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Hardware Model-Based Traffic Sign Detection and Recognition

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Abstract
In the modern world, correctly recognizing and categorizing traffic signs is essential for improving road safety and enabling autonomous driving technologies. This study uses the **Raspberry Pi 3 Model B+** as the central processing unit to provide a hardware-based, real-time method for traffic sign detection and recognition.
Our system integrates image collection, preprocessing, and classification into a small, embedded device intended for realistic, real-world deployment, in contrast to conventional software-heavy approaches. The system makes use of a lightweight **Convolutional Neural Network (CNN)** to effectively categorize traffic signs, employs a camera module to gather visual data, and applies image enhancement techniques to improve clarity. The CNN is perfect for low-power devices like the Raspberry Pi since it is tuned to balance speed and accuracy.
Our test demonstrates that the system can accurately identify and detect a variety of traffic signs in a range of environmental and lighting situations. All things considered, this study provides a scalable, economical, and energy-efficient solution for intelligent automobiles and smart traffic systems. In order to achieve even greater performance, future advancements will concentrate on increasing recognition accuracy using more sophisticated deep learning models and utilizing cutting-edge AI technology.

Keywords
Traffic Sign Detection & Recognition, Autonomous Navigation, Raspberry Pi 3 Model B+, Embedded System, Convolutional Neural Network (CNN), Image Processing, Real-time Classification, Smart Vehicle System, Traffic Monitoring.

I. Introduction

These days, advanced driver assistance systems (ADAS) are an essential component of modern cars, especially when it comes to identifying and comprehending traffic signs, which is a crucial area of visual computing [1]. Road signs provide vital information like speed limits, directions, and cautions that assist drivers in making safe and educated decisions. They act as a kind of global language on the road. Drivers can improve their navigation skills, steer clear of possible dangers, and help create a safer and more efficient traffic flow by correctly interpreting these signs [2].
The effectiveness of traffic signs is greatly influenced by their visual design. Characteristics like shape and color aren't just aesthetic—they're critical for fast recognition. Most countries follow standardized patterns using specific colors (like red, blue, and yellow) and shapes (such as circles, triangles, and rectangles) to ensure uniformity and quick understanding across different regions. These visual cues help both humans and machines identify signs quickly, even at a glance.

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However, conditions on the road are rarely perfect. Factors such as poor weather, low light, or worn-out signage can make it difficult to see and interpret road signs clearly. These challenges highlight the need for reliable and intelligent detection systems that can operate accurately in real-world conditions [3, 4].

To tackle this, researchers have been developing various advanced techniques to improve how ADAS systems detect and understand traffic signs [5]. Some of the most promising methods involve deep learning, where models are trained to recognize signs using existing datasets, even if those datasets are relatively small. Others use approaches like multi-scale feature fusion, which enhances the system's ability to detect how large or little they appear in a picture [6].

To put it simply, the continuous research and development of traffic sign analysis is not merely a technological undertaking; rather, it is an essential step in creating safer roads for all. ADAS helps drivers stay vigilant, make smarter judgments, and ultimately lower the risk of accidents on the road by fusing smart technology with practical applications.

The process of identifying road signs is often divided into two primary steps in the majority of current systems: determining the type of sign and estimating its potential location. This enhances the system's accuracy and effectiveness.

In this study, a new and more effective technique has been presented to increase the speed and precision of traffic sign detection. The system goes through a few image preprocessing processes before it even starts to recognize signs. These procedures aid in image preparation and cleaning, which facilitates the system's ability to comprehend and accurately identify the indicators.

A detailed workflow has been developed to clarify the entire procedure. This well-organized graphic demonstrates how every component of the system cooperates to achieve the end result. This figure, which is displayed in **Figure 1**, provides a visual representation of the entire procedure, from data preparation to precise traffic sign detection and identification.

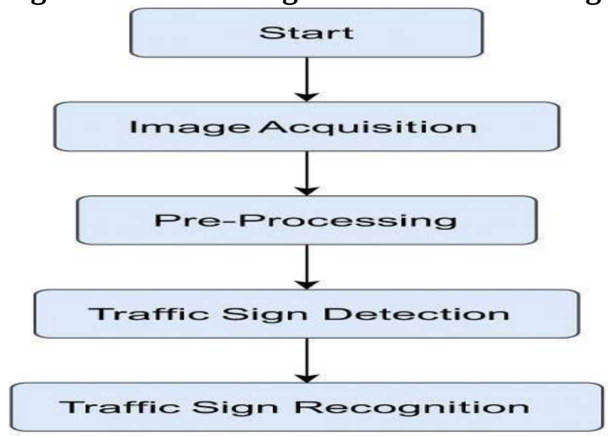

Fig. 1. Block diagram of Traffic Sign Detection and Recognition

II. Related Work

Many researchers have looked into different ways to improve how traffic signs are detected and recognized, aiming to make the process more accurate and efficient. One interesting method combines detection, tracking, and recognition using techniques like **Adaboost**, color-sensitive Haar wavelet features, and the use of motion (temporal) data to figure out speed limits [7]. This system was trained on a dataset with around 4,000 images, covering 23 types of traffic signs. The number of examples for each sign type ranged from 30 to 600. To check how well the system worked, a separate set of 1,700 images was used for testing—and it reached an impressive accuracy of 94%.

Another study [8] focused on using a neural network approach to recognize single-digit speed limit signs found on roads in Europe and the U.S. This method was built using the **MAPS** software framework. However, it didn't provide specific classification results for each type of sign. The system, which included both tracking and detection features, was tested on 281 different traffic signs.

In [9], a traffic sign classification model based on color segmentation and shape-based verification was developed. The detection process relied on selecting an appropriate neural

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network according to the sign's shape and RGB color properties.

A different study [10] employed a **multi-layer perceptron neural network**, which was trained on a dataset containing 2,880 images. This model was further tested on 1,233 images of speed limit signs, achieving an accuracy rate of 92.4%. However, the research did not specify whether the same traffic sign instances were repeated across different image groups.

Another method [11] utilized a dataset containing 1,300 pre-processed images from six categories five corresponding to speed limits and one representing noise. The study tested various segmentation-based techniques using binary image processing. Additionally, research in [12] compiled an extensive dataset featuring 36,000 images of Spanish traffic signs from 193 classifications, leveraging pictogram identification techniques. A different approach [13] explored the use of histogram features and Region of Interest (ROI) extraction for traffic sign recognition. However, the results obtained in this study were below expectations, with the proposed methodology failing to achieve the desired performance levels.

A direct comparison of the studies mentioned above is difficult, as many of them utilized proprietary datasets, restricting accessibility for validation by other researchers. To address this challenge, a study in [14] applied the publicly available **GTSRB** dataset to develop a novel **Convolutional Neural Network (CNN)**-based architecture for traffic sign detection and classification. **Faster R-CNN** for multi-object recognition was used in another study [15], which included various datasets with automobiles, traffic signs, and traffic lights.

CNNs were used by the authors in [16] to create a technique specifically intended for identifying Indian traffic signs. Building on this, a real-time detection system that can detect both audio and video was developed in another study [17]. It analyzes auditory cues using the **VGG** model and uses **YOLOv5** to identify indications in video data. When compared to earlier techniques, this integrated strategy performed better, making it more practical.

Processed images were stored in the **Portable Pixel Map (PPM)** format without compression. Each image was carefully annotated to indicate the presence and type of visible traffic signs. All label information, including class identifiers and bounding box data, is compiled in a structured **CSV** file to support supervised learning models.

B. Dataset Characteristics and Relevance to the Proposed System

In the present work, the **GTSRB dataset** [20] is adopted as a benchmark to train and validate the traffic sign classification model due to its comprehensive structure and real-world diversity. The dataset comprises over **50,000 annotated images** categorized into **43 distinct traffic sign classes**. It presents a wide range of visual variations, including differences in orientation, illumination levels, weather conditions, partial occlusions, and spatial positioning of signs within each frame—factors that closely resemble real-time driving environments.

The complete dataset includes **51,840 images**, with dimensions ranging from **15×15 to 250×250 pixels**. The traffic signs within these images are not consistently centered, which introduces natural complexity for detection tasks. The dataset is systematically divided into two parts: **39,209 images** are reserved for training, while the remaining **12,630 images** form the testing set. To prevent data leakage, images containing the same physical sign are confined to a single subset. Additionally, a small portion of the training data is allocated for model validation and performance tuning.

Each image is linked to a specific traffic sign label, such as "Speed Limit 50 km/h," "Speed Limit 60 km/h," or "Road Work." The traffic signs are divided into four primary categories—**Warning, Prohibitory, Mandatory**, and **Others**—in order to better arrange them and make them easier to use with various recognition algorithms. Sample photos from

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each of these categories are displayed in **Figure 2**. The hardware arrangement in this study, which consists of the **OV5647 5MP 1080P IR-CUT camera module** coupled to a **Raspberry Pi 5 Model**, is also tested using these samples as benchmarks.

III. Dataset

Images from a number of visits taken in the spring and fall of 2010—mostly in the Bochum region of Germany—are included in the **GTSRB** collection. The data was collected in a variety of illumination circumstances, including brilliant daylight and low-light dusk, and covers a broad range of driving locations, such as city streets, country roads, and highways. The dataset is extensive and varied for training and testing traffic sign recognition algorithms because it also includes a variety of weather situations. **Figure 2** displays a few exemplary samples. The traffic signs included in the dataset follow the guidelines established by the **Vienna Convention on Road Signs and Signals**, ensuring consistency and standardization in their appearance.

A. Image Acquisition and File Structure

The **GTSRB dataset** was created using images captured with a high-resolution **OV5647 5MP 1080P IR-CUT** camera, which was set to automatic exposure to adjust for different lighting conditions. These images were originally captured in **Bayer pattern** format. To reconstruct accurate color images, an edge-adaptive and constant-hue **demosaicking technique** was applied, transforming them into **RGB**.

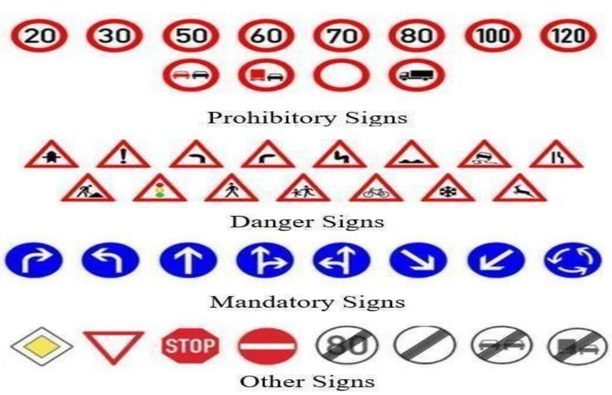

Fig. 2. Representative Classes of Traffic Signs Included in the GTSRB Dataset

IV. Embedded Hardware Integration and Software Stack

A. Raspberry Pi 5 Model

In order to better handle demanding tasks like real-time picture processing and traffic sign recognition, the **Raspberry Pi 3 Model B** was utilized in this study with an improved 4 GB RAM arrangement. With a **64-bit quad-core ARM Cortex-A53** processor clocked at **1.4 GHz**, this little computer offers a solid mix between performance and energy economy, making it ideal for computer vision and artificial intelligence projects.

The board can function both locally and remotely thanks to its integrated support for **Ethernet, Bluetooth 4.2**, and **Wi-Fi (802.11 b/g/n/ac)**. Additionally, it has a full-size **HDMI** and four **USB 2.0** output connections, and a **40-pin GPIO header** for attaching other **peripherals**. One of the main features of this setup is its interoperability with the **OV5647 5MP IR-CUT camera module**, which is connected directly to the Raspberry Pi via the dedicated CSI (Camera Serial Interface) port.

To get the system operational, the operating system is first installed onto a **microSD card**, which is then inserted into the Raspberry Pi. The setup process is completed by configuring wireless connectivity, setting up user credentials, and enabling remote access (such as SSH or VNC).

To install the operating system, the **official Raspberry Pi Imager** tool is used to flash the OS image onto the microSD card. For this project, a **32GB SanDisk microSD card** was used to ensure sufficient space for the operating system, project files, libraries, and temporary image storage used during traffic sign detection and recognition tasks. The system's software backbone is made up of crucial software libraries like **Open CV** and **Python**, which are

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compatible with the OS thanks to its **Linux foundation**.

It has a **Camera Serial Interface (CSI)** connection. Clear images may be captured with this camera even in a variety of lighting situations. The **Raspbian OS** (based on **Debian**) that the Raspberry Pi runs on offers a reliable environment for executing **Python** scripts and necessary libraries like **OpenCV** and **TensorFlow Lite**, which are both utilized in this study to identify and categorize traffic signs.

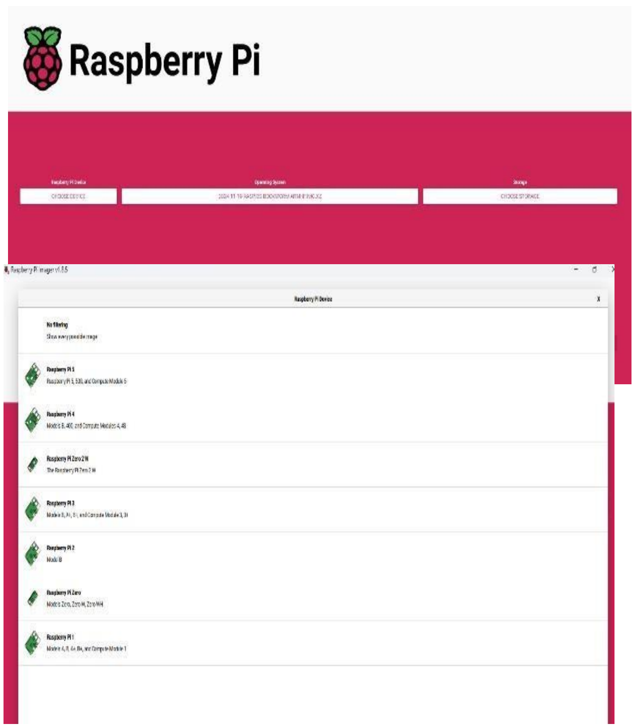

Fig. 4. Selection window displaying available Raspbian OS

The system in this study runs on the **64-bit version** of the **Raspbian operating system** (*Debian Bullseye*), which is specially designed for Raspberry Pi hardware. This version was selected because it offers better performance and works well with modern computer vision libraries, making it ideal for real-time processing. While Raspbian is available in both 32-bit and 64-bit versions, the 64-bit edition is more efficient at managing memory, which is particularly beneficial for the **4GB RAM** configuration of the **Raspberry Pi 5 Model** used in this research.

The OS is installed by flashing the image file onto a **microSD card** using the official **Raspberry Pi Imager** tool.

For this project, a **32GB SanDisk microSD card** was chosen to provide enough storage for the operating system, necessary dependencies, and the images captured during the project.

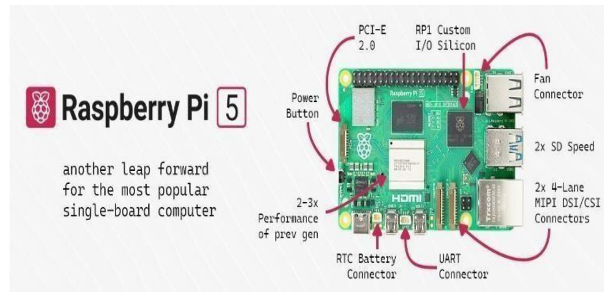

Fig. 5. Basic hardware features and specification summary of the Raspberry Pi 5 Model.

IV. Result and Analysis

A **Raspberry Pi 5** and a **webcam** were used to effectively identify and recognize traffic signs in real time. To identify and categorize traffic signs, the trained model continually analyzes camera picture frames. When no sign is detected, the system displays the message **"No Sign Detected"** on the output screen, as illustrated in **Fig. 4**.

Testing and validation accuracies were noted at several training phases in order to assess model performance. As indicated in **Table I**, results were taken every **50 epochs**, and the highest performance was observed after **200 epochs**.

No of Epochs	Testing Accuracy	Testing Loss	Validation accuracy	Validation loss
50	0.9952	0.0160	0.9968	0.0149
100	0.9965	0.0112	0.9980	0.0077
150	0.9984	0.0050	0.9788	0.0079
200	0.9972	0.0113	0.9980	0.0084

TABLE I. Accuracy for Testing and Validation at Different Epochs

- **No Sign Detected**

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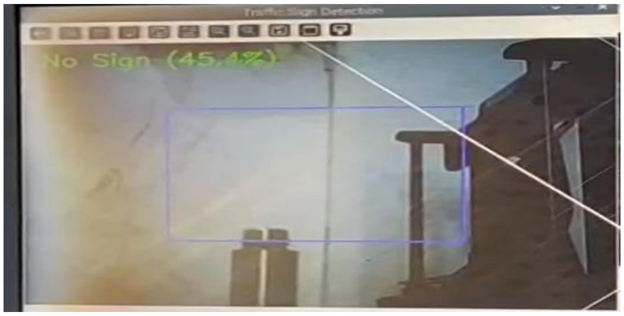


Fig. 10(A). Output image showing
No Sign Detected

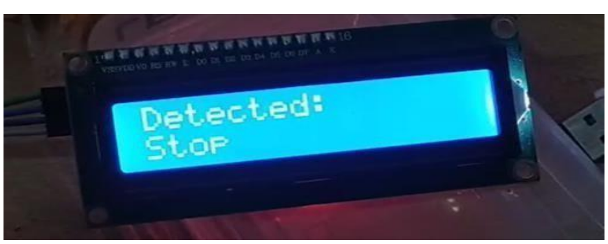
Fig. 10(B). Output image showing **No Sign Detected**

In addition to the above, the system also successfully detects key traffic signs used for basic road navigation, including:

- **Stop Sign**

Fig. 11(A). Output image showing
Stop (53.9%)

Fig. 11(B). Output image showing
Detected: Stop



- **Turn Right Sign**

Fig. 13(A). Output image showing right **(59.2%)**

Fig. 13(B). Output image showing
Detected: Right

Fig. 14. Complete hardware model of traffic sign detection using **Raspberry Pi**

- **Turn Left Sign**

Fig. 12(A). Output image showing
Left (59.28%)
Detected: Left

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Fig. 12(B). Output image showing

Conclusion and Future Scope

In this research, a hardware-based system for traffic sign detection and recognition was successfully developed and implemented using a Raspberry Pi 5 and the OV5647 5MP IR-CUT camera module. The system effectively identifies and classifies various traffic signs in real-time, demonstrating its potential for integration into intelligent transportation systems and advanced driver-assistance systems (ADAS). The model provides dependable performance with minimal latency by utilizing machine learning approaches and efficient image processing algorithms, which makes it appropriate for practical applications.

The implementation of a small, affordable hardware configuration highlights the viability of implementing such systems in embedded settings, particularly when resources are limited. This work provides important insights into real-time difficulties such as changing lighting conditions, motion blur, and hardware restrictions, bridging the gap between software simulations and actual implementation.

All things considered, the research demonstrates the feasibility of fusing open-source software with reasonably priced hardware to provide responsive, intelligent systems for the detection and recognition of traffic signs. Future improvements might incorporate deep learning models for improved accuracy and adaptability, grow the sign collection for wider use, and integrate GPS for location-based context.

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