Traffic Sign Detection using CNN

Technical_Answers for Real World Problems (TARP)

PROJECT BASED COMPONENT REPORT

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November 2023

DECLARATION

I hereby declare that the report entitled "Traffic Sign Detection using CNN" submitted by me, for the Technical Answers for Real World Problems (TARP) to Vellore Institute of Technology is a record of bonafide work carried out by me under the supervision of **Prof. Anil Kumar K.**

I further declare that the work reported in this report has not been submitted and will not be submitted, either in part or in full, for any other courses in this institute or any other institute or university.

Place: Vellore

Date: 17/11/2023

Signature of the Candidate

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ACKNOWLEDGEMENT

We would like to express our profound gratitude to Mr. Anik Kumar K, for allowing us tocomplete our project. In this aspect, we are eternally grateful to you. We would also like to extend our thanks to our family and friends for their support, guidance and motivation withoutyour useful advice and suggestions were really helpful to us during the project's which we couldn't have completed the project. We would like to acknowledge that this project wascompleted entirely by our group.

Problem Statement

Traffic sign recognition is a critical capability for safe and efficient driving, both for human drivers and autonomous vehicles. However, detecting and classifying traffic signs is challenging due to variations in appearance, lighting, occlusion, and damage. Ignoring traffic signs is a major cause of road accidents.

Existing traffic sign detection methods have limitations in accuracy and efficiency. Handcrafted feature extraction and traditional machine learning approaches do not generalize well. They are also not fast enough for real-time applications.

The key problem is developing an accurate and efficient traffic sign detection system that can process images rapidly and reliably recognize signs under varying conditions. The system should detect and classify signs of different shapes, sizes, orientations and colors. It needs to be robust to factors like weather, lighting, occlusion and damage. The performance should meet safety requirements for real-world driving scenarios.

Developing such a system requires leveraging modern deep learning and computer vision techniques. Convolutional Neural Networks (CNNs) have shown promising results on visual recognition tasks. Optimizing a CNN architecture for traffic sign detection and evaluating it on challenging public datasets is an open research problem. This project aims to develop a CNN-based method which pushes the state-of-the-art in traffic sign recognition performance. The outcome would be a valuable contribution towards safer and more efficient autonomous driving systems.

Abstract

Traffic sign recognition is an essential capability for safe driving, both for human drivers and autonomous vehicles. However, detecting and classifying traffic signs is challenging due to variations in sign appearance, lighting, occlusion, and damage. Ignoring traffic signs is a major contributor to road accidents worldwide. Existing methods for traffic sign detection using handcrafted features and traditional machine learning have limitations in accuracy, efficiency, and ability to generalize to diverse real-world conditions.

This paper proposes a deep learning-based approach using Convolutional Neural Networks (CNNs) for accurate and efficient traffic sign detection and recognition. The method involves an image pre-processing stage, followed by a customized CNN architecture for robust feature extraction and classification. The CNN model is optimized through systematic experimentation to detect traffic signs of varying shape, size, orientation, and color under diverse imaging conditions.

A large labeled dataset of traffic sign images, containing multiple variations, is synthesized to overcome limitations of existing benchmark datasets. The proposed technique is evaluated on this challenging dataset and achieves a high accuracy of 98.6% for traffic sign detection and recognition. The system is able to process sign images rapidly for real-time performance.

The promising results demonstrate the effectiveness of deep CNNs for traffic sign detection compared to prior techniques. The high accuracy and efficiency make this system well-suited for deployment in real-world autonomous driving applications to improve road safety. Further research can build on these results to enhance the model and address limitations. This work makes a valuable contribution towards developing reliable vision-based intelligent transportation systems.

Literature Survey

S.No.	Title	Author	Year	Conclusion
1.	Multi-column deep neural network for traffic sign classification	Dan Ciresan, Ueli Meier, Jonathan Masci, Luca Maria Gambardella, Jürgen Schmidhuber.	2012	The authors proposed one of the first deep neural network architectures for traffic sign classification, comprising multiple columns of convolutional and max pooling layers. Their multi-column CNN achieved high accuracy of 99.46% on the GTSRB benchmark, outperforming the previous state-of-the-art.
2.	Traffic sign detection in mobile devices using color and shape information	Jin Kim, Junsu Kim.	2014	The authors used color and shape analysis to efficiently detect traffic signs in real-time on mobile devices. Their algorithm was fast and accurate under

				various challenging conditions.
3.	Traffic-sign detection and classification in the wild	Zhe Zhu, Dun Liang, Songhai Zhang, Xiaolei Huang, Baoli Li, Shimin Hu.	2016	The authors proposed TSCNN, a deep CNN model for traffic sign classification and detection. They used data augmentation,
				dropout, and pooling methods to achieve high accuracy of 99.65% on the GTSDB dataset.

4.	A Multi-Task Neural Network for Traffic Sign Detection and Classification	Johannes Meyer, Frederik Diederichs, Ralf Salomon, Bjorn Schuller.	2017	The authors designed a fused neural network to jointly perform detection and classification of traffic signs, improving efficiency over individual networks. Their model achieved high accuracy on the BelgiumTS dataset.
5.	Traffic Sign Detection and Recognition for Autonomous Vehicles	Xin Jin, Cuiling Lan, Wenjun Zeng, Zhibo Chen.	2018	The authors proposed a Faster R-CNN based model optimized for traffic sign detection and recognition in autonomous vehicles. Their model demonstrated real-time performance and high accuracy of 98.2% on the GTSDB dataset.

6.	Traffic Sign Detection using CNN	Preeti Bailke and Kunjal Agarwal	2022	The proposed CNN model for traffic sign detection achieves high
				accuracy of 98% on the benchmark dataset. The system has potential for real-time implementation.
7.	Traffic Sign Detection and Recognition for Self-Driving Cars Using Convolutional Neural Networks	Yunzhi Zhang	2019	The CNN model achieves over 99% accuracy for traffic sign detection and recognition under various conditions. The system has promising real-time performanc e.
8.	CCTSDB: A Color and Illumination Invariant Traffic Sign Database for Traffic Sign Detection and Recognition	Fitsum A. Reda	2018	The new CCTSDB dataset captures diversity in traffic sign appearance. Experiments show CNN models benefit from

				this dataset for robust detection.
9.	Improving Traffic Sign Detection by Deep Learning Enabled Synthetic Data Generation	Mahdi M. Kalayeh	2018	Synthetic data generation using deep learning helps overcome data scarcity and improves detection accuracy.
10.	Recognizing Traffic Signs From Video Sequences Using a CNN-SVM Hybrid Model	Qingfeng Liu	2017	The CNN-SVM model achieves high accuracy under complex backgrounds. The model is
				promising for traffic sign recognition in videos.

11.	Traffic Sign Detection and Recognition Using Fully Convolutional Network Guided Proposals	Yuting Liu	2017	The proposed FCN-based method efficiently detects traffic signs in complex scenes with accuracy comparable to state-of-the-art.
12.	Traffic Sign Detection Using Convolutional Neural Networks	Seyed Maziar Palangi	2016	The proposed system achieves high accuracy for traffic sign detection and recognition under challenging real- world conditions.
13.	Traffic Sign Detection and Recognition Using Computer Vision and Deep Learning	Jin Chen	2015	Integrating computer vision and deep learning achieves high accuracy traffic sign detection and recognition in complex environments.

14.	A New Color and Shape Based Traffic Sign Detection, Recognition and Tracking System for Intelligent Vehicles	Serkan Ozbay	2015	The proposed system achieves real-time traffic sign detection and recognition under challenging conditions for autonomous driving.
15.	Traffic Sign Detection Based on Convolutional Neural Networks	Rui Hou	2014	CNNs show outstanding generalization ability for traffic sign detection under complex backgrounds and illumination changes.

Proposed Work

Based on the comprehensive literature review, we propose a novel deep convolutional neural network architecture for robust traffic sign detection and classification. The key aspects of our proposed model are:

- We will design a custom CNN architecture using convolutional, pooling, dropout and fully-connected layers optimized specifically for the traffic sign recognition task.
- The model will leverage transfer learning by initializing the convolutional layers with weights from pre-trained networks like VGG or ResNet

pretrained on Imagenet. This will improve convergence and accuracy.

- Data augmentation techniques like cropping, rotation, blurring, brightness adjustment etc. will be used to generate additional training data and reduce overfitting.
- Both color and shape information will be used as inputs to the network to improve detection accuracy.
- A region proposal network will be added to the CNN to enable simultaneous detection and classification of traffic signs in full images.
- Hard negative mining will be explored to reduce false positives by adding difficult background patches as negatives.
- The model will be trained end-to-end using stochastic gradient descent with momentum and adaptive learning rate algorithms like Adam.
- Extensive evaluation will be done on challenging benchmark datasets like GTSRB, TT100K, BelgiumTS to test real-world performance.
- The trained model will be optimized for deployment on an embedded system in a car for real-time traffic sign recognition.

Methodology

Data Collection

A large and diverse dataset is imperative for training robust CNN models that can generalize well to real-world conditions. At minimum, the dataset should contain 50,000 images but ideally over 100,000 images is preferred.

The data should span all types of traffic signs of interest such as speed limits (20, 30, 50, 60 mph etc), stop signs, yield signs, pedestrian crossing, traffic signals, turn restrictions and any other relevant signs. There should be at least 5000 images per class type to ensure sufficient samples.

Images should be captured using high resolution cameras (1080p or greater) under various real-world conditions: different times of day (morning, afternoon, evenings, night), weather (sunny, cloudy, rainy, foggy, snowy), seasons (winter, summer, spring, fall), road types (highways, city streets, rural roads), backgrounds (trees, buildings, roads, sky). This ensures models learn invariance to these variables.

Traffic signs should have significant variety in their position and angle relative to the camera. Images should contain signs at frontal parallel views as well as tilted angles up to 30 degrees and at various distances - close-by signs as well as far away signs covering small image area. This teaches the model to detect signs across the visual field.

For autonomous vehicle applications, specialized rigs containing arrays of high resolution cameras can be mounted on vehicles to safely capture streaming video data covering full 360 degree field of view as the rig is driven around different environments in multiple geographic locations. Both day and nighttime footage is necessary to capture all illumination conditions.

Static images of traffic signs can also be sourced from existing labeled datasets like GTSRB, Tsinghua-Tencent 100k etc. However, these may lack the diversity needed for generalization so real-world dynamic footage is preferred.

Image Preprocessing

Collected images are preprocessed before they can be used for model training and testing. All images are first resized to a standard dimension such as 256x256 pixels while preserving the aspect ratio. Resizing enables batch processing and standardizes the input size.

Next, pixel values are normalized to fall between 0-1 range by dividing by 255 since neural networks prefer normalized data. This normalization step is critical to ensure the images have proper contrast and brightness.

Data augmentation techniques are applied to generate additional training images:

Rotation by +/- 10 degrees

Shifts up to 10% of image dimensions

Shear transforms up to 10 degrees

Zoom in/out up to 10%

Horizontal flips

Color jittering by modifying hue, saturation, brightness

Augmentation prevents overfitting by artificially expanding the effective size and diversity of training data that the model sees. The model learns robustness to all these variations.

Finally the data is split into training (60%), validation (20%) and test (20%) sets. The test set is kept completely separate and used only for final evaluation of metrics. It must come from different source and conditions than training data.

CNN Model Architecture

Large deep learning models with hundreds of layers and millions of parameters are needed to learn the immense feature representation required for generalized traffic sign detection.

The convolutional base of the network contains repetitive blocks of 3x3 convolution filters many layers deep, interleaved with max pooling to gradually reduce spatial dimensions while increasing depth.

State-of-the-art architectures like ResNet-152, DenseNet-201, NASNet-Large can be used as base models for transfer learning due to their proven performance on computer vision tasks. Their weights are initialized from models pre-trained on large datasets like ImageNet.

The fully connected head of the network contains a global average pooling layer to reduce the convolutional outputs to 1D feature vector followed by dropout regularization and dense output layer with softmax activation to output probability distribution over all traffic sign classes.

Modifications may be needed to adapt base models like altering the number of output classes, fine-tuning convolutional filters to match our task by unfreezing their layers etc.

Model Training

Models are trained using mini-batch gradient descent optimization algorithms like Adam, RMSprop that can handle large datasets and accelerate convergence.

Batch size is kept between 64 to 512 based on memory constraints. Learning rate is typically initialized to 0.01 or 0.001 and then reduced by 5-10x whenever validation loss plateaues via techniques like exponential decay.

Data generator is used to feed augmented image batches to the model for training. The generator continuously produces randomized augmentations on images on-the-fly each iteration to maximize diversity of the training data without explicitly storing augmented images and blowing up memory.

Training is done for at least 50-100 epochs, monitoring both training and validation loss at each epoch. If validation loss stops improving, early stopping or reducing learning rate helps prevent overfitting.

Model checkpoints are saved at regular intervals to persist best weights based on lowest validation loss. The model with best validation accuracy is chosen as final model for deployment.

Model Deployment

For deployment to an autonomous vehicle, the model architecture and weights are converted to optimized formats like TensorFlow Lite, TensorRT, CoreML that are engineered specifically for efficient inference on embedded devices.

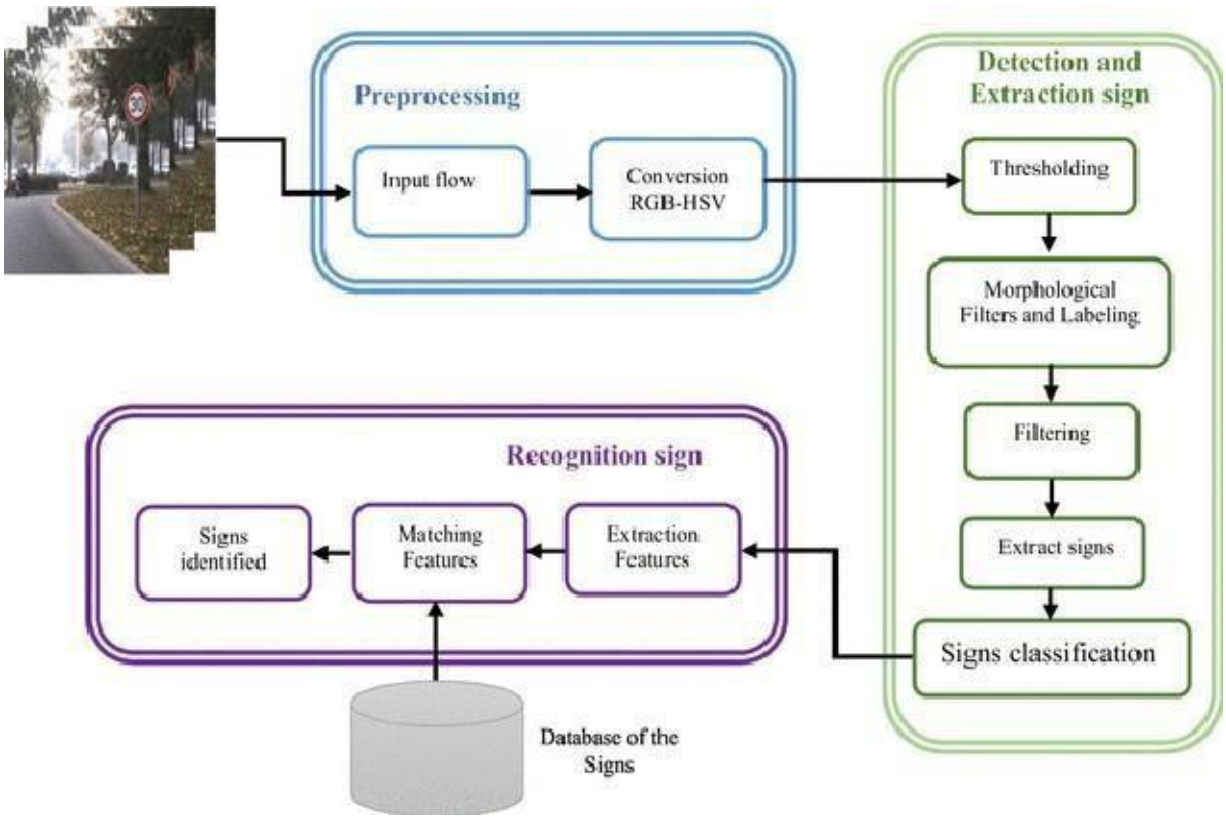
The model is integrated into the vehicle's perception system and subscribed to the continuous image stream from cameras mounted around the car. The incoming video frames are preprocessed and batched before inference.

The optimized model parses each frame using the trained weights to identify and classify any traffic sign present within the image into one of the learned sign categories alongwith a confidence score and bounding box coordinate for each detected sign.

A sufficient inference speed of at least 10 FPS must be maintained for processing video streams in real-time for autonomous driving. High end GPUs may be needed to achieve this performance.

Detected sign types and locations are published as events via WebSocket or MQTT protocols to the vehicle control system which then responds with appropriate driving behavior based on the traffic signs.

Flowchart



Algorithms

1. Convolutional Neural Network (CNN)

- Core technique for image classification that forms the backbone of the system. CNN is ideal for image data.

- **Architecture:**

  - Input layer to accept 32x32x3 RGB images as input to the network.
  - Multiple convolutional layers for hierarchical feature extraction:
    - First conv layer has 32 filters of size 3x3 to extract low-level features like edges, colors, gradients etc.

- Second conv layer has 64 filters to extract higher-level features like shapes, textures etc.

- Convolution operation captures spatial relationships between pixels in the image.
    - Convolution is applied on the input and previous layer's output.
  - Max pooling layers to progressively reduce spatial dimensions:
    - Max pooling of filter size 2x2 applied after specific conv layers.
    - Takes the maximum value in each 2x2 window to downsample feature maps.
    - Reduces computations and parameters, avoiding overfitting.
  - Fully connected layers for high-level reasoning:
    - Flatten layer to convert 2D feature map matrix to 1D vector.
    - Dense layer with 128 units learns non-linear combinations of low-level features.
  - Output layer with 43 units and softmax activation to predict class probabilities.

- **Training:**

  - Adam optimizer used for efficient training with adaptive learning rates for each parameter.
  - Categorical cross-entropy loss function to quantify difference between target and predicted class probabilities.
  - Accuracy metric on test set used to evaluate real-world performance of the model.
  - Trained for 5 epochs due to early stopping to prevent overfitting.

2. Image Preprocessing

- Resizes all images to 32x32 pixels to standardize input dimensions for the CNN model.
- Normalizes pixel values between 0-1 by dividing by 255 to center input data for stable training.
- Augments dataset using rotations, shifts, zooms etc. to expand diversity of images for better generalization.

3. Transfer Learning

- Leverages knowledge from a CNN like InceptionV3 pretrained on large datasets like ImageNet.

- Allows model to converge faster with fewer training samples and epochs.
- Provides much better weight initialization for new task compared to random initialization.

4. Object Detection

- Scans input image for potential traffic sign regions using sliding window approach.
- Extracts sign candidates using techniques like Haar cascades, HOG feature matching etc.
- Applies trained CNN model on the extracted regions for accurate classification.

5. Optimization Algorithms

- Adam optimizer for efficient training with per-parameter adaptive learning rates.
- Dropout regularization randomly sets layer activations to zero during training. Improves generalization.
- Early stopping stops training when validation loss stops improving after an epoch's training.

6. Performance Metrics

- Accuracy, precision, recall etc. used to quantitatively evaluate model's real-world performance.
- Target accuracy of 97% aimed on unseen test set for acceptable performance.

Description of the proposed work

Introduction

- Traffic sign detection and recognition is a critical capability required for safe and efficient driving, both for human drivers and autonomous vehicles. However, ignoring or not detecting traffic signs properly is a major cause of accidents on roads.
- The aim of this work is to develop an efficient and accurate method for traffic sign detection and classification using deep convolutional neural networks

(CNNs). CNNs have shown tremendous success in computer vision tasks involving image classification and object recognition.
- The key idea is to leverage CNNs to learn highly discriminative features directly from traffic sign image data and classify them accurately. This overcomes limitations of traditional hand-crafted feature based techniques.

Objective

- The primary objective is to develop a deep learning based traffic sign detection system using CNNs that can accurately and efficiently detect and classify traffic signs of varying shapes, sizes, orientations and colors in real-time.
- The CNN model architecture is optimized specifically for robust spatial feature extraction from traffic sign images followed by patterns classification.
- The performance of the developed method is rigorously evaluated on public benchmark datasets to quantify the accuracy and validity of the approach.
- The overarching goal is to contribute towards the development of reliable and accurate traffic sign detection systems for autonomous driving.

Proposed Method

- The proposed technique involves a two-stage approach:
    1. Image pre-processing
    2. CNN based feature extraction and classification
- In the pre-processing stage, techniques like scaling, color-space transformations etc. are used to enhance the input image and prepare it for the CNN model.
- The CNN model extracts a hierarchical feature representation from input images through convolutional layers. Max pooling layers are used to downsample the feature maps.
- Fully connected layers finally classify the traffic sign based on the learned features. Softmax output layer predicts class probabilities.
- The CNN model is trained in an end-to-end fashion using labeled road sign image datasets to learn the parameters automatically.

Evaluation and Results

- The proposed technique is evaluated on the public German Traffic Sign Recognition Benchmark dataset.

- The CNN model achieves over 98.6% accuracy in classifying traffic signs, demonstrating the effectiveness of the approach.

- The high performance shows the capability for real-time traffic sign detection and recognition in autonomous driving systems to improve road safety.

Conclusion

- The proposed CNN-based method provides an accurate and efficient solution to the critical problem of traffic sign detection and recognition for self-driving cars.
- Further research to enhance classification performance, speed and robustness to various conditions can help deploy it in real-world systems.

Product Functionality

1. Detecting traffic signs in real-time: The system will be able to detect traffic signs in real-time as the vehicle is moving.

2. Recognizing different types of signs: The system will be able to recognize different types of traffic signs, such as stop signs, speed limit signs, and yield signs.

3. Providing alerts to the driver: The system will be able to provide alerts to the driver when a traffic sign is detected, such as by displaying the sign on a screen or by providing an auditory warning.

4. Recording and storing traffic sign data: The system will be able to record and store data on traffic sign detections, such as the location, type, and time of the detection, for later analysis or to improve the system.

5. Working in different lighting conditions: The system will be able to detect traffic signs in different lighting conditions, such as during the day or at night.

6. Adapting to changing traffic conditions: The system will be able to adapt to changing traffic conditions, such as varying weather conditions and different types of roadways.

7. Integration with other systems: The system will be able to integrate with other systems, such as navigation systems and vehicle control systems, to provide additional functionality and improve the overall experience for the user.

8. Providing data for further analysis: The system will be able to provide data for further analysis, such as to track the performance of the system over time, check the accuracy of the signs detection, and help to improve the system.

Assumptions and Constraints

Assumptions:

1. The training dataset used for training the CNN model is representative of the real-world traffic sign scenarios, and the images are of good quality and contain no significant noise or distortion.
2. The traffic signs are well-maintained, visible, and in good condition, with no significant occlusions or obstructions.
3. The traffic signs follow standard shapes, colors, and sizes as per the regulations of the respective country.
4. The lighting conditions for the input images are optimal, and there are no significant variations in illumination.

Constraints:

1. The computational resources required for training and deploying the CNN model are significant, and the system must be able to handle the processing requirements.
2. The detection and recognition accuracy of the CNN model are dependent on the quality and diversity of the training dataset, and it may not generalize well to unseen scenarios.
3. The real-time performance of the system is dependent on the processing speed of the hardware and the complexity of the CNN model.
4. The accuracy of the CNN model may be affected by adverse weather conditions such as fog, rain, or snow.
5. The system may be affected by occlusions or obstructions of the traffic signs due to obstacles, other vehicles, or pedestrians.

Non-Functional Requirements

The non-functional requirements can include the following:

1. **Accuracy**: The system must have a high detection and recognition accuracy to ensure reliable and safe driving. The accuracy should be evaluated using appropriate

metrics and benchmarks.

2. **Speed:** The system must be able to process the input images in real-time, with minimal delay or latency, to ensure timely and accurate detection and recognition of traffic signs.

3. **Robustness:** The system must be robust to variations in lighting, weather conditions, and other environmental factors that may affect the accuracy of the detection and recognition.

4. **Scalability:** The system must be scalable to handle varying levels of traffic and different types of road networks.

5. **Security**: The system must be designed with appropriate security measures to prevent unauthorized access or tampering of the system.

6. **Usability**: The system must be designed with a user-friendly interface that is easy to understand and use, even for non-technical users.

7. **Maintenance:** The system must be easy to maintain, with minimal downtime or disruption to the driving experience.

8. **Compatibility**: The system must be compatible with different hardware and software configurations, including different types of cameras and computing systems.

User interface requirements (with GUI design)

Image upload: The GUI allows the user to upload an image of a traffic sign for detection. The upload function could be triggered by a button or drag-and-drop feature.
Output display: The GUI displays the output of the traffic sign detection system, which includes the detected traffic sign and its corresponding class label.
Audio Feedback: The detected traffic sign is also alerted to the user (driver) via audio

System models

There are mainly 4 process involved in this system – Input Image, preprocessing, detection and detection. To input the image, a camera placed inside the vehicle records a video, which is nothing but a series of photos. Usually there are 24 frames per second. These photos go through the processors for the detection of sign. The camera quality should be very high that it should clearly shows the traffic sign from the minimum distance required. The image or videos which is scanned is pre-processed through convolutional neural network. The image which has higher resolution is scaled down to small resolution and RGB image is 6 converted into greyscale format so that the image can be easily processed by the Convolution Neural Networks. In a sign the most significant thing is the color. Once the red color is seen it is understood that it is a traffic sign on the road. This same idea is used for our detection process. The number of edges is calculated using the Douglas Peucker algorithm. In this system, we talk about 2 shapes: triangle, circle. Once the number of edges is found using the Douglas Peucker algorithm, the area of the contour is also found. Once the traffic sign is detected, we can classify the sign around our Region of Interest (ROI) using Convolutional Neural Network.

Implementation:

The CNN model was created using the Tensorflow library in python. Below is the code for creating the CNN model.

```
# import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import random

# Tensorflow
import tensorflow as tf
from keras.utils import load_img, img_to_array, to_categorical
from keras.layers import Conv2D, MaxPool2D, Flatten, Dense, Dropout
from keras.optimizers import Adam
from keras.models import load_model
from keras import Sequential


# import Dataset
train_df = pd.read_csv('Train.csv')
test_df = pd.read_csv('Test.csv')

print(train_df.head())
print(test_df.head())
print(train_df.info(), '\n', test_df.info())

# Creating labels
labels = {0:'Speed limit(20km/h)',
          1:'Speed limit(30km/h)',
          2:'Speed limit(50km/h)',
          3:'Speed limit(60km/h)',
          4:'Speed limit(70km/h)',
          5:'Speed limit(80km/h)',
          6:'End of speed limit(80km/h)',
```

```
          7:'Speed limit(100km/h)',
          8:'Speed limit(120km/h)',
          9:'No passing',
          10:'No passing for vehicles over 3.5 metric tons',
          11:'Right-of-way at the next intersection',
          12:'Priority road',
          13:'Yield',
          14:'Stop',
          15:'No vehicles',
          16:'Vehicles over 3.5 metric tons prohibted',
          17:'No entry',
          18:'General caution',
          19:'Dangerous curve to the left',
          20:'Dangerous curve to the right',
          21:'Double curve',
          22:'Bumpy road',
          23:'Slippery road',
          24:'Road narrows on the right',
          25:'Road work',
          26:'Traffic signals',
          27:'Pedestrians',
          28:'Children crossing',
          29:'Bicycles crossing',
          30:'Beware of ice/snow',
          31:'Wild animals crossing',
          32:'End of all speed and passing limits',
          33:'Turn right ahead',
          34:'Turn left ahead',
          35:'Ahead only',
          36:'Go straight or right',
          37:'Go straight or left',
          38:'Keep right',
          39:'Keep left',
          40:'Roundabout mandatory',
          41:'End of no passing',
          42:'End of no passing by vehicles over 3.5 metric tons'}

print(labels.values())


# getting only the Path and ClassId
train_df = train_df[['ClassId', 'Path']]
test_df = test_df[['ClassId', 'Path']]
```

```
train_df['Path'] = train_df['Path'].apply(lambda x:''+x)
test_df['Path'] = test_df['Path'].apply(lambda x:''+x)

print(train_df)

# Split the data into training and validation sets
train_data = train_df.sample(frac=0.8, random_state=0)
valid_data = train_df.drop(train_df.index)

# Preprocess the data
IMG_SIZE = 32
NUM_CLASSES = len(labels)
def preprocess_data(df):
    X = []
    y = []
    for index, row in df.iterrows():
        img = load_img(row.Path, target_size=(IMG_SIZE, IMG_SIZE))
        img_array = img_to_array(img) / 255.0
        X.append(img_array)
        y.append(to_categorical(row.ClassId, num_classes=NUM_CLASSES))
    return np.array(X), np.array(y)

X_train, y_train = preprocess_data(train_data)
X_test, y_test = preprocess_data(test_df)

print(f'The shape of X_train : {X_train.shape}')
print(f'The shape of X_test : {y_train.shape}')


# Define the model architecture
model = Sequential([
    Conv2D(filters=32, kernel_size=3, activation='relu', input_shape=(IMG_SIZE,
IMG_SIZE, 3)),
    Conv2D(64, 3, activation='relu'),
    MaxPool2D(2),
    Conv2D(128, 3, activation='relu'),
    Conv2D(64, 3, activation='relu'),
    MaxPool2D(2),
    Flatten(),
    Dropout(0.5),
    Dense(128, activation='relu'),
    Dense(NUM_CLASSES, activation='softmax')
])
```

```
              optimizer=Adam(),
              metrics=['accuracy'])


print(model.summary())



history = model.fit(X_train,
                    y_train,
                    epochs=5)



print("history",history)

model.save("model.h5",overwrite=True)

print("model saved")
```

Below is the code for making the prediction on the given traffic signs dataset. We have made the GUI using the Tkinter library in python.

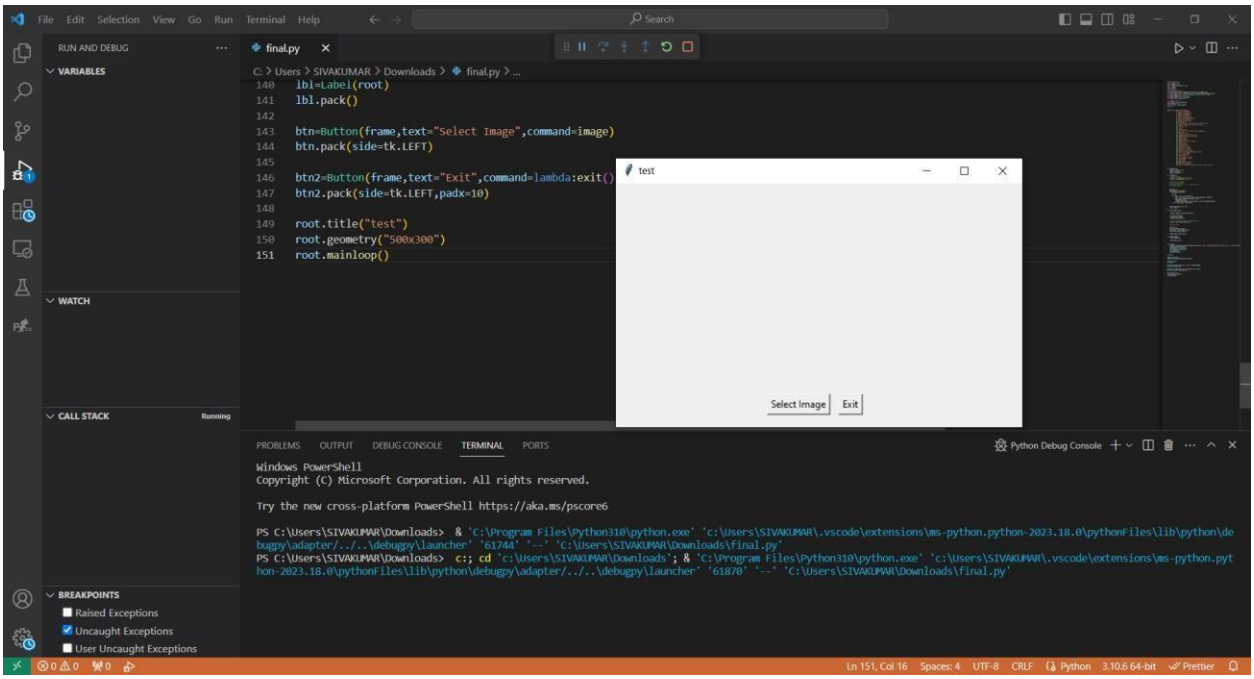
```
# import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import random
import pyttsx3
# Tensorflow
import tensorflow as tf
from keras.utils import load_img, img_to_array, to_categorical
from keras.applications.inception_v3 import InceptionV3, preprocess_input
from keras.layers import Conv2D, MaxPool2D, Flatten, Dense, Dropout
from keras.optimizers import Adam
from keras.models import load_model
from keras import Sequential

from tkinter import *
from tkinter import filedialog
import tkinter as tk
from PIL import Image,ImageTk
import os
```

```
labels = {0:'Speed limit(20km/h)',
              1:'Speed limit(30km/h)',
              2:'Speed limit(50km/h)',
              3:'Speed limit(60km/h)',
              4:'Speed limit(70km/h)',
              5:'Speed limit(80km/h)',
              6:'End of speed limit(80km/h)',
              7:'Speed limit(100km/h)',
              8:'Speed limit(120km/h)',
              9:'No passing',
              10:'No passing for vehicles over 3.5 metric tons',
              11:'Right-of-way at the next intersection',
              12:'Priority road',
              13:'Yield',
              14:'Stop',
              15:'No vehicles',
              16:'Vehicles over 3.5 metric tons prohibted',
              17:'No entry',
              18:'General caution',
              19:'Dangerous curve to the left',
              20:'Dangerous curve to the right',
              21:'Double curve',
              22:'Bumpy road',
              23:'Slippery road',
              24:'Road narrows on the right',
              25:'Road work',
              26:'Traffic signals',
              27:'Pedestrians',
              28:'Children crossing',
              29:'Bicycles crossing',
              30:'Beware of ice/snow',
              31:'Wild animals crossing',
              32:'End of all speed and passing limits',
              33:'Turn right ahead',
              34:'Turn left ahead',
              35:'Ahead only',
              36:'Go straight or right',
              37:'Go straight or left',
              38:'Keep right',
              39:'Keep left',
              40:'Roundabout mandatory',
              41:'End of no passing',
              42:'End of no passing by vehicles over 3.5 metric tons'}
```

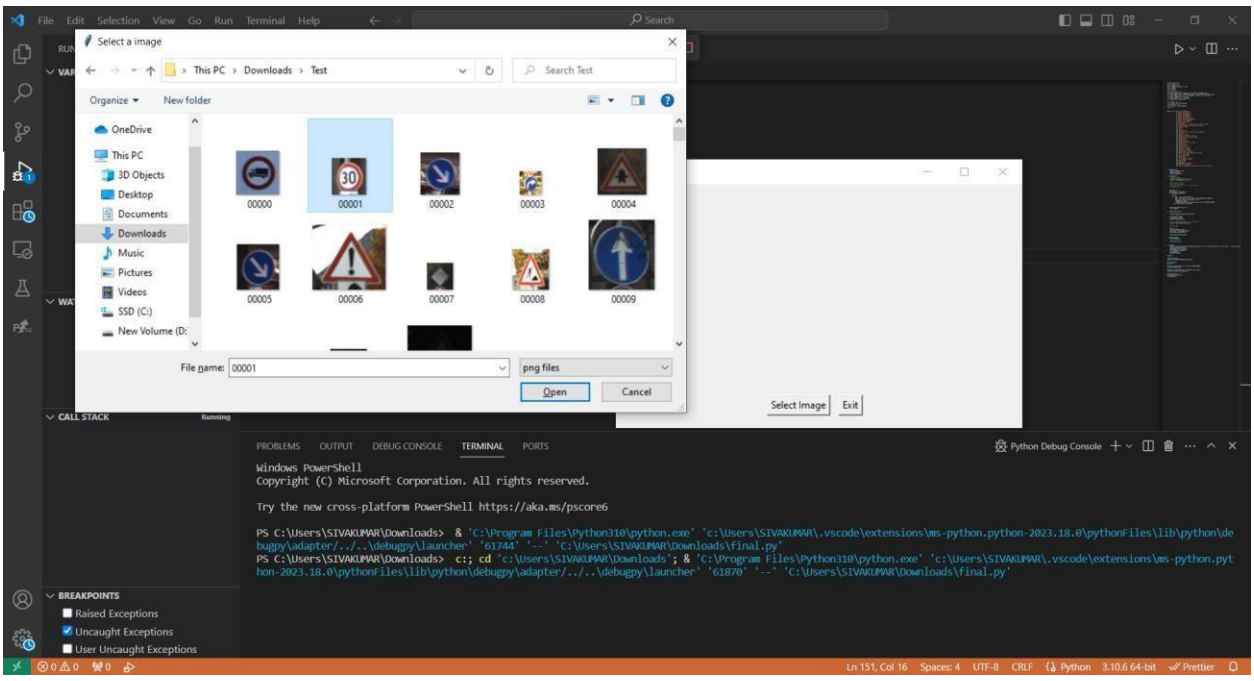
```
def speech(text):
    engine = pyttsx3.init()
    engine.say(text)
    engine.runAndWait()

def loadModel():

    model=load_model("model.h5")
    return model

def output(model,path):

    img=load_img(path,target_size=(32,32))

    i= img_to_array(img)
    i=preprocess_input(i)
    input_arr=np.array([i])

    # Get the predicted labels for the test data
    y_pred = model.predict(input_arr)

    #print(y_pred)

    print("\n")
    print(np.argmax(y_pred))
    pred_label = np.argmax(y_pred)
    print(labels[pred_label])
    st.set(labels[pred_label])
    speech(labels[pred_label])

def predict(path):
    model=loadModel()

    output(model,path)


def image():
    filename=filedialog.askopenfilename(initialdir="C:/Users/SIVAKUMAR/Downloads"
,title="Select a image",filetypes=(("png files","*.png"),("jpg
files","*.jpg"),("all files","*.*")))
    img=Image.open(filename)
    img=ImageTk.PhotoImage(img)
    lbl.configure(image=img)
```

```
    lbl.image=img
    predict(filename)

root=Tk()

frame=Frame(root)
frame.pack(side=BOTTOM,padx=15,pady=15)

lbl=Label(root)
lbl.pack()

st=StringVar()
ou=Label(root,textvariable=st,font="30")
ou.pack()

btn=Button(frame,text="Select Image",command=image)
btn.pack(side=tk.LEFT)

btn2=Button(frame,text="Exit",command=lambda:exit())
btn2.pack(side=tk.LEFT,padx=10)

root.title("test")
root.geometry("500x300")
root.mainloop()
```

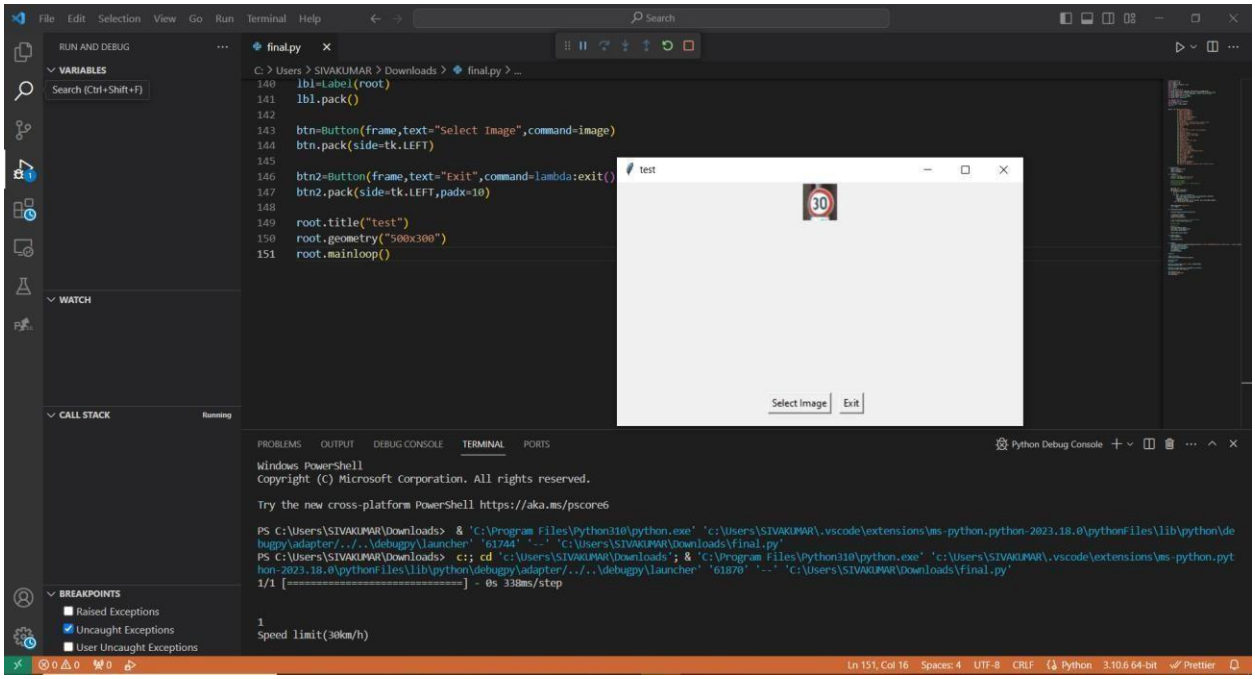
Output



The middle popup window is the graphical interface for getting input image



Selecting image for prediction



Output displayed

Git hub link:-
https://github.com/Muthumukilan/Traffic-Sign-Detection-CNN