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Real-Time Traffic Sign Recognition using Image Processing and CNN

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Abstract
The processing recognition of driving signs in autonomous vehicles, known as Traffic Sign Recognition (TSR), has considerably advanced in recent years. This work utilizes deep learning techniques, specifically a Convolutional Neural Networks (CNN) classifier, for robust recognition of traffic signs. The dataset used for this analysis consists of thousands of images featuring different categories of traffic signs including speed limit, warning, and do not enter signs. The model is subjected to multiple preprocessing steps such as image resizing, normalization, and augmentation to improve generalization capabilities and reduce overfitting during training. The accuracy achieved after training on the CNN model was 98.02% on the test set, showing effectiveness in recognizing traffic signs with respect to different lighting conditions, occlusion, and background noise.

Besides this, the model was put through a comparative analysis with other machine learning approaches such as Support Vector Machines (SVM), Random Forest, and Gradient boosting; confirming that CNN is a better solution due to its image spatial and hierarchical feature extraction capabilities. The project has also implemented video-based traffic sign detection and recognition within OpenCV, increasing the practicality of the model. This research presents a robust, scalable, and efficient solution for traffic sign recognition, contributing significantly to the advancement of autonomous vehicle technologies.

Keywords — Convolutional Neural Network, Detection of traffic signs, Image processing techniques.

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I. INTRODUCTION

At present, there are numerous technologies that have been developed to assist with driving. One of the many elements that help developers create a driving assistance system is Traffic signs or road signs. This helps guide the driver toward actions that may be hazardous or harmful. Traffic sign recognition is an example of object detection. Today, the development of deep learning has enhanced the speed and precision of detecting objects. Automatic driving systems and driving assistance systems are some new features being added these days. These systems need to autonomously understand the environment which involves understanding the road lane, vertical distance between vehicles, obstacles, traffic signs, etc. Among other things, traffic signs demonstrate the vehicle's safety, define current traffic conditions, certain actions and driving direction that are either permitted or forbidden, or even alert as dangerous. Additionally, they may assist the driver in assessing the condition of the road and consequently the ideal driving directions.

II. Literature review

In "Thai Traffic Sign Detection and Recognition for Driver Assistance, "Sakan Promlainak, Kuntpong Woraratpanya, Jirapat Kuengwong, and Yoshimitsu Kuroki (2018) propose a system for detecting an recognizing Thai traffic signs. Using a cascade classifier with Histogram of Oriented Gradient (HOG) features, the system detects traffic signs, while a Support Vector Machine (SVM) learner performs recognition. [1]

Namyang and Phimoltares (2021) proposed a Thai traffic sign classification and recognition system utilizing histogram of oriented gradients (HOG) and color layout descriptor (CLD) features with support vector machine (SVM) and random forest classifiers, achieving an accuracy of 93.98%. The study emphasizes the distinct characteristics of Thai traffic signs and addresses their classification into regulatory, warning, construction, and guide signs. Additionally, the recognition process employs optical character recognition (OCR) and template matching based on normalized correlation coefficient for identifying signs. This approach enhances driving assistance technologies by accurately interpreting traffic sign information in various conditions.[2]

In "Research and Application of Traffic Sign Detection and Recognition Based on Deep Learning," authors Liu, Ran, Wang, and Hou (2018) reviewed various methods of traffic sign detection. Liu and Ran (2001) used HSV color space models for sign classification, achieving 95% accuracy. Furthermore, Hou (2017) introduced a fast traffic sign detection method utilizing a cascade system, showing 2-7 times faster performance compared to traditional techniques. These studies underline the advancement in real-time traffic sign recognition technologies, crucial for developing intelligent transportation systems.[3]

In "Real-Time Detection and Recognition of Live Panoramic Traffic Signs Based on Deep Learning," Xiangsong Meng, Xiangli Zhang, Kun Yan, and Hongmei Zhang (2018) introduced a novel approach for detecting small objects, particularly traffic signs, in panoramic high-resolution images. Utilizing a YOLOv3-based Traffic Signs Network (TSNet), the authors improved accuracy and real-time performance by integrating a sliding window algorithm and Delete Subsets Non-Maximum Suppression (DS-NMS) method. Compared to traditional methods, TSNet achieved significant enhancements in object detection speed and accuracy, addressing the challenges of small object recognition in high-resolution images.[4]

J D Zhao, Z M Bai, H B Chen "Research on Road Traffic Sign Recognition Based on Video Image" In 1999, H.X. Liu developed a robust collision mitigation system incorporating vehicle and traffic sign detection using neural networks. In 2000, Osaka University's system achieved a 97% detection rate for speed signs but faced challenges in recognition with a 46.5% success rate. Researchers like Liu and Ran (2001) used the HSV color space model with neural networks to enhance accuracy up to 95%. In 2013, Wang and Ren achieved 93.52% accuracy with a hierarchical method on the German benchmark dataset. Recent innovations focus on cascade systems and data-driven approaches for rapid detection and accurate recognition in real-time applications. The Viola-Jones cascade detector enhances accuracy by detecting sign shapes in video frames. Experimental results show the system's ability to correctly detect and recognize Thai traffic signs in near real-time, offering practical solution for driver assistance system.[5]

III. Methodology

Each of the 43 folders in the dataset represents a particular class. The folder's size ranges from 0 to 42. We iterate through the classes using the OS module, appending pictures along with their respective labels to the data and labels lists. The content of pictures can be opened into an array by using the PIL library. In the end, all images and respective labels were systematically arranged to form two lists, which are data and labels. In order to feed the model, the data lists need to be transformed into NumPy arrays. The shape of the data (39209, 30, 30, 3) tells us that there are 39,209 images which are 3030 pixels, and the last three tells us that data is made of colored images(RGB value). The task of separating or partitioning the training and testing data is performed by train_test_split() function found in the sklearn package. We change the labels in y_train and t_test into one-hot encoding using to_categorical method from the Keras.utils package. For class classification, the best way to compile is with the Adam optimizer (because it works quite well). And the loss"categorical_crossentropy". After building the architecture of the model, I worked with model.fit to train it. The batch sizes experimented with were 32 and 64. The accuracy was consistent after 15 epochs with 64 batches.

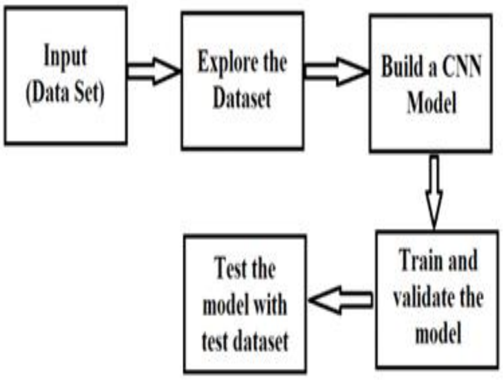

Figure 1 – Dataset block diagram

We'll use a CNN model to classify the photos into their appropriate groups (Convolutional Neural Network). For picture categorization, CNN is the best option.

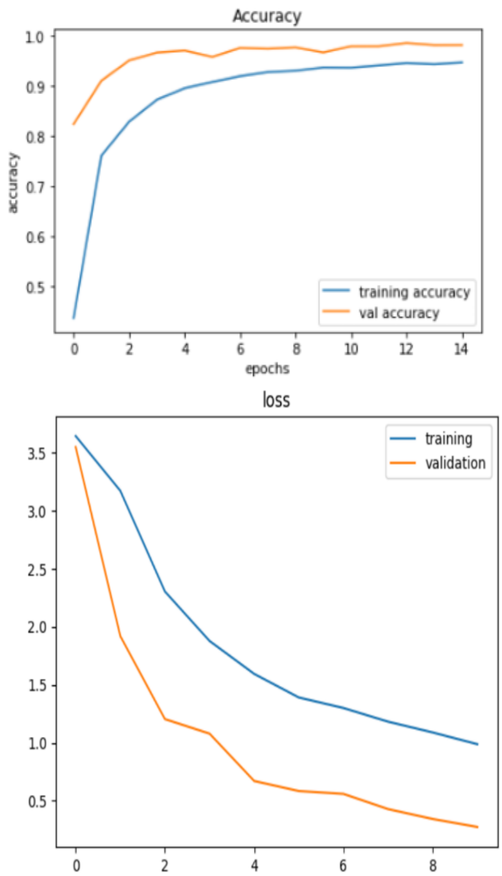

Figure 2 – Accuracy and Loss graph

our model fared better. The accuracy was stable after 10 epochs. On the training dataset, our model had a 98%

Algorithm	Feature Extraction	Performance on Large Datasets	Computational Cost
SVM	Required (HOG, SIFT)	poor	High
RF	Required (HOG, SIFT)	moderate	Moderate
CNN	Not Required (learns features)	Excellent	High

accuracy rate. We visualize the graph for accuracy and loss using matplotlib.

The details connected to the image path and their appropriate class labels are contained in a test.csv file in our dataset. Using pandas, we extract the image path and labels. Then, in order to forecast the model, we must scale our photographs to 3030 pixels and create a NumPy array with all of the image data. We used the accuracy score from sklearn.metrics to see how our model predicted the real labels. In this model, we were able to attain a 95% accuracy rate. Now we are going to build a graphical user interface for our traffic signs classifier with Flask. Flask is a GUI toolkit in the standard python library.

Model	Precision	Recall	F1-Score	Support
SVM	0.02	1.00	0.03	32
CNN	1.00	0.51	0.68	394
RF	1.00	0.77	0.87	74

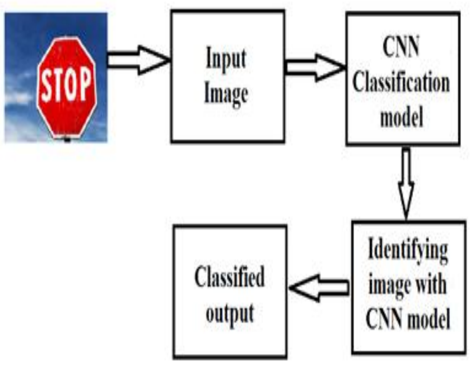

Figure 3 - Proposed block diagram

IV. Result and Discussion

Sample traffic sign data set used in designing the model. The sample traffic sign data set used is German traffic sign data set.

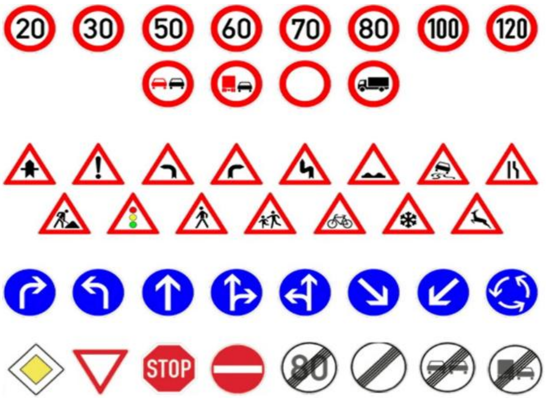

Figure 4 – Traffic Sign

We have successfully identified the traffic signs in various environments with the aid of the provided algorithms and additional Python libraries. Thus, using the provided Kaggle dataset, we were able to dataset-based training sets. utilizing the dataset. A file for the H5 classifier is produced. We can obtain the results fast with that classifier file. With a 95% accuracy rate, the system can classify the input images.

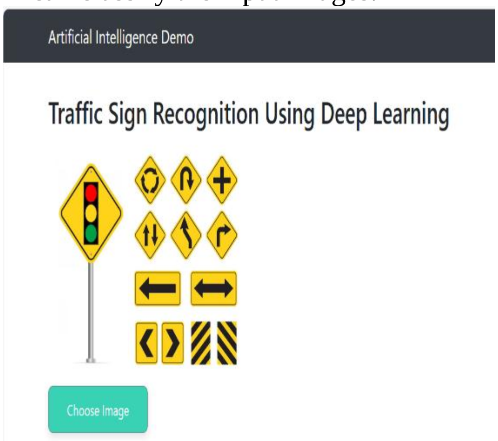

Figure 4 –Upload Image

The images are captured from the sensors in the cars. That image is given as input to the system. With help of a convolutional neural network (CNN) and Keras, images are classified. Dataset is used for training our algorithm, there are different sets of data present in the dataset. There are data of different climatic conditions and different tampered sign boards. During those difficult situations our algorithm with help of CNN and Keras, we are able to achieve a high accuracy rate for classifying the traffic signs.

V. Conclusion

In this article, we identify a faced deep learning problem concerning traffic sign detection based on convolutional neural networks (CNNs) and Keras. It focuses on analyzing and classifying all types of traffic signs identified in the dataset. By employing image preprocessing techniques, this approach is capable of detecting and recognizing traffic signs using the Traffic Sign Detection, Recognition, and Classification dataset from Kaggle. With the help of these outcomes, the traffic signs can be identified. It assists the user in two ways, when the user is in a manual mode, it aids him by providing the results on the dashboard screen and when the car driver is set to automatic, it assists the car to steer clear of dangers by recognizing the traffic signs. The result from my tests indicates that the accuracy for this technique is exceptionally high.

VI. FUTURE SCOPE

The algorithm has a problem of a feedback loop due to the fact that its operation is based on constantly determining the presence of a sign which can continuously lead to false detections. Improvements can be made by changing the parameters or thresholds of what is considered a valid sign. Better models can be obtained through improvement of the model features and parameters with the use of more datasets from other nations**.**

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