VOICE ASSISTED TRAFFIC SIGN RECOGNITION SYSTEM USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

The purpose of traffic signs is to alert drivers of crucial information. Consequently, road safety depends on knowing how to read traffic signals, and accidents might happen when people aren't aware of this. For the better part of a century, researchers have focused on traffic sign detection. The foundation of a reliable traffic sign detecting system is the ability to detect signs accurately and in real-time. A real-time traffic sign recognition system that can aid drivers with voice assistance is presented in this research. There are two subsystems that make this system work. At first, a trained Convolutional Neural Network (CNN) is used to identify and recognise the traffic signs. Once the traffic sign has been identified, a text-to-speech engine will narrate it to the driver. In order to implement Deep Learning-based real-time detection and identification, an effective Convolutional Neural Network (CNN) model is trained on a benchmark dataset. The benefit of this system is that it can notify the motorist of traffic signs, even if they aren't looking at them, don't understand them, or miss them entirely. The advancement of driver less cars also relies on this kind of technology.

Keywords: CNN, Dl, ML, Traffic sign, voice assisted, speech.

I INTRODUCTION

Autos have become an essential mode of transportation, thus every country has implemented safety regulations to keep its roads safe. In particular, online traffic signs aid in conveying the rules that need to be observed in that particular area and provide useful data to the drivers. A website traffic indicator's goal is to convey information clearly and concisely with little to no reading comprehension required. The inability of drivers to recognise road signs and signals, which may result in accidents, can be attributed to a variety of circumstances. These include drivers' lack of attention, unfamiliarity with the road conditions, habitual sidetracking, and purposeful or accidental blind spots. Additionally, drivers in rural regions may have trouble understanding what a road sign is trying to tell them since they aren't familiar with the many traffic signs used in cities. Because they don't think they're necessary, some drivers regularly ignore specific signs of website traffic. Another contributor to this lack of knowledge is the varied attitudes of the drivers. Serious accidents, which might even result in loss of life, can occur when drivers are either unfamiliar with or have a lack of understanding of traffic signals. This article proposes a method to address the aforementioned problems by accurately seeing and identifying website traffic signals in real-time and relaying this information to drivers. Both autonomous and lorry assisting systems may benefit from this kind of technology. The YOLO Convolutional Semantic Network (CNN) architecture is used to run the system [1]. The system may be used as a real-time online traffic sign discovery system with quicker detection costs and optimised accuracy of the version. As they drive, drivers might benefit from the narrated message of a particular traffic sign. Intricate website traffic signs, unfamiliarity, and missing traffic indicators are all things that the audio narrative may help with.

We are already entering a new era in which, because to technological improvements, crashes are either very rare or quite common. Actually, modern Intelligent Transportation Systems (ITS) have been around in the automotive industry to save lives, increase revenue, and make driving safer and easier. Autos with an auto-pilot mode have emerged, thanks to some clever developments. The independent trucks are now in the public eye. The market for autonomous vehicles has exploded. However, these features are reserved for a few high-end vehicles that the general public will not be able to afford. It was necessary for us to devise a framework that contributes to making driving easier to a certain extent. We found the scale of traffic accidents in India to be shocking after doing an overview. According to reports, almost

53 accidents occur on the roads every hour. More than 16 people die as a direct result of these catastrophes every hour. Anyone endangers not only themselves but also other drivers, tourists, and pedestrians on the road when they fail to obey traffic signs while operating a motor vehicle. Consequently, we developed this technology that uses the real-time video feed to automatically calculate website traffic indicators. These indications are then given out to the driver, who may then make the specified option.

II SURVEY OF RESEARCH

[1] Title: Quick Snap: Integrated, Real-Time Object Recognition, John Redmon, Susan Divvala, Robert Girshick, and Ali Farhadi wrote it.

Here, we introduce YOLO, a novel approach to object recognition. Classifiers have been used in the past for detection purposes in item finding. We instead frame item identification as a regression problem with spatially separated bounding boxes and related class probabilities. In a single assessment, a single semantic network can predict bounding boxes and class probabilities straight from entire pictures. Since the whole detection pipeline is a single network, its performance can be optimised end-to-end by focusing on discovery. As a whole, our architecture is lightning fast. At 45 structures per second, our fundamental YOLO model processes photographs in real-time. Fast YOLO, a condensed version of the network, achieves double the mAP of other real-time detectors while processing 155 structures per second, which is amazing. When compared to more sophisticated detection algorithms, YOLO is less likely to anticipate false positives based on history but makes more localization blunders. The ultimate goal of YOLO is to discover very broad descriptions of things. When it comes to generalising from natural images to other domains like art, it beats other detection methods like DPM and R-CNN.

[2] Title: Identification of traffic signs using colour data, R. Janssen, W. Ritter, and F. Stein

We provide a novel method for finding and identifying website traffic indicators in this study. A video camera mounted on a truck or automobile may capture colour pictures. The first stage is to use a pixel classifier to colour segment these images. Theories are generated by the colour mixtures that are typical of website traffic indicators. With the help of a pictogram classifier, these hypotheses are proven. Thousands of website traffic situations have successfully tested our method. On a Sparc-10, it takes around one second to process a 512 by 512 framework. In conjunction with a wide range of academic institutions, Daimler-Benz is launching this initiative as part of the PROMETHEUS research programme in Europe.

[3] The Automatic Discovery and Acknowledgment of Web Traffic Indicators Using Colour Division, Forming Matching, and Support Vector Machines (SVM) This work was authored by S. B. Wali, M. A. Hannan, A. Hussain, and S. A. Samad.

The primary objective of this study is to develop a reliable TSDR system that incorporates an enhanced dataset of website traffic indicators in Malaysia. The developed method requires less computing power and has a low false positive rate; it remains stable under changing lighting, rotation, translation, and viewing angles. Photo preprocessing, discovery, and acknowledgment are the three operational stages of the system's growth. Using a support vector machine (SVM) classifier and an RGB colour division and form matching example, the system achieved impressive results in terms of accuracy (95.71%), false positive rate (0.9%), and processing time (0.43 s). This statistical evaluation of the recognition efficiency was done by presenting the area under the receiver operating attribute (ROC) curves. Classifying traffic signs, especially in the Malaysian region, would benefit greatly from the existing system's very high accuracy and relatively cheap processing time. System security and reliability in real-time applications would undoubtedly be enhanced by the reduced false positive rate.

[4] TITLE: Colour discovery and division for highway and traffic signage. H. Fleyeh is the writer.

Three novel approaches to road sign shadow detection and segmentation are presented in this work. Vehicles equipped with digital cameras capture the footage. In order to extract the colours of the road signs, new algorithms are used after converting the RGB photos into IHLS shade space. The approaches show great efficacy when tested on hundreds of outdoor photographs taken under varying lighting situations. This study is integrated with the ongoing ITS research at Dalarna University in Sweden.

[5] Authors: S. S. Md Sallah, F. A. Hussin, and M. Z. Yusoff Work Title: Shape-based roadside sign detection and identification for embedded application using MATLAB

We provide a formula for embedded applications that can detect and recognise traffic indicators in this study. The formula relies on the Hough transform method of line detection to determine the shape of the road sign. Highway indication proportions of area and perimeter are now determined by forming measures. We compare the variables to the layout library that we have built. This study reports the results of a precision test that used the suggested formula on most of the traffic signs in Malaysia. On average, the cost of finding and recognition is 83.67%.

A. Shustanov and P. Yakimov's [6] method for web traffic indication recognition using convolutional neural networks and graphics processing units

In recent times, deep learning approaches to solving category problems have gained significant popularity. Most current and future computer vision tasks have been improved by convolutional semantic networks because of their fast execution and high recognition rate. In this article, we propose a convolution neural network implementation of a method for acknowledging website traffic metrics. The TensorFlow library and CUDA, a massively parallel architecture for multi threaded programs, are used to train the neural network. A mobile GPU performs the whole treatment for online traffic indication finding and recognition in real time. Preliminary findings demonstrated that the created computer vision system is quite efficient.

III EXISTING SYSTEM

The abundance of traffic signs in metropolitan areas could make it difficult for drivers in less densely populated areas to decipher their meaning. People on the road tend to disregard some traffic signs since they don't believe they're important. Another reason for this lack of knowledge is the drivers' different perspectives.

Dis Advantages:

Serious accidents might happen if drivers aren't acquainted with the roads. Not to mention the possibility of dying.Along with the conventional method, there is a voice-assisted system.

IV PROPOSED SYSTEM

We are currently developing a system that will greatly improve our ability to detect and understand online traffic reports in real time, as well as communicate them to drivers. Vehicles that drive themselves and technologies that help trucks both make use of this kind of technology. It is built using a Convolutional Semantic Network (CNN) version, which has quicker detection costs.

ADVANTAGES

One such use is as a system to identify traffic signs in real-time. One way to help drivers is to narrate the message that is shown on traffic signs. In the narrated form. There is a solution to the problems of not seeing the traffic signs, not being acquainted with them, and their complexity.

V METHODOLOGY

A traffic indication's goal is to convey information accurately and rapidly with little analytical expertise required. Reasons why drivers don't pay attention to road signs, which may cause accidents, include: being distracted, not knowing enough, not wanting to pay attention, purposefully or inadvertently not finding traffic signs, and side-stretching.

To ensure the safe and efficient flow of online traffic, road signs are required. Failure to properly observe and understand traffic signs is a leading cause of road accidents. The technology may help identify the Web traffic sign and notify the driver over speakerphone so that they can make the necessary judgements. Automated and traffic-assistance driving systems rely heavily on expert systems for web traffic indicator finding and identification. Quickly and accurately identifies online traffic indicators, which is a huge help to drivers and autonomous driving systems. The primary goal of the traffic sign board recognition is to lessen the strain on the current road network by means of various travel demand management procedures. The expert semantic network outperformed the competing CNN architectures thanks to its four convolution layers, two max pooling layers, failure, squash, and thick layers. The skilled network has an accuracy of 98.52%.

UPLOAD DATASET

Using this module we can load medicinal plant dataset from the location of the project to Train the CNN algorithm

GENERATE TRAINING AND TESTING IMAGES

ImageDataGenerator: that rescales the image, applies shear in some range, zooms the image and does horizontal flipping with the image. This ImageDataGenerator includes all possible orientation of the image.

train_datagen.flow_from_directory is the function that is used to prepare data from the train_dataset directory Target_size specifies the target size of the image.

test_datagen.flow_from_directory is used to prepare test data for the model and all is similar as above.

fit_generator is used to fit the data into the model made above, other factors used are steps_per_epochs tells us about the number of times the model will execute for the training data.

epochs tells us the number of times model will be trained in forward and backward pass.

GENERATE CNN MODEL

In this module we are generating CNN Model with train_datagen and test_datagen generated by ImageDataGenerator class. Here we have training this CNN algorithm multiple time to get the better accuracy using epochs. Finally we will get the best CNN model with average accuracy 99%

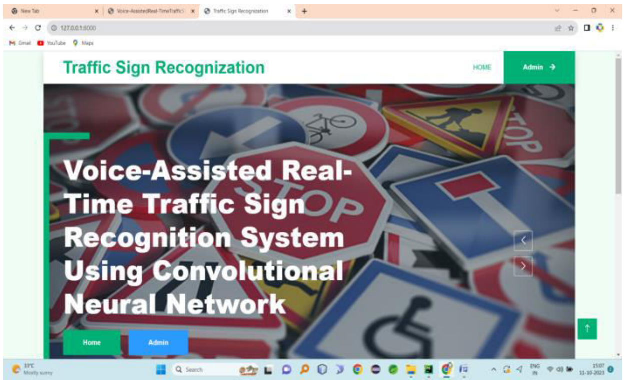
UPLOAD TRAFFIC SING

Using this module we can upload test image AND pass the test image to the model to recognize traffic sing

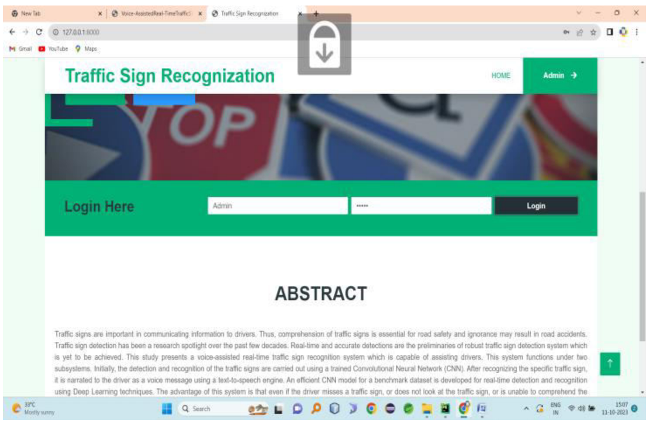
RECOGNIZE TRAFFIC SING

Using this model will call the CNN Model which is already generated and take the image from the 4th step and pass to model. Then the model will identify the traffic sing. And gives voice alert message

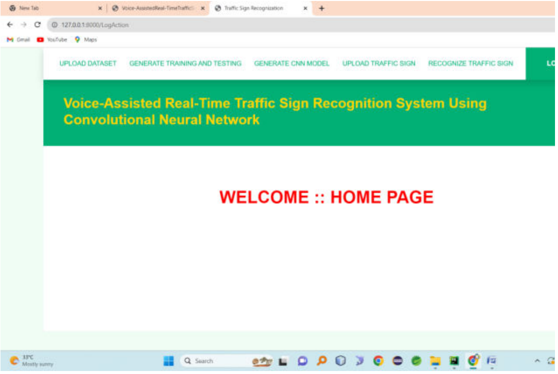
INDEX PAGE



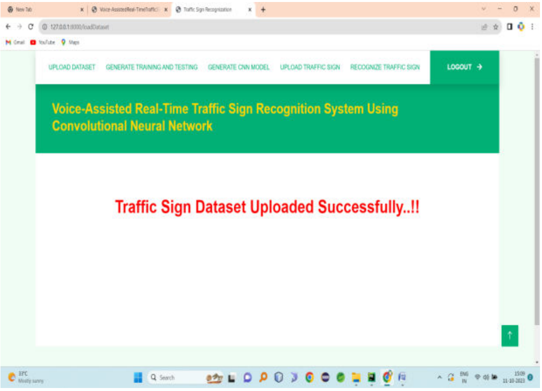
Login



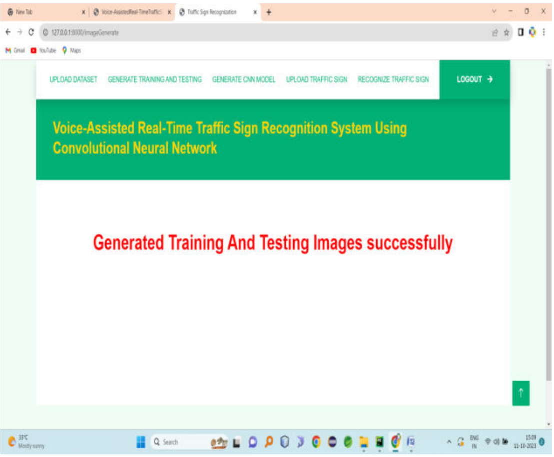
Home page



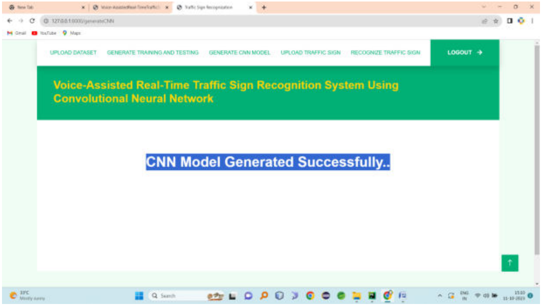
Dataset upload



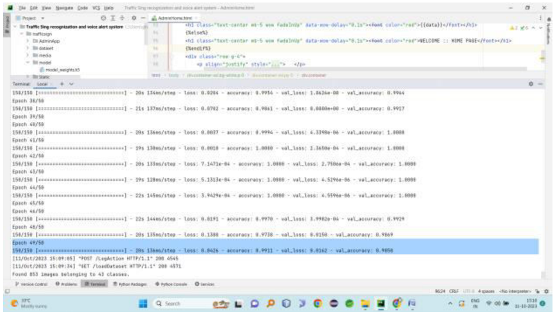
Generate training and testing images



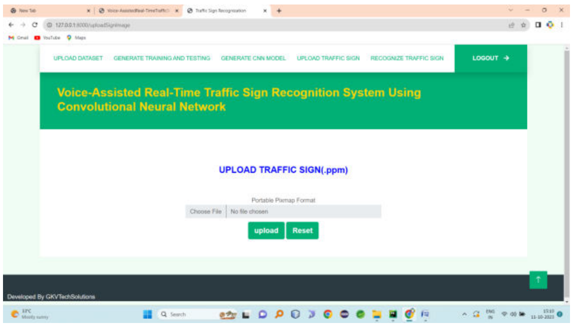
CNN Model generated



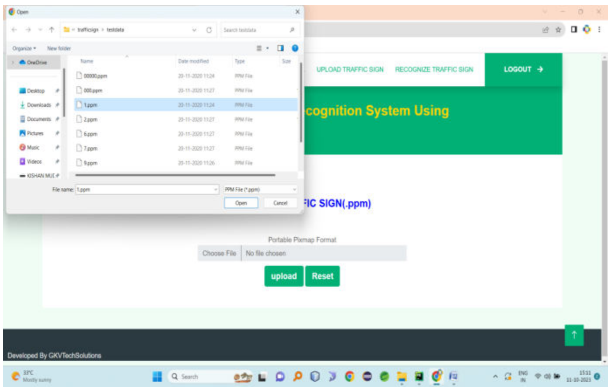
CNN model final accuracy



Upload traffic sing



Uploading traffic sing image



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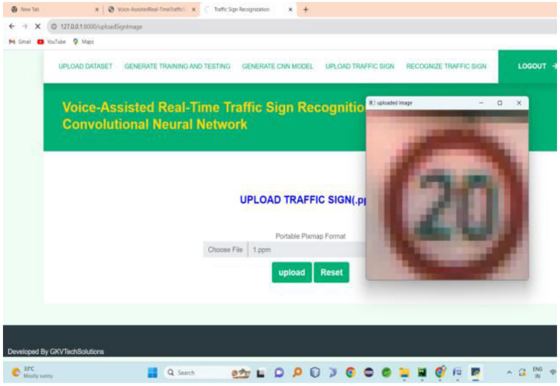
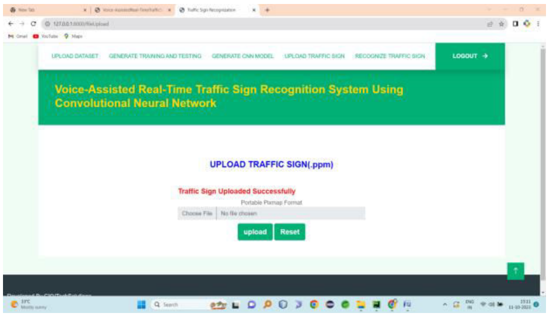
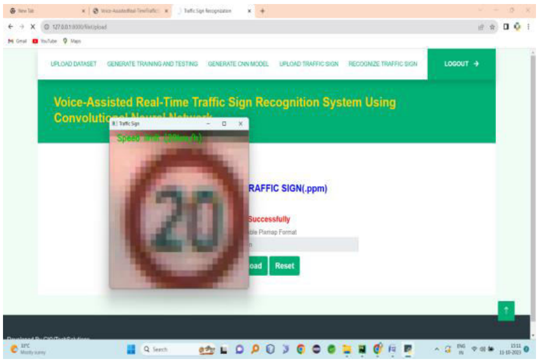
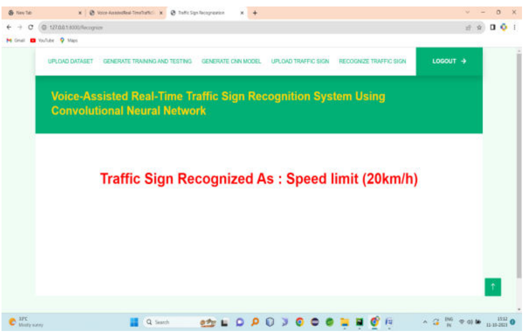


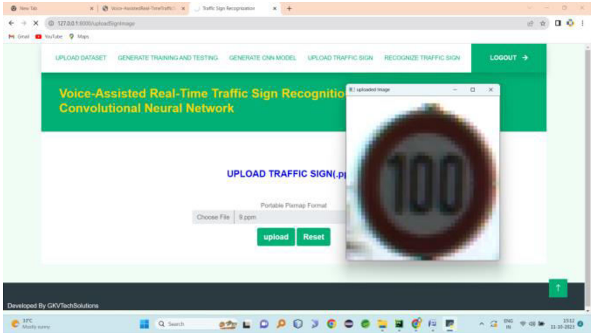
Upload status



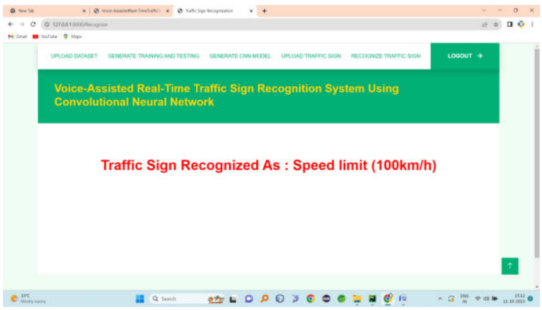
Recognized traffic sing

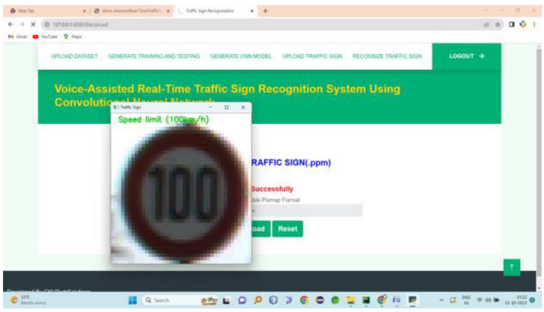






After recognization





CONCLUSION

With a discovery speed of 55 FPS, we have offered a long-lasting solution for real-time traffic indication identification in this assignment. A mean average accuracy of 64.71 percent has also been achieved. While maintaining a constant discovery pace, fine-tuning the hyper-parameters and modifying the YOLO architectural configurations may significantly increase the accuracy of today's technique. Methods such as training the CNN with partly visible signs, using 3D restoration formulae, and employing uncertain C-means clustering may further reduce the harmful effects of partially obscured online traffic indicators, damaged traffic indications, and severe weather. Our paper's proposed solution can find traffic signs at a very high frame rate of 55 FPS and achieve a mean typical accuracy of 64.71%. The system's real-time efficiency is ensured by having a structure rate of more than 30 FPS. Even better, with the combination of accurate recognition and the voice assistant function, you can avoid or at least mitigate most issues caused by ignoring traffic signs.

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