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Intelligent Traffic Sign Detection using CNN

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Abstract

With the rise of autonomous driving and smart transportation, traffic sign detection is key to road safety and efficient navigation. Traditional methods struggle with lighting, weather, and occlusions, so we propose an Intelligent Traffic Sign Detection System using CNNs for accurate, real-time classification. Trained on the GTSRB dataset with over 50,000 images across 43 categories, our CNN model reduces manual preprocessing and improves accuracy. Data augmentation ensures robustness to real-world conditions. Achieving 92-95% accuracy, the system integrates with autonomous vehicles, providing real-time detection and alerts to enhance road safety and navigation.

Keywords—Traffic Sign Detection, Convolutional Neural Networks, Autonomous Vehicles.

1. INTRODUCTION

With the rapid growth of autonomous driving and smart transportation systems, ensuring road safety and efficient traffic management has become more important than ever. Traffic signs play a vital role in guiding drivers by providing essential information about speed limits, road conditions, prohibitions, and directions. However, factors like driver fatigue, distractions, poor visibility, and misinterpretation often lead to mistakes in recognizing and following traffic signs. These errors contribute to accidents, traffic violations, and inefficiencies in transportation systems [1].

As the number of vehicles on the road continues to rise, relying solely on human interpretation of traffic signs is becoming increasingly impractical. Traditional rule-based methods, such as color segmentation, edge detection, and shape recognition, often fail under challenging conditions like low light, bad weather, and occlusions. Similarly, conventional machine learning techniques like Support Vector Machines (SVMs) and K-Nearest Neighbors (KNNs) depend on manually extracted features, which limits their adaptability to real-world traffic environments [2].

To overcome these limitations, deep learning—particularly Convolutional Neural Networks (CNNs)—has proven to be highly effective for traffic sign detection and classification. CNNs can automatically extract meaningful features from images, reducing the need for manual preprocessing while significantly improving accuracy and real-time performance [3]. By leveraging artificial intelligence and computer vision, CNNs enable reliable traffic sign recognition even under difficult conditions [4].

This paper presents an Intelligent Traffic Sign Detection System using CNNs to detect and classify traffic signs in real time. Designed to handle various lighting conditions, weather challenges, and motion blur, the system is well-suited for integration into autonomous vehicles and Advanced Driver Assistance Systems (ADAS). By improving sign detection accuracy and real-time responsiveness, this solution contributes to safer roads and more efficient transportation systems [5][6].

2. RELATED WORK

Recently, deep convolutional neural network have been a huge success in object detection. R. Girshick proposed the rich feature hierarchies for accurate object detection and semantic segmentation(RCNN)[3], which achieves excellent object detection accuracy by using a deep ConvNet to classify object proposals. But it is slow because it performs a ConvNet forward pass for each object proposal, without sharing computation. Spatial pyramid pooling networks (SPPnets) [4] were proposed to speed up it by sharing convolutional feature map. The SPPnet method only computes a convolutional feature map for the entire input image. SPPnet also has notable drawbacks. Its training is a multi-stage pipeline and not end-to-end method. Fast R-CNN [5] enables end-to-end detector training on shared convolutional features and shows compelling accuracy and speed. The Fast R-CNN still uses the Selective Search method [6] to generate 2000 regions proposals. Faster R CNN [7] introduces a training scheme that alternates between fine-tuning for the region proposal task and then fine-tuning for object detection. YOLO [8] reframes object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. SSD [9] using a small convolutional filter on feature maps to predict object categories and offsets in bounding box locations to improve the performance of object detection. Inspired by these works, traffic signs as a specific categories of object detection can be expected to obtain a better performance than ever before. R. Qian et al. used region based convolutional neural network(R-CNN) for detection and recognition of China's prohibition, mandatory and warning 3 classes of traffic signs[10]. J. Jin et al. designed a hinge loss stochastic gradient descent optimization method to train a 3 layers network for traffic signs recognition [11]. The proposed methods usually limited to a predefined set of traffic signs because of the shortage of the traffic signs data.

A. Convolutional Neural Networks:

A Convolutional Neural Network (CNN) processes images through multiple layers to automatically extract meaningful features for classification. The process begins with the input layer, where an image is fed into the network as a matrix of pixel values. The convolutional layer applies filters (kernels) that slide over the input, performing element-wise multiplication and summation to detect patterns such as edges, textures, and shapes. To introduce non-linearity, a Rectified Linear Unit (ReLU) activation function is applied, ensuring the model can learn complex patterns. Next, the pooling layer (using Max Pooling or Average Pooling) reduces the spatial dimensions of feature maps, preserving important information while minimizing computational complexity. The extracted features are then flattened and passed through a fully connected (FC) layer, where each neuron is connected to all previous neurons, allowing for better decision-making.

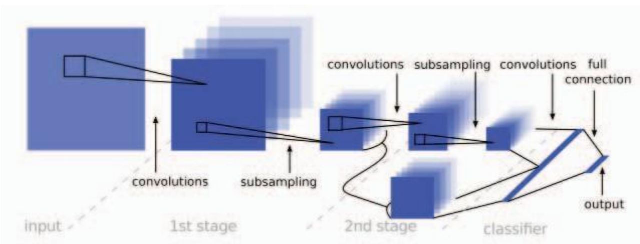

Fig. 1: Convolutional Neural Networks working.

Finally, in the **output layer**, a **Softmax** function assigns probability scores to different classes, enabling the network to predict the most likely category. By leveraging this hierarchical approach, CNNs effectively learn and recognize patterns, making them highly efficient for tasks like **traffic sign detection**, where automatic feature extraction and real-time processing are crucial for safety and navigation.

B. Real time detection and voice alerts

In real-time traffic sign recognition, a Convolutional Neural Network (CNN) processes live video feeds from a vehicle's camera to detect and classify traffic signs. The system follows a structured pipeline, starting with image acquisition, where frames are captured continuously from the camera. These frames undergo preprocessing, including resizing, normalization, and contrast enhancement, to ensure consistent input quality.

Next, the processed image is passed through the CNN model, which extracts relevant features such as edges, shapes, and color patterns. The model, trained on datasets like GTSRB, uses multiple convolutional layers to identify distinguishing characteristics of traffic signs. Max-pooling layers help reduce spatial dimensions while retaining essential features, and fully connected layers map these extracted features to specific traffic sign categories. The final classification is achieved using a softmax activation function, which assigns probability scores to each possible traffic sign class, determining the most likely match.

Once a traffic sign is recognized, the system triggers a voice alert based on the detected sign. This is accomplished by mapping the classification output to a predefined text-to-speech (TTS) module. For example, if the CNN identifies a "Stop" sign, the system will generate an audio warning saying "Stop sign ahead". Similarly, for speed limits, it may announce "Speed limit 60 km/h" to inform the driver. The TTS module can be implemented using Google TTS, Amazon Polly, or offline solutions like Festival or PicoTTS for real-time audio output.

3. TRAINING TRAFFIC SIGN MODEL

Traffic sign detection is a crucial component in autonomous driving and advanced driver-assistance systems (ADAS). In this work, we utilize Convolutional Neural Networks (CNNs) to develop a robust and efficient traffic sign detection model. Inspired by Faster R-CNN [1], our approach integrates a Region Proposal Network (RPN) to enhance detection accuracy and efficiency. The model is trained on the German Traffic Sign Recognition Benchmark (GTSRB) dataset, which provides a diverse set of real-world traffic sign images under various environmental conditions

A. Data Set

The German Traffic Sign Detection Benchmark (GTSDB) dataset is used to train the model. The dataset consists of 900 images with 1,200 annotated traffic signs, covering various road conditions such as different weather, occlusions, and lighting variations. The signs are categorized into 43 distinct classes.

To improve robustness, data augmentation techniques are applied, including:

- **Rotation & Scaling:** Simulating different camera perspectives.
- **Brightness Variation:** Handling day-night and weather-related changes.
- **Motion Blur:** Mimicking real-world moving vehicle scenarios.
- **Noise Injection:** Simulating sensor imperfections.

B. Training and Testing

We employ a Faster R-CNN model fine-tuned using pre-trained VGG16 and ResNet-50 architectures. The model is optimized using the Adam optimizer with an initial learning rate of 0.001, decreasing every 10,000 iterations. The training process consists of 50 epochs with a batch size of 32.

4. TRAFFIC SIGN DETECTION WITH VOICE ALERTS

In real-world driving conditions, drivers may often overlook traffic signs due to distractions, high vehicle speed, poor lighting, or weather conditions. Failure to recognize these signs can lead to accidents, traffic violations, or inefficient driving. To mitigate this problem, the proposed system provides real-time traffic sign detection and voice alerts to assist drivers, ensuring they remain aware of critical road signs without diverting their attention from the road.

A. Real-Time Recognition

The system employs a Convolutional Neural Network (CNN), specifically a Faster R-CNN model with a Region Proposal Network (RPN), to detect and recognize traffic signs from live video feeds. A camera mounted on the vehicle continuously captures frames, which are preprocessed and fed into the CNN for feature extraction and classification. The RPN generates region proposals, highlighting potential areas containing traffic signs. These proposals are refined, classified, and assigned confidence scores. If the confidence level surpasses a predefined threshold, the system confirms the detection and proceeds to the next stage.

The model is trained on the German Traffic Sign Detection (GTSD) dataset, which includes various traffic signs categorized into warning signs, prohibitory signs, mandatory signs, and information signs. To enhance robustness, the dataset is augmented with variations in lighting, motion blur, and rotations to simulate real-world conditions.

Fig. 2: Recognizing Stop Sign with confidence

B. Voice Alert Mechanism

Once a traffic sign is detected and classified, a text-to-speech (TTS) engine converts the recognized sign into an audio message. Examples:

- **Speed Limit Sign:** "Speed limit 80 kilometers per hour."
- **Stop Sign:** "Stop sign ahead, slow down."
- **No Entry Sign:** "No entry, please take an alternate route."

These voice prompts allow the driver to react instantly without the need to look at the dashboard or road signs, reducing cognitive load and improving response time.

C. Handling Challenging Conditions

The system is designed to work under various real-world conditions, including:

- **Varying Illumination:** Adaptability to day and night conditions using brightness normalization.
- **Motion Blur:** Filters improve image sharpness.
- **Partial Occlusion:** Model trained with occluded images.
- **Rotations and Perspective Distortions:** Data augmentation ensures robust detection.

Fig. 3: Recognizing Stop Sign with confidence

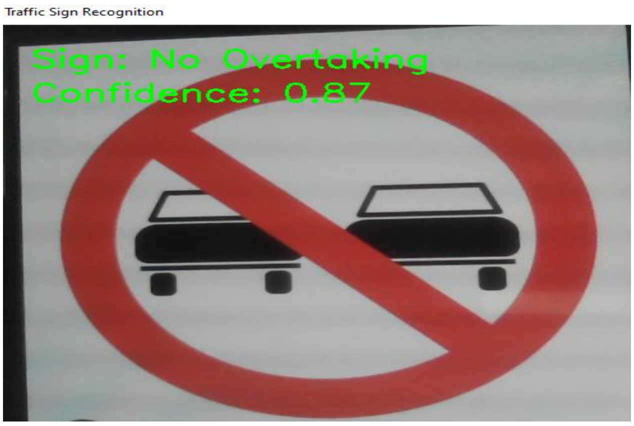

Fig. 4: Recognizing Speed Limit

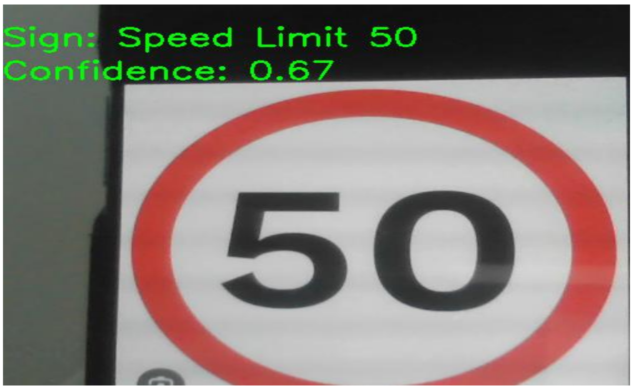

Fig. 5: Recognizing No Overtaking Sign

5. Conclusion

In this project, a real-time traffic sign recognition and voice alert system was developed to assist drivers in identifying road signs efficiently while driving. The system utilizes a deep learning-based Convolutional Neural Network (CNN), specifically Faster R-CNN, to detect and classify traffic signs in real time. By leveraging the German Traffic Sign Detection (GTSD) dataset, the model achieves high accuracy in recognizing various traffic signs under different environmental conditions, including variations in lighting, motion blur, and occlusions.

To enhance driver awareness, the system integrates a text-to-speech (TTS) engine that provides instant voice alerts upon detecting a traffic sign. This ensures that even if the driver fails to notice a sign visually, they receive an auditory notification, improving road safety and reducing the risk of traffic violations. The system processes video input from an onboard camera, evaluates the detected sign's confidence level, and then generates the corresponding voice output.

The experimental results demonstrate that the proposed system performs effectively with minimal delay, making it suitable for real-world deployment in vehicles. Future enhancements will focus on optimizing the model for embedded systems, improving detection accuracy in extreme weather conditions, and integrating additional driver assistance features for a more comprehensive safety solution.

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