Implementation of Various Machine Learning Algorithms for Traffic Sign Detection and Recognition

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Abstract - *The Traffic Sign Recognition System, abbreviated to TSRS, could be useful in autonomous, i.e., self-driving cars which is one of the most booming technologies in the domain of transportation, artificial driver aid, traffic surveillance, and traffic safety. To handle traffic-related challenges, it is vital to recognize traffic signs. There are two aspects to the traffic sign recognition system: localization (or detection) and recognition. The traffic sign from the input image is located and recognized by constructing a rectangle area in the localization section. The rectangle box then offered the result for which traffic sign is positioned in that particular region in the recognition part. We describe the implementation of ML algorithms for traffic sign detection and recognition in this paper. In this paper, we compared the accuracies obtained from implementing various machine learning algorithms such as KNN, multinomial logistic regression, CNN and random forest. The practical purpose of detecting and recognizing the correct meaning of traffic signs is a bit difficult. For real time object (traffic signs) detection the YOLO model has been used. This helps to detect traffic signs while the vehicle is in speed. This feature will definitely help the technologies of autonomous vehicles for detection, recognition and interpretation of traffic signs in real time.*

Key Words: KNN, Image recognition, Logistics Regression, YOLO v4, CNN, IOU, SOTA, ROI

1.INTRODUCTION

Analysis of traffic signs is a very crucial topic in the field of computer vision (CV) and intelligent programming (artificial intelligence). The Traffic signs along the roads are designed to instruct and inform the drivers of the current status and other extra important information on the road.

Traffic signs hold an important place in the road traffic systems. The main function of the traffic signs is to showcase the contents that must be noticed in the current road sections, to prompt the drivers in front of the road the danger and difficulty in the environment, to warn the driver to drive at the predefined speed, to provide a favorable guarantee for safe driving. Hence, the detection and recognition of traffic signs is a very important research field, which is of great significance to prevent road traffic accidents and protect the personal safety of drivers. Autonomous vehicles are getting more popular day by day and all leading automobile companies are competing to produce the most efficient and secure automobile. Some companies working in the autonomous transport field are Tesla, Cruise, Ford, Waymo, etc. Traffic sign recognition and detection are important functions that must be performed by an autonomous vehicle. Detecting the traffic signs involves locating the sign from its surrounding. Recognition involves the actual classification of the detected sign. These two operations come under the Image detection and recognition field of AI & ML. Traffic sign recognition and detection gives the autonomous vehicle a lot of information about the road conditions like turns, speed breakers, construction work going on, etc. and all of this information can help the car to make decisions regarding changing speeds, stopping, direction change, etc. Efficient detection and recognition can ensure a smooth and, more importantly, safe ride for the passengers. For this, the autonomous vehicles are equipped with several cameras which constantly monitor the road for traffic signs.

In recent times, in-depth learning methods have proved high performances and results for many tasks such as image classification. In this paper, we have discussed the implementation of 4 algorithms namely KNN, multinomial logistic regression, random forests, and CNN, for the detection of traffic signs from their images. And also discussed the object detection algorithm i.e Yolo v4 for traffic signs detection from different classes of images. These algorithms come under the supervised learning paradigm of ML in which the algorithm is trained upon a dataset to predict / classify the test data.

In this paper, we discuss the implementation of four ML algorithms viz. KNN, multinomial logistic regression, CNN and random forests for the sake of traffic sign detection and recognition.

2. LITERATURE REVIEW

Ilkay Cinar et al. in their paper [1] mention that it is critical that the traffic signs used to maintain traffic order be understood by vehicles. Traffic signs adhere to international standards, allowing drivers to learn about the route and the surroundings while on the road. To increase traffic safety, traffic sign recognition technologies have lately been installed in automobiles. Machine learning approaches are employed in picture identification. The author of this study has a dataset of 1500 photos of 14 distinct traffic signs that are commonly seen on Turkey's roadways. Convolutional neural networks from deep learning architectures were used to extract picture features in this dataset. The 1000 characteristics acquired were categorized using machine learning techniques' Random Forest approach. This categorization technique yielded a success rate of 93.7%.

Mehdi Fartaj and Sedigheh Ghofrani in their paper [2] mentioned that A robotic car that autonomously travels on roadways must identify traffic signs. Because most traffic road signs are blue and red, we initially employ the Hue-Saturation- Intensity (HSI) color space for color-based segmentation in this article. The road signs are identified accurately using crucial geometrical properties. Following segmentation, it is time to classify all identified road signs. We use and compare the performance of three classifiers for this purpose: distance to border (DTB), FFT sample of signature, and code matrix. For the first time, we apply the code matrix as an efficient classifier in this paper. Although the acquired accuracy using code matrix is higher on average than the two mentioned classifiers, the major benefit is simplicity and hence lower processing cost.

David Soendoro and Iping Supriana in their paper [3] mentioned that To recognise traffic signs, this study presents a system that combines the Color-based Method with SVM. The color-based method using CIELab + hue was chosen because it produces good results when it comes to localizing traffic signs. It is initially used to convert the picture to a binary format. The binary picture is then processed with canny to get more accurate traffic sign detection results. The preprocessed picture is tested for traffic sign shape using the Ramer-Douglas-Peucker method, which will estimate each closed object form in the preprocessed image. When it detects a closed object, it is impossible to identify occluded and connected road signs.

Nazmul Hasan et al. in their paper [4] mentioned TSRS (Traffic Sign Recognition System) might be useful in self-driving cars, artificial driver assistance, traffic surveillance, and traffic safety. To address traffic-related challenges, traffic sign recognition is required. The traffic sign recognition system is divided into two components: location and recognition. In the localization section, a rectangular rectangle is used to find and identify the traffic sign zone. Following that, in the recognition section, the rectangle box offered the result for which traffic sign is placed in that specific region. In this research, we offer a method for recognising traffic signs. We worked on 12 different signs for traffic sign detection and identification. To do this, we employed Support Vector Machine and Convolutional Neural Network separately to identify and recognise traffic signals.

Akshata V. S. and Subarna Panda in their paper [5] mentioned that their study discusses a real-time system for both recognition and classification of traffic signs. This model is three-staged, the first step of which is picture segmentation, the second stage is the detection/localization of the traffic sign, and the last stage is the classification phase that is based on the input image. The color enhancement technique is used to extract red patches in the picture. To identify the content of the traffic signs collected, Convolutional Neural Networks (CNN) are used for detection, classification, and identification. Introduction: In recent years, the primary aim of Advanced Driver Assistance System (ADAS) has been to give the driver with critical information concerning traffic signals and warning signs on the road ahead.

Zsolt T. Kardkovacs et al. in their paper [6] mentioned that Traffic Sign Recognition (TSR) is one of the most essential background research issues for allowing self-driving vehicles. There is no time for elaborate transformations or advanced image processing algorithms in autonomous driving systems; instead, they demand a solid and real-time understanding of a scenario. This requirement becomes more difficult to accomplish in a city-like setting, since various traffic signs, advertisements, parked cars, and other moving or background elements complicate detection. While various solutions have been published, they have all been tested on highways, in the countryside, or at extremely low speeds. In this work, we provide a brief summary of the major difficulties and known solutions to these problems, as well as a generic method to address real-time concerns in metropolitan areas.

L. Breiman in his paper [7] mentioned that Random forests are a tree predictor combination in which each tree is reliant on the values of a random vector sampled separately and with the same distribution for all trees in the forest. As the number of trees in a forest grows enormous, the generalization error approaches a limit. The generalization error of a forest of tree classifiers is determined by the strength of the individual trees in the forest as well as their association. Using a random selection of features to divide each node produces error rates that are comparable to Adaboost but more resilient to noise.

Mr. Jean de Dieu TUGIRIMANA et al. in their paper [8] mentioned that many years ago, the convolutional neural network was used to identify and recognise road traffic signs (CNN). CNN has played an important role in the field of computer vision, and a variant of CNN has proven to be successful in classification tasks across multiple domains; however, CNN has two drawbacks: one is its failure to consider important spatial hierarchies between features, and the other is its lack of rotational invariance. They further discuss the use of CapsNet (or Capsule Network) to recognize and classify road traffic signs.

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Table -1: Table for Accuracies of implemented algorithms in the reviewed papers

Accuracies of algorithms in the reviewed papers			
Paper no.	SVM	CNN	Capsule Network
1	NA	NA	97.60%
2	98.2%	NA	NA
3	NA	97%	NA
4	96.40%	98.33%	NA
5	96%	NA	NA

3. PROPOSED SYSTEM

Datasets used:

1. The first dataset is downloaded and extracted from the German Traffic Sign Recognition Benchmark (GTSRB), a multi-class, single-image classification challenge which was given in 2011 at the (IJCNN) International Joint Conference on Neural Networks [10]. It contains more than 50,000 images. Over 12,000 images are available for testing and over 39,000 images are available for training. A total of 43 classes are available. Figure 1. shows some images from this dataset.

2. The second dataset contains 877 images of various different unique classes for the objective of road sign recognition. Bounding box annotations in the PASCAL VOC format and four classes are such as traffic light, stop, speed limit and crosswalk.

(a)

(b)

(c)

Fig -1: Some images from the first dataset: (a) 20 km/h speed limit sign, (b) Pedestrian crossing sign, (c) Wild animal crossing sign

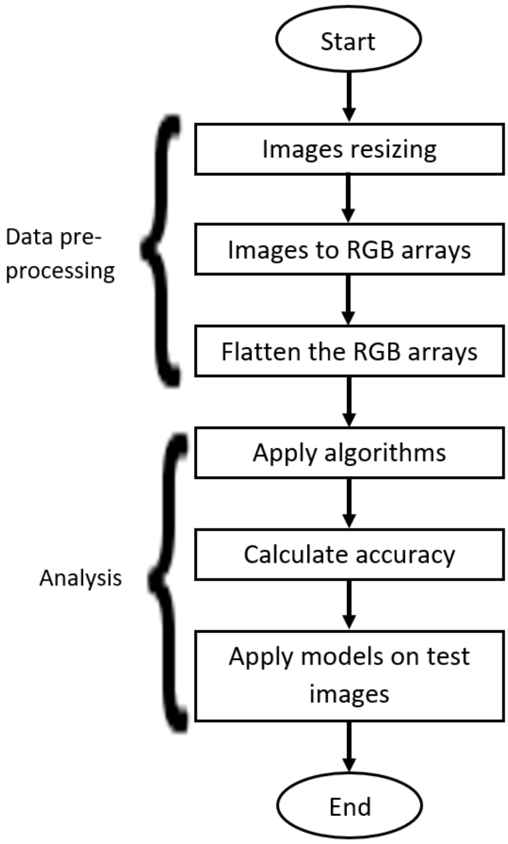

Fig -2: Flowchart for traffic sign recognition

Data pre-processing:

1. **Image resizing:** The images had different sizes so to make their sizes the same they were resized to 30x30 pixels.

2. **Convert images to RGB arrays:** Each of the images were converted into a matrix with each element of the matrix being a tuple of the RGB values of the pixels present in the image.

3. **Flattening the matrices:** These matrices were then flattened, i.e. reduced to one-dimensional arrays, so that classification algorithms can be applied to them.

Analysis:

1. **Apply algorithms:**

   Algorithms applied for image recognition:

   a. **K-Nearest Neighbors (KNN):** KNN is an algorithm of machine learning that can be used for both regression and classification processes. It always checks the labels for a selected number of data points around the target data point, to make predictions about the class the data point falls into. KNN is a relatively simple but powerful algorithm, and for those reasons, it is one of the most popular machine learning algorithms.

b. **Multinomial logistic regression:** Logistic regression, like all regression analysis, is a predictive analysis. It is used to define data and to explain the relationship between single binary dependent variables and one or more independent variables, ordinal, interval, or ratio-level independent variables. Multinomial logistic regression is an extended version of logistic regression that can be used for classification purposes when the data has more than two classes.

c. **Random forest:** Random forests are a set of tree predictors in which the values of a random vector, gathered independently and with the same distribution for all trees in the forest, are used to anticipate each tree's behavior [1]. A random selection (without replacement) is made from the instances in the training set to construct each tree. They vote for the most popular class once a huge number of trees have been created. Random Forest algorithm is useful for both regression and classification. The number of trees used is 100 in our experiment.

d. **Convolutional Neural Networks (CNN):** CNN is used for all artistic situations to learn in-depth neural network algorithms in many image-related tasks. Inside the convolution layer convolution captures image location information by implementing the kernel function. CNN contains input, output, and hidden layers. The hidden layer also contains layers which are convolutional, pooling, fully connected, and normalization layers. We have used Adam optimization and categorical cross-entropy loss function in our experiment.

(The above four algorithms are implemented on the first dataset for traffic sign recognition only.)

2. **Calculate Accuracy:** The formula for accuracy is mentioned in the “Results and discussions” section of this paper.

3. **Applying the models on test images.**

- **You Only Look Once (YOLO V4):** YOLO v4 is a SOTA (state-of-the-art) real-time Object Detection model. YOLO is a one-stage detector. One of the two primary cutting-edge techniques for the task of object detection that prioritizes inference speeds is the one-stage method. The classes and bounding boxes for the entire image are predicted in one-stage detector models; the ROI (Region of Interest) is not chosen. An image and the actual values for the bounding boxes are provided as input.

The entire input image is partitioned into a square grid, and each object is detected in the grid cell that contains its center. The B bounding boxes and the corresponding confidence ratings will be predicted for each grid cell. This rating shows how accurate the box is and how certain the model is that the object is inside the box. IOU of predicted values and the ground truth values of the bounding box is the Confidence score. Till now we have tested Yolo v4 on only 4 classes of images i.e., Crosswalk, stop, traffic signals, speed limit. Fig -3, Fig -5, Fig -6 and Fig -7 are some resultant images of above classes.

(The above algorithm is implemented on the second dataset for both localization / detection and recognition of traffic signs.)

Fig -3: Crosswalk Sign detected by YOLOv4

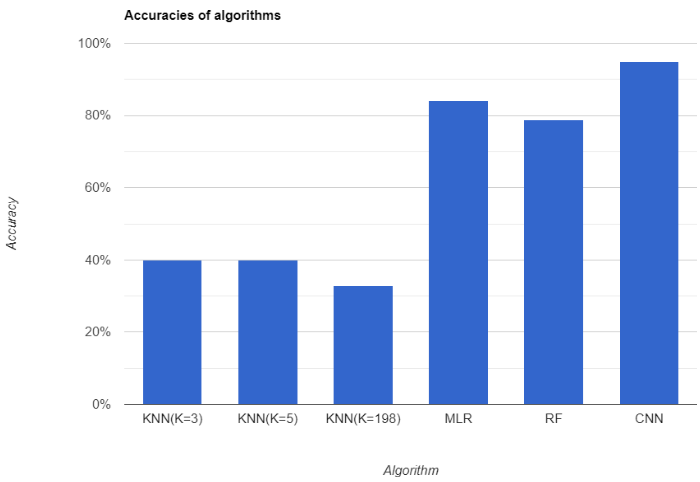

Fig -4: Accuracies of algorithms used

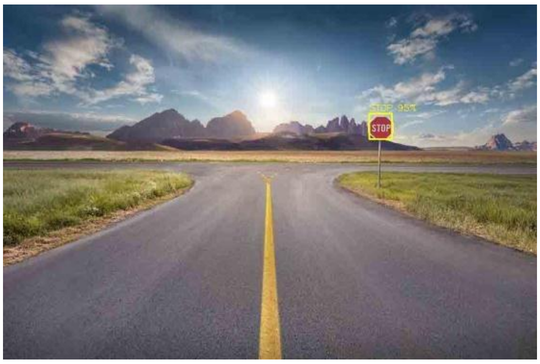

Fig -5: Stop Sign detected by YOLOv4

Fig -6: Traffic Signals detected by YOLOv4

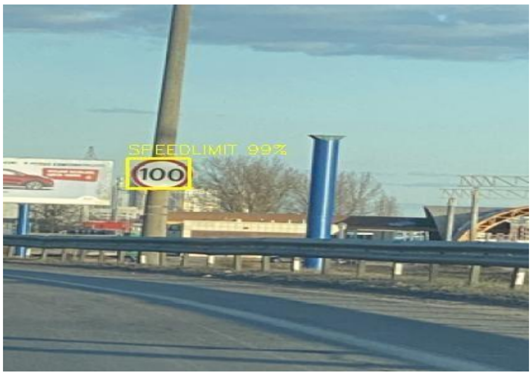

Fig -7: Speed Limit Sign detected by YOLOv4

4. RESULTS AND DISCUSSION

Accuracy:

The calculated accuracies for each algorithm are shown in Fig -4 The bar graph helps to compare the performances of the algorithms.

During the training phase, the proposed CNN model employs an Adam optimizer. It is a very successful optimization strategy for deep neural network training that combines the benefits of AdaGrad (Adaptive Gradient Algorithm) and RMSProp (Root Mean Square Propagation) After evaluating the model on test data, a loss of 5.56% and an accuracy of 98.93% are obtained. The categorical cross entropy loss function is used in the model. Methods such as EarlyStopping and ReduceLRonPlateau are employed to provide an efficient and optimal training procedure. The EarlyStopping method examines the value of the loss function and waits 12 epochs before halting if the value of the model performance metrics being monitored does not improve.

The accuracy of the model is calculated using formula:

Acc = (TP+TN)/(TP+TN+FN+FP)

Where:

TP = True Positive

TN = True Negative

FN = False Negative

FP = False Positive

According to the above formula we have calculated the accuracy for various models. The True Positive and True Negative elements are added together in the numerator of Accuracy formula, and all of the confusion matrix entries are added together in the denominator. True Positives and True Negatives are the items on the main diagonal of the confusion matrix, which represent the items that the model properly identified. The denominator additionally takes into account all the elements that the model mistakenly classified that are not on the main diagonal.[9]

5. CONCLUSIONS AND FUTURE SCOPE

Through this paper we demonstrated the efficiency of different algorithms in detecting and recognizing Traffic signs. Traffic sign recognition systems are an important aspect that autonomous vehicles use to make a decision based on the detected sign. An efficient TSRS helps to provide the rider with smooth, safe and halt-less driving. The experiment consequences of this paper display that the Convolutional neural network is an effective method for image classification and recognition. It makes it a lot simpler for the researcher to work on it due to its simple architecture, and a high-performance classifier for a tough and lot-complicated task like traffic sign recognition. As mentioned earlier, the KNN, Multinomial LR, Random forests and CNN fail to recognize the sign when the traffic sign in the image is titled or the sign is not the majority part of the image. This can be highly ineffectual in real life scenarios in which the image of the traffic sign will not always be straight and will have several other things in the background. Thus, YOLOv4 is implemented for localization of the sign from its surroundings. However, since YOLOv4 is implemented on the second dataset having only 4 classes, its efficiency can't be compared to the rest of the three algorithms. Our future plans include implementation of YOLOv4 and other localization algorithms on a larger dataset. The other three recognition algorithms will be then implemented on the traffic-sign-containing-sub-image given by the localization algorithms and then a combined analysis can be done.

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