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DRIVERS ASSISTANCE FOR TRAFFIC SIGN RECOGNITION USING DEEP LEARNING

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Abstract

Road safety is a paramount concern worldwide, with traffic signs playing a crucial role in guiding drivers and pedestrians and preventing accidents. However, individuals with visual impairments or those distracted while driving may overlook or misinterpret traffic signs, leading to potential hazards. To address this challenge, this project proposes the development of a Voice Alarm System for Traffic Signs is designed to detect and classify traffic signs dynamically and alert drivers via audio cues. The core architecture leverages a hybrid deep learning approach combining Convolutional Neural Networks (CNN) and MobileNet. CNNs are utilized to capture detailed spatial features and robust patterns from the traffic imagery, while the MobileNet framework ensures lightweight, high-speed processing ideal for resource-constrained edge devices and real-time vehicular deployment. The framework evaluates the model's robustness by utilizing the widely recognized German Traffic Sign Recognition Benchmark (GTSRB) dataset, the model achieves a classification accuracy of over 99% with an ultra-low inference footprint, establishing its readiness for embedded real-time automotive execution. Ultimately, this research validates that depth wise model down-scaling provides a highly dependable and computationally economical solution for driver-assistance for traffic sign recognition.

Keywords

Deep learning, Convolutional Neural Networks (CNN) and MobileNet, German Traffic Sign Recognition Benchmark (GTSRB), Traffic Signs.

I. INTRODUCTION

Accidents on the roadways are becoming more common in the modern day as vehicle numbers rise, and statistics indicate that the country of India leads all other nations in terms of the amount of incidents. Many factors, like lax regulation, negligence, etc., contribute to this. People failing to understand or heed traffic signs represent one of the causes. Therefore, we created a traffic sign recognizer that may alert the automobile's operator of impending traffic signs and instruct them to obey them. Thus, fewer car accidents may occur. In the world of travel, applications such as computer vision, advanced driver assistance systems (ADAS), and fully self-driving cars all rely on the ability to recognize traffic signs. For vehicles to properly interpret and respond to the data sent by these traffic lights, they must recognize and classify traffic signs. Traffic sign recognition systems have come a long way in the last decade thanks to the development of deep learning, especially in CNN. Deep learning models have shown promise in tackling difficult problems in artificial intelligence, such as object recognition and identification. Traffic sign recognition systems can adapt to variations in light. Take advantage of the structured learning properties of deep ANNs to learn climate, obstacles, and different sign layouts. These algorithms can extract meaningful

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representations from the original image data by eliminating the need for manual feature generation and improving the robustness and accuracy of the identification process.

An important step in ensuring vehicle legality and soundness is accurate traffic conditions. Most of this work is physically demanding. Photograph street signs using smartphone cameras and recognizable evidence signs to determine if they were made outside of a line of people. Immediate detection of damaged or missing impressions can improve health while reducing the number of specializations. The process of changing hands, recognizing signs on the road, and programming location is a crucial step in computerizing this process. For the PC people's category, the subject of road sign acknowledgement is constantly in the spotlight, and currently there are computations for improved collaboration and recognition. However, these plans are only intended for certain categories, especially for signs related to individual automobiles and sophisticated driver assistance technologies.

A typical traffic sign recognition process usually involves two phases. The first phase is called traffic sign recognition and involves finding and measuring traffic light indicators in images of real scenes. Traffic sign classification is the next phase and typically requires manual classification of the collected traffic signs into appropriate individual classes. Despite the growing popularity of autonomous driving systems, recognizing real traffic signs using computer-developed algorithms remains a major challenge due to different target variables.

II. LITERATURE REVIEW

Identification of road signs using machine learning is currently attracting a lot of attention. Several investigations are being carried out to examine various tactics, frameworks, and techniques to enhance the reliability as well as precision of road sign method identification. Here, we provide an overview of the research highlighting some important improvements in this research area.

As urbanization accelerates further, intelligent public transportation systems are emerging and developing. By recognizing traffic signs as an important component of intelligent traffic systems, it is expected to spread in autonomous driving and driver assistance systems. Based on research on domestic and foreign traffic signs, this research focuses on traffic sign classification and identification, and also includes the current status, technical issues and development trends. Three new feature-based traffic sign recognition algorithms were implemented, including image preprocessing, feature extraction, and classification, in combination with important features of traffic sign shape and internal structure. [1]. Intelligent road systems include traffic sign recognition, which offers great potential for use in self-driving cars and other driver assistance technologies. Different methods such as traditional pattern matching, SVM, random forest, and CNN are used for traffic sign recognition, depending on the attributes that make up the traffic sign image. Method is used. [2] The new CNN suggested in this paper. Comparing the method of feature extraction to conventional CNN methods using the German Traffic Sign Recognition Benchmark (GTSRB) and the Belgian Traffic Sign Dataset (BTSD), pattern extraction performs better in terms of accuracy, has fewer constraints, and uses small models. simple to train. The outcomes show that our technology works better at identifying traffic than the conventional CNN approach.

This framework uses image preparation techniques to separate captured relevant information from the constantly overflowing video. The proposed method is roughly divided into five sections: "information classification", "information processing/organization", "preparation", and "test". [3] The framework uses various image preparation strategies to improve image quality, remove non-directive pixels, and detect edges. The highlight extraction function is used to detect the highlights of the image. The images are sorted according to their highlights with the help of an AI compute-supported vector engine. When the signal is highlighted, an audio signal is played at that point to

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warn the driver. Signs containing various activities fall into his three categories: Administrative signs, warning signs, and information signs. The character has his 4 interesting forms and his 8 unique tones. A lot of techniques which employ algorithms for image processing to recognize road sign board are being developed in the last year. The categorization issues of the present approach are avoided by using edge recognition. The problem with dynamic thresholding, which occurs in actual time situations, is faced by color-based categorization [4]. Another method for extracting road signs from clips of video is the suggested method. Grey scale transformation and edge recognition are used in this job's first phase of pre-processing the video frame. The following phase is the item identification.

III. EXISTING SYSTEM

This model emphasizes an existing method that which is designed using Traditional Machine Learning algorithms.It uses handcrafted feature extractors like Histogram of Oriented Gradients (HOG) or Local Binary Patterns (LBP) combined with classifiers such as Support Vector Machines (SVM) or Artificial Neural Networks (ANN) and massive deep convolutional neural networks (e.g., VGG16/VGG19, ResNet50) applied via transfer learning directly onto traffic sign datasets.

IV. PROPOSED METHOD

The proposed system replaces heavy networks with a heavily optimized, lightweight MobileNet architecture (leveraging ReLU activation functions) combined with a Voice Alarm module provides an excellent balance of low latency and high accuracy for real-time driver assistance or autonomous vehicles.

V. METHODOLOGY

A. Dataset:

In the proposed system, the German Traffic Sign Benchmarks (GTSRB) Dataset is used. Fig. 1 shows the 43 different traffic signs that are considered to train the model. It has 51,900 single images distributed among the 43 classes including the training and the test dataset.

Fig. 1. Traffic Signs Taken into consideration

B. Data Preprocessing:

To perform image processing, images need to be converted into numpy arrays (i.e. numeric values). After loading the images, they are resized to 30*30 pixels. Post this, the labels of the image are mapped with the image and hence the dataset is ready to be trained.

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C. MobileNet Backbone Feature Extractor:

- **Depthwise Separable Convolutions:** Instead of standard convolutions, the model splits the operation into a Depthwise Convolution (filtering per channel) followed by a Pointwise Convolution 1x1 convolution combining channels). This dramatically reduces computational parameters and floating-point operations (FLOPs).
- **ReLU Activations:** Standard rectified linear units ($f(x) = \max(0, x)$) or bounded variants like ReLU6 ($f(x) = \min(\max(0, x), 6)$) are injected after every convolutional layer to introduce non-linearity without heavy computational overhead, preventing numeric overflow on mobile hardware.

4. Classification Head:

- **Global Average Pooling (GAP):** Reduces the spatial dimensions of the final feature maps to a 1x1xC vector, minimizing overfitting risk.
- **Dense Layer & Softmax:** A final fully connected layer transforms features into raw logits, and a Softmax activation produces class probabilities representing specific traffic signs (e.g., *Speed Limit 50*, *Stop*, *Yield*).

5. Dual-Output Multi-Modal Generation Engine:

- **Text Processing Unit:** Maps the predicted class ID to a string literal via a lookup dictionary and pushes it to a Head-Up Display (HUD) or application UI.
- **Voice Synthesizer (TTS):** Feeds the mapped text string into a lightweight Text-to-Speech engine to broadcast audio alerts to the driver.

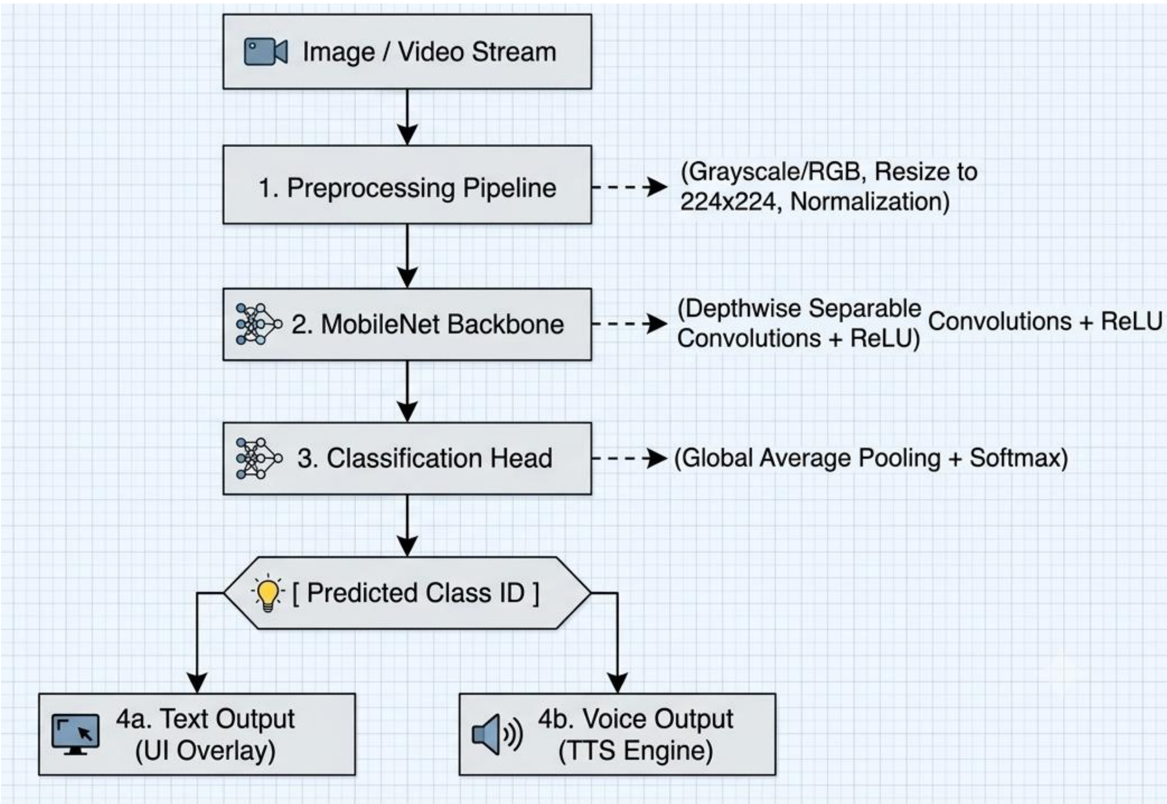

Fig 2. System Architecture

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V. DEEP LEARNING ALGORITHMS

Convolutional Neural Network:

Step1: convolutional operation

Convolutional operations serve as the first stepping stone for our strategy. This phase provides a brief introduction to neural network filters or feature detectors. In addition, we discuss functional maps, their parameters, detection levels, how patterns are detected, and how results are presented.

Step 2: Pooling Layer

This section describes pooling and helps you understand how pooling usually works. However, in this case, a particular type of pooling (max pooling) plays a central role. However, consider different tactics, such as medium (or full) pooling. This part ends with a presentation using visual interactive tools.

Step 3: Flattening

Here, we provide an overview of the flattening process and how to move from pooling to flattened layers in convolutional neural networks.

Step 4: Full Connection

This part summarizes everything that was explained in the previous section. Understanding this helps us understand how a convolutional neural network works and how the "neurons" it generates classify photos.

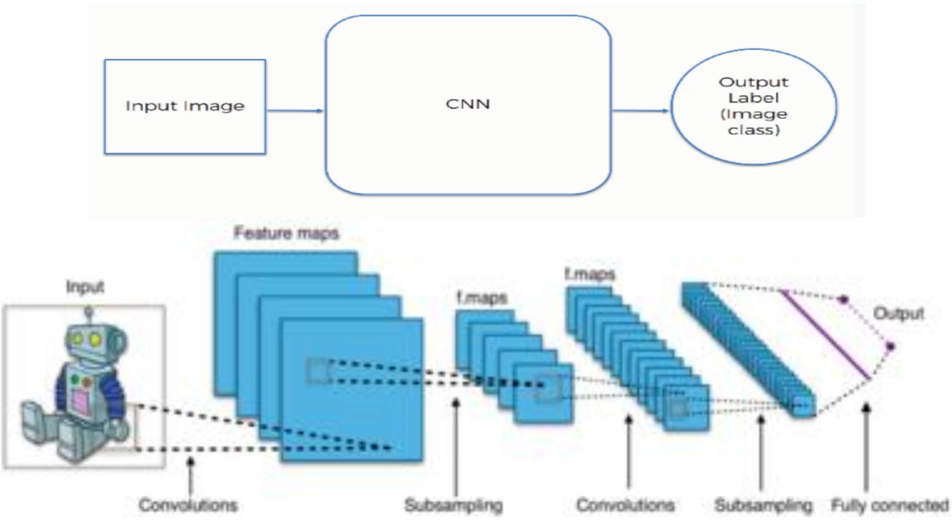

Fig 3. CNN Architecture

2 Mobile Net :

The utilization of Mobile Net algorithm in the detection of plant diseases through machine learning and deep learning is a groundbreaking approach. Mobile Net, known for its efficiency and lightweight architecture, proves to be instrumental in developing robust models for plant disease detection on mobile devices. By leveraging the power of convolutional neural networks (CNNs) within the Mobile Net framework, this technology enables real-time analysis of plant health through image processing. Mobile Net's capacity to efficiently handle computational tasks on resource-constrained platforms, such as smartphones, facilitates the deployment of portable and accessible plant disease detection solutions. The algorithm's ability to balance accuracy and computational efficiency is crucial in ensuring timely and accurate identification of diseases, empowering farmers and agricultural professionals to take swift corrective actions. Through the amalgamation of Mobile Net and advanced image recognition techniques, this research strives to enhance the efficacy and accessibility of plant disease detection, contributing to sustainable agriculture and food security.

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VI. RESULTS

Fig 4: Upload Traffic sig

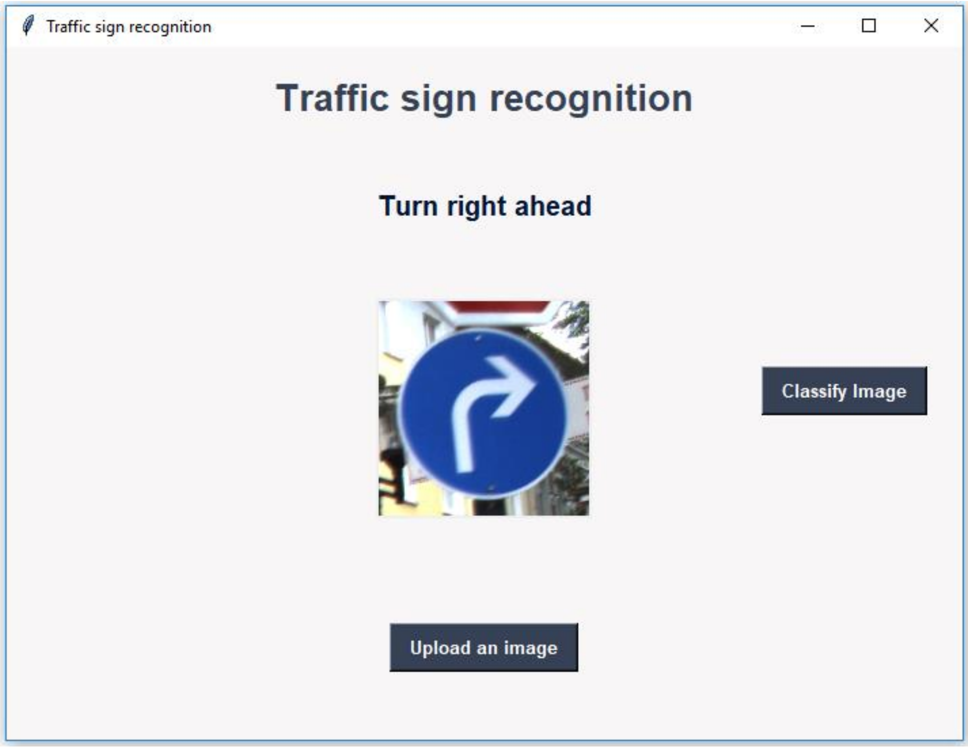

Fig 5. Traffic sign Recognised as Turn Right A head

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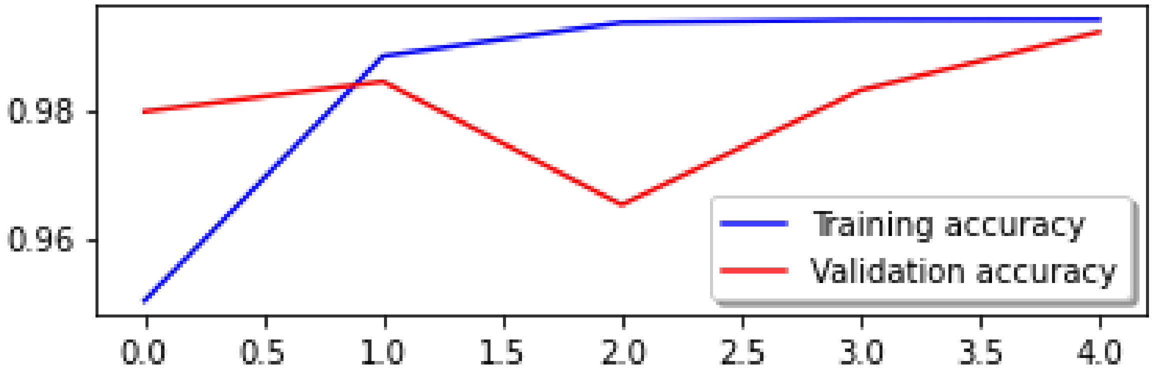

Fig 6. Mobile Net Training Accuracy

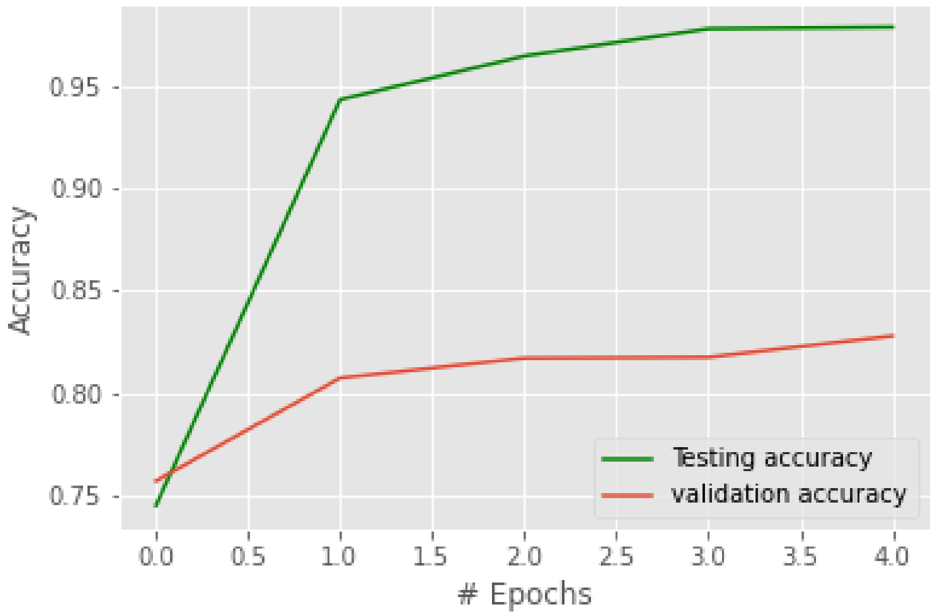

Fig 7. CNN Training Accuracy

VII. CONCLUSION

In this project we are detecting and recognizing the traffic signs. As, it was considered that in the computer vision community, the recognition and detection of traffic signs are a well-researched problem. Here, we are solving this problem by our proposed method, that is which is performed using Mobile Net. We are training the dataset of the traffic sign images with the help of Mobile Net and testing the signs using the Flask framework through a frontend application. Our proposed model is detecting and recognizing the traffic signs very accurately.

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