variance in detection accuracy and processing time between traditional methods (manual method using convex mirrors) and the proposed system.

a. ***Detection Accuracy***: Higher consistency in performance compared to traditional systems.
b. ***Processing Time***: Minimal latency in the proposed system ensures timely alerts.

Chapter 5

Conclusion and Future Scope

The blind spot detection system designed for improving road safety is one of the best examples of advancement in vehicular technology. With the help of machine learning, image processing, and sensor-based technologies, the system achieves the most important goal of solving the problem of blind spot monitoring, which is one of the leading causes of accidents around the world. The utilization of the MobileNet-based object detection model on the ESP32 microcontroller guarantees that the system is affordable and practical for other applications, primarily in developing countries.

The fact that the system can receive real-time data from cameras and ultrasonic sensors enables it to identify objects in a vehicle's blind spot and warn the driver instantly. This not only helps to get a better view of what is happening on the road but also decreases the time needed to respond to a threat, which can minimize the chance of an accident. The deployment of the models using TensorFlow Lite guarantees their efficiency within the hardware limits, proving the possibility to implement complex AI models in low-power embedded systems.

The results obtained in the experiments confirm the effectiveness of the system and demonstrate the advantages of the proposed approach, such as a shorter time for signal processing and higher accuracy of detecting malignant formations compared to conventional approaches. The performance of the system has been tested on different situations like traffic in city, highway, and different lighting conditions, which makes it ideal solution.

But that is not the final destination yet. The proposed system has a great potential for future development. Other possibilities include expanding coverage of other blind zones, so that a vehicle is surrounded by a safety dome of sorts. Integrating vehicle to vehicle (V2V) can help in sharing of information between the vehicles and make a network of vehicles safe on roads.

In conclusion, the blind spot detection system provides a good basis for the intelligent safety system of vehicles. If there are successive enhancements and improvements, it can be of great help in the reduction of road accidents and the promotion of the safer road environment.

Chapter 6

Appendix

Microcontroller Code:

```
#define TRIG_PIN_1 4  // Trigger pin for Sensor 1
#define ECHO_PIN_1 5  // Echo pin for Sensor 1
#define TRIG_PIN_2 18 // Trigger pin for Sensor 2
#define ECHO_PIN_2 19 // Echo pin for Sensor 2

#define BUZZER_PIN 21 // Buzzer pin
#define REL_PIN 32   // Relay pin
#define TOGGLE_PIN_1 34 // First switch pin
#define TOGGLE_PIN_2 35 // Second switch pin
#define led_1 2 // First LED pin
#define led_2 0 // Second LED pin

const int MINIMUM_DISTANCE = 10;  // Minimum range in cm
const int MAXIMUM_DISTANCE = 30; // Maximum range in cm

bool useSensor1 = true;  // Flag to toggle between sensors

// Function to measure distance
long getDistance(int trigPin, int echoPin) {
  digitalWrite(trigPin, LOW);
  delayMicroseconds(2);
  digitalWrite(trigPin, HIGH);
  delayMicroseconds(10);
  digitalWrite(trigPin, LOW);

  long duration = pulseIn(echoPin, HIGH);
  long distance = duration * 0.034 / 2; // Convert to cm
  return distance;
}

// Function to beep the buzzer with variable intervals
void beepBuzzer(int interval) {
  digitalWrite(BUZZER_PIN, HIGH);
  delay(interval / 2);
  digitalWrite(BUZZER_PIN, LOW);
  delay(interval / 2);
```

https://github.com/Ragul-11/Blind-Spot-detection

Python Code

```python
import numpy as np
import cv2
from PIL import Image
from time import time
```

```python
def find_available_cameras():
    """Check and return a list of available camera indexes."""
    available_cameras = []
    for i in range(10):  # Check for the first 10 camera indexes
        cap = cv2.VideoCapture(i)
        if cap.isOpened():
            available_cameras.append(i)
            cap.release()
    return available_cameras

# Find and print available cameras
if __name__ == "__main__":
    cameras = find_available_cameras()
    if cameras:
        print(f"Available cameras: {cameras}")
    else:
        print("No cameras found.")
```

https://github.com/Ragul-11/Blind-Spot-detection

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