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Automatic Vehicle Speed Controlling System by Detecting Traffic Sign Boards, Potholes and Speed Bumps

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ABSTRACT

In an effort to reduce accidents and promote adherence to traffic laws, this study attempts to detect and identify potholes, speed bumps, and traffic sign boards in a variety of backgrounds and lighting conditions. The "Automatic Vehicle Speed Controlling System by Detecting Traffic Sign Boards, Potholes, and Speed Bumps" is a cutting-edge automotive safety and control system designed to increase road safety and manage vehicle speed. To enable autonomous real-time recognition and interpretation of potholes, speed bumps, and traffic signs, as well as to regulate the vehicle speed in accordance with the detected feature, the system incorporates advanced technologies such as computer vision, deep learning, and embedded systems. This work provides a novel solution to these issues by autonomously detecting potholes, speed bumps, and traffic sign boards on highways by utilizing deep learning algorithms and image processing capabilities. In this technology, photos captured by cameras mounted on vehicles are analysed using computer vision algorithms. By using a deep learning algorithm, the system can accurately identify and classify traffic sign boards and abnormalities in the road, including potholes and speed bumps, from the recorded data. Based on this classification, the system may adjust the vehicle's speed.

KEYWORDS*:* Deep Learning, Computer vision, Open CV, Automatic Vehicle Speed Controlling System (AVSCS)

I. INTRODUCTION

In order to enhance driving experiences and boost road safety, recent advancements in car technology have focused on integrating technological systems. The driver's manual interpretation of traffic signs and awareness of the characteristics of the road, such as the presence of potholes and speed bumps, are the primary factors in the traditional technique of controlling a vehicle's speed. However, by fusing deep learning, computer vision, and embedded systems, this method provides an automatic, real-time solution to these issues. Using a variety of carefully placed cameras on the vehicle, the system's main job is to record and analyse the surrounding road environment.

Among the relevant data that the computer vision component module extracts from traffic signboards are speed limits, warning signs, and regulation directions. Potholes and speed bumps are detected by the technology at the same time as anomalies in the road. When the system detects certain road parameters, it automatically adjusts the vehicle's speed to conform with established traffic laws and ensure a safe and comfortable driving experience. The system applies the specified speed restrictions to traffic signs by interpreting the data. An extra degree of safety is provided by the system's capacity to automatically modify vehicle speed in order to lessen discomfort and potential damage from potholes and speed bumps. This speed control system's main objectives are to prevent crashes, enhance driver comfort, and promote overall road safety.

Deep learning models, which are well-known for their ability to analyse and understand complex patterns in data, are used to handle visual data from the vehicle's cameras. In order to continuously monitor potholes, speed bumps, and traffic sign boards, these camera modules are positioned strategically. Because it was trained on a variety of datasets, the deep learning model is able to accurately identify and classify various traffic sign boards, potholes, and speed bumps. Computer vision techniques are used to concurrently achieve real-time analysis and road condition detection. After that, image processing techniques are used to analyse the road surface and find any irregularities. A comprehensive image of the driving environment is then produced by combining this data with the output of the deep learning model. Dynamically modifying the vehicle's speed is included into the system based on the information collected by the computer vision and deep learning models. Motor driver, DC, Raspberry Pi, and Arduino Nano make up an embedded system that controls speed. Vehicle speed is controlled by the motor based on the feature that the deep learning model has identified and deciphered. The system extracts the relevant board speed restriction and applies it after reading the information on a traffic signboard. When potholes and speed bumps are present, the system automatically adjusts the speed of the car to ensure a safe and comfortable ride.

II. RELATED WORK

Road accidents are primarily caused by faulty traffic rule following and ignorance. where traffic signs and traffic signals are the two forms of traffic regulations. The primary focus is on ADAS-compliant e-vehicles, which are a future form of mobility. The suggested method will help drivers and lessen traffic accidents brought on by drivers' ignorance of traffic laws by combining deep learning and CAN protocol to detect traffic signs and control the speed of electric vehicles. This technology records traffic signs on the road by mounting a camera on the windshield of the car. Through an Ethernet connection, the camera sensor will transmit the signal containing the collected image to the ADAS/AD ECU, where it will be processed. Following processing, the Deep Learning CNN method in the ADAS/AD ECU Microcontroller is used to identify it. Then, via CAN protocol, the ADAS/AD ECU instructs the Transmission ECU to limit the current speed to a predetermined point, and it uses the cluster display to warn the driver.

[1]. Autonomous vehicles are gaining popularity among academics and the automotive industry since automakers are still having trouble manufacturing fully functional driverless cars. In the real world, safe driving is contingent upon a variety of factors, including the separation between one's car and other vehicles, people, animals, speed limit signs, traffic signals, and other dynamic, chaotic surroundings. One essential feature for an autonomous vehicle to have been automated traffic sign detection and recognition, or ATSDR.

Many researchers have used a variety of deep learning-based models for real-time ATSDR. Several deep learning models used in real-time ATSDR have been studied in this study. Previous studies have shown that YOLO and SSD are more effective models for ATSDR than CNN, R-CNN, Fast R-CNN, and Faster RCNN, and that they can recognize traffic signs in real time.

[2]. One of the hardest things for autonomous driving systems to accomplish is controlling a vehicle's speed. The novel method for motor controlling speed in accordance with speed requirements to scan speed limit sign boards uses a Convolutional Neural Network (CNN) algorithm. The effectiveness of the system hinges on CNNs' ability to precisely recognize and classify objects in images, which are then used to extract speed limit information from signage. The robot chassis speed is controlled by an Arduino microcontroller using the CNN's output. Through experiments and simulations on a real testbed, it shows how effective the system is and that it can maintain the desired speed with a manageable degree of error.
[3]. Numerous traffic problems might be caused by potholes in the road. They could lead to vehicle issues, suspension system degeneration, additional repair needs, and auto accidents. Finding potholes as soon as possible at a reasonable cost is essential for road upkeep and rehabilitation. This indicates how important it is to have automated technology that can quickly and precisely detect possible structural problems with roads. The deep learning-based DenseNet121 architecture is recommended by this study as a method for spotting potholes in roads. The objective of the provided methodology is to identify the presence of potholes in the road photographs inside the dataset. In this investigation, potholes on the road were detected with 99.3% accuracy using the DenseNet121 network. For this dataset, the ResNet50, InceptionV3, VGG19, and InceptionResnetV2 models were used in parallel processing and comparison, with identical parameters. The most accurate model among all of these was DenseNet121.
[4]. Pothole identification is crucial when choosing the optimum road management techniques and maintenance. In this work, Yolov3 and deep learning were utilized to create a pothole recognition system. A pothole detection model that is accurate is created using YOLOv3, a deep learning technique. Given the vast range of pothole sizes and forms, it is expected that the detection model's accuracy, with an average precision of 95.43%, ranged from 33% to 69%. [5]. In order to create cost-effective self-driving automobiles, this paper presents a workable method for combining an artificial intelligence-based detection system with a microcontroller-based speed control system. The particular focus of this work is on using a camera and artificial intelligence-assisted video stream processing to identify potholes and speed bumps. To solve this problem, a popular and straightforward technique known as SSD (Single Shot Multi box Detector) is used. This is the greatest choice since it is lightweight and accurate enough to be utilized in real-world circumstances and on mobile devices.
The main processing device has been the Raspberry Pi because of its small size and powerful capabilities. A warning system has been installed to notify the driver when a pothole or speed bump is about to occur. This technology can also send a signal to the car's speed controller unit instructing it to slow down in order to avoid crashes or damage to the vehicle. The speed control unit uses an L298 motor drive and an ATmega328 microprocessor, both of which are based on microcontroller technology.
[6]. Environmental awareness plays a major role in autonomous driving vehicle speed regulation. Autonomous vehicles must obey traffic laws as shown by traffic signs. This paper proposes a novel approach to recognize stop signs and calculate their distance in order to control the longitudinal velocity of an autonomous vehicle. The car approaches the stop sign and then vanishes from the camera's field of vision, making it difficult to get it to stop at the proper distance. Therefore, it is essential to know the placement of the stop line in order to exactly identify where to stop the car. To identify stop signs, AdaBoost cascade classification is employed. Three different feature types serve as its foundation: Haar-like features, Local Binary Patterns (LBP), and Histogram of Oriented Gradients (HOG). The performance results of all three are compared and analysed in order to determine which classifier performs the best. It is recommended to determine the stop line using a traditional computer vision technique. The real-time

evaluation of the distance to the stop sign and stop line is necessary to apply the proper decelerating torque and bring the vehicle to a complete stop. [7]. The prevalence of autonomous driving technology is growing, however the majority of deep learning algorithms for traffic sign target detection have a large number of parameters and require a considerable inference time. Based on the YOLOV4-tiny network, this study suggests the CA-YOLOV4-tiny traffic sign detecting algorithm. Feature extraction incorporates the attention mechanism, label smoothing prevents overfitting, and mosaic data enhances the model's generalization capacity. The MAP on the TT100K traffic sign dataset is 6.77% higher at 81.71% than it is for YOLOV4-tiny. The experimental results show that the model identification accuracy may be highly increased by CA-YOLOV 4-tiny without sacrificing reasoning speed, and that reasoning speed has also been greatly increased after quantization. With this, the vehicle-side target detection network's issues with excessive processing power and slow reasoning speed are resolved. [8]. In addition to annoying commuters, potholes in the road make it more difficult to deliver products and services. Current methods of detecting potholes need manual road inspections using specific sensors installed on cars that have undergone particular modifications. The technique requires a lot of labour and time to finish. This article presents a novel convolution neural network (CNN) based pothole identification technique. The process combines sensory and visual data to detect potholes. In the carried out experimental investigations, the proposed technique achieved 87.20% precision, 92.7% recall, and 89.9% F1-Score. [9]. Maintaining employee safety at work is one of the primary issues of road maintenance in these difficult times. This can, in part, be accomplished with the aid of an autonomous system that aims to depend less on humans. The systems that are suggested in this paper include pothole detection and dimension estimation. The recommended solution employs YOLO (You Only Look Once), a deep learning-based algorithm, to find potholes. In addition, a triangle similarity measure derived from image analysis is used to determine the dimensions of potholes. Results from the proposed technique for pothole recognition and dimension estimation are relatively accurate. Furthermore, the proposed technology helps reduce the time required for road maintenance. The technique uses a custom-created dataset comprising images of various sized and shaped potholes, both wet and dry. [10]. This paper presents an image processing method, machine learning, and sensor-based strategy for pothole and hump detection. Potholes and humpbacks must be identified early on in order to prevent damage to vehicles and maintain road safety. The development of automated methods for detecting humpbacks and potholes has become more and more common in recent years. The suggested method uses cameras and sensors to collect data regarding the condition of the roads, analyse the data, and identify locations of speed bumps and potholes. Deep learning algorithms are used to find patterns in data and generate accurate predictions. The suggested method is dependable; under a range of illumination and meteorological conditions, it achieves the objective with an estimated 90% accuracy. The recommended solution is put into practice in real time, and its conditions are tested. The study is conducted in terms of improved road safety and lower maintenance costs using the recommended solution.[11]. Road pothole detection is essential to preserving the integrity of any engineering structure. It takes a lot of labour to manually identify and classify potholes. Thanks to the introduction of various sensor-based, laser imaging, and image processing systems, road inspections now require less human interaction. Nevertheless, machine learning-based methods have a number of disadvantages, such as high cost, poor accuracy, and risk during detection, since they require human feature extraction for the prediction. This suggested effort aims to employ deep learning techniques to produce better pothole detection results. To train the model, pothole images are collected from multiple sources and combined into a single dataset. Many pothole datasets are available online, and a lot of data is needed for training deep learning-based methods. Additionally, augmentation is used to the dataset to enhance training. This is due to the fact that augmentation provides images from different angles, which aids in model optimization and produces records with an accuracy of roughly 98%. [12].

Ref	Year	H/w Components	S/w & Technology	Accuracy
1	2022	Sensors, Processors, CAN bus, ECU, Camera module, Power supply	Deep learning, User Interface (UI), CAN protocol	NA
2	2021	Camera module, Processor	YOLO, SS	NA
3	2023	Camera module, Arduino microcontroller, Power supply	CNN	NA
4	2022	Camera module	DenseNet121	99.3%
5	2022	NA	Yolo V3	69%
6	2021	Microcontroller, Raspberry pi camera module, Raspberry pi, ATmega 328 microprocessor, L298 motor driver	SSD	NA
7	2018	Camera module, Microcontroller, Power supply	AdaBoost, Canny edge detection	NA
8	2023	NA	YoloV4-tiny	74.94%
9	2021	Custom sensor, Processor, Communication module, Power supply	CNN, IOT	87.20%
10	2020	NA	YOLO	NA
11	2023	Camera module, Sensor	Machine learning	90%
12	2022	NA	Deep learning	98%

III. PROPOSED METHODOLOGY

The Automatic Vehicle Speed Controlling System is a cutting-edge technology that makes use of embedded technologies, deep learning, and computer vision to improve road safety. The purpose of this technology is to automatically modify a vehicle's speed by detecting potholes, speed bumps, and traffic sign boards. This system's essential parts are a camera module, motor driver, Arduino Nano, Raspberry Pi, and DC motor.

1. Image Acquisition and pre-processing

Real-time picture and video feeds from the surroundings are captured by the camera module during the image acquisition process. A clear view of the road ahead is provided by the camera's mounting location on the car. Afterwards, the Raspberry Pi receives the collected photos to be processed further. To improve their quality and prepare them for examination, the photos go through pre-processing once they are taken. The photos are resized to a standard size in this phase, and they are also turned to grayscale and filtered to lessen blur. To guarantee the visibility of speed bumps, potholes, and traffic signs in a range of lighting conditions, pre-processing also entails changing the brightness and contrast.

2. Detection using Mobilenetv2

A lightweight deep learning model called MobileNetV2, which is fast and efficient, is used at the centre of the detection process. This model has already been trained. With the help of a varied dataset that includes photos of these items in various circumstances, the MobileNetV2 model is trained to identify traffic sign boards, potholes, and speed bumps. This reduces the amount of time and computational resources required for training by using transfer learning to modify the pre-trained model to meet our unique needs. The traffic sign detecting system recognizes and categorizes several sign kinds, including stop signs, caution signs, and speed limits. This categorization is important since it dictates the course of action the car must take. By examining the texture and shape patterns that set potholes and speed bumps apart from typical roads, the model is trained to identify these anomalies on the surface of the road.

3. Embedded System Integration

The deep learning model is run and the photos are processed by the Raspberry Pi, which serves as the central processing unit. The Raspberry Pi notifies the Arduino Nano of pertinent information when it detects a pothole, speed bump, or traffic sign. Upon receiving these signals, the Arduino Nano, which governs the motor driver, modifies the speed of the DC motor appropriately. For example, when the Raspberry Pi detects a speed restriction sign that indicates a lower speed, it notifies the Arduino Nano to reduce the vehicle's speed by regulating the power delivered to the DC motor via the motor driver. Likewise, in order to prevent possible harm or discomfort, the system signals the car to slow down when it detects a pothole or speed bump.

4. Real-Time Speed Control

The speed is dynamically adjusted by the speed control mechanism in accordance with the objects that are detected. Pulse Width Modulation, or PWM, is provided to the motor driver via the Arduino Nano, which interprets the signals from the Raspberry Pi. By altering the voltage applied to the DC motor, this modulation regulates its speed. This control system's real-time feature makes sure that the vehicle reacts quickly to any changes in the traffic signs or road conditions.

5. System Evaluation and Testing

The accuracy and dependability of the system must be guaranteed by thorough testing and calibration. Testing the system in varied real-world circumstances, such as variable weather, shifting lighting, and varied road environments, is part of this process. Using the input from these experiments, the embedded system's parameters are optimized for best performance, and the deep learning model is refined.

IV. PROPOSED ARCHITECTURE

The Automatic Vehicle Speed Controlling System (AVSCS) architecture that is being proposed combines computer vision, deep learning, and embedded technologies in order to identify potholes, speed bumps, and traffic signboards and then control vehicle speed. This system intends to improve road safety and driving comfort by utilizing technologies such as MobileNetV2 for fast deep learning inference and hardware components including a Raspberry Pi, Arduino Nano, motor driver, and DC motor.

Computer vision algorithms, which process visual data acquired by a camera module mounted on the vehicle, are at the heart of the architecture. These algorithms are in charge of recognizing and deciphering different types of road features, such as speed bumps, potholes, and traffic signals. Deep learning models, MobileNetV2, in particular are used because of their portability and effective real-time inference capabilities.

The Raspberry Pi starts the procedure by using the attached camera module to record a live feed of the road ahead. After being pre-trained to identify particular objects like speed bumps, potholes, and traffic signs, the deep learning model is applied to this raw visual data. Resource-constrained embedded computers such as the Raspberry Pi are ideal platforms for implementing MobileNetV2, due to its low computational cost and great accuracy. The system initiates the necessary procedures to regulate the vehicle speed when it detects pertinent road elements. For example, the system determines the ideal speed limit when it detects a speed restriction sign and modifies the vehicle's speed accordingly. In a similar vein, the technology slows down the car when it notices a pothole or speed bump to guarantee a smooth and secure ride.

The incorporation of an embedded system consisting of an Arduino Nano and a Raspberry Pi facilitates smooth coordination and communication amongst the AVSCS's component parts. The central processing unit, or Raspberry Pi, manages deep learning inference, image processing, and decision-making algorithms. The Raspberry Pi and the vehicle's actuators, such as the motor driver and DC motor, are connected by means of the Arduino Nano, on the other hand.

Based on the inputs from the Raspberry Pi, the motor driver, managed by the Arduino Nano, modifies the speed of the DC motor, which modifies the vehicle's velocity. The technology is more effective in dynamic driving settings because of this closed-loop control mechanism, which guarantees accurate and responsive speed modulation in real-time.

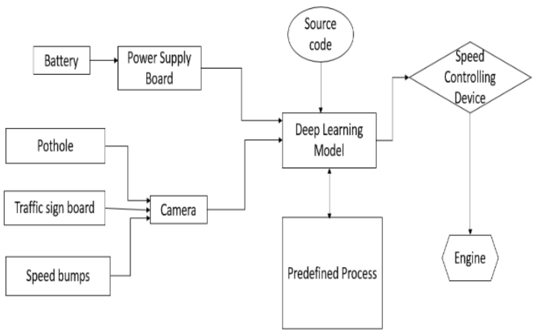

Figure 1. Block diagram AVSCS

V. SOFTWARE IMPLEMENTATION

The integration of deep learning models and computer vision algorithms forms the foundation of this system. Due to their speed and efficiency, convolutional neural networks (CNNs), in particular lightweight architectures like MobileNetV2, are well-suited for on-device inference tasks. For object detection tasks, a lightweight deep learning model called MobileNetV2 is used. The selection of MobileNetV2 is based on its accuracy and efficiency in operating well on embedded systems such as the Raspberry Pi. Large datasets were used to pre-train this model, which was then optimized for the particular job of identifying speed bumps, potholes, and traffic signs. In milliseconds, the model recognizes and categorizes items based on the camera's collected photos. For decisions to be made in real time that impact the speed of the vehicle, this quick processing is essential.

The process starts with the Raspberry Pi camera module capturing a picture. An image is loaded into the MobileNetV2 model once it has been taken. The kind and location of objects found within the frame are output by the model. For example, the model detects a speed limit sign and extracts the speed limit value. Similar to this, potholes and speed bumps can be distinguished in the photos by their unique characteristics.

1. Data collection and Annotation

As is often the case with autonomous driving systems, gathering data is the first step towards building any machine learning model. Images and video footage taken by the camera module that is attached to the Raspberry Pi serve as the main source of data for our program. This car-mounted camera monitors the road conditions continually, making sure that everything from speed bumps to potholes and traffic signs is covered. For the model to be robust and generalizable, it is imperative that the quality and diversity of the data be high. Consequently, the data must cover a range of lighting conditions, weather scenarios, and geographic regions.

Annotation is the following stage after data collection, where photos are labelled to identify and classify potholes, speed bumps, and traffic signs. Since the correctness of these labels directly affects how well the deep learning model performs, this annotation process is labour-intensive and demands close attention to detail. This procedure is made easier by annotation tools, which let users draw bounding boxes around interesting things and give them descriptive descriptions. For example, the location of a speed bump, the size of a pothole, and the speed restriction sign would all be marked with their respective annotations.

In this project, annotation tool used is Make Sense AI.

Figure 2. Uploading image file for annotation

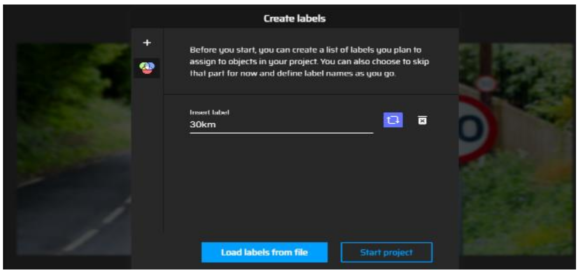

Figure 3. Label creation

Figure 4. Informative area selection using bounding boxes

Precise annotation is essential since it affects the computer vision model's performance directly. The usefulness of the system can be jeopardized by improperly annotated data, which might cause misclassification or fail to discover objects. In order to guarantee that the model gains knowledge from accurate, well-labelled data, a thorough and comprehensive annotation process is necessary. After that, a deep learning model MobilenetV2, in particular that is renowned for its effectiveness and strong performance in image classification tasks is trained on the annotated data.

2. OpenCV

Integration of deep learning, embedded systems, and computer vision has significantly advanced the field of intelligent transportation systems. One noteworthy use is the creation of an automated car speed control system that can recognize potholes, speed bumps, and traffic sign boards. A software library for machine learning and computer vision is called OpenCV (Open-Source Computer Vision Library). In addition to accelerating the use of machine perception in commercial products, its main goals were to establish a standard infrastructure for computer vision applications. Together with the MobileNetV2 deep learning model, this system makes use of OpenCV, a potent open-source computer vision library.

Real-time photos of the driving environment are first captured by the camera module, which powers the system. Next, the Raspberry Pi receives these photos and processes them using OpenCV. A vehicle's capacity to properly and efficiently absorb visual information from its surroundings is a key component of an autonomous vehicle speed control system. Efficient feature extraction from raw picture data collected by the camera module is made possible by OpenCV's extensive collection of image processing techniques. Certain road elements, like potholes, speed bumps, and traffic signs, must be recognized and categorized using these characteristics.

For a wide range of image processing applications, such as picture acquisition, filtering, transformation, and feature extraction, OpenCV offers an extensive toolkit. In order to prepare the raw photos for additional analysis and detection activities, several tools are essential. After preprocessing is finished, MobileNetV2 can be used to detect traffic signs in the photos.

3. Convolutional Neural Network

Deep neural networks with a focus on visual data analysis are known as convolutional neural networks, or CNNs for short. Real-time image processing and object detection in AVSCS rely on CNNs as the core. Models like MobileNetV2, which balance accuracy and computing resources efficiently, are used by using techniques like transfer learning. Road signs, potholes, and speed bumps may all be easily identified and interpreted from video feeds by CNNs because they are particularly good at jobs involving visual identification. Resource-constrained platforms such as the Raspberry Pi can benefit greatly from the deployment of MobileNetV2, a lightweight CNN architecture designed for mobile and embedded devices. It achieves a balance between mathematical efficiency and model correctness.

The AVSCS records live video of the road ahead using a camera module, usually a webcam. Next, the Raspberry Pi-based MobileNetV2 CNN processes this video feed. The network gathers feature from the input photos using a sequence of convolutional and pooling layers, allowing it to identify and categorize different items and road conditions. The CNN is trained on an extensive dataset that includes annotated photos of potholes, speed bumps, and traffic signs. This allows the model to become proficient in identifying these objects in a variety of lighting and environmental scenarios.

The CNN initiates the necessary control steps to guarantee vehicle safety and adherence to traffic laws when spotting a pothole, speed bump, or traffic sign board in the video stream. For example, the system can detect a stop sign and apply the brakes or decrease the speed of the car to a safe level. Likewise, in order to limit passenger discomfort and lower the possibility of vehicle damage, the system can modify the suspension or speed of the car upon recognizing a pothole or speed bump.

4. MobileNet-V2 model

Deep learning and computer vision have advanced significantly with the introduction of MobileNet-V2, a cutting-edge convolutional neural network architecture. Google developed MobileNet-V2, which is optimized for deployment on resource-constrained devices like embedded systems and smartphones. It is

aimed to give great performance in terms of speed and accuracy along with computational efficiency.
The capacity of autonomous vehicles to recognize and react to a variety of road conditions and signage in order to guarantee safe and effective operation is a crucial component of their performance. An automatic vehicle speed control system relies heavily on MobileNet-V2, a streamlined and effective convolutional neural network that can recognize potholes, speed bumps, and traffic sign boards with accuracy. With its low processing resource requirements and great accuracy, MobileNet-V2 is perfect for implementation on embedded systems such as the Raspberry Pi. In comparison to conventional convolutional networks, depth-wise separable convolutions, which are a feature of the MobileNet-V2 network design, drastically cut down on both cost and parameter count. Performance is not compromised by this efficiency because MobileNet-V2 still maintains strong accuracy standards appropriate for real-time applications.

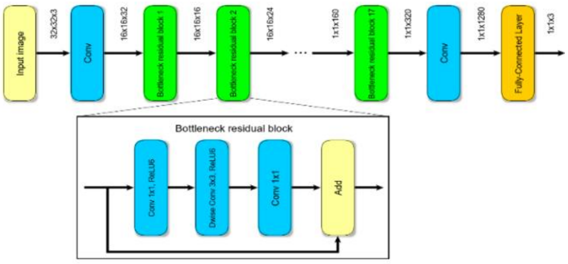

Figure 5. MobileNet-V2 architecture

The Raspberry Pi receives these frames as part of an automated car speed control system. Real-time video feeds of the car's surrounds, including potholes, speed bumps, and traffic sign boards, are captured by the camera module. These photos are loaded onto and processed by the Raspberry Pi, which uses its built-in MobileNet-V2 for object detection and classification. Traffic indicators like as stop signs, speed limits, and alerts for anomalies in the road are recognized by MobileNet-V2, which has been optimized for certain jobs after being pre-trained on extensive datasets. The Raspberry Pi evaluates information when it detects traffic signs, such as yield, stop, or speed limit signs, and then sends an Arduino Nano the appropriate control signal.
Traffic sign detection entails identifying signs such as stop signs and varying speed limits. The technology detects surface abnormalities on the road using image processing techniques. With great accuracy, MobileNet-V2, which was trained on a dataset of pothole photos, can discriminate between normal road surfaces and potholes. The way pothole and speed bump detection work is similar. Based on their unique geometric characteristics in the collected photos, speed bumps are recognized. Its depth-wise separable convolutions make it an excellent choice for real-time detection, allowing the system to react quickly to modifications in the driving environment.

VI. HARDWARE IMPLEMENTATION

A camera module installed on the car serves as the system's first component, taking pictures of the road in real time. The Raspberry Pi, the system's main processing device, receives these images. A pre-trained MobileNetV2 model—a deep learning framework designed with mobile and embedded vision applications in mind—comes with the Raspberry Pi. Speed bumps, potholes, and traffic sign boards may all be identified and classified using MobileNetV2's image processing capabilities. This model's lightweight architecture enables real-time image processing, which makes it appropriate for the kind of spontaneous decision-making that is necessary for vehicle speed controlling.
The Arduino Nano receives signals from the Raspberry Pi when it detects pertinent road elements. The

Raspberry Pi and the motor driver are connected by the Arduino Nano, a small and flexible microcontroller. The DC motor that powers the car is managed by the motor driver, which is linked to the Arduino Nano. The Arduino Nano modifies the motor speed in accordance with the signals it receives from the Raspberry Pi. For example, the Arduino Nano lowers the motor's speed to adhere to the designated limit when it detects a speed limit sign. Similar to this, the system can slow down the car or perform any necessary evasive manoeuvres to protect passenger safety and vehicle integrity when it detects a pothole or speed bump.
Precise wiring and communication standards enable the integration of these parts. Using the CSI (Camera Serial Interface) connector, the camera module is connected to the Raspberry Pi, allowing for fast data transfer for picture analysis. Through a serial interface, the Raspberry Pi and Arduino Nano exchange data, with the Raspberry Pi providing the Arduino with processed data. The Arduino Nano is linked to the motor driver, which is often an H-Bridge type. The Arduino Nano provides the pulse-width modulation (PWM) signals required to regulate the speed and direction of the DC motor.

1. Camera module

The Automatic Vehicle Speed Controlling System (AVSCS) relies heavily on the camera module, namely the webcam, to identify different road conditions and traffic signs. As a sensory device, the camera module records live video feeds of the environment around the car with exceptional precision and fidelity. The module processes the visual inputs in real-time by utilizing computer vision algorithms to extract relevant information about road conditions, potholes, speed bumps, and traffic signs.
The camera module is tasked with identifying and interpreting traffic signboards, among other things. The system can identify and interpret traffic signs that indicate speed restrictions, legal directives, or warnings by analysing the collected picture. This data is vital for the AVSCS to process in order to modify the vehicle's speed in accordance with applicable traffic laws and improve overall road safety.
Additionally, the camera module is essential for identifying irregularities in the road like speed bumps and potholes. The technology is able to detect possible dangers in real time by analysing variations in the geometry and properties of the road surface. With the usage of this function, the AVSCS can proactively alter the vehicle's speed and trajectory to reduce the possibility of damage or accidents brought on by uneven roads.

Figure 6. Webcam

2. Raspberry pi

The Raspberry Pi is essential to the creation of an automated car speed control system that uses computer vision and deep learning methods to identify potholes, speed bumps, and traffic signboards. This system makes use of the small and potent Raspberry Pi, which serves as the main computing unit for activities involving the processing of images and making decisions in real time. The Raspberry Pi is equipped with a camera module that records the road ahead continually. This module provides real-time data feeds that are essential for distinguishing different road characteristics and obstructions.

When processing an incoming video feed, the Raspberry Pi uses a pre-trained deep learning model, like MobileNetV2, to identify potholes, speed bumps, and traffic signboards. Because of its efficiency and compatibility with low-processing devices, such as the Raspberry Pi, MobileNetV2 is especially well suited for this application. The vehicle's speed can be adjusted by the system in accordance with established speed limits or other pertinent directions by using the model's ability to identify and categorize traffic signs. As with speed bumps and potholes, it enables the system to slow down the car to protect the integrity of the vehicle and the safety of its occupants.

Figure 7. Raspberry pi 3

3. Arduino Nano

An integral part of the Automatic Vehicle Speed Controlling System is the management and execution of low-level control activities by the Arduino Nano, which is necessary for the system's overall operation. The Raspberry Pi makes high-level decisions, and the Arduino Nano acts as a link between low-level mechanical actions and decisions. The Raspberry Pi gives it instructions on how to change its speed. For example, the Arduino Nano receives a signal from the Raspberry Pi to modify the speed when it detects a speed restriction sign. Similar to this, the Arduino Nano receives a signal from the Raspberry Pi to slow down the car in order to guarantee a safe passage over a pothole or speed bump.

The motor driver, which is managed by the Arduino Nano, controls the speed and direction of the DC motor that powers the car. The Arduino Nano sends pulse-width modulation (PWM) signals to the motor driver, which uses the processed data to determine the motor's speed. Real-time smooth and accurate speed adjustments are made possible by the Arduino Nano's ability to comprehend PWM signals and precisely manage the motor speed.

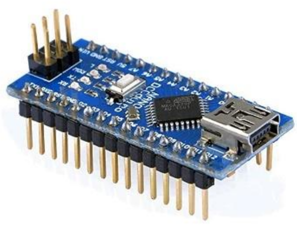

Figure 8. Arduino Nano

4. Motor driver (L293D)

The Arduino Nano serves as an interface between the motor driver and the high-level processing unit (Raspberry Pi) and receives the control commands produced by the Raspberry Pi. These directives are converted into signals that the motor driver can understand by the Arduino Nano. The motor driver, which is usually an H-bridge circuit, is in charge of directing and accelerating the DC motor in response to signals from the Arduino Nano. It allows for fine control over the motion of the vehicle by adjusting the voltage and current provided to the DC motor.

Through control of the vehicle's acceleration and deceleration, the driver guarantees that the vehicle reacts appropriately to a variety of road circumstances and traffic laws. The motor driver slows the motor down when the system notices a sign with a speed limit. Alternatively, the motor driver can accelerate the motor to ensure that it complies with traffic regulations and maximizes travel time if a higher speed restriction is identified or if the obstruction is removed.

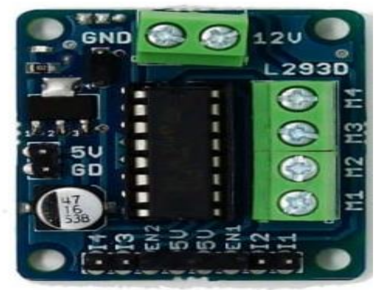

Figure 9. L293D Motor driver

5. DC motor

The seamless integration of the embedded system guarantees that the vehicle can react to road conditions and traffic signs on its own, improving safety and compliance without requiring the driver to manually intervene. When the Raspberry Pi comes across a traffic sign, like a speed limit, it decodes the sign and calculates the proper speed for the car. The technology foresees the need to slow down in order to prevent possible harm or pain if it detects a pothole or speed bump. The Arduino Nano, which serves as a bridge between the Raspberry Pi and the motor driver, receives these decisions. The Raspberry Pi issues orders to the Arduino Nano, which converts these into precise control signals for the motor driver.

The motor driver modifies the DC motor's power output in response to incoming signals. It is in direct communication with the motor. The motor driver lowers the voltage applied to the DC motor when a lower speed is needed, which causes the car to slow down. On the other hand, the motor driver raises the voltage to enable the DC motor to accelerate the vehicle if the system recognizes that it is safe for it to return to a faster speed.

Figure 10. DC motor

In order to dynamically alter the vehicle's speed, the DC motor functions as the actuator in this system by translating electrical inputs into mechanical motion.

Hardware components	Specifications
Camera Module	Camera
Raspberry pi	4GB of RAM
Arduino nano	Atmega328P

Motor driver	L293D

Table 1. Specifications of hardware components

VII. HARDWARE INTEGRATION

The meticulous placement of a camera module, Raspberry Pi, Arduino Nano, motor driver, and DC motor is necessary for the hardware integration of an automatic vehicle speed control system. Taking pictures of the surroundings of the car in real time, the camera module acts as the main sensor. The robust Raspberry Pi microprocessor, to which it is linked, uses a trained MobileNetV2 model to process these photos. Potholes, speed bumps, and traffic signals are all recognized by this model, which is well-known for its effectiveness in embedded and mobile applications. The deep learning inference is executed by the Raspberry Pi, which analyses the video data to categorize different types of roads and traffic signals.

The Raspberry Pi establishes a serial connection with the Arduino Nano as soon as it recognizes a particular traffic sign or obstruction. In order to convert the commands from the Raspberry Pi into control signals for the motor driver, the Arduino Nano serves as an intermediate microcontroller. Because the responsibilities are separated, the Arduino Nano can handle real-time control functions, allowing the Raspberry Pi to concentrate on complicated picture processing.

The motor driver, which is coupled to the Arduino Nano, controls the direction and power of the DC motor that propels the vehicle. The motor driver modifies the speed of the motor in accordance with commands received from the Arduino. For example, the Raspberry Pi instructs the Arduino to lower the motor's speed in response to the detection of a speed restriction sign. In a similar vein, the system can reduce speed when it notices a pothole or speed bump to guarantee a comfortable and secure ride. Enough

power is supplied to the mechanical and computational components of the system by a battery pack that meets the needs of the DC motor. A steady operating environment and the prevention of power surges that can harm delicate components depend on proper wiring and power control.

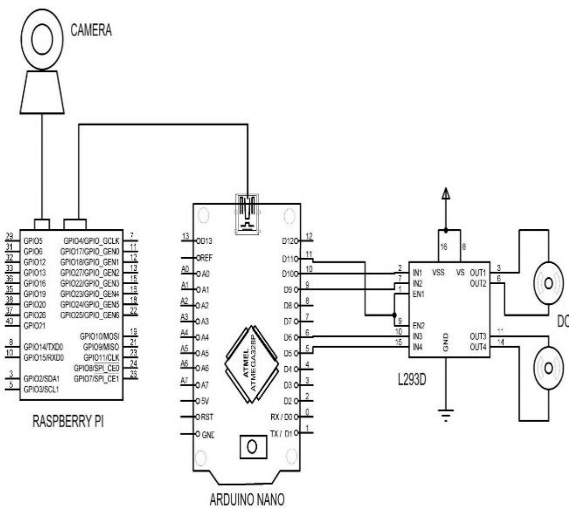

Figure 11. Circuit diagram

VIII. IMPLEMENTATION AND RESULT

The MobileNetV2 deep learning model has been trained to identify and categorize various traffic sign kinds, such as stop signs and speed limit signs with 40 and 80 km/h designations. It is additionally trained to recognize speed bumps and potholes on the surface of the road. The system initiates the necessary actions to guarantee safe vehicle operation upon detecting these components.

The DC motor driver runs the DC motor attached to the vehicle wheel by means of a matching rotations per minute restriction for each detecting characteristic. The system modifies the vehicle's speed in accordance with the indicated restriction when it detects a speed limit sign. For example, when the system detects a 40 km/h speed restriction sign, it tells the embedded system to adjust the wheel-mounted motor driver's speed to the matching limit in revolutions per minute (rpm).

When a stop sign is detected, the system begins to gradually slow down the vehicle until it comes to a complete stop, ensuring that traffic laws are followed and intersection accidents are avoided.

The technology informs the embedded system to adjust the motor driver's speed to the appropriate revolutions per minute upon recognizing potholes and speed bumps on the road surface for safer driver experience.

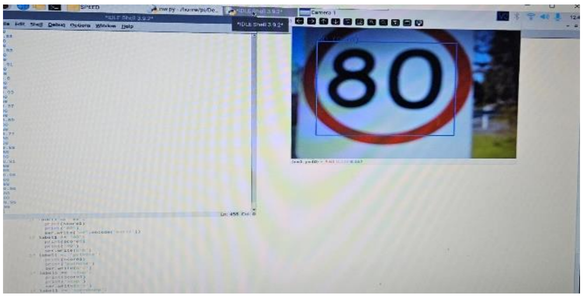

Figure 12. 80 km/h speed limit board detection

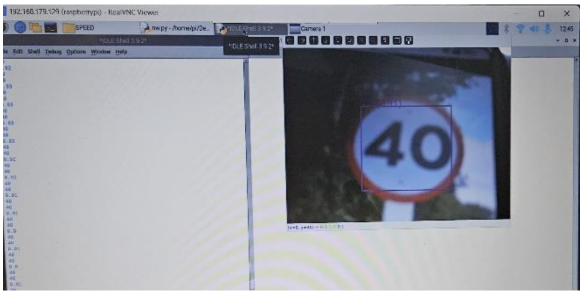

Figure 13. 40 km/h speed limit board detection

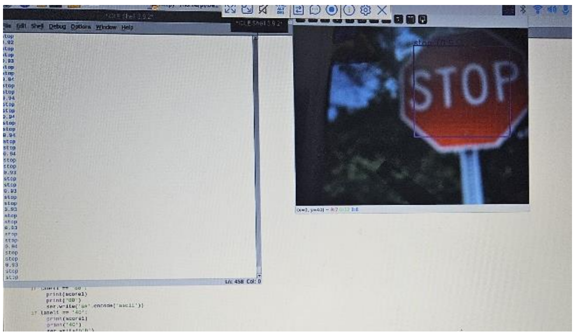

Figure 14. Stop sign detection

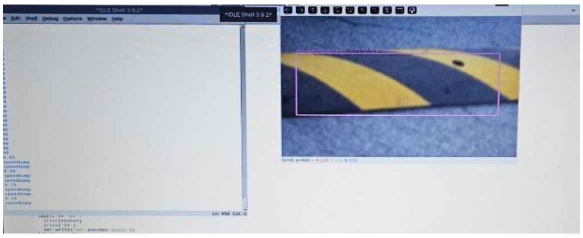

Figure 15. Speed bump detection

Figure 16. Pothole detection

Precision-Confidence curve

An Automatic Vehicle Speed Controlling System's Precision-Confidence curve, which uses computer vision and deep learning to detect potholes, speed bumps, and traffic sign boards - 40 km/h, 80 km/h, and stop signs, offers a critical assessment of the system's accuracy at different confidence thresholds. Using a camera module to take pictures of the road, a Raspberry Pi for processing, and an Arduino Nano to communicate with the motor driver and DC motor for speed control, the system makes use of MobileNetV2 for effective real-time detection. Plotting precision (the ratio of genuine positive detections to total detections) against confidence levels (the likelihood that the model assigns to its predictions) is what the curve does.

In order to provide safety and dependability in autonomous driving, a high precision at lower confidence levels suggests fewer false positives. On the other hand, overfitting or a lack of training data may be indicated by a sharp decline in precision at higher confidence thresholds. By balancing detection accuracy and system responsiveness, the curve helps to fine-tune the confidence threshold. Developers can enhance overall driving safety and performance by optimizing the system to reliably modify vehicle speed, assuring compliance with traffic signs and timely responsiveness to road circumstances.

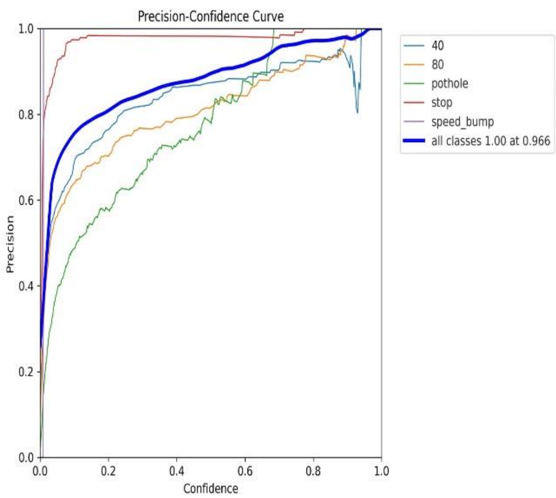

Figure 17. Precision-confidence curve

IX. CONCLUSION

The Automatic Vehicle Speed Controlling System marks a major development in intelligent transportation systems with the integration of computer vision, deep learning, and embedded technologies. Its importance in the current transportation infrastructure is highlighted by its ability to improve traffic management, road safety, and the driving experience in general. This ground-breaking technology not only demonstrates the promise of cutting-edge technologies like computer vision and deep learning to improve transportation systems, but it also increases road safety by regulating vehicle speed in reaction to potholes, speed bumps, and traffic signs. By integrating it into vehicles, it will be possible to create intelligent and adaptable driving experiences that will make roads safer for all users.

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