Multi-stage Deep Learning Technique for Improving Traffic Sign Recognition

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***Abstract*—The automatic detection and interpretation of all roadside signs with text information is a very challenging and difficult problem. The main challenge is to distinguish signs with important information which are similar in shapes, sizes, and colors. In this research, we offer a multi-stage deep learning-based approach combined with Optical Character Recognition (OCR) for automatic identification and recognition of text in speed limit traffic signs. The proposed technique consists of novel concept in which deep learning detection and OCR interpretation of attributes is introduced. The technique has been evaluated on real world dataset. A comparison of the data obtained utilizing the proposed approach revealed a significant improvement in speed sign recognition accuracy and misclassifications.**

Keywords—deep learning, speed limit sign recognition, fully convolutional neural network (FCN), optical character recognition

I. Introduction

Detecting and recognizing traffic signs automatically and information written on them is a challenging problem and an essential part of road environment with a variety of applications [1]-[2], including improved driver assistance systems, road surveys, and intelligent vehicles. Many traffic signs include information such as speed limits, road conditions, and warnings such as construction, school zones, and railway stops, among other things, which are extremely valuable for road surveys, unmanned intelligent vehicles, and Vulnerable Road Users (VRUs).

Researchers have been looking into a variety of issues with regard to identifying information written on traffic signs and they have had some success detecting particular signs. Even though there exists much research in detecting and recognizing both traffic signs based on symbols [3]-[4] and recognizing text in real time environment [5]-[7], a smaller number of research has been specifically conducted on recognizing text on traffic signs [8]-[9]. The research in this area is mostly divided into two categories: region-based approaches and Connected Component (CC)-based methods [5]-[7]. Local features such as texture are used in region-based text detection methods [4] to locate text regions while information such as intensity, colour distribution, and edges are used by CC-based methods to segment text characters individually. The majority of current state-of-the-art approaches combine detection and recognition [10]-[11] while advanced deep learning-based approaches were applied by certain researchers. Tabernik et al. [12] proposed a system based on Convolutional Neural Network (CNN) and mask R-CNN for detecting and recognizing traffic-signs in wide range with better performance for many traffic-sign categories, including several complicated ones with large intra-class variability. Lee et al. [13] proposed utilising CNN to recognise traffic signs and estimate boundaries, and they produced reliable results on a low-power mobile device. Using region focusing and parallelization, Avramovic et al. [14] suggested a neural-network-based traffic approach for detecting and identifying signals in high-definition images. On the German Traffic Sign Recognition Benchmark (GTSRB), Bangquan et al. [15] suggested a real-time embedded traffic sign recognition using efficient CNN and achieved 98.6% accuracy. OCRs were employed by certain researchers for text recognition tasks in a variety of applications. For meal tracking and tracing, Čakić, et al. [16] employed OCR for number recognition. However, when confronted with images including shadows, the experiment failed. Solanki et al. [17] employed OCR to identify and recognize traffic signs with encouraging results for test images shot at various time intervals and in various weather situations. Zhu et al. [18] introduced a cascaded segmentation-detection network for text-based traffic sign recognition which used a fast neural network to identify texts on the extracted Regions of Interests (RoIs) after using a fast neural network to segment candidate traffic sign regions producing candidate RoIs.

Our major goal is to introduce a new approach that will increase the accuracy of speed limit detection in our complicated AusRAP (Australian Road Assessment Program) attributes detection system. AusRAP aims to detect and identify all road attributes so that road safety may be assessed. Misclassification of attributes with text that have similar colors, shapes, and sizes is a key issue we are currently dealing with. We present a new approach for recognizing speed limit signs using the techniques of deep learning segmentation and OCR interpretation to decrease misclassifications and enhance accuracy. The following are the key objectives of this paper.

1. A multi-stage deep learning-based technique for improving speed sign recognition accuracy in our AusRAP safety attributes detection system is proposed.

2. Novel concept of introducing OCR combined with deep learning to detect text on speed signs is proposed and investigated.

3. A vast number of experiments have been carried out using real-world video data received from industry partners which consists of video data from all state roads in Queensland.

4. A comparative analysis of experimental results is presented.

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The following is the structure of this research paper: The proposed approach is described in Section II. The experiments are described in section III, while the results and discussion are offered in section IV. In section V, a comparative analysis is presented. Section VI concludes the research with recommendations for further research.

II. Proposed Technique

Fig. 1 depicts an overview of the proposed technique. The proposed technique consists of a multistage detection and recognition stage. In detection stage, deep learner model is trained on all AusRAP attributes. All speed limit signs are classified as a single attribute at this stage. In recognition stage, RoIs are obtained from input images based on detected pixels in detection stage. RoIs are fed to OCR which outputs actual speed limits. The recognized speed limits are used to replace speed classes in predicted frames and final output frames with recognized attributes are produced. Each attribute contains different color pixels for visualization purposes.

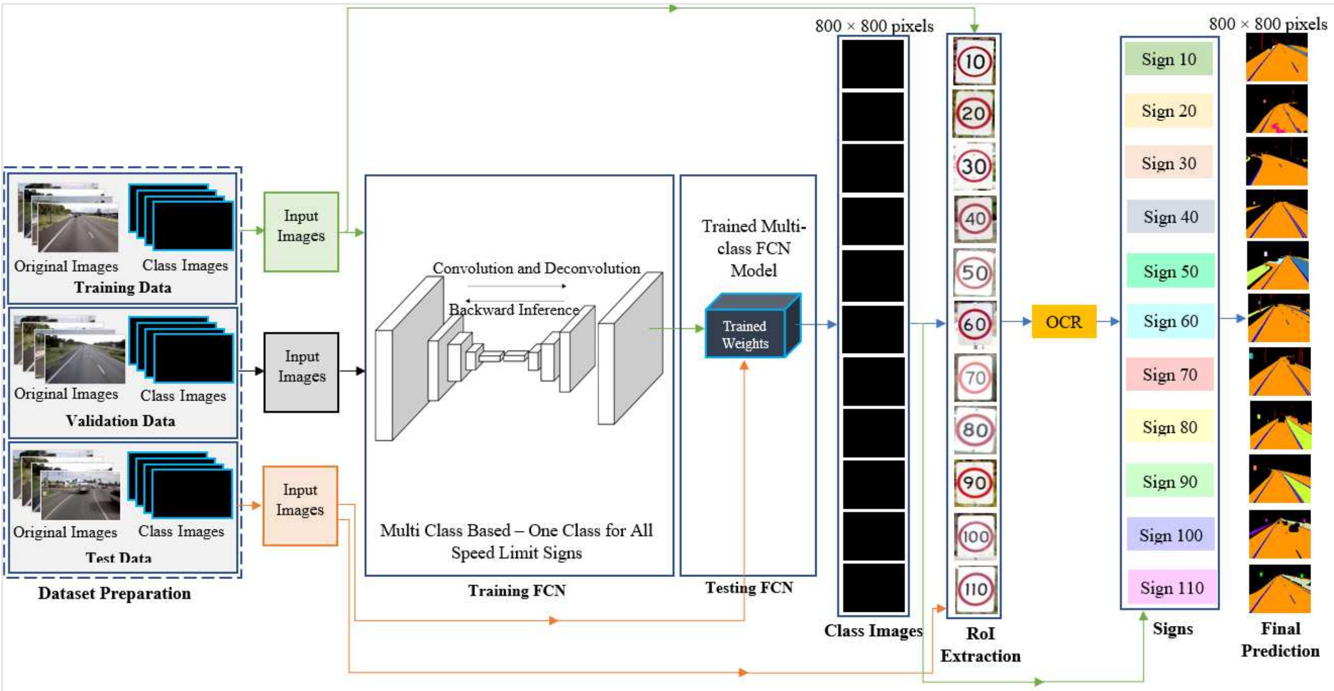

Fig. 1. Architecture of the proposed technique.

As illustrated in Fig. 1, the proposed technique has several steps: data preparation, FCN training, FCN testing, RoI extraction and OCR classifier.

A. Dataset Preparation

The Queensland Road videos provided by our industry partners, the Department of Transport and Main Roads (DTMR), Queensland, and the Australian Road Research Board (ARRB), were utilized to construct the training, validation, and test images used in this research. In the data preparation step, three custom datasets for training, validation, and testing were developed. Original resized images and annotated resized images transformed to class images make up each of these datasets. Images were annotated with Adobe Photoshop CC 2019 software, and then transformed to class images with a MATLAB program. All images were resized to 800×800 pixels using a MATLAB program.

Altogether, there are 61 AusRAP attributes to be identified. Road markings, road defects, traffic signs, roadside objects such as barriers, deep drainage ditches, rigid structures, aggressive vertical faces, boulders, unprotected barrier ends, pedestrian fencing, trees, poles, guideposts, flexiposts, sidewalks, medians, dedicated bicycle paths, pedestrians, bicycles, motorcycles, etc. are among the attributes. Chevron alignment marker, railway passive sign, railway stop signage, pedestrian crossing sign, merge lane sign, intersection legs-3 sign, intersection legs-4 sign, curvature sign, roundabout sign, one way sign, minor roadworks sign, major roadworks sign, signed shared roadway, school zone warning sign, slip lane sign, and all speed limit signs are among the traffic signs identified in this study. Among these 61 attributes, 11 attributes are speed limit signs. All speed limit sign boards have speed limit text written in black color around a red color circle in white background. The shapes of all the speed limit sign boards are all rectangular.

A program developed using MATLAB software was used to carefully determine 61 RGB colors for each of the 61 attributes in the dataset, avoiding colors that are already present in the dataset. Each attribute was given its own class, and all background information was grouped together in a class named "unlabeled" resulting in a total of 62 classes. Annotated images have been included in test dataset for the comparative analysis with Ground Truth (GT) and prediction images and determine the prediction accuracy. In this research, the training dataset consisted of 549 images while test dataset consisted of 106 images. For each attribute, minimum 20 objects were included in the training dataset. One dataset was utilized for testing and calculating the final prediction in each experiment.

B. Training FCN

The deep learning model is based on FCN architecture. It consists of 800 × 800 × 3 inputs and same number of outputs.

It uses the pre-trained model: imagenet-vgg-verydeep-19 beta 16, number of convolutional layers having similar padding, rectified linear activation function, max pooling for down sampling and Adam optimizer using the backpropagation algorithm.

FCN was trained utilizing a single class for all speed limit signs during the training stage. To obtain the highest accuracy, network parameters such as the number of iterations, layers, etc., have been tuned experimentally. There was a total of 61 attributes in the system. However, with the usage of a single class for all speed limit signs, the number of classes was decreased to 52. At each 5,000 iterations, FCN models were automatically produced incrementally. Validation accuracy was calculated for each model using validation dataset. Out of the 32 models auto generated at the end of 160,000 iterations, the model having the highest accuracy and lowest misclassifications was selected as the best model for OCR stage.

C. Testing FCN

The best trained model from the training step is assessed on test data in the testing/prediction stage. The testing stage is comprised of many stages: determining the RoIs where the speed limit sign is expected to be placed, detecting all possible candidates within these regions, applying contextual constraints to reduce candidates, OCR interpretation, and production of final prediction results combining all 61 attributes. The prediction images produced by best FCN model class numbers as prediction and appear in black color. The regions recognized as having the speed limit class were extracted from these class images and utilized to extract the same regions in their original images. An appropriate threshold value was applied before extracting RoI images to reduce large number of detected candidate regions with noise, unlikely candidates, and smaller dots like objects identified as speed limit signs. These images were saved as RoI images. The algorithm's following stage is to recognize text inside the located area after the speed limit sign has been discovered. All the RoI images extracted in this way were then fed to an OCR for interpretation. In OCR, pre-processing techniques were applied to RoI images to remove noise and isolate the speed limit text from the background. Then, the speed limit was read and the signs in the prediction class images were updated with the recognized speed limit sign. If OCR detects the RoI image not as a speed limit sign, that region was updated as unlabeled class. The process within OCR is described in detail in section D below. Fig. 2 below shows some of the sample RoIs which were input to OCR.

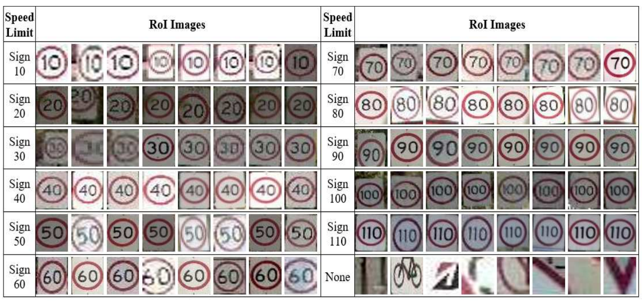

Fig. 2. RoI images as input to OCR.

D. OCR Classifier

In OCR stage, RoIs extracted from input frames based on trained FCN's decision are fed to OCR which outputs recognized speed sign. In this research, even though the RoI image appears as an easy input for OCR to classify, it is a challenging task in real scenario because of the non-uniform background around text which cause poor text segmentation. In this research, the following steps were followed when implementing OCR.

Step 1: Remove edges of the RoI images as they contain part of the background.

Step 2: Increase the size of the regions a bit to incorporate additional background pixels around the text characters.

(Eventually, this supports improving the internal heuristics used in determining the polarity of the text on the background. Therefore, RoI images were resized by a specifying scale factor.)

Step 3: Convert RoI images to binary images by replacing all pixels in the input having luminance greater than specified level with 1 (white) and all other pixels with the value 0 (black).

Step 4: Remove the circle around the speed limits.

(For better results by OCR, RoI images were pre-processed, and OCR received particular regions in the RoI image that it should process. In this research, these regions are those regions that just contain the numbers. A CC analysis was used to isolate the text in RoI images. Almost in all RoI images, there was a red color circle around the text. By applying this analysis, the circle around the speed limit was removed.)

Step 5: Dilate RoI images to grow the text a bit to get a bigger RoI around them.

Step 6: Determine the bounding boxes around the text.

Step 7: Erode the binary image and make the numbers thinner to remove artifacts.

(After eliminating the background variation, the numbers were apparent in the binary image. However, there can be few artifacts surrounding the numbers that might obstruct accurate detection by OCR. Additional pre-processing using morphological reconstruction was used to remove these artifacts and introduce a cleaner image for OCR. To remove these artifacts, the binary image was eroded, and the numbers were thinned.)

Step 8: Remove all the connected components of area lesser than 150 pixels from the binary image.

(There are small, connected regions within the RoI image which are not likely to contain any text. Therefore, all the CCs (objects) that have fewer than 150 pixels area were removed from the binary image, producing another binary image.)

Step 9: Disable the automatic layout analysis using the "TextLayout" parameter to help improving the results.

(If the text is scattered and irregularly located in the background, the heuristics used for document layout analysis within OCR becomes unsuccessful in determining the text blocks within the image, and, consequently, the text recognition becomes faulty. Therefore, the automatic layout analysis is disabled using the "TextLayout" parameter to help improving the results. After applying these pre-processing steps, the numbers are now well segmented from the background.)

Step 10: Constraint OCR to only choose the best equivalents from the set "0123456789".

(Now the processing of RoI image is finished and only characters are visible. However, still there is a possibility to falsely recognize several non-numeric characters in the image as digits. This may take place when a non-digit character closely looks similar to one of the digits. There can be "noise" in the results due to alphabet letters. Therefore, another approach to improve the results was using priori knowledge about the text within the image. In this research, the text we are interested in contains only numeric digits. Therefore, the results are further improved by limit OCR to only choose the best equivalents from the set "0123456789".)

Step 11: Remove any trailing characters, such as white space or new lines using the deblank function.

Step 12: Display the recognized text on the original image.

Images in Fig. 3 show how RoI images are processed in OCR to get the final prediction for some sample speed limit signs.

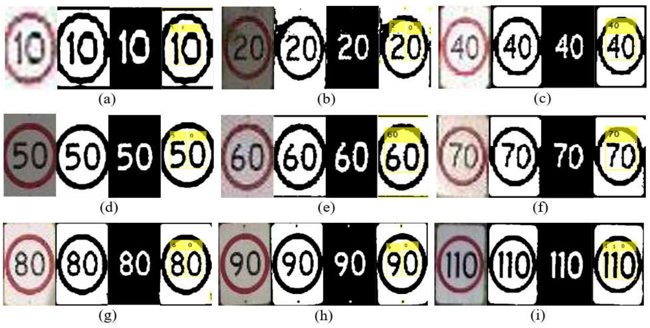

Fig. 3. Prediction results of OCR for sign 10 (a), sign 20 (b), sign 40 (c), sign 50 (d), sign 60 (e), sign 70 (f), sign 80 (g), sign 90 (h), and sign 110 (i).

III. Experimental Results

For the proposed approach, several tests were carried out on a High-Performance Computing (HPC) facility. FCNs were created in the Anaconda environment using Python (version 3.5) and TensorFlow. We present classification accuracy attribute wise and pixel wise as a percentage, which is a widely used criterion for visual object recognition. The fraction of correctly classified pixels over the total number of pixels in an object is referred to as pixel wise accuracy in this context. The fraction of correctly classified objects over the total number of objects for an attribute is known as attribute-wise accuracy. The majority prediction for the areas corresponding to an object is used to identify an attribute as a prediction. Misclassifications were calculated as a proportion of the total number of misclassified images for each attribute divided by the total number of images in the test dataset. Two types of experiments (proposed technique with OCR and without OCR) were used to assess the effectiveness of the proposed approach.

1) Proposed technique without OCR: A multi-class model with all separate classes including 11 speed signs (total 61 classes) and accuracy for all the 61 attributes were recorded at intervals of 5,000 iterations. The model having comparatively a higher accuracy as well as lower misclassifications were selected as the best model and this model was saved. Accuracy and misclassifications obtained for speed signs at the best model were recorded as shown in Table I.

2) Proposed technique with OCR: A multi-class model was trained for all the 61 attributes by including all the 11 speed limit signs in one class and all the other attributes in separate classes. The model having comparatively a higher accuracy as well as lower misclassifications was selected as the best model and was saved. The best model was obtained at 115,000 iterations whose accuracy of speed sign classes were recorded as 97.5% and 96% respectively attribute wise and pixel wise. RoI images from corresponding original images were extracted and these RoI images were passed to an OCR to recognize text in speed limit signs. Table II shows the results achieved from the proposed techniuqe with OCR.

TABLE I. Best Classification Accuracy and Misclassifications Obtianed by Proposed Technique Without OCR

Speed Limit	Accuracy (%)		Misclassifications (%)
	Attribute wise	*Pixel wise*	
Sign 10	50.00	48.00	0.94
Sign 20	33.34	13.00	1.89
Sign 30	0.00	0.00	0.94
Sign 40	33.34	28.00	0.94
Sign 50	0.00	0.00	0.94
Sign 60	66.69	36.00	2.83
Sign 70	14.29	12.00	3.77
Sign 80	100.00	76.00	0.00
Sign 90	50.00	50.97	0.94
Sign 100	75.00	46.00	0.94
Sign 110	50.00	36.00	0.94

IV. Result Analysis and Discussion

As indicated in the figures below, the results have been displayed and evaluated. Fig. 4 shows the best prediction results obtained for some speed limit signs from a multi class model (Prediction 1) and a multi class-based model with one class for all speed limit signs with OCR (Prediction 2) at 115, 000 iterations. For easy comparison, each prediction result is shown with both the original and GT picture. As shown in Fig. 4, prediction pictures from a multi-class experiment with one class for all speed limit signs with OCR are almost identical to the corresponding GT images. Prediction images obtained without OCR from a multi-class experiment include a lot of noise and a lot of misclassifications.

TABLE II. BEST CLASSIFICATION ACCURACY AND MISCLASSIFICATIONS OBTIANED BY THE PROPOSED TECHNIQUE WITH OCR (ONE CLASS FOR ALL SPEED LIMIT SIGNS)

Speed Limit	Attribute Wise Accuracy (%)	Misclassifications (%)
Sign 10	50.00	0.00
Sign 20	100.00	0.00
Sign 30	100.00	0.00
Sign 40	100.00	0.00
Sign 50	50.00	0.00
Sign 60	83.33	0.00
Sign 70	42.86	0.00
Sign 80	50.00	0.00
Sign 90	100.00	0.00
Sign 100	50.00	0.00
Sign 110	100.00	0.00

When observing Table I, it is seen that sign 10, sign 30, sign 40, sign 60, sign 90, sign 100, and sign 110 obtained 100% attribute wise accuracy with 0% misclassifications for sign 10. Among them, sign 30, sign 40, sign 90, sign 100, and sign 110 have very high pixel wise accuracy equal or above 90% and 75% pixel wise accuracy for sign 60. Sign 70 also have a comparatively higher accuracy (71.44% attribute wise and 77% pixel wise). Among them, sign 20 has the lowest attribute wise accuracy which is 33.34%. As shown in Table II, sign 20, sign 30, sign 40, sign 90, and sign 110 have 100% attribute wise accuracy for multi class-based experiment with one class for all the speed limit signs with OCR. Sign 60 also has a considerably higher attribute wise accuracy which is 83.33%. Sign 10, sign 50, sign 80, and sign 100 got 50% attribute wise accuracy. All the speed limit signs have 0% misclassifications as well.

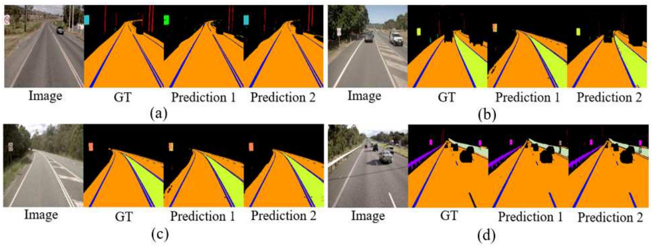

Fig. 4. Prediction results of sign 70 (a), sign 80 (b), sign 90 (c) and sign 100 (d) obtained by the proposed technique with OCR at 115, 000 iterations.

V. COMPARATIVE ANALYSIS

The findings acquired by the proposed approach have been evaluated and compared. Table III compares the attribute-wise accuracy of the proposed approach with FCN8 [20], DeepLabV3+ [21], and the proposed technique with OCR. Table IV illustrates a comparison of misclassifications acquired with and without OCR using the proposed approach.

When observing Table III, it is seen that attribute wise accuracy of sign 20, sign 30, sign 40, sign 50, sign 60, sign 70, sign 90, and sign 110 have significantly increased with proposed multi-stage deep learning technique with OCR (column 4) when compared with both FCN8 and DeepLabV3+ without OCR. At the same time, accuracy of sign 80, and sign 100 have decreased when compared with both FCN8 and DeepLabV3+ without OCR. The accuracy of sign 10 has significantly improved in the proposed technique with OCR comparative to DeepLabV3+ and remains the same comparative to FCN8. The attribute wise accuracy with proposed technique without OCR is much lower than with OCR (column 2). As shown in Table IV, misclassifications also have decreased to 0% by the proposed technique with OCR. All misclassifications were non-speed sign numbers, so they were not misclassified as any other speed limit sign. This is the main advantage of proposed technique over other existing techniques. Therefore, it is reasonable to conclude that the proposed technique is well suited for improving speed sign accuracy. The results of pixels recognized as speed limit signs by the segmentation network without (Prediction 1) and with (Prediction 2) OCR are shown in Fig. 5. Prediction 1 images contain a significant misclassification percentage for each segmented speed sign, making the target class decision-making work difficult. Sample images in Prediction 2 demonstrate excellent segmentation results, eliminating the pixelwise misclassification problem from the segmentation network.

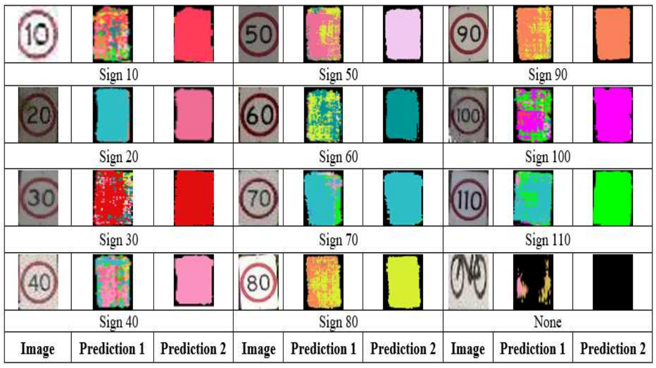

Fig. 5. Sample prediction results output by the proposed technique.

TABLE III. COMPARISON OF CLASSIFICATION ACCURACY (%)

Speed Limit	Attribute Wise Accuracy (%) Without OCR		Proposed Technique With OCR
	FCN8 [20]	*DeepLabV3+ [21]*	*FCN8*
Sign 10	50.00	0.00	**50.00**
Sign 20	33.34	0.00	**100.00**
Sign 30	0.00	0.00	**100.00**
Sign 40	33.34	66.69	**100.00**
Sign 50	0.00	25.00	**50.00**
Sign 60	66.69	80.00	**83.33**
Sign 70	14.29	28.58	**42.86**
Sign 80	100.00	75.00	**50.00**
Sign 90	50.00	50.00	**100.00**
Sign 100	75.00	75.00	**50.00**
Sign 110	50.00	100.00	**100.00**

TABLE IV. COMPARISON OF MISCLASSIFICATIONS

Speed Limit	Misclassifications (%)	
	Proposed technique without OCR	***Proposed technique with OCR***
Sign 10	0.94	**0.00**
Sign 20	1.89	**0.00**
Sign 30	0.94	**0.00**
Sign 40	0.94	**0.00**
Sign 50	0.94	**0.00**
Sign 60	2.83	**0.00**
Sign 70	3.77	**0.00**
Sign 80	0.00	**0.00**
Sign 90	0.94	**0.00**
Sign 100	0.94	**0.00**
Sign 110	0.94	**0.00**

VI. CONCLUSION AND FUTURE WORK

The proposed multi-stage deep learning technique for improving speed sign recognition accuracy has been presented and discussed in this research. The proposed technique has been implemented and evaluated on large real-world dataset. Many experiments were conducted to compare the performance of the proposed technique with and without OCR and find the best classification accuracy and minimum misclassifications. The evidence from experiments demonstrated that the proposed technique can produce high accuracy and accurately identify speed limit signs with zero misclassification rates. The performance of the proposed technique for many speed limit signs was promising overall including 100% classification accuracy for most of the speed limit signs. Recognition accuracy was vastly improved by the proposed technique with OCR component. In our future work, we will evaluate our technique on all state roads in Queensland and extend it to recognize text in other traffic sign boards such as minor and major roadworks signs, school zone warning, one way sign and warning signs.

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