RESEARCH PAPER

Vision Based Traffic Sign Identification With Opencv And Voice Alert System

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Abstract : Road safety has been highly impacted due to the rapid growth of the use of motor vehicle transport, which has caused injuries and fatalities due to accidents on the road. The accidents on the road are caused due to the bad driving habits of the drivers, such as distraction, drowsiness, speeding, and the inability to recognize or act on the traffic signs on the road. To overcome the challenges faced on the road due to the main recognition of traffic signs, the proposed research work aims at developing a Traffic Sign Identification and Voice Alert System based on deep learning techniques. For the proposed system, five different deep learning models will be developed and analyzed for the identification of the traffic signs using the video stream of the images on the road. The deep learning models developed will include the Simple Convolutional Neural Network, LeNet, AlexNet, ResNet-18, and Vision Transformer. The proposed system will help the drivers recognize the traffic signs on the road using the video stream images and will alert the driver through the Text-to-Speech system. The proposed system will help the drivers to improve the road safety conditions using the accurate recognition of the traffic signs on the road.

Key words: Deep Learning Algorithms, Driver Assistance System, Image Classification, OpenCV, Traffic Sign Recognition, Voice Alert System
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1. INTRODUCTION

Human error plays an significant role in traffic accidents, especially when drivers fail to properly observe traffic sign information due to factors such as lack of focus, being overly tired, or having delayed response times. To help alleviate some of the issues associated with human error, automated traffic sign recognition (TSR) has developed to assist through identifying road signs through image and video analysis and provide appropriate alerts to the driver in an appropriate amount of time [1]. Road signs make up an integral part of the transportation infrastructure, as they provide critical information regarding things like speed limits, warnings, and directions that help guide drivers down the road safely. Unfortunately, there are times when drivers fail to see certain traffic signs due to environmental conditions such as poor light, faded signs, or being blocked by other objects; these conditions reduce the driver's ability to react appropriately to the situation [2]. Therefore, real-time TSR has quickly become a critical component in intelligent transportation systems and driver-assist technologies. Typically, a TSR system is comprised of two main sub-processes: detecting the location of the traffic sign in input image or video and determining what type of sign has been detected as a result of the first phase. Detection is responsible for determining where the traffic sign is located; while classification is responsible for determining what type of sign. Presently, many of the advanced traffic sign detection algorithms rely heavily on deep learning techniques. Many recent studies have also demonstrated effective use of CNNs in the classification of the detected traffic signs. with detection frameworks for improving real-time recognition accuracy [3]. Even with modern CNN models, real-world recognition remains challenging because traffic signs may appear blurred, low resolution, or under poor environmental conditions. Therefore, researchers have introduced robust deep CNN designs and explainable AI methods such as Grad-CAM to ensure reliable predictions and interpretability in safety- critical driving applications [4].

There are several support systems that will provide additional assistance to drivers (e.g., the integration of TSR with alert sounds that allow an audible announcement of the traffic signs that a driver has recognized), thereby reducing a driver's constant awareness of road signs and allowing for quicker responses to driving commands by using an alert voice system that will announce the sign to the driver, raising the driver's situational awareness and reducing the driver's risk of not paying attention to or misinterpreting important information when driving [2]. Furthermore, voice control assistance with TSR (using OpenCV preprocessing and CNN classification) has been developed that provides real-time text-to-speech voice feedback to help with distraction-free driving [6]. Additionally, image classification systems using the CNN architecture have been shown to work very effectively, due to ability to automatically extract essential visual features such as edge, shape, and texture, in order to classify the different types of traffic signs accurately and efficiently. Numerous studies have demonstrated that CNN-based traffic sign recognition (TSR) systems provide high recognition rates under a variety of driving conditions, which makes them a good candidate for real-time driving applications [7]. Almost all deep learning-based algorithms use CNNs.

Deep learning has become increasingly popular due to its low computational cost and ability to process real-time camera images with great accuracy. One of the main techniques being used to solve this problem is a Convolutional Neural Network (CNN), which can detect and classify traffic signs at the same time. These capabilities make them valuable tools for developing Intelligent Transportation Systems, Traffic Monitoring Systems , and Autonomous Vehicle Systems . However, traditional image processing methods, are template matching, edge detection or color segmentation, often fail to produce satisfactory results when applied to road environments as a result of the numerous factors that complicate these tasks, such as background noise, variability in lighting conditions, and occlusion of traffic signs. Because of this, researchers interested in solving this problem have started looking for deeper learning techniques as an alternative to traditional image processing techniques to learn automatically from the data what are the features required for classification. Thus, it will be possible to generalise more readily with the data analyses than would be available when attempting to create manually crafted algorithms. Based on the research presented above, we would like to work to develop a Traffic Sign Board for use with your vehicle.

Road safety is dependent on traffic sign recognition as the traffic signs offer drivers a variety of instructions, including speed limits, warnings and directions. To help reduce accidents caused by missing signs or delayed driver response, automated systems have been created for Traffic Sign Recognition (TSR). Some systems will also provide drivers with a real-time voice alert immediately after recognition to inform them of the position of the sign [11]. The camera through which TSR systems capture road scene images then detects a specific region of the image where a sign is located, classifies the sign's category, and plays an audio announcement, allowing for a faster reaction time on the part of the driver, without taking their eyes off the road.

Although there are some real-world obstacles to recognizing traffic signs (such as noise, obscured backgrounds, and different illumination), the process of recognizing traffic signs through pre-processing, extraction of HOG features with anSVM classifier and applying it to recognize signs can be improved on every level. These processes will improve speed, quality of the input data for the HOG-based weights and allow for more accurate recognition of the shape of the different types of signs, thus enabling more accurate discrimination between the different types of traffic signs (12).

Currently, there are some recent based on deep learning object detection methods that had done well for detecting traffic signs in real time. Accurate classification, in addition to detection, is a requirement for reliable TSR systems. A proposed method for real-time recognition combines both detection methods and an attention-based deep CNN model trained on the GTSRB dataset with very high classification accuracy to enable implementation for smart vehicle environments [14]. By implementing an attention-based CNN model, the traffic sign feature learning is improved by focusing on the most relevant traffic sign regions – thus providing greater certainty of prediction even under conditions where the sign may be small in size, partly obscured or captured at a distance.

The goal of this research initiative is the formation of a fully automated method of detecting traffic signs via videos and creating audio cues for drivers depending upon their location. This approach will serve to decrease the incidence of driver accidents due to missed or unseen signs. In addition, the system will assist drivers by providing detailed and current information about the signs in their vicinity through the use of OpenCV, which allows for the takes in video coming from cameras and applying several forms of image preprocessing to improve image aspects such as resizing, reducing noise, and normalising the images before the images are used for detecting the traffic signs. Then we applied several deep learning models (CNN, LeNet, AlexNet, ResNet, and Vision Transformer)for detecting the different types of traffic signs, also we trained and evaluated each of those models on how accurately they detected traffic signs.After the detection of the system will generate an audio warning, so the driver is aware of the hand signal, via the text-to-speech (TTS) library. It can then provide the same information that is displayed on the signboard to the driver through audio output, reducing the annoyance of looking at the signboard too often while increasing driver awareness.

2. LITERATURE REVIEW

During the past few years, the recognition of traffic signage has become significantly more important due to its fundamental role in intelligent transportation systems Advanced Driver Assistance Systems and Autonomous Vehicles (AVs). One of the primary benefits of traffic sign recognition is that it can reduce the number of accidents that occur due to driver distractions, inappropriate visibility conditions and/or lack of situational awareness; therefore, a great deal of research has been completed using computer vision and deep learning technology to enhance detection and classification of traffic signs and improve real-time alert systems for drivers.

In [1], researchers developed a method for identifying traffic signs and an audio alert system which would produce an audible alert to drivers when a sign has been identified. This solution trained on the German Traffic Sign Recognition Benchmark, which included 43 classes of signs and over 51,900 images, and the authors reported a highly accurate classification of signs combined with an audio alert to increase driver awareness without requiring the driver to visually attend to the alerts. The authors concluded that the combination of CNN-based recognition of traffic signs with an audio feedback system provides a substantial benefit in assisting drivers and decreasing the likelihood of drivers missing traffic signs.

In this research paper, the server's preprocessing techniques of resizing images, normalizing image data and augmenting data affected the ratio of correctness that could be achieved in recognising objects. The experimental results obtained demonstrated how these and other preprocessing techniques affected the robustness of the models as well as the consistency of the detection when tested under different environmental conditions - thus providing evidence for the use of such systems in autonomous driving applications. In [3], a system was developed for detecting traffic signs and providing computer-based alerts via text-to-speech (TTS) for drivers. Traffic signs detected included speed limit, stop and no entry signs with detection coming from a live video feed.

Various studies have attempted to improve CNN recognition accuracy by constructing deep networks. An example is found at [4], in which the authors provided a non-augmented architecture for identifying traffic signs and obtained an approximate 95% validation accuracy using this architecture as a basis. Their conclusions support the usefulness of using CNNs to automatically extract complex features from images of traffic signs and accurately classify those images, and they provided evidence that deeper models lead to improved representation of complex patterns within traffic sign images.

A traffic sign recognition system with voice support is outlined [5]. A two-step approach of using OpenCV to perform preprocessing and then executing CNN to do classification will allow for immediate audio feedback after detecting traffic signs while consistently yielding reliable results across weather/ environmental conditions. The proposed solution also emphasizes minimizing distractionswhen you are behind the wheel and consolidating these computer vision/reconnaissance systems into one system using voice alerting to develop real world solutions for use while driving.

The authors of [6] did a comparative analysis of detection and recognition of traffic signals by using CNNs, Faster R-CNNs, and YOLOv4. The CNN-based classifiers had very high classification accuracy on the available benchmark datasets whereas YOLOv4 performed the best for detecting traffic signals in real-time. It can be seen from the study that there are tradeoffs between the speed of detection and the accuracy of the classification for real-time traffic signal recognition systems. These findings suggest that performance will need to be balanced against computational efficiency.

In the paper [7], describe explainable deep learning framework for traffic sign recognition that performs adequately in dark or noisy conditions. Further, techniques applied to increase understanding (for example, Grad-CAM) can be used to explain what features were learned from images, allowing the user to see how the model made its predictions, thus increasing transparency and ultimately leading to greater trust in a model than would be provided by a conventional deep learning model. The study highlights how important interpretability is for systems that recognize traffic signs particularly when putting into practice intelligent transportation systems that rely on public safety.

Some articles demonstrate the relevance of user-centered design approaches; hence, reliability and accuracy are considered important; therefore, the accuracy of models alone cannot be used to judge traffic sign recognition systems. Through employing the use of robust preprocessing and effective model design, reliable performance can be achieved even in environments that may affect traffic sign recognition systems (e.g., lighting changes, occlusion, and clutter). Moreover, users will get real-time notifications without the need for visual attention from the driver by employing the use of auditory feedback mechanisms. Collectively, these approaches suggest the need for intelligent traffic sign recognition systems achieve proper balance between accuracy, robustness, and real-time response with safety as a key factor.

2. METHODOLOGY

A. System Overview

The proposed traffic sign identification and voice alert is developed as a complete end-to-end intelligent system that combines strengths of deep learning-based vision perception, real-time video processing, and voice alert systems. It is designed to automatically recognize traffic signs from the live of the camera and provide visual and voice alerts to help the driver make critical decisions in real-time.

This system begins with the process of capturing video frames from the live video feed of the camera interface using the OpenCV library. This captured video frame is then processed using a series of preprocessing steps, including color space transformation, resizing, and normalization, to ensure the captured video frame is compatible with the trained deep learning models. The processed video frame is then fed into the trained deep learning models, which classify the traffic sign by learning discriminative features from the video frame.

After the identification of the traffic sign by the deep learning models, the predicted class index is then linked to the corresponding traffic sign label through the label mapping process. The identified traffic sign label is then placed on the video frame, providing a real-time feedback. Additionally, the voice alert process is also initiated by the Python-based text- to-speech engine, which translates the identified traffic sign label into an audio message.

The whole system is built using Python, where the PyTorch library is used for the training of the models, the OpenCV library is used for the processing of the video, and the text-to-speech library is used for the audio output of the system. The modularity of the system allows for the use of different deep learning models, which can be easily added in the future. The proposed framework clearly shows the effective integration of computer vision, deep learning, and speech technologies, which can be applied in the field of traffic sign recognition in real-time systems.

B. Dataset Collection and Label Mapping

The traffic sign recognition system will use labeled image dataset that contains different types of traffic signs. The image dataset will include regulatory signs, warning signs, and mandatory signs. The image dataset will be organized in a directory structure that is consistent with the ImageFolder format. The ImageFolder format is a directory structure that contains a folder for each class of image. The inclusion of images that have been taken under varying lighting conditions and angles will enhance the effectiveness of the models that are trained on the image dataset. The inclusion of images that have been taken under varying background conditions will also enhance the effectiveness of the models that are trained on the image dataset.

A separate CSV file will be maintained for the purpose of storing the mapping of class indices and the corresponding traffic sign names. The use of a separate CSV file for storing the mapping of class indices and the corresponding traffic sign names will enhance the readability of the output that is generated by the models. The use of a separate CSV file for storing the mapping of class indices and the corresponding traffic sign names will also enhance the flexibility of the models that are trained on the image dataset. The use of a separate CSV file for storing the mapping of class indices and the corresponding traffic sign names will also enhance the ease of maintenance of the models that are trained on the image dataset.

C. Data Preprocessing and Data Loading

All the images in the dataset go through the same preprocessing step, which is done using torchvision's transforms. The images are resized to the same dimension, 224 x 224 pixels, and then converted into tensor form for the network. Normalization of the images is done to ensure the same pixel value distribution for the images. Normalization helps the network converge faster and improves the overall generalization capability of the network. The preprocessing step is the same for both the training and the testing phases.

After the preprocessing step, the dataset is split into 80% for the training phase and 20% for the validation phase. The reason for the validation phase is to evaluate the performance of the network objectively. Two different DataLoader objects are created for the training and the validation phase. The shuffle parameter for the DataLoader for the training phase is set to true to improve the generalization capability of the network. The batch size for the network is set to 32, which can efficiently use the resources of the GPU or the CPU for the stable update of the gradient.

E. Model Architectures

To analyze the performance traffic sign task, five deep learning models with different depths and learning approaches were implemented and analyzed. These models range from transformer models to deep residual learning to shallow CNNs. These kinds of comparative analyses are useful for comprehending how various feature learning techniques impact the functionality and real-time performance of traffic sign classification systems.

Convolutional Neural Network:

The CNN model architecture also follows the hierarchical feature learning approach. When the image of the traffic sign is given as input to the CNN model, the convolutional filters scan the image in the spatial domain to extract low-level features such as edges and color transitions. As the image passes through the next convolutional layers, it extracts abstract features such as the boundary of the traffic sign and the representation of the symbol inside. The max pooling layers reduce the spatial size of the image, thus reducing the complexity of the algorithm and preserving the important features. The final layer is a classifier that gives the classification based on the features. This algorithm creates a highly efficient and interpretable learning process for traffic sign classification.

LeNet:

The LeNet technique utilizes a specific sequence of convolution and pooling to gradually decrease the spatial resolution while increasing the abstraction of features. The algorithm utilizes average pooling instead of the conventional max pooling. This helps to focus on the spatial information. However, it is not effective for complex features. In the case of traffic sign classification, the LeNet algorithm mostly learns shape-based representations. The algorithm is simple and hence suitable for benchmarking purposes.

AlexNet:

AlexNet is an extension of existing classical CNN algorithms in terms of depth and the number of filters used. The algorithm allows for hierarchical learning of complex features using its convolutional layers with nonlinear activation functions. The initial layers are used for learning features such as color and texture, while the deeper layers are used for learning features such as symbols and shapes related to signs. The addition of fully connected layers allows for better representation of the features learned by the algorithm. AlexNet has more parameters compared to other CNN algorithms and hence requires more computations.

ResNet:

Residual Network (ResNet-18) is a deep CNN architecture that was proposed specifically to resolve issues of degradation and vanishing gradients, which are common in traditional deep CNNs. ResNet-18 uses residual learning, which incorporates shortcut connections that enable feature maps to bypass one or more convolutional layers, thus enabling the network to learn residual functions rather than direct functions. ResNet-18 uses a series of residual blocks, which are essentially residual layers, to learn hierarchical representations of features from low-level edges to high-level semantic representations. ResNet-18 is particularly useful in traffic sign recognition, as its deep and stable architecture enables it to effectively distinguish between visually similar traffic signs by learning fine-grained spatial and structural information, thus improving its accuracy and efficiency, which makes it particularly useful in real-time applications.

Vision Transform:

Vision Transformer (ViT-B/16) is a transformer-based model that processes images differently from the CNN approach. The ViT model segments the images into small patches and utilizes self-attention to learn the global relationships between different parts of the image. This allows the ViT model to understand the whole structure of the images, which is beneficial in situations where traffic signs are not fully visible or appear in different orientations. The ViT is considered a more modern approach that can potentially produce good classification results for the images. In this project, the ViT is incorporated in the model to test the effectiveness of the CNN feature learning method in comparison with the attention learning method of the ViT model. The classification head of the ViT is changed according to the number of traffic sign classes.

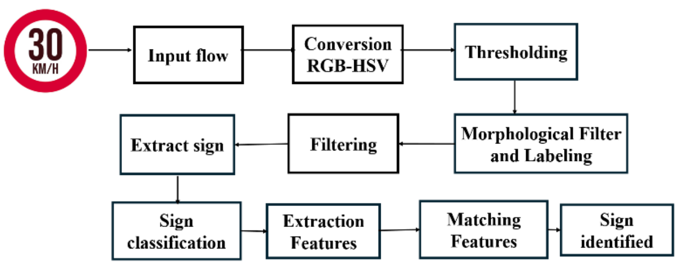

Fig 1: Vision-Based Sign Processing Flow

H. Real-Time Video Capture and Preprocessing using OpenCV

OpenCV is employed to interact with the camera and obtain video frames in real time. Each captured frame was subjected to a number of preprocessing tasks before being fed into the classification model. The first preprocessing task involved the transformation of the captured frame from the BGR color channel to the RGB color channel to facilitate compatibility with the deep learning models. The captured frame was then resized to a fixed size of 224 × 224 pixels to facilitate consistency with the input size used during training. To facilitate consistency and improve the performance of the model, the pixel values of the frame were normalized using the same normalization parameters used during the training process. The preprocessed frame was then transformed into a tensor and fed into the chosen deep learning model for processing. The model then provided a real-time prediction the corresponding traffic sign class, and upon successful detection, the detected sign was relayed to the driver using a Text-to-Speech-based voice alert system.

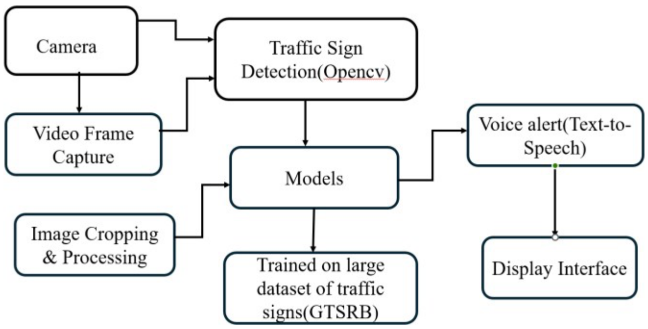

Fig 2: System Architecture of the Proposed Model

J. Voice Alert Generation using pyttsx3

To increase the level of driver awareness, the system talks up immediately after recognizing the traffic sign. This is made possible by use of the text-to-speech (TTS) engine, which is implemented with the help of Python's pyttsx3 library. The speaking rate is set in such a way that the driver can clearly hear the announcement. To avoid the system shouting the same traffic sign repeatedly, as the frames may contain the same sign label many times, the system talks only when it recognizes a new sign label. This voice alert system can help the driver understand the signs without having to look at the signs all the time.

3. RESULT AND ANALYSIS

A. Training Performance Analysis

The performance analysis of the training reveals how each of the assessed deep learning models learns uniquely. The shallow models such as SimpleCNN and LeNet have rapid learning and rapid convergence but plateau in performance early on, preventing them from learning the more complex features of the traffic signs. AlexNet goes further with increased training accuracy but also experiences changes in validation performance, showing how it depends on parameter updates. ResNet-18 uses residual learning to achieve convergence, generalization, and prevention of overfitting. The Vision Transformer requires a few more training steps but still retains its relationship between the training and validation sets, showing that learning is taking place. The global context is being appropriately captured through its attention mechanism-based features, hence its stable and improved performance.

B. Accuracy Comparison of Deep Learning Models

A brief analysis of the relative performance of the models suggests that there is a significant difference in the various models of deep learning architecture. The shallow models of SimpleCNN and LeNet have an average accuracy, but they are not capable of dealing with more complex or similar traffic signs. The AlexNet has a higher accuracy than the baseline by expanding the depth of the features extracted from the image, but it also has a higher computation cost. The ResNet-18 has a high accuracy by maintaining the high score throughout the model using the residual connections and the good feature representation. The Vision Transformer takes it to the next level by attaining the highest accuracy by the self-attention mechanism in learning of the global context of the image, which allows the traffic sign recognition to work properly even with the changing visual representations.

Table 1:Models accuracy comparison

Model	Accuracy (%)
CNN	78
Lenet	72
Alexnet	81
Resnet	85
Vision Transform	92

C. Performance Evaluation

The research study is centered on the Vision Transformer (ViT) because it had the highest accuracy compared to other models. There graph below shows the performance of the ViT, CNN, LeNet, AlexNet, ResNet18, and other models, indicating the superiority of the ViT because of its complex architecture. The ViT has the ability to capture global information, unlike other CNN models, which have the ability to detect local features only, hence improving the detection of objects because of the variations in lighting conditions, scales, and complexity of the background.

The accuracy of the model improves steadily as the epochs increase, indicating the effectiveness of the learning process and feature extraction. The fact that the training and validation accuracy converge indicates good generalization capability and minimal overfitting. Similarly, the losses for the training and validation data converge steadily, indicating good learning behavior for the entire epoch. Thus, that the ViT achieves higher accuracy, reliability, and robustness than the other models. The ability of the ViT to understand the global image representation makes it the most suitable for the identification of traffic signs in real-time scenarios, thus improving the detection of signs using the voice alert system.

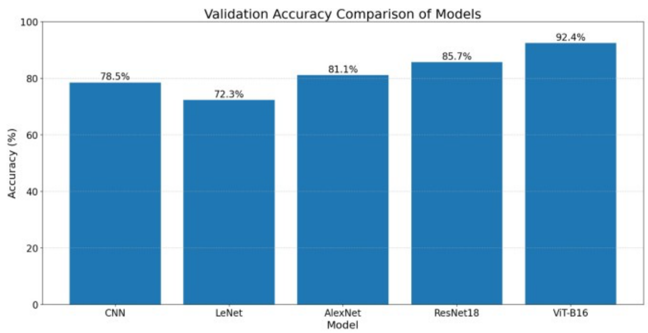

Fig 3: Validation accuracy comparison of different deep learning models

Fig 4: ViT-B16 Accuracy Performance

Fig 5: Loss convergence of the Vision Transformer model

D. Real-Time System Implementation

The system demonstrates real-time traffic sign integration of a cohesive frontend and backend. Utilizing OpenCV to capture live video feed from the camera, each frame of the video is constantly analyzed and fed into the pre-trained deep learning model for classification. Real-time recognition of various signs such as Stop, Yield, General caution and Speed Limit is achieved while the video is playing. Simultaneously, the voice alert module comes into effect and begins to alert the user in real-time as soon as the signs are recognized on the screen, ensuring that users are aware of the road signs without having to focus on the screen.

The results have proven the viability of the system, ensuring that real-time performance is achieved with minimal delays. The integration of deep learning-based traffic sign recognition, OpenCV for handling video feed, and text-to- speech systems makes this system more efficient and reliable for the purpose of intelligent transportation and road safety systems.

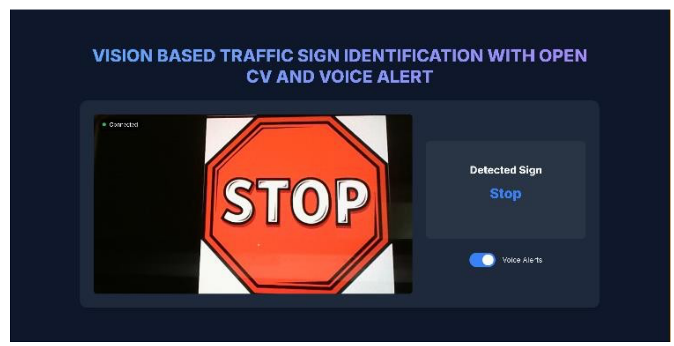

Fig 6: Stop traffic sign detection and voice alert.

Fig 7: Yield detected sign and voice alert

Fig 8: 30km/h Speed limit detection and voice alert

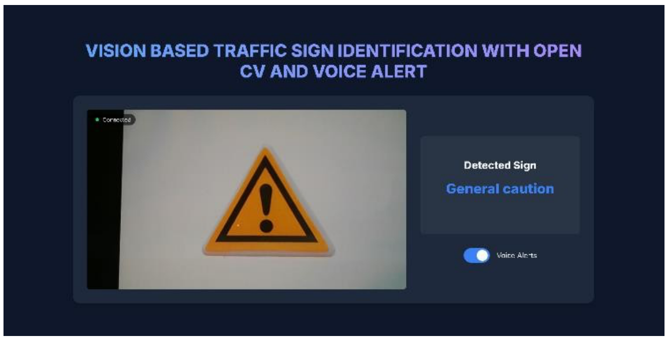

Fig 9: General caution detection and voice alert

Fig 10: Yield detected sign and voice alert

4. CONCLUSION

In this paper, we have proposed a vision-based system that recognizes traffic signs and provides voice alerts. The system combines the real-time video processing capability of OpenCV with deep learning for traffic sign recognition. The system is able to recognize traffic signs from a video captured by a camera, thus reducing driver distraction and ensuring road safety. We have used various deep learning models to identify the model that would work best for traffic sign recognition. The result shows that the model that works best for traffic sign recognition is the Vision Transformer (ViT-B16) model, which has the highest accuracy in learning the characteristics of traffic signs. The training and validation plots show that the model is able to train and validate well. The combination of the model with OpenCV ensures smooth real-time processing, and voice alerts are effective. The system is robust, scalable, and deployable, especially in Advanced Driver Assistance Systems (ADAS) and Intelligent Transportation Systems (ITS). Future research will concentrate on improving robustness to different lighting and environmental conditions, increasing the number of traffic signs, and optimizing the system for embedded systems to enable true in-vehicle real-time processing on edge computing platforms.

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