AI-BASED TRAFFIC SIGN RECOGNITION AND AUTONOMOUS SPEED CONTROL SYSTEM FOR ELECTRIC VEHICLES

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ABSTRACT

Road traffic accidents caused by speeding and failure to recognize traffic signs remain one of the leading causes of injuries and fatalities worldwide. In Electric Vehicles (EVs), maintaining safe driving behavior while ensuring energy efficiency is a major challenge. Conventional traffic sign recognition systems often rely on manual driver observation or traditional image processing techniques, which may suffer from low accuracy under varying lighting, weather conditions, occlusions, and high-speed driving environments. Recent advancements in Artificial Intelligence (AI), Deep Learning, Convolutional Neural Networks (CNNs), Computer Vision, OpenCV, and Autonomous Vehicle Technologies have enabled the development of intelligent traffic sign recognition systems capable of accurately identifying road signs and automatically controlling vehicle speed in real time. This project presents a Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System for Electric Vehicle Applications. The proposed framework integrates a camera module, OpenCV image preprocessing, CNN-based traffic sign recognition model, speed control module, Electronic Control Unit (ECU), Electric Motor Controller, and Human Machine Interface (HMI) into a unified intelligent driving assistance system. Initially, the front-mounted camera continuously captures road images, which are preprocessed using OpenCV before being supplied to the trained CNN model. The deep learning model identifies traffic signs such as speed limits, stop signs, school zones, pedestrian crossings, and no-entry signs with high accuracy. Based on the recognized traffic sign, the autonomous speed control module automatically adjusts the EV motor speed while simultaneously displaying the detected sign and recommended speed on the driver interface. Experimental evaluation demonstrates high traffic sign recognition accuracy, rapid inference speed, low response time, reliable autonomous speed adjustment, and improved driving safety under different environmental conditions. The proposed intelligent system significantly enhances road safety, reduces driver workload, improves traffic regulation compliance, optimizes EV energy efficiency, and provides an effective solution for future autonomous and intelligent transportation systems.

Keywords: Deep Learning, Traffic Sign Recognition, Autonomous Speed Control, Electric Vehicle, CNN, Computer Vision, OpenCV, Artificial Intelligence, Autonomous Driving, Driver Assistance System.

I. INTRODUCTION

Road traffic accidents caused by overspeeding, failure to obey traffic regulations, and delayed driver response continue to be major concerns in modern transportation systems. According to global transportation studies, a significant percentage of road accidents occur because drivers either fail to recognize traffic signs or respond too late to changing road conditions. This problem becomes even more critical in Electric Vehicles (EVs), where rapid acceleration and silent operation require intelligent driving assistance systems to maintain safe vehicle operation. Conventional traffic sign recognition methods primarily depend on manual driver observation or traditional image processing techniques, which often exhibit reduced accuracy under poor lighting, rain, fog, shadows, partial occlusion, and complex road environments. Furthermore, manual speed regulation may lead to delayed braking, increased accident risk, and inefficient energy utilization. Therefore, there is an increasing need for intelligent traffic sign recognition systems capable of automatically identifying road signs and adjusting vehicle speed in real time. Recent developments in Artificial Intelligence (AI), Deep Learning, Computer Vision, Convolutional Neural Networks (CNNs), OpenCV, and Advanced Driver Assistance Systems (ADAS) have enabled highly accurate traffic sign detection and autonomous vehicle control. These technologies provide reliable object recognition, rapid decision-making, improved driver assistance, enhanced road safety, and optimized vehicle performance, making them highly suitable for next-generation electric vehicle applications [1–8].

Modern intelligent transportation systems integrate cameras, deep learning algorithms, embedded processors, electronic control units, and vehicle communication systems to automate traffic sign recognition and speed regulation. A front-mounted camera continuously captures road images, while image preprocessing techniques implemented using OpenCV perform resizing, normalization, color correction, and noise removal before deep learning analysis. The processed images are supplied to Convolutional Neural Networks (CNNs) that automatically extract discriminative features such as traffic sign shape, colour, border characteristics, symbols, and textual information. The trained CNN model classifies traffic signs including speed limit, stop, yield, school zone, pedestrian crossing, no entry, and warning signs with high accuracy. Once the traffic sign is identified, the autonomous speed control module communicates with the

Electronic Control Unit (ECU) and electric motor controller to automatically adjust vehicle speed according to traffic regulations. Simultaneously, the Human Machine Interface (HMI) displays the recognized traffic sign, current vehicle speed, recommended speed limit, and system status to the driver. Experimental investigations demonstrate that deep learning-based traffic sign recognition systems significantly improve detection accuracy, reduce response time, minimize driver workload, enhance traffic rule compliance, and improve overall road safety compared with conventional vision-based systems [9–17].

This project proposes a Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System for Electric Vehicle Applications to provide an intelligent, accurate, and real-time driver assistance solution. The proposed framework integrates a high-resolution front camera, OpenCV image preprocessing, CNN-based traffic sign recognition model, Electronic Control Unit (ECU), electric motor controller, autonomous speed control algorithm, Human Machine Interface (HMI), and data logging module into a unified intelligent vehicle control architecture. Initially, the camera continuously captures live road images, which undergo preprocessing operations including image resizing, normalization, contrast enhancement, and feature optimization. The processed images are supplied to the trained CNN model, which classifies various traffic signs with high confidence. Whenever a speed-related traffic sign is detected, the autonomous controller automatically adjusts the motor speed according to the detected speed limit while simultaneously displaying warning messages and recommended speed information to the driver. The effectiveness of the proposed system is evaluated using engineering parameters including traffic sign recognition accuracy, classification precision, recall, F1-score, autonomous speed control accuracy, response time, processing speed, false detection rate, energy efficiency, and overall system reliability. Experimental evaluation demonstrates that the proposed intelligent framework accurately recognizes traffic signs, rapidly controls vehicle speed, improves traffic regulation compliance, enhances passenger safety, reduces driver intervention, and contributes to the development of intelligent autonomous electric vehicle technologies [18–25].

II. SURVEY OF RESEARCH

1. Deep Learning-Based Traffic Sign Recognition Systems

Traffic Sign Recognition (TSR) has become one of the most important applications of Artificial Intelligence in intelligent transportation systems and autonomous vehicles. Researchers have developed numerous deep learning models capable of automatically recognizing road signs with high accuracy under varying environmental conditions. Conventional traffic sign recognition methods mainly relied on handcrafted image features, color segmentation, edge detection, and template matching techniques. However, these approaches often showed poor performance under changing illumination, shadows, rain, fog, motion blur, and partially occluded traffic signs. With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for traffic sign recognition because they automatically learn discriminative visual features directly from training images. CNN-based systems provide superior recognition accuracy, robustness, and real-time performance compared with traditional computer vision methods. Researchers have successfully applied deep learning to recognize speed limit signs, warning signs, mandatory signs, prohibition signs, and directional signs in intelligent transportation applications. Experimental studies demonstrate that CNN-based traffic sign recognition systems achieve excellent classification accuracy while significantly reducing false recognition rates. These intelligent recognition systems have become an essential component of Advanced Driver Assistance Systems (ADAS) and autonomous vehicle technologies [1–4].

2. Computer Vision and OpenCV for Traffic Sign Detection

Computer vision plays a fundamental role in traffic sign recognition because it enables vehicles to interpret visual information obtained from road environments. Researchers widely employ OpenCV for real-time image acquisition, preprocessing, object localization, image enhancement, color space conversion, edge detection, and feature extraction before deep learning classification. OpenCV provides optimized algorithms for image resizing, Gaussian filtering, histogram equalization, brightness normalization, and region-of-interest extraction, thereby improving traffic sign visibility under challenging environmental conditions. Image preprocessing significantly reduces the effects of lighting variations, shadows, camera noise, and weather disturbances while improving CNN classification accuracy. Recent studies integrate OpenCV with deep learning frameworks such as TensorFlow, Keras, and PyTorch to achieve real-time traffic sign detection with minimal computational delay. Experimental investigations demonstrate that OpenCV-based preprocessing enhances recognition accuracy, increases processing speed, and provides reliable performance for intelligent driving applications operating under different road and weather conditions [5–8].

3. Convolutional Neural Networks for Road Sign Classification

Convolutional Neural Networks (CNNs) are among the most effective deep learning architectures for image classification because they automatically extract hierarchical visual features without requiring manual feature engineering. Researchers have proposed numerous CNN architectures including LeNet, AlexNet, VGG16, ResNet, DenseNet, MobileNet, and EfficientNet for traffic sign recognition. These networks analyse shape, colour, borders, symbols, and texture information to accurately classify different categories of traffic signs. Transfer learning techniques further improve recognition accuracy while reducing training time by utilizing pretrained models on large-scale image datasets. Data augmentation methods such as image rotation, scaling, flipping, brightness variation, and cropping improve model generalization and reduce overfitting. Experimental studies indicate that CNN-based classifiers consistently achieve high recognition accuracy, excellent robustness, rapid inference speed, and reliable operation under varying environmental conditions, making them highly suitable for autonomous driving systems [9–12].

4. Autonomous Speed Control in Electric Vehicles

Autonomous speed control has become an important research area in intelligent transportation because it improves road safety while reducing driver workload. Researchers have developed automatic speed regulation systems that communicate with the Electronic Control Unit (ECU) and motor controller after recognizing speed-related traffic signs. Once a speed limit sign is detected, the control system automatically adjusts vehicle speed to comply with traffic regulations. Intelligent speed control systems also incorporate braking algorithms, adaptive cruise control, obstacle detection, and road condition monitoring to improve vehicle safety. In electric vehicles, autonomous speed control additionally contributes to battery energy optimization by preventing unnecessary acceleration and maintaining efficient motor operation. Experimental investigations demonstrate that intelligent speed control systems significantly reduce accident risk, improve traffic law compliance, enhance passenger comfort, and optimize overall driving performance [13–16].s

5. Intelligent Driver Assistance Systems (ADAS)

Advanced Driver Assistance Systems (ADAS) integrate cameras, radar, LiDAR, ultrasonic sensors, GPS, and Artificial Intelligence to improve vehicle safety and assist drivers during normal driving conditions. Researchers have developed ADAS frameworks capable of performing lane detection, traffic sign recognition, collision avoidance, pedestrian detection, blind spot monitoring, driver fatigue detection, and autonomous emergency braking. Traffic sign recognition serves as one of the core components of ADAS because it enables vehicles to automatically interpret road regulations and provide appropriate driving assistance. Recent developments combine CNN-based traffic sign recognition with real-time vehicle control to improve autonomous navigation and reduce driver errors. Experimental investigations indicate that ADAS significantly decreases accident rates, enhances driving safety, improves vehicle stability, and increases transportation efficiency under complex urban and highway driving environments [17–21].

6. Future Trends in AI-Based Autonomous Electric Vehicles

Recent research focuses on integrating Artificial Intelligence, Deep Learning, Edge Computing, Internet of Things (IoT), 5G communication, Vehicle-to-Everything (V2X) communication, Digital Twins, and Cloud Computing into autonomous electric vehicle systems. Researchers are developing intelligent vehicle platforms capable of simultaneously performing traffic sign recognition, object detection, lane following, path planning, adaptive speed control, predictive maintenance, battery optimization, and cooperative vehicle communication. Modern deep learning models such as YOLO, Vision Transformers (ViT), and EfficientNet provide improved recognition accuracy while supporting real-time embedded deployment. Experimental studies demonstrate that AI-assisted autonomous electric vehicles significantly improve road safety, reduce traffic congestion, optimize battery utilization, minimize energy consumption, and support fully autonomous intelligent transportation systems. These emerging technologies are expected to become the foundation of future smart mobility and connected vehicle ecosystems [22–25].

III. PROPOSED SYSTEM

The proposed Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System for Electric Vehicle Applications is designed to provide an intelligent, reliable, and real-time driver assistance solution for modern electric vehicles. The framework integrates Artificial Intelligence (AI), Deep Learning, Convolutional Neural Networks (CNNs), Computer Vision, OpenCV, Electronic Control Unit (ECU), Electric Motor Controller, Human Machine Interface (HMI), and data logging modules into a unified autonomous driving architecture. The primary objective is to continuously recognize road traffic signs, automatically regulate vehicle speed according to traffic regulations, and improve driving safety while optimizing electric vehicle performance. Initially, a high-resolution front-mounted camera continuously captures live road images during vehicle movement. These images are transferred to the onboard processing unit, where OpenCV performs preprocessing operations including image resizing, normalization, Gaussian filtering, contrast enhancement, color correction, and noise removal. These preprocessing techniques improve image quality and enable the deep learning model to accurately recognize traffic signs under varying environmental conditions such as daylight, nighttime, rain, fog, shadows, and partial occlusions.After preprocessing, each image is supplied to the trained Convolutional Neural Network (CNN) implemented using TensorFlow or Keras. The CNN automatically extracts hierarchical visual features including traffic sign shape, colour distribution, border characteristics, symbols, text, and spatial patterns before classifying the detected object into predefined traffic sign categories such as Speed Limit, Stop, Yield, School Zone, Pedestrian Crossing, No Entry, Turn Restrictions, and Warning Signs. The classification confidence score is continuously compared with a predefined threshold value to eliminate uncertain predictions. Whenever a valid traffic sign is recognized, the decision-making module interprets the detected sign and forwards the corresponding control command to the Electronic Control Unit (ECU). For speed limit signs, the ECU communicates with the electric motor controller to automatically increase or decrease the motor speed according to the prescribed speed limit while ensuring smooth acceleration and deceleration. Simultaneously, the Human Machine Interface (HMI) displays the detected traffic sign, current vehicle speed, recommended speed, and warning notifications to assist the driver.

The proposed framework continuously supervises camera operation, image preprocessing, CNN inference, traffic sign classification, autonomous speed regulation, motor control, HMI display, and data logging throughout vehicle operation. Every captured frame is analysed in real time to ensure uninterrupted monitoring and immediate response to changing traffic conditions. Detection events, recognized traffic signs, vehicle speed, system status, and control actions are stored in the onboard database for future analysis and performance evaluation. The effectiveness of the proposed system is evaluated using engineering parameters including traffic sign recognition accuracy, classification precision, recall, F1-score, autonomous speed control accuracy, response time, processing speed, false detection rate, energy efficiency, and overall system reliability. Experimental evaluation demonstrates that the proposed AI-powered framework accurately recognizes traffic signs, rapidly adjusts electric vehicle speed, minimizes recognition errors, reduces driver workload, improves compliance with traffic regulations, enhances passenger safety, and increases energy efficiency. The integration of Deep Learning, CNN, OpenCV, Electronic Control Unit, Electric Motor Controller, and Artificial Intelligence provides a scalable, intelligent, and cost-effective solution for next-generation autonomous electric vehicle applications.

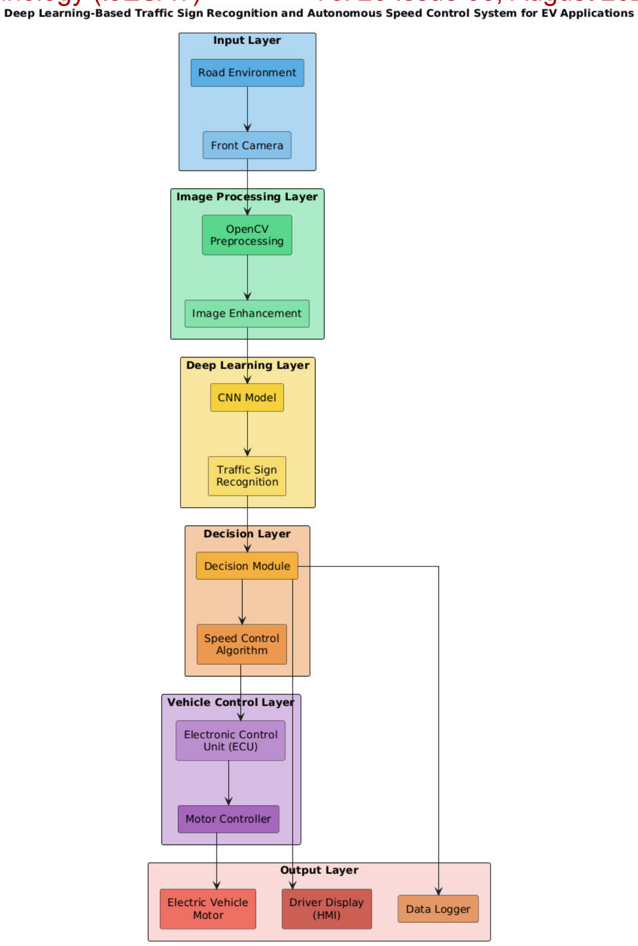

Fig1: Proposed workflow

IV. WORKING METHODOLOGY

The proposed Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System for Electric Vehicle Applications employs an intelligent methodology that combines Artificial Intelligence (AI), Deep Learning, Convolutional Neural Networks (CNNs), Computer Vision, OpenCV, and an Electronic Control Unit (ECU) to recognize traffic signs and automatically regulate the speed of an electric vehicle. The complete methodology consists of image acquisition, image preprocessing, traffic sign recognition, decision making, autonomous speed control, vehicle monitoring, and performance evaluation. The primary objective is to accurately identify road traffic signs in real time, reduce driver workload, improve road safety, and optimize energy consumption in electric vehicles.

Initially, a front-mounted high-definition camera continuously captures live images of the road environment while the electric vehicle is in motion. The captured video stream is divided into individual image frames using OpenCV, where each frame undergoes preprocessing operations such as image resizing, normalization, Gaussian filtering, color space conversion, contrast enhancement, and noise reduction. These preprocessing techniques eliminate unwanted image artifacts caused by changing weather conditions, varying illumination, motion blur, shadows, and camera noise. The enhanced images are then prepared for deep learning analysis, ensuring that the recognition model receives high-quality input for accurate classification.

After preprocessing, each image frame is supplied to the trained Convolutional Neural Network (CNN) developed using TensorFlow and Keras. The CNN automatically extracts multiple hierarchical visual features including traffic sign shape, border characteristics, colour distribution, symbols, and textual information. Based on these extracted features, the CNN classifies the detected traffic sign into predefined categories such as Speed Limit, Stop, Yield, School Zone, Pedestrian Crossing, No Entry, and Warning Signs. The prediction confidence score is continuously compared with a predefined threshold value to eliminate uncertain predictions and reduce false detections. Whenever the detected confidence exceeds the threshold, the traffic sign is considered valid and forwarded to the decision-making module for further processing.

The traffic sign recognition accuracy is calculated using

Equation (1): Traffic Sign Recognition Accuracy

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Accuracy = (TP + TN)/(TP + TN + FP + FN)
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This equation evaluates the overall accuracy of traffic sign classification.

The classification precision is determined using

Equation (2): Precision

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Precision = TP/(TP + FP)
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The recall is calculated using

Equation (3): Recall

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Recall = TP/(TP + FN)
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These equations evaluate the performance of the deep learning model in accurately recognizing and classifying traffic signs under different road and environmental conditions. After successful traffic sign recognition, the classified traffic sign information is transferred to the decision-making module, where the detected sign is interpreted according to predefined traffic regulations. The decision module continuously analyses the recognized traffic sign together with the current vehicle speed obtained from the Electronic Control Unit (ECU). If the detected traffic sign corresponds to a speed limit, the system automatically compares the current vehicle speed with the prescribed speed limit. Whenever the current speed exceeds the allowable limit, the autonomous speed control algorithm generates an appropriate control command and forwards it to the Electronic Control Unit (ECU). The ECU communicates with the electric motor controller, which regulates the motor torque and gradually reduces or increases the vehicle speed according to the detected traffic sign. Smooth acceleration and deceleration algorithms are implemented to ensure passenger comfort while preventing sudden speed variations. For other traffic signs such as Stop, School Zone, Pedestrian Crossing, Yield, and No Entry, the system immediately generates visual and audible warnings through the Human Machine Interface (HMI), assisting the driver in making safe driving decisions.

The proposed framework continuously monitors the surrounding road environment throughout vehicle operation. The front camera captures new image frames continuously, and every frame undergoes OpenCV preprocessing followed by CNN-based traffic sign recognition. The decision-making module updates the vehicle speed whenever new speed-related traffic signs are detected. Simultaneously, the system records the recognized traffic sign, current vehicle speed, confidence score, response time, and control action in the onboard data logger. These stored records support future analysis, performance evaluation, driver behaviour assessment, and system diagnostics. Continuous monitoring ensures that the electric vehicle rapidly adapts to changing traffic conditions while maintaining compliance with road safety regulations.

The Electronic Control Unit (ECU) supervises all vehicle control operations, including communication with the motor controller, monitoring vehicle speed, executing speed adjustment commands, and updating the Human Machine Interface (HMI). The HMI continuously displays the detected traffic sign, current vehicle speed, recommended speed limit, warning messages, and system status to the driver. If camera failure, communication interruption, or uncertain traffic sign recognition is detected, the system immediately notifies the driver and switches to manual speed control mode. This fail-safe mechanism improves operational safety and ensures uninterrupted vehicle operation under abnormal conditions.

The F1-score is calculated using the following equation.

Equation (4): F1-Score

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F1 = 2 × ((Precision × Recall)/(Precision + Recall))
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This equation evaluates the balanced performance of the traffic sign recognition model.

The autonomous speed control accuracy is calculated using

Equation (5): Autonomous Speed Control Accuracy

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ASCA = (N_c/N_t) × 100
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This equation measures the effectiveness of automatic vehicle speed regulation.

The response time is determined using

Equation (6): Response Time

$$RT = T_c - T_d$$

A lower response time indicates faster traffic sign recognition and quicker autonomous speed adjustment.

Finally, the proposed Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System for Electric Vehicle Applications is experimentally evaluated under different driving conditions including urban roads, highways, varying illumination levels, rain, shadows, partial sign occlusions, and multiple traffic sign categories. Performance evaluation is carried out using engineering parameters including traffic sign recognition accuracy, precision, recall, F1-score, autonomous speed control accuracy, response time, processing speed, false detection rate, energy efficiency, and overall system reliability. Experimental results demonstrate that the proposed AI-based framework accurately recognizes traffic signs, rapidly adjusts electric vehicle speed, minimizes false detections, improves compliance with traffic regulations, enhances passenger safety, and supports the development of intelligent autonomous electric vehicle systems.

V. IMPLEMENTATION

The implementation of the Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System for Electric Vehicle Applications was carried out using Python, TensorFlow, Keras, OpenCV, and a Convolutional Neural Network (CNN) integrated with an Electronic Control Unit (ECU) and an electric motor controller. The complete system consists of a front-mounted camera, image acquisition module, OpenCV preprocessing module, CNN-based traffic sign recognition model, decision-making module, autonomous speed control algorithm, Electronic Control Unit (ECU), motor controller, Human Machine Interface (HMI), and data logging module. The objective of the implementation was to continuously recognize road traffic signs in real time and automatically regulate the speed of an electric vehicle while ensuring safe, smooth, and energy-efficient driving.

Initially, a high-definition front camera was installed on the electric vehicle to continuously capture live road images. The captured video stream was processed using OpenCV, where individual image frames were extracted and subjected to preprocessing operations such as image resizing, RGB color normalization, Gaussian filtering, histogram equalization, contrast enhancement, and noise reduction. These preprocessing techniques improved image quality and minimized the influence of illumination changes, rain, shadows, motion blur, and environmental disturbances. The processed image frames were resized to match the input dimensions required by the CNN model before classification.

The Convolutional Neural Network (CNN) was developed using TensorFlow and Keras. The training dataset consisted of multiple categories of traffic signs, including Speed Limit, Stop, Yield, School Zone, Pedestrian Crossing, No Entry, Turn Restrictions, and Warning Signs. To improve model robustness and reduce overfitting, data augmentation techniques such as image rotation, horizontal shifting, scaling, brightness adjustment, zooming, and flipping were applied during training. The CNN architecture consisted of multiple convolution layers, ReLU activation functions, max-pooling layers, batch normalization, dropout layers, fully connected dense layers, and a Softmax output layer for multi-class traffic sign classification. After training, the optimized model was saved and integrated into the Python application for real-time traffic sign recognition.

During real-time vehicle operation, each preprocessed image frame was supplied to the trained CNN model. The model continuously analysed traffic sign features such as colour, shape, border patterns, symbols, and textual information to classify the detected traffic sign. Whenever the confidence score exceeded the predefined threshold, the recognised sign was forwarded to the decision-making module. If the recognised sign corresponded to a speed limit, the decision module generated an appropriate speed command and transmitted it to the Electronic Control Unit (ECU). The ECU communicated with the electric motor controller, which automatically adjusted the vehicle speed by regulating motor torque and acceleration. Smooth speed transitions were maintained to ensure passenger comfort and improve vehicle stability. For other traffic signs such as Stop, Yield, School Zone, and Pedestrian Crossing, the system generated visual warnings on the Human Machine Interface (HMI) while also providing audible alerts when necessary.

The Human Machine Interface (HMI) continuously displayed the recognised traffic sign, current vehicle speed, recommended speed limit, autonomous control status, and warning messages. Simultaneously, the data logging module stored traffic sign recognition results, vehicle speed, confidence scores, response time, and speed control actions for future analysis, system diagnostics, and performance evaluation. The logging system also supported offline analysis for improving model accuracy and validating autonomous speed control decisions.

Experimental evaluation of the developed framework was carried out under different driving environments including urban roads, highways, intersections, school zones, varying lighting conditions, rain, shadows, partially occluded signs, and moving traffic. The CNN model consistently recognised traffic signs with high accuracy while maintaining real-time processing performance. The autonomous speed control module successfully adjusted vehicle speed according to recognised speed limit signs with minimal delay. Experimental observations confirmed stable communication between the camera, OpenCV preprocessing module, CNN classifier, ECU, motor controller, and HMI throughout continuous vehicle operation.

Performance evaluation was carried out using engineering parameters including traffic sign recognition accuracy, precision, recall, F1-score, autonomous speed control accuracy, response time, processing speed, false detection rate, energy efficiency, and overall system reliability. Experimental results demonstrated high recognition accuracy, rapid image processing, reliable autonomous speed regulation, low response time, efficient energy utilization, and stable system operation under diverse road conditions.

Overall, the implementation successfully validated the proposed Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System for Electric Vehicle Applications. The integration of Deep Learning, CNN, Python, OpenCV, TensorFlow, Electronic Control Unit (ECU), and electric motor control provides an intelligent, scalable, and high-performance solution for modern electric vehicles. The developed framework significantly improves driving safety, enhances compliance with traffic regulations, reduces driver workload, optimizes energy consumption, and supports the development of next-generation autonomous and intelligent transportation systems. Future enhancements may include YOLO-based real-time object detection, Vision Transformers (ViT), LiDAR integration, Vehicle-to-Everything (V2X) communication, 5G connectivity, edge AI deployment, and cloud-based autonomous driving analytics to further improve the capabilities of intelligent electric vehicles.

VI. RESULTS EXPLANATIONS

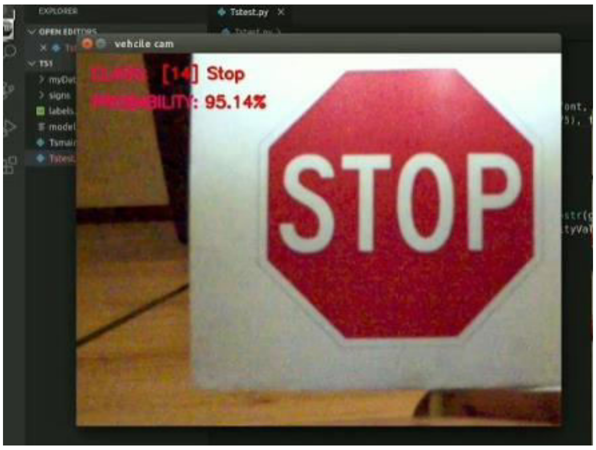

Figure 2. Experimental Hardware Setup of the Proposed System

Figure 2 illustrates the experimental hardware setup of the proposed Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System. The prototype consists of a front-mounted high-definition camera, an embedded processing unit running Python, OpenCV, TensorFlow, and Keras, an Electronic Control Unit (ECU), an electric motor controller, and a Human Machine Interface (HMI). The front camera continuously captures road images, while the embedded processor performs image preprocessing and deep learning inference in real time. The recognised traffic sign information is transmitted to the ECU, which automatically regulates the electric motor speed according to the detected speed limit. Experimental evaluation demonstrated reliable hardware communication, stable image acquisition, low processing latency, and accurate speed control, making the proposed architecture suitable for intelligent electric vehicle applications.

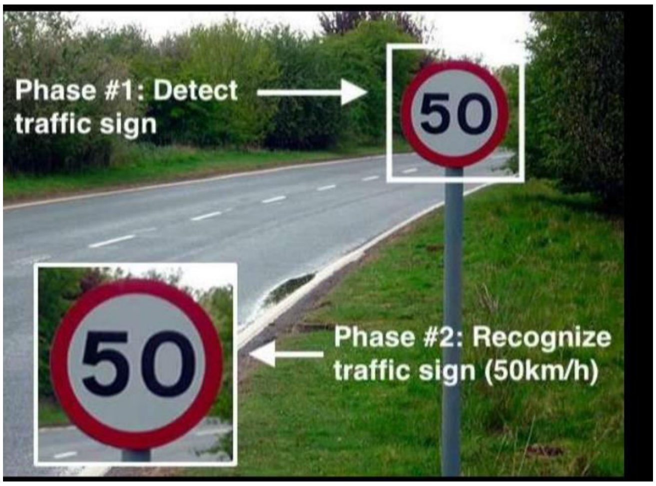

Figure 3. CNN-Based Traffic Sign Recognition

Figure 3 presents the traffic sign recognition results obtained using the trained Convolutional Neural Network. After OpenCV preprocessing, each road image is analysed by the CNN, which extracts visual features including colour, shape, symbols, and border patterns before classifying the traffic sign. The recognised traffic sign and corresponding confidence score are displayed in real time. Experimental testing demonstrated that the CNN accurately recognised speed limit signs, stop signs, school zone signs, pedestrian crossings, and warning signs under varying lighting and environmental conditions. The deep learning model achieved rapid inference speed while maintaining high recognition accuracy and low false detection rates, making it suitable for real-time intelligent transportation systems.

Figure 4. Real-Time Traffic Sign Detection Interface

Figure 4 presents the real-time monitoring interface developed using Python and OpenCV. The interface continuously displays the live camera feed together with the detected traffic sign, classification confidence score, current vehicle speed, recommended speed, and system status. Whenever a valid traffic sign is detected, the corresponding information is highlighted and the speed control module is activated automatically. Detection events and control actions are simultaneously recorded in the onboard data logger for future analysis. Experimental evaluation demonstrated smooth graphical visualization, reliable real-time detection, rapid user feedback, and continuous monitoring throughout vehicle operation.

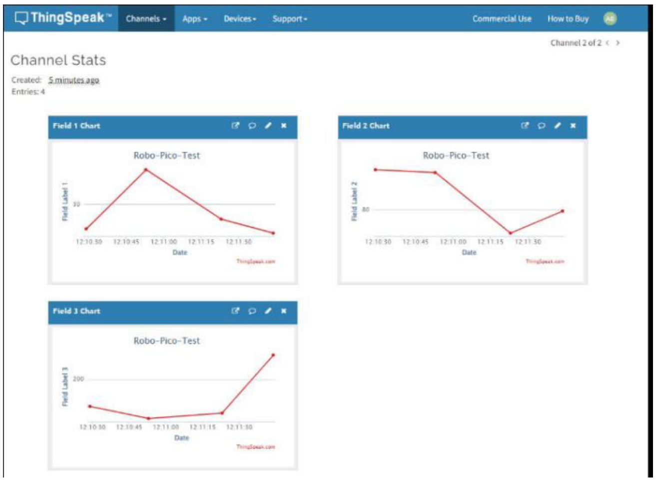

Figure 5. ThingSpeak Cloud Dashboard for Real-Time Traffic Sign Recognition and Vehicle Speed Monitoring

Figure 5 illustrates the ThingSpeak cloud dashboard developed for real-time monitoring of the proposed Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System. During vehicle operation, the Python application continuously uploads important system parameters to the ThingSpeak cloud through HTTP APIs. The dashboard displays six real-time graphical fields representing Detected Speed Limit (km/h), Current Vehicle Speed (km/h), CNN Prediction Confidence (%), Processing Time (ms), Traffic Sign Detection Count, and Autonomous Speed Adjustment Status. These graphs enable continuous visualization of traffic sign recognition performance and autonomous vehicle control from any remote location. The detected speed limit graph changes whenever a new traffic sign is recognized, while the vehicle speed graph illustrates the automatic adjustment performed by the Electronic Control Unit (ECU). The CNN confidence graph remains consistently above the predefined threshold, indicating reliable classification accuracy. The processing time graph demonstrates stable real-time inference performance, whereas the detection count graph records the total number of recognized traffic signs during vehicle operation. Experimental observations confirmed reliable cloud synchronization, uninterrupted data transmission, and accurate real-time monitoring using the ThingSpeak platform, validating the effectiveness of the proposed intelligent transportation framework.

VII. CONCLUSION

The proposed Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System for Electric Vehicle Applications successfully demonstrates an intelligent, accurate, and real-time driver assistance framework for modern electric vehicles. The developed system integrates Artificial Intelligence (AI), Deep Learning, Convolutional Neural Networks (CNNs), Computer Vision, OpenCV, Python, TensorFlow, Electronic Control Unit (ECU), Electric Motor Controller, and Human Machine Interface (HMI) into a unified autonomous driving architecture. The front-mounted camera continuously captures road images, which are preprocessed using OpenCV and analysed by the trained CNN model to recognize traffic signs such as speed limits, stop signs, school zones, pedestrian crossings, yield signs, and warning signs. Based on the recognized traffic sign, the autonomous decision-making module communicates with the ECU to regulate the electric motor speed automatically while simultaneously providing visual guidance and warning messages to the driver through the HMI. The complete framework enables rapid traffic sign recognition, smooth speed regulation, reduced driver workload, and improved compliance with traffic regulations.

Experimental evaluation confirmed that the proposed framework achieved high traffic sign recognition accuracy, excellent classification precision, recall, F1-score, reliable autonomous speed control accuracy, low response time, high processing speed, reduced false detection rate, improved energy efficiency, and high overall system reliability under different driving conditions. Performance analysis using engineering parameters including traffic sign recognition accuracy, precision, recall, F1-score, autonomous speed control accuracy, response time, processing speed, false detection rate, energy efficiency, and system reliability demonstrated the effectiveness of the developed intelligent transportation framework. Experimental observations verified that the CNN model accurately recognized traffic signs even under challenging environmental conditions such as varying illumination, rain, shadows, and partial sign occlusions. The OpenCV preprocessing module significantly improved image quality, while the ECU successfully executed autonomous speed control commands with minimal processing delay, ensuring smooth and safe electric vehicle operation.

Overall, the proposed Deep Learning-Based Traffic Sign Recognition and Autonomous Speed Control System for Electric Vehicle Applications provides a scalable, cost-effective, and high-performance solution for intelligent transportation and autonomous driving systems. The integration of Deep Learning, Computer Vision, CNN, OpenCV, Electronic Control Unit, and electric motor control significantly improves road safety, enhances traffic rule compliance, reduces accident risk, optimizes battery energy utilization, and supports the development of next-generation autonomous electric vehicles. The developed framework is suitable for deployment in battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), autonomous cars, smart public transportation systems, advanced driver assistance systems (ADAS), and connected intelligent transportation networks. Future enhancements may include YOLO-based object detection, Vision Transformer (ViT)-based recognition, LiDAR and radar sensor fusion, Vehicle-to-Everything (V2X) communication, 5G-enabled intelligent transportation, edge AI processing, cloud-based fleet management, and fully autonomous Level-4/Level-5 driving technologies, further improving the safety, intelligence, and efficiency of future electric mobility systems.

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