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Traffic Sign Detection and Recognition Based on Convolutional Neural Network

Premamayudu Bulla
VFSTR Deemed to be University
premamayudu@gmail.com
India

Abstract: As autonomous vehicles are developing and maturing the technology to implement the domestic autonomous vehicles. The critical technological problem for self-driving vehicles is traffic sign detection and recognition. A traffic sign recognition system is essential for an intelligent transportation system. The digital image processing techniques for object recognition and extraction of features from visual objects is a huge process and include many conversions and pre-processing steps. A deep learning-based convolutional neural network (CNN) model is one of the suitable approach for traffic sign detection and recognition. This model has overcome significant shortcomings of traditional visual object detection approaches. This paper proposed a traffic sign identification and detection system. The proposed design and strategy are implemented using the Tensorflow framework in google colab environment. The experiment is applied on the publicly available traffic sign data sets. The defined deep convolution neural network based model experimental results achieved 94.52% and 80.85% precision and recall respectively. Improving the seep of recognition and identifying appropriate features of traffic sign objects are addressed using deep learning-based encoders and transformers.

Keywords-Traffic signs, Deep Convolution Neural Network, traffic sign recognition system, classification.

I. INTRODUCTION

Traffic signs are critical components of the city's transportation infrastructure. There are several reasons for having roadside traffic warning signs and symptoms, including informing drivers ahead of them of possible hazards and problems, enforcing a set speed limit, and providing a positive assurance of their own safety as well as the safety of others [1]. Thus, traffic sign recognition and identification might be a significant study route with substantial ramifications for minimizing road traffic accidents and assuring driver safety. Identification and detection of traffic signals are made possible by various identifying features included in traffic lights [2]. Colors and forms are the most critical aspects that help and enhance driving conditions. In addition, the colors used in traffic signs are standardized across the globe, with the notable exception of yellow, which is used as a secondary color. As a result, traffic sign colors may be used to categorize them into several groupings. [3]. There is still much room for development in traffic sign classification, even though traffic sign detection is still a long way off. Figure 1 demonstrates the different environmental conditions must be addressed in the road transport system.

Figure 1 various environmental conditions in the road transport

Pre-processing, detection, and recognition are the three main modules used in this study to detect traffic signals and symptoms. The input is pre-processed in the pre-processing modules to remove noise and improve the image. The image is used to generate possible road signs during the detection phase. The image is split based on color characteristics. Segmented potential zones are used as input in the recognition step. It is feasible to identify possible traffic

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indications and symptoms using the segmented image generated at this step. The neural network categorizes and recognizes detected symptoms during the recognition stage of detection [4].

II. RELATED WORK

[5] Fourier descriptors are used for sign-shape classification and discarding noninterest regions in post-processing. They proposed a three-stage system, which included chromatic and achromatic scene elements segmentation. [6]A novel approach incorporates color invariants into image segmentation, and a pyramid histogram of oriented gradients (PHOG) features into shape matching to detect new traffic signs. [7]Combining solid image analysis and pattern recognition approaches, they solved the challenge of traffic sign detection in mobile mapping data. Instead of using sliding window detection, the new technique relied on extracting interest regions. [8] Traffic signs are identified in the 3D space by applying for the traffic sign position beforehand, color, laser reflectivity, and 3D geometric elements. They use the CCS to symbolize the color and regard all traffic sign colors as a single class. They did not consider harsh lighting conditions and significant occlusions while determining traffic signs. [9]The GMM and CQFL techniques for improving traffic sign recognition speed and accuracy are both stated as ways to achieve this goal. As a result of this approach's extensive model parameters, the researchers recommended it. The pruning and quantization of the model may also be utilized to minimize model parameters in this technique. [10]Despite the numerous challenges associated with recognizing objects in outside settings, recognize traffic signs in a video sequence. For the first module, linear SVMs were used to classify shapes, while a second module was constructed with Gaussian kernels to classify and identify features in the inner area of the form. In the absence of a tracking mechanism, a candidate sign is regarded legitimate if found and recognized in at least two series frames. Otherwise, it is regarded as a false alert. [11]The identification of interest areas in the traffic sign using a sliding window approach. They want to use a sliding window technique to lessen the number of distinct traffic sign regions that need to be identified. They also created efficient filters based on the detection of traffic and the information contained within. However, they did not consider the weather conditions while selecting areas of interest in the traffic signals.

[12]–[19] Object identification and recognition have significantly benefited from recent attention paid to deep neural networks (DNNs), which have been developed for pattern recognition research and computer vision. [20] An innovative approach to object categorization that included two deep learning components, namely the FCN and DCN, was presented in this paper (CNN). [21] A road sign identification system based on the LeNet model was tested in a German traffic dataset with a 99 percent accuracy rate. [22] A deep end-to-end network was constructed that employed a two-stage adjusting technique to extract region recommendations. [23]It has been hypothesized that a deconvolution subnetwork and a multiscale convolutional neural network (MDN) can be integrated into a single system. Thus, an efficient and reliable traffic sign recognition model may be trained. [24]The ITSRB and ITSDB ice environment traffic sign identification and detection benchmarks have been proposed and are designated in the COCO2017 style. The attention network was used to develop a high-resolution classification system for traffic signs (PFANet), and ablation research was conducted on the parallel fusion attention module. [25] To minimize the duplication, parameters, and speed of the networks, a new convolutional neural network (CNN) was developed. [26] Traffic sign identification was made using neural networks. In particular, it is considered the spatial domain data for traffic sign detection. [27]An efficient traffic sign recognition system with two stages was shown. A LINX Mobile Mapper system was initially utilized to collect and analyze 3D point cloud data in the system. A deep neural network was utilized to categorize the point cloud projection on RGB pictures. [20]A small-scale deep convolutional neural network (CNN) may be used to detect traffic signs in various contexts. [28] A convolutional neural network (CNN)-based system for recognizing Arabic traffic signs was developed (CNN).

Our method is unusual because traffic sign recognition is carried out in the frequency domain rather than the spatial domain, unlike other approaches. Using a variety of datasets, these methods have been able to achieve excellent accuracy in traffic sign identification. Regardless of the extreme weather, the application setting heavily influences the recognition rates.

III. PROPERTIES OF TRAFFIC SIGNS

Traffic signs have distinguishing characteristics that set them apart from other objects. They come in two-dimensional shapes, including rectangles, triangles, circles, and octagons. Most traffic signs employ virtually simple primary colors (red, green, or blue), except for yellow [29]. Figure 2 shows that each traffic sign has a unique color and that the colors of text engraved on each sign are distinct.

The transfer of the learning mechanism is the mainstay of the CNN proposed here. Extensive data set is used to train the Deep CNN. Then a small number of popular traffic training samples are used to identify the regional convolutional neural network (RCNN). This results in a multiresolution feature combination network fabric that can study many valuable

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features of small objects. The traffic sign detection framework is separated into spatial sequence classification and regression tasks [30]. The real-time CNN detection with traffic sign recognition must be understood to be fully appreciated. Pre-processing road traffic signals using the Hough transform significantly increase their recognition accuracy and response speed. Pre-processing, detection, and classification are all covered in this study, depicting the traffic-sign recognition system in action. The static color picture is enhanced in the pre-processing stage, and the shade space is then adjusted. The shape and color information of the image is used to segment the road signs, and then the Hough transform is used to identify circular road traffic signs [31].

(a) (b)

Figure 2 sample of traffic signs

IV. METHOD OVERVIEW

This research shows how traffic signs detection and identification improved using transfer learning. Transfer learning neural networks are initially trained using a vast number of images. A large-scale image training system like Image Net [32] can be used to train a neural network. Neural networks are capable of performing classification and detection tasks and micro-training tiny data samples. Because of the migration learning method, pre-skilled networks have amassed a wealth of image functions that may be applied to a wide range of images. This learning may be used for various tasks by fine-tuning the network. It is possible to gradually improve the feature representation learned for a specific job by adjusting the weights in the network. Using transfer learning, both the number of images and the time spent on training may be cut in half. Transfer learning is used to highlight the parking sign detector's benefits. The CNN was pre-trained with 50,000 training images from a CIFAR-10 data set. As a result, this pre-trained CNN was fine-tuned using only 41 training images. If CNN is not pre-trained, stop sign detectors will need extra images.

The GPU is recommended for network training by the Parallel Computing Toolbox. An object detection model called R-CNN [23], [33] uses. Traffic sign areas may be classified using Convolutional Neural Networks (CNN) [34]. Instead of using a sliding window to categorize each location, the R-CNN detector only deals with areas that may contain objects. Thus, CNN's processing costs are decreased significantly. R-CNN [23], [33] is an object detection model that

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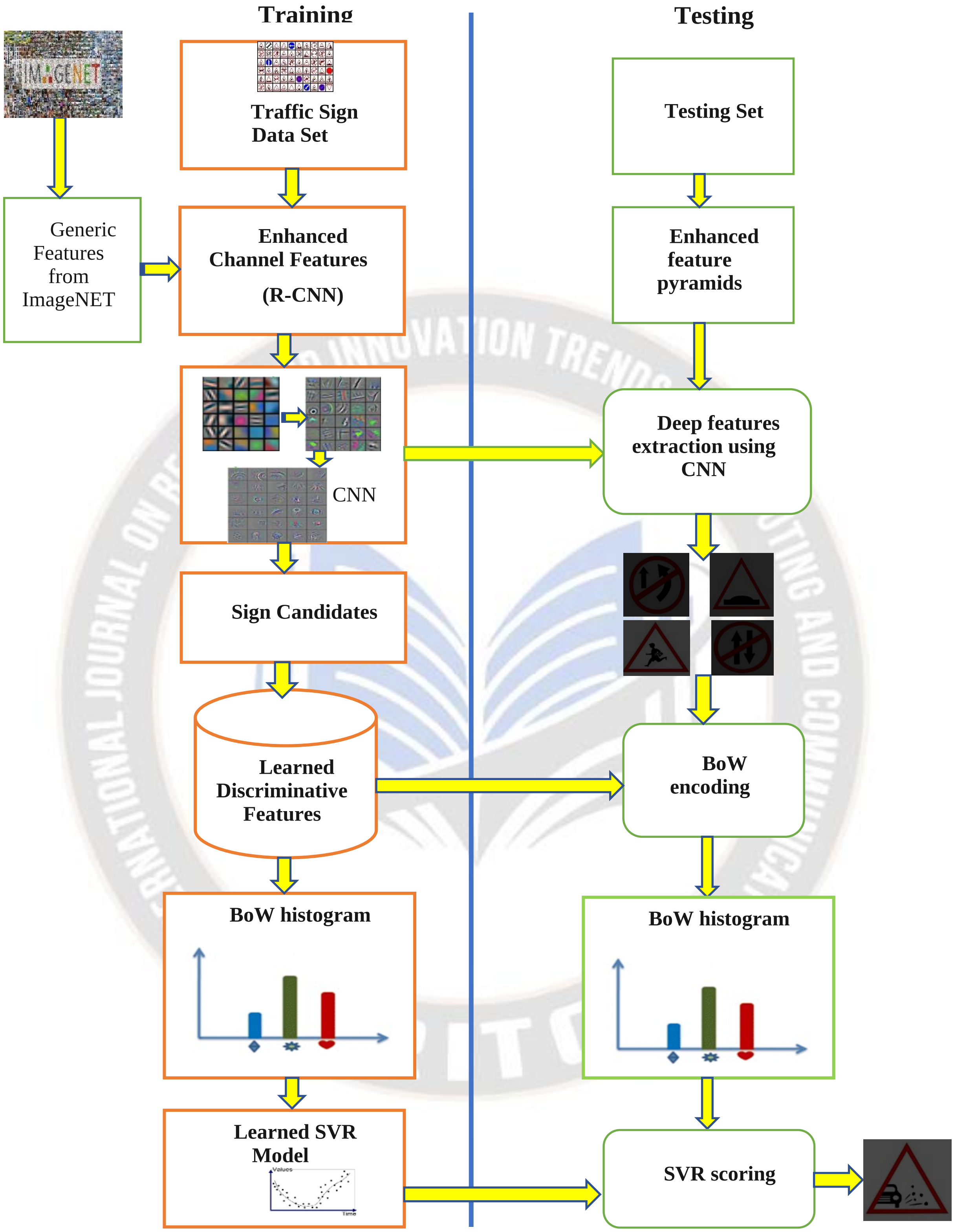

Figure 3 Proposed flow diagram for traffic sign identification and detection system

uses Convolutional Neural Networks to classify picture regions in pictures [34]. The R-CNN detector does not use a sliding window to categorize every region but just those areas that are likely to have an item. In CNN, this method significantly reduces the number of computations. The proposed system for traffic sign identification has phases, including offline training and online checking out, as shown in Figure 3. Visual saliency, color, gradient, and orientation

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are concatenated into a single vector during the offline training stage and incorporated into the ground-fact signs in distinct channels to represent a sign picture. The vectors are then trained using deep CNN layers for deep feature extraction approach. Using the learned features, a collection of traffic sign applications is generated from the training images.

For sign and non-sign candidates, discriminative codewords are utilized to encode BoW histograms. Finally, the histograms are used to train an SVR model that can distinguish between candidates for signs and those who aren't, and weights are assigned depending on how well the candidates' intersection ratios match the real world. Consequently, three modules are learned during training: Deep CNN, discriminative codewords, and the SVR model, which may be utilized for traffic sign candidate scoring.

V. PROPOSED APPROACH

This section explains the suggested traffic sign detecting method. We break it down into two parts, one for improved feature pyramid detection and the other for discriminative codeword selection (DCS) for SVR. Multiresolution image decomposition is one of the most essential approaches for picture analysis [34]. Feature pyramids are multiresolution picture features. A collection of picture pyramids may be created by upsampling or downsampling the source image into multiple resolutions. Feature pyramids have proven effective for object recognition at high speeds [23], [34], [35]. That is different from other visual pyramids that tend to focus just on one particular aspect of a picture, such as the sign or non-sign, and ignore any differences in perceived importance between the two. We improve the feature pyramid to calculate picture channel features by including information on projected saliency. A subjective visual feature known as "picture saliency" determines which portions of an image stand out and draw in viewers. A person's focus is initially drawn to aspects of the natural world that stand out. It's been a long time since designers have depended on their own salience device to create objects and traffic signs.

This might appear to be necessary to drivers and pedestrians in several situations. An image pyramid is formed by resampling the original image at multiple resolutions. Using the saliency map and the original image as a starting point, the image pyramid is built up from the saliency values of each pixel. In addition, the LUV color space, one gradient magnitude channel, and six orientation channels [35] are all calculated. Function vectors are created by concatenating the summations of pixels in each channel picture block at various pyramid levels. To compute a function, pixels in the most relevant picture areas might be assigned a significant weight. The likelihood of false positives is minimal when it comes to non-salient picture locations that don't contain traffic signs. Consequently, the most visible parts of the image, such as road signs, have a better chance of being recognized. The following computation cues are used to generate a saliency map that allocates higher weights to sign pixels and lower weights to non-sign pixels. They both use visual picture features, but one relies only on prior knowledge of a traffic sign's position in an image.

As a result, the image's most prominently located traffic signs will have the Itti–Koch saliency estimate notion used in the first suggestion to represent sign-specific visual saliency. As a result of traffic signboards often having dominant color and form contrast against backgrounds and the Itti–Koch technique exactly serving this purpose, we used the Itti–Koch methodology to compute the center-surrounding difference in color and orientation channels. The multiscale picture elements are combined into a single topographical saliency map in the Itti- Koch technique. When a dynamic neural network selects the attended areas in decreasing order of importance. The approach makes the challenging task of visual understanding easier by quickly and computationally efficiently detecting significant locations. However, traffic sign detection has two problems with the Itti–Koch technique [12]. To compute opponency values, it uses the red/green (R G), green/red (G R), blue/yellow (B Y), and yellow/blue (Y B) color pairings.

$$R\_G(c,s) = |(R(c) - G(c))\Theta(G(s) - R(s)) \qquad (1)|$$

The red, green, and blue channels are represented by "R," "G," and "B," correspondingly. It is possible to compare the "center" fine-scale c and the "surround" coarser scale s to the ratio of the original image's length to the image's resizing/subsampling ratio. Point-by-point subtraction of the variously rescaled pictures receives the across-scale middle surround difference. The G R(c,s), B Y (c,s), and Y _B(c,s) functions are all computed using the same formula (1). This cannot be used to detect traffic signs. This is because each type of traffic sign has a distinct color to distinguish it from its surroundings.

To identify as many ground-truth traffic signs, we adjust the feature pyramid method's settings, such as the pyramid level numbers, sliding window size and duration/width ratios, and improved detection score. These improved detection score might be used as the sliding window input to identify a check image and create a collection of sign candidate rectangles that contain both true and false positives. As a result, many detections from adjacent locations and pyramid levels are produced. For each detection, a box and a score are utilized. Detections with less than 50% of their bounding boxes included in another detection's bounding box are skipped in favor of those with higher scores. After that, a few low-scoring recurrent detections are purged, albeit some false positives are left behind. The SVR approach is discussed in

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the following sections to eliminate false positives while still retaining the true positives in the dataset.

VI. EXPERIMENTS

Three publicly available data sets are used to evaluate the suggested method for detecting traffic signs. Data sets from Germany, Sweden, and Belgium are included in the GTSD Benchmark [3], STSD Data Set [20], and BTSD Data Set [21]. GTSD's images depict a wide range of environments (urban, rural, and highway) at various times of day and night. Images were taken at a resolution of 1360 × 800 pixels, with traffic sign widths varying from 16 to 128 pixels in length. The data set consists of 600 photographs for training and 300 photos for checking out. It contains 5905 training pictures and 3101 testing images for BTSD. About 20,000 STSD pictures are included in the database, with 20% of them personally labelled. To evaluate the proposed traffic sign detector's performance, we partition the images in GTSD and BTSD into three primary groups using the approach described in [3] and [21].

Figure. 4. Model predictions(green:correct, red:incorrect)

(a) (b) (c) (d) (e) (f)

Figure 5. Six traffic sign categories. (a) 50_sign, (b) give way, (c) no stopping no standing, (d) pass right side, (e) pedestrian crossing, and (f) priority road from left to right.

The [20] method is used for STSD, and six categories are highlighted in Figure 5. Initially, a random sample of 2,000 negative instances is selected for training, and a further 2,000 examples are bootstrapped into future training rounds. During each round of training, the false positives that have been found are utilized as negative samples for the following round. A multiscale, multi-aspect ratio technique is used to train the detector. The scale and aspect ratio is altered from a starting point of 32 32 pixels from 0.5 to 2 and 0.8 to 1.5, respectively. The 32 pyramid levels are applied in every picture. The detector has a 4-pixel resolution. Non-maximum suppression [9] reduces the number of surrounding candidates whose overlap exceeds a certain threshold. We employ dense HoG as the local image features to produce the BoW codebook and histogram in the SVR identification step. In the grid search technique, the values of C are 27 and 22, respectively. Compared to the SVR output, the threshold for identifying sign candidates is set at 0.6. According to [22], a criterion of 0.5 is used to determine whether or not the detected sign candidates should be retained.

Table 2 Comparison of The Proposed Technique with State-of-the-Art Techniques in Terms of AUC (%)

Dataset/ Methods	GTSD			BTSD		
	M Mandatory	D Danger	P Prohibitory	M Mandatory	D Danger	P Prohibitory
ChnFtrs in[22]	96.98	100	100	94.79	96.40	86.51
HoG+SVM[3]	92.00	98.85	100	89.85	91.23	82.4
VJ+HIS [21]	61.12	79.43	72.6	92.32	95.91	84.27
Proposed method	99.87	100	100	97.78	99.88	93.45

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Table 3 Comparison of The Proposed Technique with State-of-the-Art Techniques on the STSD Data Set

Sign Type	Precision (%)		Recall(%)	
	Method [20]	Proposed	Method [20]	Proposed
Pedestrian crossing	96.03	98.52	91.77	93.45
Designated lane right	100	100	95.33	97.53
No standing or parking	97.14	99.2	77.27	81.46
50kph	100	100	76.12	80.56
Priority Road	95.66	97.89	74.24	79.68
Give way	59.26	71.5	47.26	52.39
Overall	91.35	94.52	77.00	80.85

B. Experimental Results

This step uses various data sets to test the trained traffic sign detector. Table 2 summarises overall detector performance by evaluating the AUC of detectors on GTSD and BTSD for all three superclasses. The following observations have now been made. For GTSD, the majority of techniques (e.g., key channel features in [22], HoG + SVM in [3], and the suggested method) have accuracy and recall values close to 100% for every superclass. Because GTSD only has a limited number of pictures to test, so the findings are easy to saturate. On the other hand, it can be demonstrated that the suggested method improves performance by 3% when compared to [22]'s integral channel features in the required class. Second, the recommended solution beats competing methods by around 3% to 7% for each superclass in the case of BTSD.
Comparative studies are being conducted on the STSD data collecting. According to [20], we use accuracy and consider metrics when doing assessments. Table 3 demonstrates that our proposed solution beats the methodology outlined in [20] for each type of traffic sign by between 2% and 13%. Precision and recall are improved by 3.17 percent and 3.85 percent on average for all signal kinds when using the suggested approach. Some tough classifications like "give way," for example, may be detected with accuracy and recall of 72 percent and 52 percent, respectively, compared to the findings in [20]. Finally, the recommended method consistently beats the alternatives on all three data sets. Two things are to blame for this: To compute features, a proposed method considers the visual saliency of the sign.
DCS can discover codewords that distinguish between traffic signs and non-sign applications to distinguish between true-positive and false-positive signals when representing an image. The proposed method develops a DCS image representation methodology before performing SVR identification. In a picture, the saliency estimate highlights the traffic sign pixels and de-emphasizes the non-sign pixels, which significantly enhances memory and precision. The accuracy of the detection is much improved by using this DCS technique.

C. Discussion

Advanced assessment tests are conducted in three groups to determine the impact of various technological additions on the suggested approach. It was decided to utilize the BTSD data set for this study because it has the most state pictures and traffic signs out of the three and covers a greater range of actual photographing conditions than the other two sets did here are a few examples of what we've been up to lately.
In comparison to the previous plan, describe how this one differs. As a pyramid, this is how you approach it: It was selected to compare the original rapid feature pyramid strategy in [9] for item recognition. Figure 6 presents the results, which reveal that the required, dangerous, and prohibitive superclasses all relate to the same superclass. Each superclass increases AUC of 3–4 percent when using an enhanced feature pyramid with a saliency estimate instead of the original technique. This is due to the state of incorporation state saliency, which offers bigger weights to picture areas that are more likely to include site visitors' symptoms and lower weights to non-salient regions that are less likely to contain traffic indicators. Since the symptoms are more likely to be observed in the salient locations, false alarms in the less prominent areas are less likely to occur. The AUC rises by around 3% when the suggested codeword selection-based SVR identification is included for false-alarm reduction. As a result of selecting the greatest choice, this has occurred.
An SVR model created utilizing BoW histogram quantization of traffic sign images can distinguish authentic sign applicants from fake sign candidates based on the codewords used in the image quantization process.

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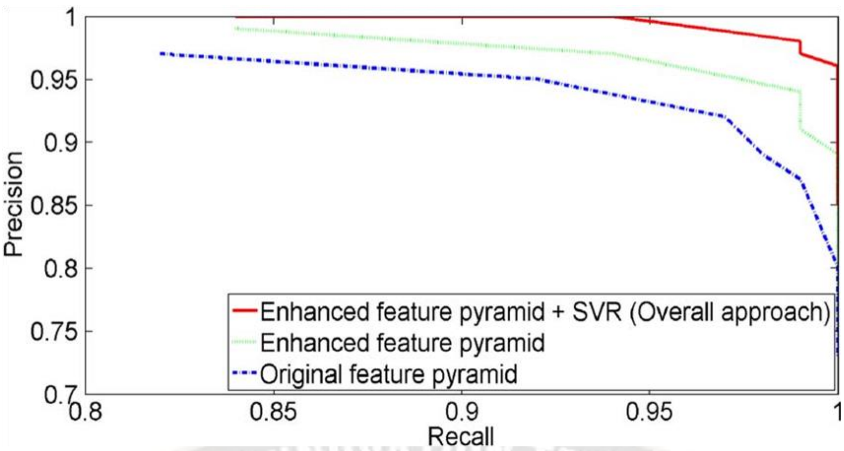

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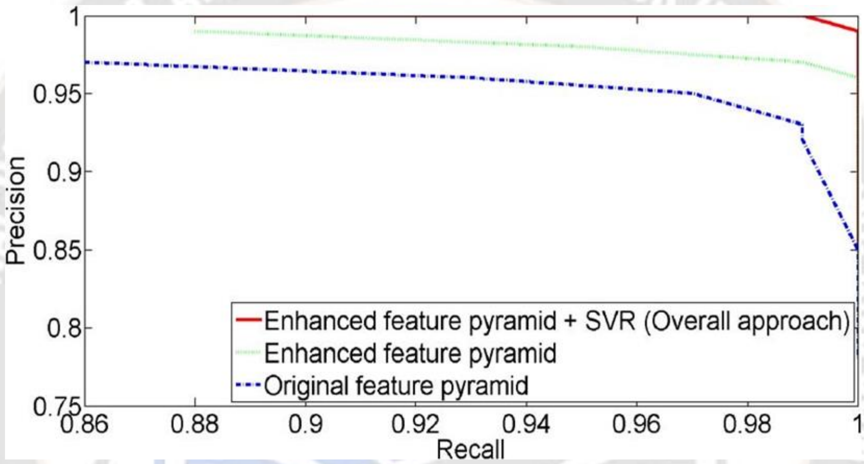

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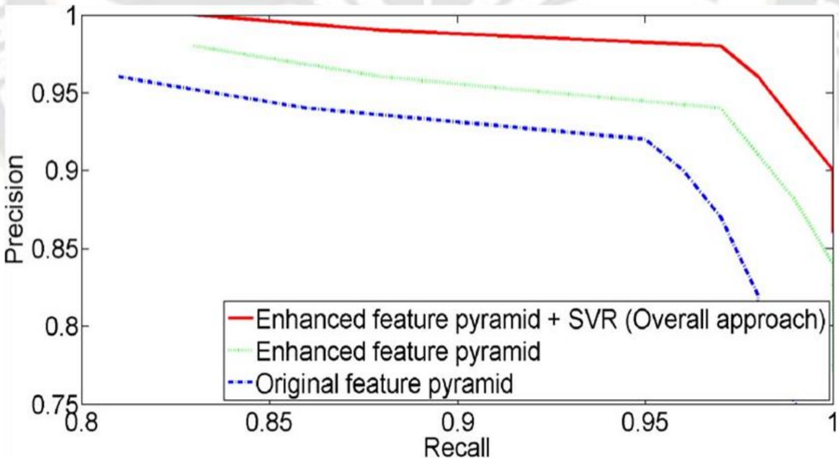

(c)

Figure. 6. Precision and recall comparison between original feature pyramid and enhanced feature pyramid plus SVR approach features on three data sets (a)GTSD (b)BTSD (c) STSD

Additionally, we evaluate the performance of utilizing spatial records to estimate saliency vs. not using them at all. Out of a total of 6–7 percent overall performance increase, the results show that the spatial saliency records contribute 1.1 percent. Spatial information may be used because most traffic signs can be seen in a specified area of a standard car-mounted camera.

There are a few alternatives to the proposed method for estimating saliency value. The proposed method is compared to the Itti–Koch method from [12] and the graph-based visual

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saliency (GBVS) method from [13]. Figure 7 displays the AUC assessment findings for the BTSD fact set. The proposed technique for estimating saliency is clearly superior to all existing methods. Keep in mind that, as discussed in section IV-A, greater performance is in part attributable to top-down information, which contains potential spatial placements of traffic signs.

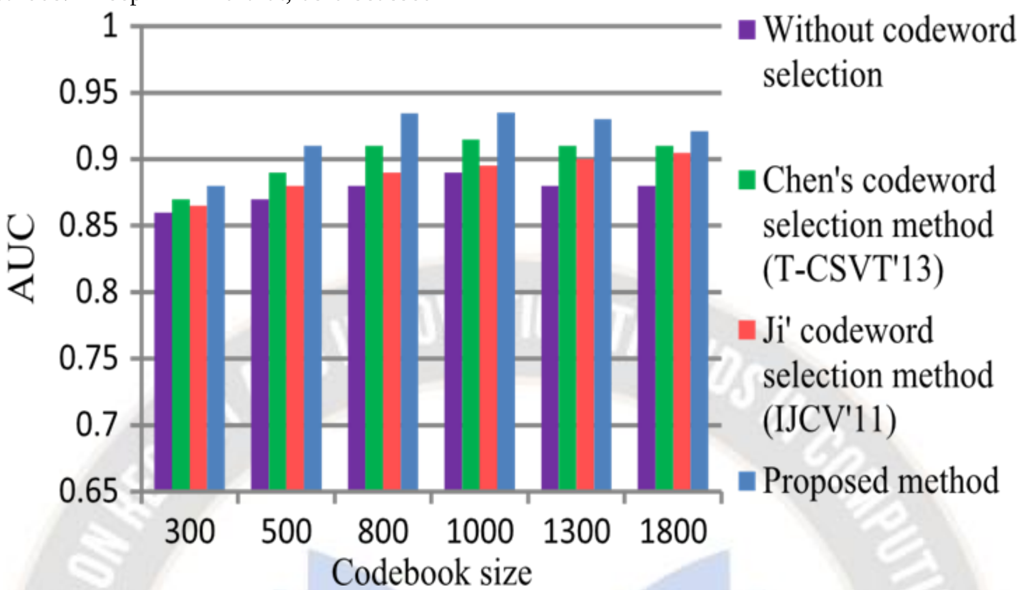

Figure. 7. Comparison of different saliency models.

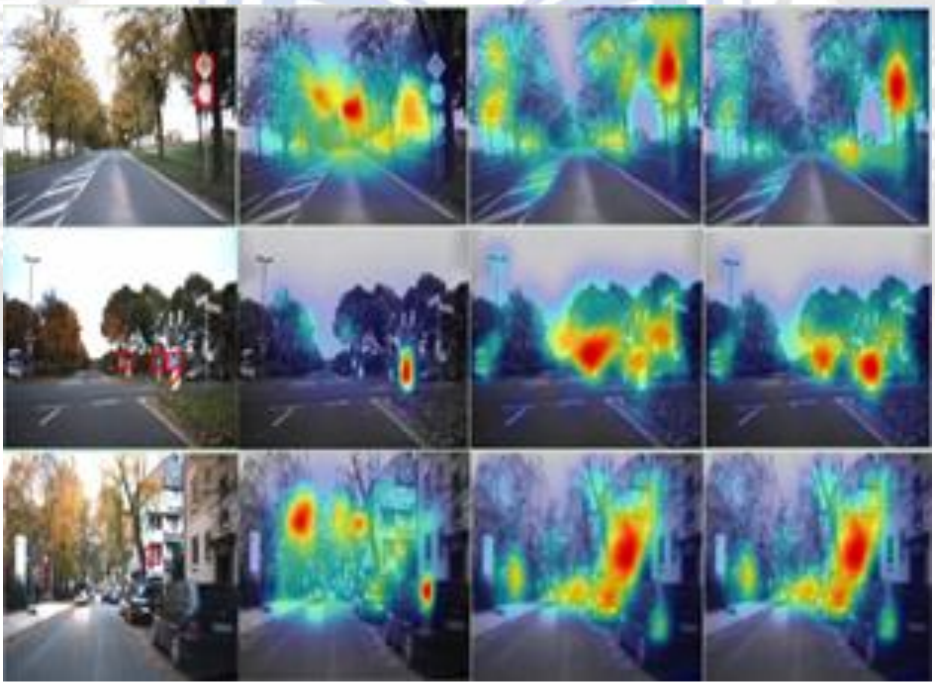

Figure 8. Detection of traffic sign marks based on saliency value

Figure 8 shows the comparison of saliency values of various approaches. The figure 8 describes that the first column shows three images containing different traffic signs highlighted in red boxes. The second and third columns show the enhanced images overlaid by GBVS saliency in [13] and the Itti–Koch saliency in [12], respectively. The fourth column shows the enhanced images overlaid by the proposed saliency. The recommended saliency approach creates an excellent augmented image by preserving the original image's saliency map and highlighting all visitors' sign bins with high saliency values. For the other options, their saliency maps can most successfully emphasize a single traffic signal box or none at all inside the unique image. False positives identified in these regions may be filtered out during the SVR score stage.

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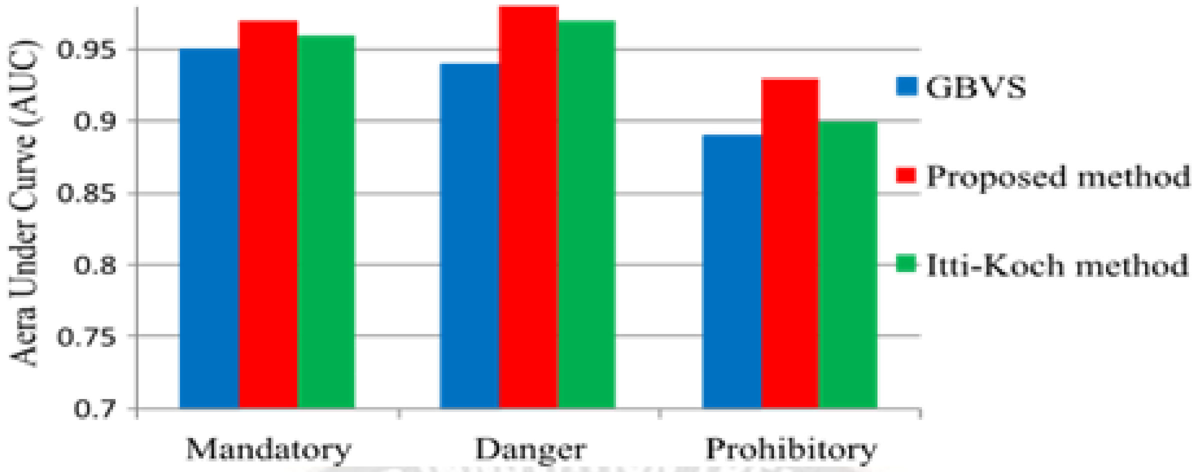

Figure 9. comparison of codebook learning using SVR detection approach

The DCS vs. Other Methods: A comparison is also compared to earlier object popularity-related codeword selection techniques [18, 19]. Figure 9 shows the overall performance of SVR detection without codeword selection. A more significant improvement area is displayed in table 2 for the "prohibitory" category in the BTSD data set, which was selected for testing. This shows that SVR detection with codeword selection has better overall performance than SVR detection without codeword selection. In addition, among the many methods, the proposed codeword selection approach provides the greatest overall performance for each set of codebook sizes. Because of its short size and high-quality performance, the suggested method for codeword selection is particularly efficient. Codebooks larger than 800 bytes might create too much noise or too few consultant words, which is a great way to reduce performance. As a result, the codebook's size gradually decreases until it hits 800 bytes.

VII. CONCLUSION

A New traffic sign detection system was created with deep transfer learning, R-CNN, Deep CNN and SVR. First, we use every visible and spatial area fact to estimate the saliency of site visitors' signals, which are then fed into the picture pyramids to produce a more robust characteristic pyramid for R-CNN. Second, we use every visible and spatial area fact to estimate the saliency of site visitors' signals, which are then fed into the picture pyramids to produce a more robust characteristic pyramid for Deep CNN. The concept of iterative codeword selection criteria for the development of the BoW codebook, which is used to encode sign candidates into histograms for the detection of SVRs According to experimental results on German, Swedish, and Belgian site visitors signal information sets, the proposed approach delivers both high accuracy and quick velocity in visitors sign detection.

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