REAL-TIME VISION-BASED MALAYSIAN ROAD SIGN RECOGNITION USING AN ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Road sign recognition is a driver support function that can be used to notify and warn the driver by showing the restrictions that may be effective on the current stretch of road. Examples for such regulations are ‘traffic light ahead’ or ‘Pedestrian Crossing’ indications. The system can help the driver to maintain a legal speed, obey local traffic instructions, or urban restrictions. A road sign recognition system can technically be developed as part of an intelligent transportation system that can continuously monitor the driver, the vehicle, and the road in order, for example, to inform the driver in time about upcoming decision points regarding navigation and potentially risky traffic situations. The present investigation targets the recognition of Malaysian road and traffic signs in real-time. Real-time video is taken by a digital camera from a moving vehicle and real-world road signs are then extracted using vision-only information. The system is based on two stages, one performs the detection and another one is for recognition. In the first stage, a hybrid color segmentation algorithm has been developed and tested. This hybrid color segmentation algorithm contains a RGB histogram equalization, RGB color segmentation, modified grayscale segmentation, binary image segmentation, and a shape matching algorithm. All these algorithms are tested using thousands of images. The hybrid color segmentation algorithm has eventually been chosen for this proposed system as it shows the best performance for detection of road signs. In the second stage, an introduced robust Custom Feature Extraction method is used for the first time in a road sign recognition approach. Finally, a multilayer artificial neural network (ANN) has been created to recognize and interpret various road signs. It is robust because it has been tested on both standard and non-standard road signs with significant recognition accuracy. This proposed system achieved an average of 99.90% accuracy with 99.90% of sensitivity, 99.90% of specificity, 99.90% of F-measure, and 0.001 of false positive rate (FPR) with 0.3 s computational time. The accuracy of the developed system is comparatively high

and the processing time is comparatively low that can be useful for classifying road signs particularly on highways around Malaysia. This low FPR can increase the system stability and dependability in real-time applications.

ABSTRAK

Pengenalan tanda jalan raya merupakan fungsi sokongan pemandu yang boleh digunakan untuk memberitahu dan memberi amaran kepada pemandu dengan menunjukkan sekatan yang tertimbul di sepanjang jalan raya. Sebagai contoh, 'lampu isyarat di hadapan' atau tanda-tanda 'lintasan pejalan kaki’. Sistem ini boleh membantu pemandu untuk mengekalkan kelajuan yang ditetapkan, mematuhi arahan lalu lintas tempatan, atau sekatan lain. Secara teknikal, sistem pengenalan tanda jalan raya boleh dibina sebagai sebahagian daripada sistem pengangkutan pintar yang boleh memantau pemandu, kenderaan dan jalan raya agar, dapat memberitahu pemandu dalam masa yang terdekat tentang keadaan lalu lintas yang mungkin membawa padah. Penyiasatan kini tertumpu dalam pengenalan tanda jalan raya dan lalu linstas di Malaysia dalam masa nyata. Video diambil dalam masa nyata di dalam kenderaan yang bergerak dengan menggunakan kamera digital dan tanda jalan raya sebenar kemudiannya diekstrakkan dengan menggunakan maklumat penglihatan sahaja. Sistem ini berdasarkan dua peringkat, termasuklah, proses pengesanan di peringkat pertama dan proses pengenalan di peringkat kedua. Di peringkat pertama, algoritma warna segmentasi hibrid telah dibangunkan dan diuji. Algoritma segmentasi warna hibrid tersebut mengandungi penyamaan histogram RGB, segmentasi warna RGB, segmentasi skala kelabu yang telah diubah suai, segmentasi imej binari, dan algoritma pemadanan bentuk. Semua algoritma ini dinilai dengan menggunakan beribu-ribu imej. Algoritma segmentasi warna hibrid akhirnya telah dipilih bagi sistem yang dicadangkan ini disebabkan algoritma tersebut menunjukkan prestasi yang terbaik dalam mengesan tanda jalan raya. Di peringkat kedua, kaedah pengekstrakan yang teguh digunakan buat kali pertama dalam pendekatan pengenalan tanda jalan. Akhirnya, rangkaian neural buatan multilayer (ANN) telah diwujudkan untuk mengenal dan mentafsir pelbagai tanda-tanda jalan raya. Rangkaian tersebut dikatakan kukuh setelah diuji ke atas kedua-dua tanda jalan yang standard dan tidak standard dengan ketepatan pengenalan yang tinggi. Sistem yang dicadangkan ini telah mencapai purata 99.90% ketepatan dengan 99.90% sensitiviti, 99.90% daripada kekhususan, 99.90% daripada f-langkah, dan 0,001 daripada kadar positif palsu (FPR) disertai 0.3 s masa pengiraan. Ketepatan sistem yang dibangunkan adalah agak tinggi dan masa pemprosesan adalah agak rendah dan dikatakan berguna dalam mengklasifikasikan tanda-tanda jalan raya khususnya di lebuh raya di seluruh Malaysia. FPR yang rendah tersebut boleh meningkatkan kestabilan dan kebergantungan system ini dalam aplikasi masa nyata.

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LIST OF ABBREVIATIONS

Abbreviations

AI	:	Artificial Intelligence
AIVD	:	Autonomous Intelligence Vehicle Design
ANN	:	Artificial Neural Network
ANPR	:	Automatic Number Plate Recognition
AR	:	Accuracy Rate
AUC	:	Area Under the Curve
CCD	:	Contracting Curve Density
CNN	:	Convolutional Neural Network
COSFIRE	:	Combination of Shifted Filter Responses
DOT	:	Dominant Orientation Templates
DSS	:	Driver Support System
ESOM	:	Emerging Self-Organizing Map
FFT	:	Fast Fourier Transform
FN	:	False Negative
FP	:	False Positive
FPGA	:	Field Programmable Gate Array
FPR	:	False Positive Rate
FNR	:	False Negative Rate
GPAP	:	Geometry-Preserving Active Polygon
GPS	:	Global Positioning System
GTSRB	:	German Traffic Sign Recognition Benchmark
GUI	:	Graphical User Interface
HAC	:	Hybrid Active Contour

HOG	:	Histogram of Oriented Gradients
HSB	:	Hue, Saturation, and Brightness
HSI	:	High Speed Interconnect
HSV	:	Hue, Saturation, and Value
ICP	:	Iterative Nearest Point
ITS	:	Intelligent Transportation Systems
JKR	:	Jabatan Kerja Raya
JTC	:	Joint Transform Correlation
KL	:	Kuala Lumpur
ML	:	Machine Learning
MLP	:	Multilayer Perceptron
MRF	:	Markov Random Field
MSERs	:	Maximally Stable Extremal Regions
NN	:	Neural Network
NNC	:	Nearest Neighbor Classification
OCR	:	Optical Character Recognition
PDF	:	Probability Distribution Function
PNN	:	Probabilistic Neural Network
PPV	:	Positive Predictive Value
RANSAC	:	Random Sample Consensus
RBFNN	:	Radial Basis Function Neural Network
RGB	:	Red Green Blue
RMSE	:	Root-Mean-Square Error
ROC	:	Receiver Operating Characteristic
ROI	:	Region of Interest
RSLD	:	RANSAC Symmetrical Lines Detection

SCM	:	Statistical Color Model
SIFT	:	Scale-Invariant Feature Transform
SOM	:	Self-Organizing Map
SURF	:	Speeded Up Robust Features
SVM	:	Support Vector Machine
SVR	:	Support Vector Regression
TN	:	True Negative
TNR	:	True Negative Ratio
TP	:	True Positive
TPR	:	True Positive Rate
TSR	:	Traffic Sign Recognition
UMRG	:	University of Malaya Research Grant
VMPS	:	Mobile Photogrammetry System on The Vehicle
YIQ	:	Luminance (Y), In-phase (I), Quadrature (Q)
YUV	:	Luminance (Y), blue–luminance (U), red–luminance (V)

CHAPTER 1: INTRODUCTION

1.1 Background

An automatic road sign recognition system is one of the important feature in a driver assistance system. In this dissertation, road and traffic signs are considered as a pictorial or symbolical language about the roads and traffic environments that can be interpreted by the driver and other road users. Interchangeably the terms are used in this dissertation and somewhere else might have also appeared in the combination of “road-traffic sign”, “road and traffic signs” or “road sign”. The information provide by this proposed road and traffic sign recognition system can make driving safe, easy, and suitable. Most important symbolic road and traffic signs, which contain different color and different types of shape, are considered in this dissertation.

Installation of road and traffic signs must be the appropriate position in right way and follow the state -of- the-art to ensure the clear visibility to the road users. Most of the time a valuable sign ignored by the driver and put themselves on a potential danger situation because of lack of attention, unclear visibility and multiple roads and traffic sign covered by one another, so the driver cannot make concentration to the required attentions to the road or traffic sign. An automatic system for detection and recognition of road-traffic sign has a goal of delivering assistance to the driver. It also can provide a successful contribution to that goal by providing a fast system for detection, classification, and recognition of road-traffic sign. This proposed system helps to build a fast detection and recognition of road and traffic sign consistently with great accuracy. After installation of this, the driver will get information about road and traffic signs before approaching the signs.

In this field of study, recognition of road and traffic sign can be used to support the improvement of the intelligent transport system (ITS) or help to develop a car advisory system. The recognition of road and traffic signs can continuously monitor the road-traffic environment and provide information to the driver. For example, provide information regarding next decision point, a decision about navigation and possible risk road-traffic situation to the driver timely. Road signs recognition system and ITS both are concentrate with road-traffic signs and face similar challenges for the automatic detection and recognition of road-traffic signs. A relationship between ITS and road-traffic sign recognition system is illustrated in Figure 1.1.

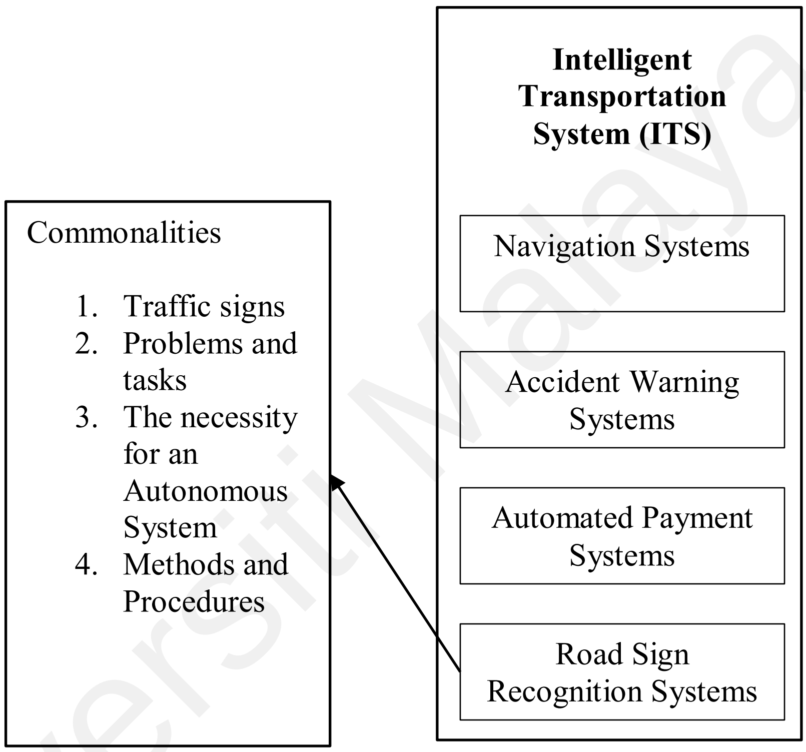

Figure 1.1: Road Sign Recognition System and ITS

ITS focuses on the innovation and integration of technology for better transport infrastructure and vehicles management applications. The purpose of intelligence transportation systems is to increase the efficiency of transportation management, security in roads and vehicles, and reduction of environmental effect with the modern communication innovations.

This dissertation aims to improve a method of the recognition of road and traffic sign for reminding the driver or alert a driver about the allowable road-traffic safety in a specific road and specific conditions, representing some circumstantial special information about environment and also to provide the guidelines information for making their travel safer, easier, and more suitable. Real-Time images were taken for this system using an onboard digital camera placed on a moving vehicle and those images were extracted from real-world scenes on the basis of their color features to detect the signs in those captured images.

1.2 Motivation

With the recognition of various kinds of sensors embedded in vehicles, recognition of traffic signs has been receiving more attention in recent years. The development of living standards, communication, and transportation system has been improved, and use of vehicles is increased. With the growing number of vehicles, traffic accident rates have also been rising. At present, road-traffic injuries have become one of the most frequent causes of accidental deaths worldwide. By 2030, road accidents will be the 5th most common reason of death around the world (Organization, 2009) including Malaysia (Sarani et al., 2012). Researchers and institutions are now working to reduce road-related incidents by integrating transportation systems with artificial intelligence. An advanced driver assistance system, which automatically detects traffic signs by using a camera mounted on the dashboard of a vehicle, functions as a road sign recognition system. This system helps the driver to be aware of the road and traffic signs, rules of driving along the road and notifies the driver of the detected signs which ultimately would help reduce the possibility of having an accident.

A road sign recognition system can technically be developed as an important aspect of an ITS and can continuously monitor the driver, the vehicle, and the road altogether, for instance, it can be used to alert the driver about upcoming choice with respect to route and potentially dangerous traffic circumstances just in time. Road sign detection and recognition (Malik et al., 2007) is an essential part of the Autonomous Intelligence Vehicle Design (AIVD) (Min & Choi, 2015). It is widely used for intelligent driving assistance (A. M. Khan, 2014), self-directed vehicles, traffic rules and regulation awareness, disabled (blind) pedestrian awareness and so on. Conversely, road sign detection and recognition can also be a part of self-driving car (Yeshodara et al., 2014) technology to determine the road-traffic environment in real-time.

Detection and recognition are one of the most challenging tasks in the field of computer vision (Hayashi, 2007) and digital image processing to detect a specific object in a real-time environment (T. Zhang et al., 2013). Researchers are paying more attention in ITS (Chakraborty & Deb, 2015). Some of them have successfully implemented road sign recognition methods to detect and recognize red-colored road signs (Wali et al., 2015) only or single classes of road signs (Biswas et al., 2014; Li et al., 2016; Y. T. Lin et al., 2016; H. Liu et al., 2015; Rizvi et al., 2014), and some of them have used specific country road signs (Chakraborty & Deb, 2015; Houben et al., 2013; Stallkamp et al., 2012; Yamamoto et al., 2013). In this field, a group of researchers has already shown distinguished performance based on annotated road signs (Cire et al., 2011; Houben et al., 2013; Stallkamp et al., 2012). Overall, for a standard road sign recognition approach in general, further improvements are needed.

1.3 Problem Statement

Road signs which are designed for human eyes are easily detectable and recognizable (Stallkamp et al., 2012), even with significant variations, but for a computer vision system, small variations cannot be adjusted automatically, thus it needs proper guidance. Standard color and shape are the main properties of standard road signs ("Malaysia Institute of Road Safety Research," 2017). Though the road sign has state of the art, various natural issues and human errors cause variations in color, shape, or both. For instance, multiple non-standard road signs may be found on Malaysian highways, as seen in Figure 1.2.

(a) (b)

Figure 1.2: Malaysian Road Signs; (A) Standard Malaysian Road Signs as Adapted from ARHAN TEKNIK(JALAN) 2A/85; (B) Non-Standard Road Signs Appearing in the Malaysian Highway System

During driving, although human can recognize and classify distinct road sign without any mistake or delay, robust and fully automated recognition of road sign remains a challenge for the machine. An ordinary street view of the most urban area in the overall like one appeared in Kuala Lumpur, Malaysia in Figure 1.3, presents very complex scenario. This complex scenario may include pedestrians, multiple vehicles, trees and banners with different colors and shapes, several others sign then road and traffic sign, and also a multiple number of the traffic sign on the road. Normally, when a person is requested to discover the road and traffic sign from that picture, he can do this effortlessly with particular. But, a computer vision system cannot do this automatically unless it is trained and designed properly.

Figure 1.3: Random Road-Traffic Environment in Kuala Lumpur, Malaysia

Though, in the computer vision and machine learning perspective, this image consists of multiple problems which are disclosed here:

1. Obstacles could be existing in the scene, such as buildings, trees, other vehicles, and pedestrians or/and even signs which block other signs.
2. The weather conditions affect the visibility of road and traffic signs such as the fog, rain, clouds.
3. Color information is very sensitive to the variations of the light conditions.
4. Road signs may not follow state-of-the-art.

Misidentification of occluded as well as non-standard road signs limit the accuracy of current road sign recognition approaches, therefore a more robust and flexible road sign recognition method is required to improve recognition reliability.

In addition, validation of the system is required to prove the proposed system is functioning properly. A real-time database can be considered to evaluate the performance of the recognition stability. The outcomes of testing need to be linked to the related concepts. Keeping these in consideration, this dissertation proposes a novel approach to the real-time Malaysian road sign recognition system.

1.4 Aims and Objectives of the Research

The main goal of this dissertation is to design, implement, and evaluate a road and traffic sign detection and recognition system toward eliminating the problems addressed in Section 1.3. The main approach is to locate the road-traffic sign location from a traffic scene by their color information. Once a road-traffic sign is located, the proposed system classifies the located object based on the extracted features of the road-traffic sign and finally provide the classification result accordingly. This goal will be achieved through following objectives:

1. To investigate the limitation of existing road sign recognition algorithms.
2. To develop a robust algorithm for road sign recognition.
3. To evaluate the system performance using real-time road sign images and comparing its performance with existing baseline methods.

1.5 Research Questions

In conducting different significant phases of this research, the following research questions are sought:

1. What are the limitations of existing road sign recognition algorithms?
2. How to define the robustness of the system?
3. How can the important identification features of road sign be extracted?
4. How to evaluate the system performance with other existing methods?
5. What is the classification performance of the algorithm compared to other classification algorithms?

1.6 Research Methodology

To achieve the aim and objectives on the proposed research, four main phases are identified as follows:

Phase1: Information gathering and problem analysis

Information gathering is done based on the issues and the analysis discussed in Section 1.4. Various approaches to road sign detection and recognition are described in the literature review section focusing on the information gathering strategies. To study existing techniques for road sign recognition and their characteristics is one of the strategies for this phase. Finding a set of rules to identify recognition strategies is one of the important tasks for this phase.

Phase2: Collecting data and Analysis to approach solution

The issue of real-time road sign recognition is dominated using two algorithms, which are detection and recognition algorithms. It is important to collecting data from real-time environments to approach a solution for the real-time problem. Real-time video and images are collected as a raw data and pre-processed for further suitability for this proposed system. Separate training and testing databases of real-time images were also prepared during this phase. Basic rules were also identified for road sign recognition process. Moreover, the correlation was also established between one road sign to another road signs during this phase.

Phase3: System design and implementation

The overall design and development of the proposed system are presented in this research which is fully functional. Specifically, a complete real-time framework with a 278-unique features model to recognize and classify distinct road and traffic sign is presented in this research. The proposed method could capture more distinctions such as increase robustness, avoid shape disorientation, minimize the detection error, and accurate recognition of road and traffic sign.

The proposed method consists of the following two stages: (1) detection and (2) recognition. Detection is performed by using video frame segmentation and hybrid color segmentation algorithms. This hybrid color segmentation algorithm contains a red, green, and blue (RGB) histogram equalization, RGB color segmentation, modified grayscale segmentation, binary image segmentation, and a shape matching algorithm. An RGB color segmentation algorithm is used for subtracting red (R), green (G) and blue (B) components of the input image. In the next step, an RGB to the grayscale converter is used to convert the subtracted image into a grayscale image. Then, a 2-dimensional 3-by-3 median filter is used to remove existing noise from the grayscale images. Next, it replaces all the input image pixels' value with the luminance that is greater than 0.18 to 1 as a white pixel, and all other pixels are replaced to 0 as a black pixel. From this process, a grayscale image is converted into a binary image. A threshold level of 0.18 is used for this conversion process because it gives the best performance for this system. After that conversion, the first step is removing all the small objects from the binary images which contain less than 300 pixels and then labeling all connected components using 8-connected objects. The next step is measuring of the image region properties, and how many candidates are available on that binary image is found. This is the target candidate to identify as a road sign. Then from the target candidate, the algorithm determines the position (X, Y-coordinate), height (H), and width (W) of every single object accordingly. For the candidate selection, candidates which have a height (H) and width (W) ratio close to 1, are considered as a target candidate. Based on the selected candidates' properties, the sign image is cropped from the original RGB input frame. That input frame is also a high resolution RGB image with target objects. Here, the detected target road sign contains enough pixel information because it is extracted from an original RGB input frame. Initially, that detected road sign image is resized to 128-by-128 pixels. Then that RGB image has been converted into a grayscale image and existing noise removed by using the 3-by-3 2-dimensional median filter. Then, the grayscale image is converted into a binary image with an average grayscale histogram level. All these procedures are verified with thousands of pictures. The hybrid color segmentation algorithm has ultimately been selected for this proposed system as it shows the best performance for detection of road signs. As a final point, a robust custom feature extraction method has been introduced for the first time in the road sign recognition system to extract multiple features from a single image.

For the recognition, an artificial neural network (ANN) is implemented by using the Neural Network Pattern Recognition Tool with MATLAB. The standard network that is used for pattern recognition, is a two-layer feed-forward network, with a sigmoid transfer function in the hidden layer, and a softmax transfer function in the output layer. Real-time video frames go through this network. However, signs which may completely be obscured by other vehicles or trees may not be recognized, although the system recognizes and interprets various standard and non-standard road signs using vision-only information. It has reached an exceptionally high recognition accuracy.

In this work, in order to achieve robust, fast detection and recognition of road signs, a hybrid color segmentation algorithm with a robust custom feature extraction method has been proposed. This feature extraction method achieves robustness in improving the computation efficiency. Further, in order to reduce the classification time, ANN based classification, which has been selected by comparing the classification performance among with other classifiers, is implemented. Experimental results show that this work achieves robust road sign recognition in comparison to the other existing methods and achieves high recognition accuracy with low false positive rate (FPR). This low FPR can increase the system stability and reliability for real-time applications. Multiple robustness testing results have indicated that this proposed system is able to achieve promising performance, even in adverse conditions.

To formulate rules into an algorithm, to select an approach to determine the relationship between one road sign to another road signs and to implement the algorithm are the three main strategies for this phase.

Phase4: Evaluation of algorithm

The very fundamental phase to every research involving system development is algorithm evaluation. In this regard, the effectiveness of the proposed algorithm used in the road sign recognition system can be ensured by calculating the accuracy level of road sign recognition. Also, it determines whether the algorithm can recognize the road sign in real-time, and compare the performance of the proposed algorithm with the others proposed algorithm. The evaluation process is done on two Malaysian traffic sign databases that consist multiple variations of image sequences with standard and non-standard form with diverse sign color and orientations. An evaluation based on the traffic signs classifiers also presented in this research and the evaluation results show that the superior selection of proposed classifier.

1.7 Principal Contribution

A color and shape independent, fully automated road sign detection and recognition system in real-time has been developed in this dissertation. The following principal contributions have been made toward achieving the objectives of the research described in the dissertation:

1. A complete framework for simultaneous road sign detection and recognition in real-time. Specifically, a color and shape independent, automatic initialization of feature extraction and robust recognition system has been focused in the framework.
2. A novel approach, custom feature extraction method has been proposed for extracting road sign features.

3. Developed a novel approach for real-time recognition of Malaysian road sign.
4. Developed an algorithm that can account for multiple variations in the road sign.

The performance of the proposed algorithm has been tested over two separate road sign databases. The lower false positive rate can increase the system stability and dependability on the real-time application. The confusion matrix of road sign recognition approach has shown the significant accuracy of the proposed model.

1.8 Organization of the Dissertation

This dissertation deals with the development technology of a fully automatic image processing system for road-traffic sign recognition in the real-time environment. In this respect, the dissertation is structured as follows.

In this Chapter, highlights of research motivation followed by research background are discussed. The research objectives consisting of research questions and specific aims are stated. The summary of the principal contributions of this dissertation is mentioned. Finally, main phases involved in the research methodology are highlighted.

Next, in Chapter 2, a number of related past exploration that is related to the proposed research is reviewed and the various contributions are discussed. A summary of existing databases use by different researchers is analyzed. Also, a brief discussion about ANN has been discussed in this Chapter.

A complete framework for the proposed automated road sign detection and recognition system is given along with necessary theoretical discussion in Chapter 3. Proposed system overview, detection methodology, step-by-step feature extraction process, ANN design, training database is also described in detail in this Chapter.

Experimental results are shown in Chapter 4 where the performance of the proposed developed system is evaluated using a publicly available database: Malaysian Traffic Sign Database. Performance comparison between proposed method and other existing methods based on evaluation parameters, evaluate the system performance based on Neural Networks (NN). Evaluate the proposed classification algorithm performance with 23 different classifiers. After all, confusion matrix and robustness testing of road sign recognition signify the proposed system accuracy.

Finally, in Chapter 5, a summary of the investigations and contributions of the overall research that includes the research findings, overall conclusions are given. Future work is also highlighted in this Chapter.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This Chapter explains different road and traffic sign detection and recognition techniques introduced previously by other researchers. This Chapter also explores the theoretical background of ANNs.

Various road-traffic sign recognition methods and algorithms have been developed (Carrasco et al., 2012; Long Chen et al., 2012; García-Garrido et al., 2012; Hoang et al., 2016; Son & Baek, 2015; Yilmaz et al., 2010). All researchers are implementing their methods to achieve a common goal (Llorca et al., 2010). Some researchers have done the detection (Aliane et al., 2014; Belaroussi et al., 2010; J. Wu et al., 2009) part, some are tracking the detection and a few have described effective recognition parts (C.-C. Lin & Wang, 2012; Shoba & Suruliandi, 2013). According to Paclík *et al.* (Paclík et al., 2006), an automated traffic sign detection system was introduced initially in Japan. In the field of road-traffic sign detection and recognition, the most common approach has two (2) main stages, where the first step is to detect and then next step is to recognize. The detection stage works to identify the proper region of interest (ROI) and the color segmentation algorithms are mostly used to doing this process. This detection stage has performed some form of shape detection and followed by recognition. In the recognition stage, detected candidates are either rejected or identified with some recognition methods, for example, shape matching (J. F. Khan et al., 2011) and some other form of classifiers such as ANN (Yamamoto et al., 2013), support vector machine (SVM) (Kumaraswamy et al., 2011), (Mariut et al., 2011), (Chakraborty & Deb, 2015), clustering (Wahyono et al., 2014), and fuzzy logic (Rizvi et al., 2014).

Mostly, the color segmentation method is used for image segmentation to make up the majority of system's detection part (Eom et al., 2012; J. B. Kim, 2013; S. Kim et al., 2012; Qun et al., 2012; Saponara, 2013; Song & Liu, 2012; Q. Zhang & Kamata, 2013; Q. S.

Zhang & Kamata, 2010). A color matching method was introduced by De La Escalera *et al.* (De La Escalera et al., 1997) where they used it to look for patterns of a specific correspondence relationship to rectangular, triangular and some circular signs. However, their proposed method faced with some difficulties regarding different road signs with the same shape. For sign recognition, a physics-based (Lauziere et al., 2001) method was used, but it needed the memory to change when illumination is variance (Lauziere et al., 2001). A neural network (Lorsakul & Suthakorn, 2007) was used to recognize road and traffic signs for an intelligent driving assistance system, but this system showed some contradictory road and traffic sign pattern results with complex image backgrounds. A real-time road and traffic sign detection plus with recognition system were developed by Ruta *et al.* (Ruta et al., 2010) to perform the recognition from a video using class-specific discriminative features. An automatic colored traffic sign detection system (Joshi et al., 2008) was developed by using optoelectronic correlation architectures. A color segmentation based real-time road and traffic sign recognition system were introduced by Deshmukh *et al.* (Deshmukh et al., 2013). Their methodology was more difficult because the system had been developed in C language that was not so strong in comparison to MATLAB or OpenCV. Therefore, it can be concluded that the main difficulties of color-based road sign detection and recognition systems are illumination, adverse weather conditions, and low lighting conditions.

The Optical Character Recognition (OCR) (Mammeri et al., 2014) tool "Tesseract" was used to detect text in road and traffic signs. The results showed a higher accuracy compared with to the Histogram of Oriented Gradients (HOG)-SVMs system. A unique system for the automated detection and recognition of text in road-traffic signs was proposed by Greenhalgh *et al.* (Greenhalgh & Mirmehdi, 2015). A half structure was employed to outline search regions inside the image, within which traffic sign candidates were found. Maximally stable extremal regions (MSERs) and HUE, saturation and color thresholding area units were used to find an oversized range of candidates. After that those units were reduced by applying constraints supported by temporal and structural data. The strategy was relatively evaluated, and it achieved an overall F-measure of 0.87. For a Malaysian road and traffic sign recognition system, Wali *et al.* (Wali et al., 2015) developed a color segmentation algorithm with SVMs and their proposed system accuracy was 95.71%. This is not sufficient for a completely stable system, so it needs further research to implement a stable version of their road and traffic sign recognition system.

As a subject of dynamic scholarly research, the traffic sign recognition is additionally a technology that is being researched and enforced within the business industries. Many vehicle manufacturers (such as Continental Automotive) develop the technology to detect and recognize the road-traffic signs as a part of smart the vehicle. In 2010, the BMW-5 series initiated the project of production of traffic sign recognition system (AG, 2012). Moreover, BMW and several vehicle manufacturers also revealed some other models of this similar technology (Y. Choi et al., 2016). Volkswagen has also introduced it on the Audi A8 (Levinson et al., 2011). Furthermore, Mercedes-Benz has also developed the traffic signs recognition systems on their E and S class vehicles. Additionally, Google has also industrialized an automotive technology which lets a vehicle to self-drive. The combination of the utilized information is stored in its map database, and that information collected from its real-time environment. The autonomous vehicle of Google is able to securely operate in complex urban situations (Markoff, 2010). However, there is an incident of Google's autonomous vehicle occurred, when a driver ran in the road (Limited, 2016). Recently, The Tesla Team announced that all their new manufactured vehicles will possess full self-driving hardware (Team, October 19, 2016).

2.2 Image Processing

Image processing is a method to perform operations on an image to obtain an improved image or to extract useful information therefrom. Today image processing is one of the fastest growing technologies. It is also a form of the core research area in engineering and machine learning disciplines. Image processing mainly includes the following three steps:

- Import image via image acquisition tools;
- Analysis and manipulation of the image;
- Production in which the result can be altered image or a report that is based on image analysis.

There are two types of methods for image processing, namely the analog and digital processing of the image. The analog image processing can be used for paper copies as prints and photographs. Image analysts use different basic principles of interpretation of these visual techniques. The processing of digital images helps in the handling of digital images with computers. The three general phases, where all data types must undergo using digital techniques, are pre-processing, enhancement and display, and information retrieval.

2.3 Color-Based Detection of Road and Traffic Signs

Color-based detection of road and traffic sign methods are varying from one researcher to another researcher. Numerous methods and techniques are used to solve color-based detection and recognition of road and traffic sign problems. A summary of the earlier research on color-based road and traffic sign detection and recognition is provided in Table 2.1.

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Table 2.1: Summary of the Earlier Research on Color-Based Detection and Recognition of Road and Traffic Sign

References	**Research Method**	**Research Findings**
(Torresen et al., 2004)	**1.** Color-based filtering **2.** Localization characters in an image **3.** Identification of the number on the label	**1.** Detection of Norwegian speed limits **2.** Approximately 91% correct detection
(Lopez & Fuentes, 2007)	**1.** Gaussian distributions **2.** High chaos **3.** Presence of rotation and partial obstruction	**1.** Detection and tracking **2.** Average 97% of Detection **3.** Per sequence two false detections
(L. Chen et al., 2011)	**1.** Color-based segmentation **2.** ROI **3.** Template matching	**1.** Intelligent vehicle SmartVII **2.** recognition accuracy of above 90% in real-time
(Saponara, 2013)	**1.** Exploiting the HSI color space **2.** Fish-eye correction **3.** RGB to HSI transformation	**1.** DSP platform **2.** About 93% detection and recognition accuracy

2.4 Shape-Based Detection of Road and Traffic Signs

The methods that use information regarding shapes for road sign identification could be a substitute when colors information is absent or when it is difficult to recognize colors. There are many efforts that have been made to progress these methods and the results are showing a good promising performance. In the subsequent overview, the researchers used shape as a most important source of information for road-traffic signs identification (Parodi & Piccioli, 1995; Piccioli et al., 1994). A summary of the earlier research on shape-based identification of road-traffic sign is provided in Table 2.2.

Table 2.2: Summary of the Earlier Research on Shape-Based Detection and Recognition of Road and Traffic Sign

References	Research Method	Research Findings
(G. Wu et al., 2007)	**1.** Radial symmetry nature **2.** Direction-discriminated voting	**1.** Method can reduce wrong detection and calculation problem **2.** Extended to detect non-systematic polygons
(Nunn et al., 2008)	**1.** Property regularity is discovered to detect candidate regions **2.** Systematic polygons (including circles) can be found	**1.** Shape described as a regular polygon or a circle **2.** Time effective method
(Gormer et al., 2009)	**1.** Color features **2.** HSV color space	**1.** Two kinds of road and traffic sign segmentation algorithms are established **2.** Applicable for only red-colored road and traffic signs
(Hoferlin et al., 2009)	**1.** Local SIFT structures **2.** Contracting curve density (CCD) **3.** Recognition state based on SIFT and SURF	**1.** Application of local SIFT structures for content-based traffic sign detection
(Le et al., 2010)	**1.** SVM **2.** Real-time video processing **3.** Hough transform and contour detection	**1.** Color detection and segmentation of traffic sign **2.** 92.91% of detection accuracy **3.** Processing speed of 20fps
(S. Kim et al., 2012)	**1.** ROI **2.** Guided image filtering	**1.** Speed sign detection rate of 93% **2.** 62 images containing 85 speed sign **3.** Applicable for speed limit sign
(J. Zhao et al., 2013)	**1.** SURF **2.** Field Programmable Gate Array (FPGA)	**1.** SURF algorithm has limitation in real-time systems **2.** Reduce the computational complexity

2.5 Color-Shape-Based Detection of Road and Traffic Signs

The color and shape combination based method for road and traffic sign detection could be a solution for individual limitation of color and shape-based road and traffic sign detection. A summary of the earlier research on color and shape combination based method for identification of road-traffic sign is provided in Table 2.3.

Table 2.3: Summary of the Earlier Research on Color and Shape Combination Based Method for Detection and Recognition of Road and Traffic Sign

References	Research Method	Research Findings
(Eichner et al., 2008)	**1.** RANSAC **2.** Neural network	**1.** 97% of sign detection rate **2.** Misclassification rate is less than 1%
(Ulay et al., 2009)	**1.** Color and shape features **2.** Color and edge material **3.** 4. HSV color domain	**1.** Low false positive rate **2.** High detection rate

2.6 Recognition and Classification

Recognition and classification of road and traffic sign may have carried out with different methods. In the real-world computer vision applications, there are many reasons exist to use the neural network for objects recognition and classification. The neural network is used because it gives the high accuracy and low processing time. Another common approach is used to recognition and classification of an object is the template matching. Template matching model is a computer vision technology, used to find a sub image of a target image corresponding to a template image. A summary of recognition and classification based on neural network, template matching, and OCR for road and traffic sign is provided in Table 2.4.

Table 2.4: Summary of the Recognition and Classification Based on Neural Network, Template Matching, and OCR for Road and Traffic Sign

References	Research Method	Research Findings
(Nguwi & Cho, 2010)	**1.** Neural network **2.** ESOM	**1.** ESOM is significantly higher than traditional Self-Organizing Map (SOM) **2.** 90% of classification accuracy
(Stallkamp et al., 2012)	**1.** Neural network **2.** Convolution neural networks (CNN's)	**1.** Correct classification rate is 99.46% **2.** Only performed recognition
(Pazhoumand-dar & Yaghoobi, 2013)	**1.** Neural network **2.** Color thresholding	**1.** Overall 88% of recognition accuracy **2.** Low false positive rate
(X. Liu et al., 2012)	**1.** Template matching **2.** HSV color space **3.** Histogram equalization **4.** Otsu algorithm **5.** Kalman filter	**1.** Stabilized cross-correlation to identify the traffic signs **2.** Detect linear shape for traffic lane and mark
(C. W. Choi et al., 2013)	**1.** Template matching **2.** Stereo vision technique **3.** Color segmentation **4.** SVM	**1.** Detection and tracking the road signs **2.** Average 85% of detection accuracy
(C. Y. Zhao et al., 2014)	**1.** Multiple template matching **2.** DOT (Dominant Orientation Templates) **3.** Pairwise binary classifier	**1.** Average 30 ms per frame **2.** Maximum 96.2% of true positive rate
(Azzopardi & Petkov, 2013)	**1.** OCR **2.** Combination of Shifted Filter Responses (COSFIRE) **3.** Gabor filters	**1.** 98.50% of recall **2.** 96.09% of Precision **3.** 99.48% of correct classification with MNIST dataset
(Greenhalgh & Mirmehdi, 2015)	**1.** OCR **2.** Half structure **3.** MSERs	**1.** Road and traffic sign text detection and recognition **2.** Overall 0.87 of F-measure

2.7 Recent Work on Road and Traffic Sign Recognition

A summary of recent work on the identification of road-traffic sign is provided in Table 2.5.

Table 2.5: Summary of Recent Work on the Detection and Recognition

References	Research Method	Research Findings
(Zaklouta & Stanciulescu, 2014)	**1.** Linear SVM **2.** HOG **3.** K-d tree and Random Forest	**1.** An overall recognition accuracy is 97% **2.** It is only applicable for speed limit road and traffic sign
(Balali & Golparvar-Fard, 2015)	**1.** Super pixel-level annotation **2.** Retrieval set encodes **3.** Histogram of various shape **4.** Color descriptors **5.** Markov Random Field (MRF)	**1.** Average 88.24% of accuracy for recognition **2.** Average 82.02% of accuracy for segmentation
(S. Yin, 2015)	**1.** HOG **2.** Rotation Invariant Binary Pattern (RIBP) **3.** Affine and Gaussian space **4.** Artificial Neutral Network	**1.** Maximum correct recognition rate is 98.62%
(Y. T. Lin et al., 2016)	**2.** Shape detection **3.** Adaptive threshold and digit recognition algorithm **4.** SAD (sum of absolute difference)	**1.** Over all recognition accuracy on circular speed limit sign is 92.40% **2.** It is only applicable for speed limit road and traffic sign
(Hanene Rouabeh, 2016)	**1.** Neural Network **2.** Decision Tree	**1.** Recognition accuracy is 93.45% **2.** It is only applicable for speed limit traffic signs
(Zhu et al., 2016)	**1.** Fully convolutional network (FCN) **2.** Deep CNN for object classification **3.** Database: Swedish Traffic Signs Dataset (STSD)	**1.** Processing time 0.45 second **2.** Average Precision 97.69% **3.** Average Recall 92.90%
(Ellahyani et al., 2016)	**1.** Invariant geometric moment to classify shapes **2.** Features extraction by HOG **3.** Classifiers are random forest and SVM **4.** Database: GTSDB	**1.** Accuracy with GTSDB is 94.21% **2.** Run time ms/frame: HSI-HOG+LSS 28.93 with random forest
(Luo et al., 2017)	**1.** Data-driven, Symbol-based and text-based system **2.** Multi-task convolutional neural network **3.** Database: GTSDB	**1.** Only three (3) categories **2.** Average accuracy 99.02% **3.** Average processing time 0.41s

2.8 Malaysian Road and Traffic Sign Detection and Recognition

In Malaysia, there are few researchers introduced road and traffic sign detection and recognition method successfully. Some of their proposed methods are unique in this field. A summary based on Malaysia, what has done in the field of road and traffic sign detection and recognition, is described in Table 2.6.

Table 2.6: Summary Based on Malaysian Road and Traffic Sign Detection and Recognition

References	Research Method	Research Findings
(Lim et al., 2012)	**1.** Lyapunov base theory **2.** RBFNN **3.** MIMO	**1.** Can produce high performance with low number of training **2.** Classification rate is RBF2 63.50% **3.** Classification rate is RBF2 64.50% **4.** Their approach cannot be a solution for real-time application
(Ali et al., 2013)	**1.** Methodology is based on processing time **2.** For the detection, color-based detection using RGB and HSV color detection methods **3.** For the recognition, ANN based and principal component analysis (PCA) based classifiers are used	**1.** Detection time for RGB and HSV color-based detection are 2.51 and 2.12s **2.** Recognition time for ANN based recognition is 1 second approximately **3.** Recognition time for PCA based recognition is 0.25 second approximately
(Lau et al., 2015)	**1.** CNN **2.** RBFNN **3.** Incremental training mode **4.** Batch training mode	**1.** RBFNN with incremental and batch training mode, minimum RMSE are 0.90 and 0.38 respectively **2.** Maximum classification rate by CNN is 99%
(Wali et al., 2015)	**1.** RGB color segmentation **2.** Shape matching **3.** SVM for recognition	**1.** Only applicable for single colored (red) road and traffic sign **2.** Processing time is 0.43 second **3.** False positive rate is 0.9% **4.** Classification accuracy is 95.71%

2.9 Road and Traffic Sign Database

There is numerous database available for the purpose of the road and traffic sign detection and recognition. Some database is considering as a real-time database and some are the offline database, and some researchers have their own database that can call a custom database or a private database. A list of widely used databases with their descriptions is presented in Table 2.7.

Table 2.7: Summary of Road and Traffic Sign Database

Database	Video/Image	Sign Class	Database Description
Sweden, Swedish Traffic Signs Dataset (Larsson & Felsberg, 2011)	Image Sequences	6 (Pedestrian crossing, Designated lane right, No standing or parking, 50 kph, Priority road, Give way)	**1.** Public database released in conjunction with SCIA 2011, 24-26 May 2011 **2.** More than 20 000 images with 20% labeled **3.** Contains 3488 traffic signs
United States of America, LISA (Mogelmose et al., 2012)	Image and Video Sequences	47	**1.** 7855 annotations on 6610 frames **2.** Sign sizes from 6x6 to 167x168 pixels **3.** Image sizes vary from 640x480 to 1024x522 pixels
Germany, GTSRB (Stallkamp et al., 2012)	Image Sequences	40+	**1.** 900 training images **2.** 1360 x 800 pixels **3.** PPM format **4.** Traffic signs in the images vary from 16x16 to 128x128
Greece, (Floros et al., 2014)	Image Sequences	5 (Stop, No entry, No parking, Circular prohibition, and triangular warning)	**1.** 191 Images per class **2.** 1920x1080 pixel

Table 2.7, Continued			
Database	**Video/Image**	**Sign Class**	**Database Description**
Greece, Grigorescu (Floros et al., 2014)	Image Sequences	3 (Pedestrian Crossing, compulsory for bikes, intersection)	**1.** 48 images **2.** 360x270 pixels **3.** PNG format **4.** 16 images per class
Spain, UAH Dataset (Maldonado-Bascon et al., 2007)	Image and Video Sequences	7 Different colors (Yellow, Yellow and Red, Blue and White, Blue and Red, White, White and Red, Red) 4 Different shapes (Circular, Rectangular, Triangular, Octagonal)	**1.** BMP format **2.** Database contains, Different colors, shapes, Signs, Sizes
Belgium, BelgiumTS Dataset (Mathias et al., 2013)	Image Sequence	62	**1.** 4591 images for training **2.** 2534 images for testing
Malaysia, Malaysian Traffic Sign Database (Lau et al., 2015; Lim et al., 2012)	Image Sequence	100	**1.** 1 sign per class **2.** Standard sign **3.** Not real-time images

2.10 Overview of Artificial Neural Networks

ANNs mimic the biological neurons of the animal nervous system. Biological neurons learn from senses and environments and thus construct animal intelligence. ANNs follow the same process where they learn from given input and output values. They are very useful where a theoretical relation between input/independent variables and out/dependent variables are quite complicated or there is no known theory at all. At present, ANNs is vastly being used in both industries and modern research labs for the essential purpose. Some of its common applications are pattern recognition, chemical compound identification, process control, stock market prediction, intelligence transportation and sign recognition.

Although a single artificial neuron is able to perform certain information processing, for complex tasks and more powerful computation, especially for linearly non-separable problems, multiple neurons are needed to be connected with one another to make an intricate network. Thus, the term “Artificial Neural Networks” comes since they consist of interconnected artificial neurons/nodes with the aim to solve a wide range of problems such as pattern recognition, pattern generation, function approximation, and memory association. So, ANNs are just modifications of previously invented single perceptron model with the purpose of solving more complicated problems. It is proved that with a single perceptron, linearly-inseparable problems such as exclusive OR (XOR) function cannot be solved (Yanling et al., 2002), whereas multiple perceptron in combination, i.e. an ANN can solve such problems without any major difficulty.

The interconnected neurons of a typical ANN system can be divided into three main layers: input layer, hidden layer(s) and output layer (Figure 2.1). Input layer neurons intake the input values from environment and output layer neurons delivers the ultimate outputs. Hidden layer neurons stay in between the input and output layer. They receive the outputs from other neurons as their inputs (starting from the input neurons) and deliver outputs to their successive layer’s neurons. Abiding by the basic mechanism, NN have been modified into several kinds which follow different architectures and different input-output mapping procedures, so that they perform better in different situations. Among them, most commonly used NN are Multilayer Feed-forward Network (MLFFN), Radial Basis Function Network (RBFN), Recurrent Neural Network (RNN), Generalized Regression Neural Network (GRNN), Adaptive Neuro-Fuzzy Inference System (ANFIS), SOM, Wavelet Neural Network (WNN) and Probabilistic Neural Network (PNN).

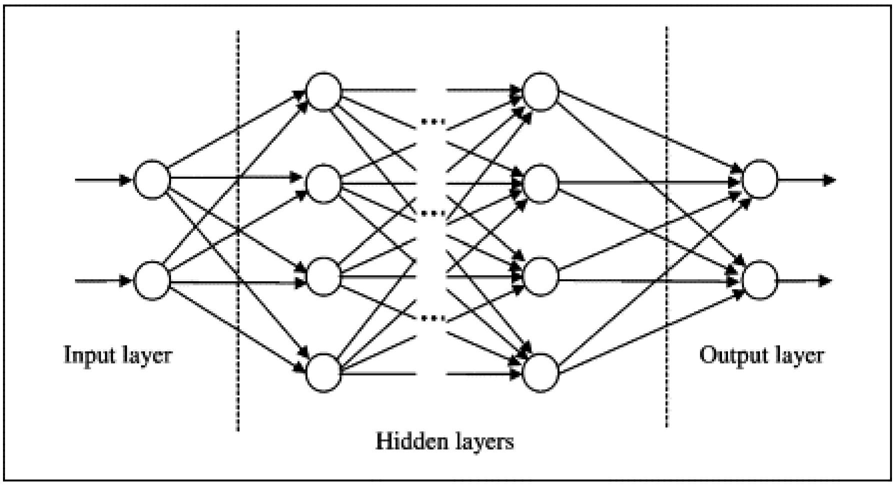


Figure 2.1: General Architecture of an ANN (Kalogirou, 2003)

2.10.1 Implementation of ANNs

2.10.1.1 Network parameters selection

Selection of some key parameters such as number of neurons in the input layer and output layer, number of hidden layers, number of neurons in hidden layers, learning rate, momentum factor, activation functions, etc. belongs to the primary step of modeling a neural network. Number of neurons in the input layer is generally equal to the number of variables whose values are known and will be used to forecast the unknown parameters, i.e. outputs and number of neurons in the output layer is the number of unknown parameters that needs to be predicted. However, choosing the number of neurons in hidden layers, number of hidden layers and learning rate does not have any exact rule; they are settled by observing the accuracy level of the outputs along with measuring the time consumption during the training process by doing trial and error, i.e. applying different network configurations with same data package (Rafiq et al., 2001).

2.10.1.2 Training

A network is trained by getting fed with lots of data comprising both input and output values. If the network is trained properly, it will estimate output values with higher precision. There are several training algorithms that are frequently used in ANN based experimentations such as Levenberg-Marquardt, Quasi-Newton, Conjugate Gradient algorithm, Orthogonal Least Squares method and so forth (Hagan & Menhaj, 1994; Zakaria et al., 2010). However, these learning algorithms have been categorized into three basic divisions which are: supervised learning, unsupervised learning, and reinforced learning (Gutierrez-Villalobos et al., 2013). Supervised learning is based on calculating the divergences of network estimated outputs from the sample outputs provided by an external source and thereby adjusting the weight values for optimal convergence. Unlike this method, unsupervised learning analyzes the input data only and helps the network find the pattern on the basis of properties or indications of the fed data. In reinforced learning, the network is trained to reach a definite goal by performing trial and error on the basis of past experiences (Shiraga et al., 2002). The first two methods, i.e. supervised and unsupervised learning, are the most widely exercised methods as they have proven to be greatly effective in plenty of ANN based applications.

2.10.1.3 Testing

The network is tested with new sets of data (i.e. trial data instead of training data) to check the accuracy of the network outputs and examine whether the network has been trained well or not. Often some particular testing methods are followed to evaluate the performance of a trained network which can be found from (Kovalerchuk et al.; Mohanraj et al., 2012). Therefore, the overall ANN employment procedure can be illustrated by the following Figure 2.2.

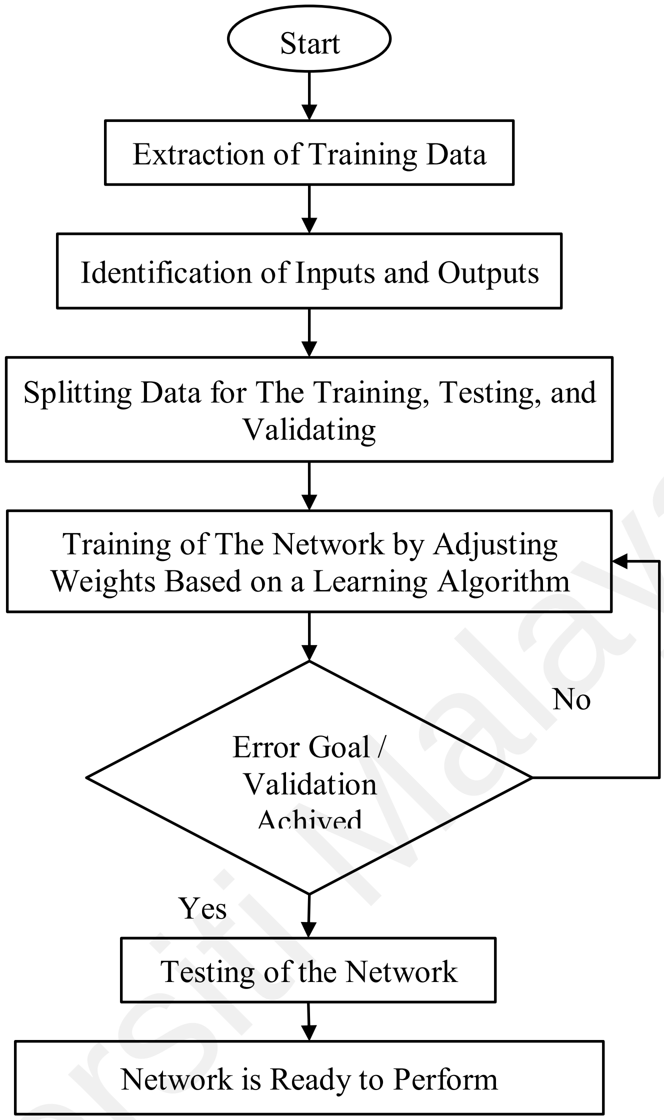


Figure 2.2: ANN Implementation Flowchart

2.11 Discussions

Several significant advantages of ANNs have led to the potential researchers to be interested in this technique which are: higher accuracy, parallel identification, simpler methodology, tolerant to noises. For these reasons, ANNs technique has been followed in this study to construct a more practical and efficient methodology for the identification of the traffic signs.

The existing academic literature shows that there are a variety of traffic sign detection and recognition systems. However, these existing systems are trained and tested on good quality images. Moreover, these systems are specifically designed for the developed countries such as America, Canada, Germany, Finland. In these countries, the relevant authorities regularly and strictly maintain these traffic signs. Hence, the existing systems can undoubtedly work better in developed countries where these signs are maintained regularly. However, in many developing countries, these signs are not maintained on a top priority basis.

After surveying different research works, the objective of the proposed system is to present a fast and robust system for road sign recognition which is a real-time vision-based. For the first time in a road sign recognition system, a robust custom feature extraction method is introduced to extract multiple features from a single input image. In this proposed approach, for reducing the processing time, a hybrid segmentation algorithm with shape measurement-based detection, and an ANN with custom features extraction are used to recognize road signs that can account for multiple variations in road signs. This hybrid segmentation algorithm is used to make this detection and recognition more robust to changes in illumination.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This Chapter describes the methodological explanation of this research. Data collection, detection algorithm, the theoretical framework of feature extraction method, and recognition algorithm development have been described. This methodological explanation is divided into eight main sections and few sub sections. A systematic overview of this proposed research has been described in the System Overview section.

A digital camera's properties and specifications for the data collection of this research has been discussed in the Image Acquisition Device section. Raw images database development and its properties have been described in The Database section for the purpose of training, testing, and validating of the proposed detection and recognition algorithms of this research. A hybrid color segmentation algorithm and its superiority have been discussed on the Color Segmentation Algorithms section for details. A novel feature extraction method has been described in detail in the Feature Extraction section, and the feature extraction performance included in the Features Extraction Performance Comparison section. A proposed recognition method for the road-traffic sign has been discussed in the Recognition of the Road Sign section within two subsections. The details of ANN architecture and training database have been explained in the sub section as Artificial neural network design and Train Data Set.

3.2 System Overview

Numerous real-world computer vision applications which have been developed require the accurate detection of target object from video sequences. Road sign recognition is one of the more challenging examples of real-world computer vision applications. Because of the high industrial relevance, many approaches for traffic sign detection and recognition have been proposed. Any proposed road sign recognition process should be able to work in the following two modes: the first mode is detection mode and it works as a primary stage to collect images from real-time road environments by capturing video from a moving vehicle. This video is segmented frame by frame and then goes through a hybrid segmentation algorithm to identify the road and traffic sign candidates. This hybrid color segmentation algorithm contains a RGB histogram equalization, RGB color segmentation, modified grayscale segmentation, binary image segmentation and shape matching algorithm. Histogram equalization improves the color constancy of all red, green, and blue regions, and RGB color segmentation extracts the red (R) region, green (G) region, and blue (B) region. If the road sign candidate is greater than zero (>0), that specific candidate saves as like an input image to an image database and that is an RGB image. The second mode is classification, which works with a robust custom feature extraction method and an ANN which is designed to train, test and validate the data. This robust custom feature extraction process is based on a size- independent method and obtains 278 features for each road sign. The overall proposed system architecture is illustrated Figure 3.1. It contains of several segments those work combinedly to complete this detection. These segments are as follows:

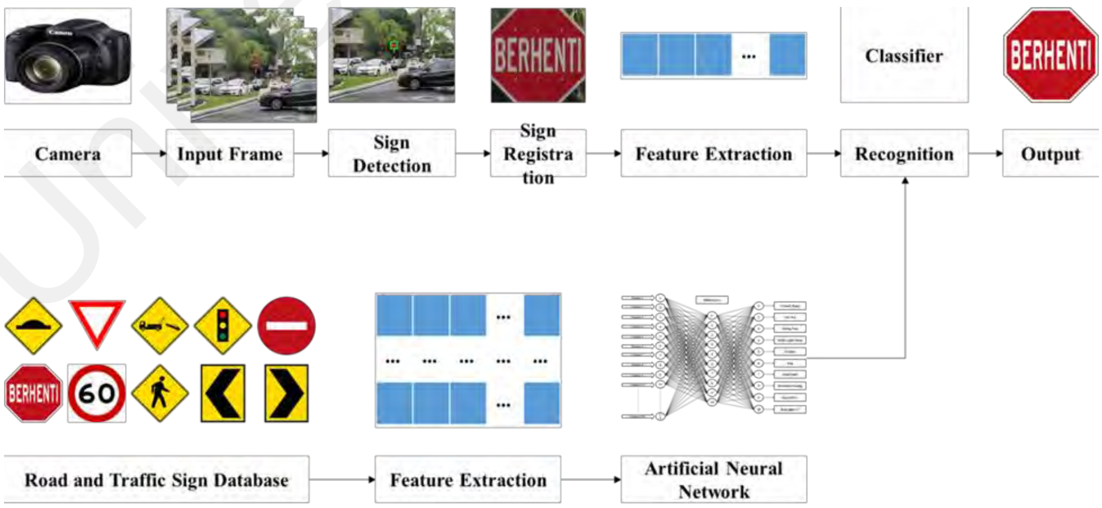


Figure 3.1: An Overview of the Proposed System

3.3 Image Acquisition Device

In this research, a Canon PowerShot SX530 HS digital camera, shown in Figure 3.2, was used for raw data (images and videos) collection as an image acquisition device. This digital camera was nominated due to the price and specification that could be acceptable. A full specification of this camera is enlisted in Table 3.1.

Table 3.1: Canon PowerShot SX530 HS (Specifications)

Features	**Specifications**
Focal Length	4.3 (W) - 215.0 (T) mm (35mm film equivalent: 24-1200mm)
Focusing Range	Normal, Auto/Manual, Macro AF
File Format	Images are JPG and Videos are MP4
Max Resolution	Image is 4608-by-3456 pixels Video is 920-by-1280 pixels Frame rate is 30 frame per second
Zoom Capability	Optical zoom is 50X and digital zoom is 4X
Maximum Aperture	f/3.4 (W), f/6.5 (T)
Shutter Speed	1-1/2000 sec.
ISO	100-3200 when it is Auto mode
White Balance	Auto, Daylight, Cloudy, Custom
Shooting Speed	Approximately 10 shots per second
Color Approaches	RGB
Video and Audio	NTSC/PAL, Stereo
Wireless Control	Wi-Fi and Near Field Communication (NFC)

Figure 3.2: Canon PowerShot SX530 HS

3.4 The Database for Raw Images

Throughout this research, raw images were collected for the development and authentication of the algorithms used for road-traffic sign detection and recognition. A set of 3000 pictures in Malaysia (University of Malaya Shuttle Bus Service Route A, B, C, D, and E) and 16 pictures were collected from other countries. All collected images were captured from the same position of the moving vehicle (left-hand side of the dashboard), but different vehicles were used dependent on the accessibility. All still images were taken physically when the cameraman saw the road-traffic signs. In addition, some videos also were taken during this research and were extracted all video frames as still images. They were collected in the real-time environment. For all images and without any exemption, the camera was set to auto mode and the dimension of the image size is 4608-by-3456 pixels with extra fine JPG format. The moving vehicle is allowing the continuous image capturing with different positions and distance in between the camera and the targeted road-traffic signs. Images in this database are divided into ten different categories depending on the nature of road-traffic sign classes. Table 3.2 shows these classes collected with the number of images belongs into in each group.

Table 3.2: Sign Database Description

Category	Number of Images
Hump sign	300
Give Way sign	300
Towing Zone sign	300
Traffic Lights Ahead sign	300
No Entry sign	300
Stop sign	300
Speed Limit sign	300
Pedestrian Crossing sign	300
Keep Left Curve Chevron sign	300
Keep Right Curve Chevron sign	300

In addition, the robustness test database contains additional road-traffic sign image from different countries. The objectives of collecting images from multiple countries are to examine the variances and associate the colors and pictograms used by these countries.

Such image testing helps to develop the reliability and stability of proposed algorithms in research for rand- traffic sign identification.

3.5 Color Segmentation Algorithms

The aim of the color segmentation algorithm is to recognize multi-colored road-traffic signs and to evaluate the suitability of the algorithms in critical conditions. Some indicative criteria of these algorithms to judge their performance are:

- Robustness to Disorientation angles.
- Robustness to Faded signs.
- Robustness to Different country's sign.
- Robustness to Natural blocked sign.
- Robustness to Artificial blocked sign.
- Robustness to Motion blur.
- Robustness to Speed.
- Robustness to Distance.

Some of the above standards are linked with other standards. The choice of a color model depends not only on the robustness of the various lighting over the scene but also on the variations of the exterior orientation of the target object.

3.5.1 Color code for Traffic signs

The following color code has been identified by Jabatan Kerja Raya (JKR) as suitable for use in the transportation of traffic control information. ARAHAN TEKNIK (JALAN) 2A / 85, defined standard traffic sign drawings for regulation, warning and guidance signs are shown with the dimensions shown in Table 3.3. In this research, a discussion now follows on the developed new color segmentation algorithms.

Table 3.3: Chromaticity Coordinates by JKR Malaysia

Color	1		2		3		4	
	x	y	x	y	x	y	x	y
Red	0.690	0.310	0.595	0.315	0.569	0.341	0.655	0.345
Orange	0.610	0.390	0.535	0.375	0.561	0.394	0.581	0.418
Yellow	0.504	0.458	0.525	0.473	0.493	0.507	0.474	0.488
Green	0.140	0.380	0.135	0.440	0.110	0.438	0.115	0.378
Dark Green	0.040	0.460	0.100	0.460	0.100	0.380	0.030	0.380
Blue	0.134	0.043	0.169	0.097	0.154	0.125	0.114	0.007
White	0.350	0.360	0.300	0.310	0.285	0.325	0.335	0.375

3.5.2 The hybrid color segmentation algorithm

A hybrid color segmentation algorithm has been developed and tested for traffic sign detection and recognition purpose. This hybrid color segmentation algorithm contains an RGB histogram equalization, RGB color segmentation, modified grayscale segmentation, binary image segmentation, and shape matching algorithm. All these five algorithms are analyzed by using more than a thousand of images for an optimum performance. Then that hybrid color segmentation algorithm is selected for the detection of road and traffic sign to get the desired outcome. An RGB pixel value is a matrix of RGB value. This is well-known as the RGB color model. Equation (1) showing how to RGB image convert to grayscale image. The gray level image average, x is determined that formula have been given below.

$$x = 0.299r + 0.587g + 0.114b \tag{1}$$

Detection of the road sign is divided into three steps, which is (I) Primary step, (II) Intermediate step and (III) Final step. Primary step works with histogram equalization algorithm. Histogram equalization improves the color constancy of all red, green, and blue regions, and RGB color segmentation extracts the red (R) region, green (G) region, and blue (B) region for low light condition, primary step process flowchart is shown in Figure 3.3.

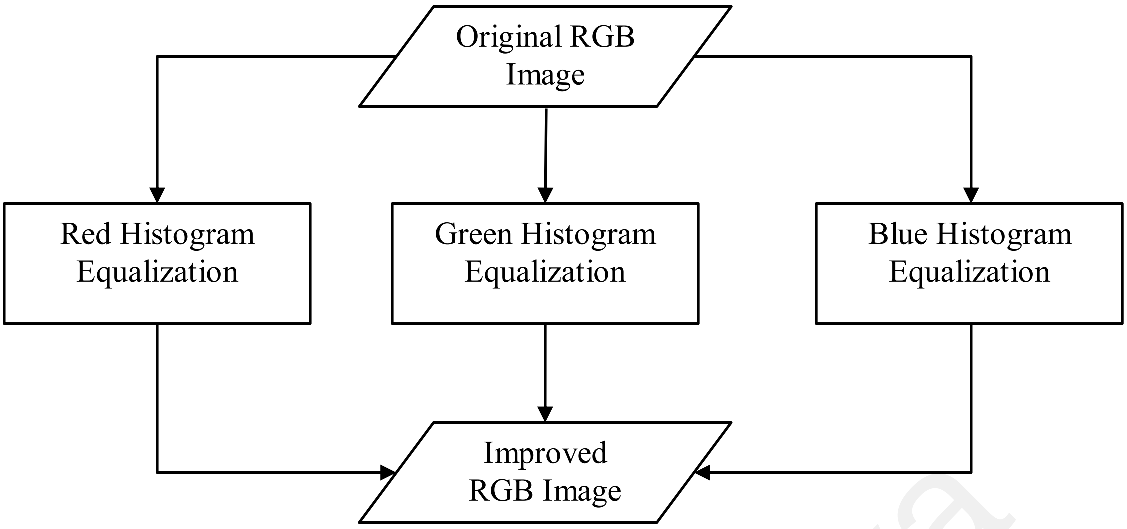


Figure 3.3: Primary Stage: Histogram Equalization

Improved RGB image goes through for further process. In Figure 3.4 shows the result of red (R), green (G), and blue (B) region of the original RGB image of a stop sign with the gray level histogram of each region. And illustrates the image color band and histogram of color band to the original frame.

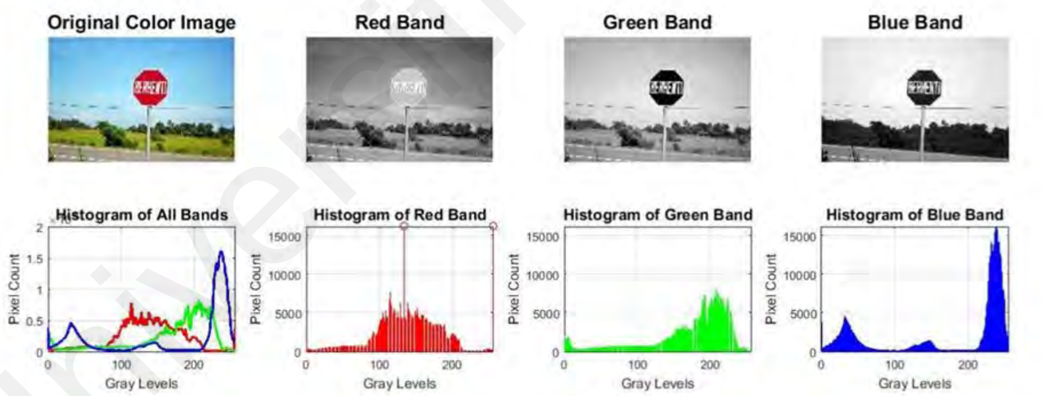
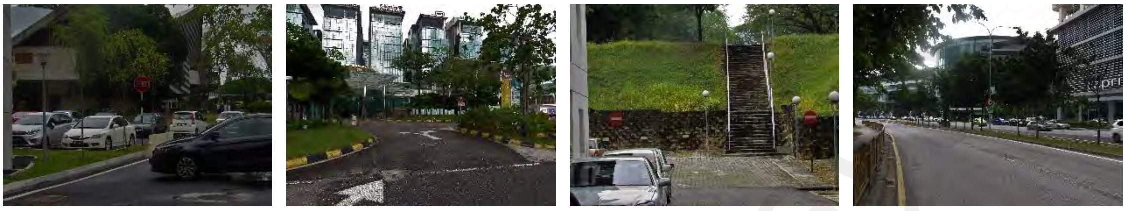
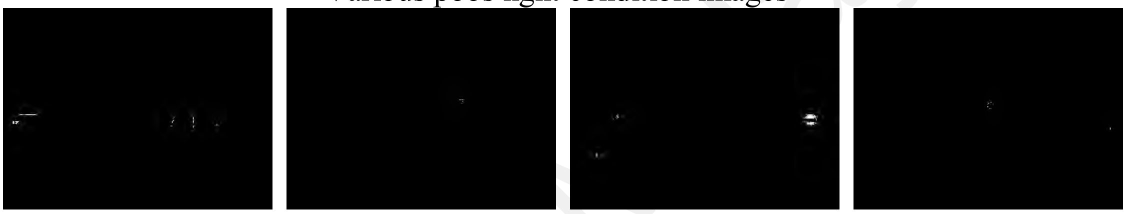


Figure 3.4: RGB Region and Gray Level Histogram

The histogram equalization algorithm is tested on images collected at various low light conditions such as evening, morning, daylight, and cloudy. The 1st line of Figure 3.5 shows example images for testing the proposed algorithm. The 2nd line shows images from the first line, which are segmented by a normal color segmentation algorithm without applying the histogram equalization algorithm described herein and the results is unsuccessful to segment the target objects. The 3rd line shows the images subsequently the expansion by histogram equalization and color constancy and presents that the colors of the characters in these images are improved. The 4th line shows the consequences of segmentation after applying the histogram equalization algorithm and successfully segmented the target objects area. At the end of this section, the entire image frame contains a high resolution, improved the RGB image, which is very important for this proposed system.

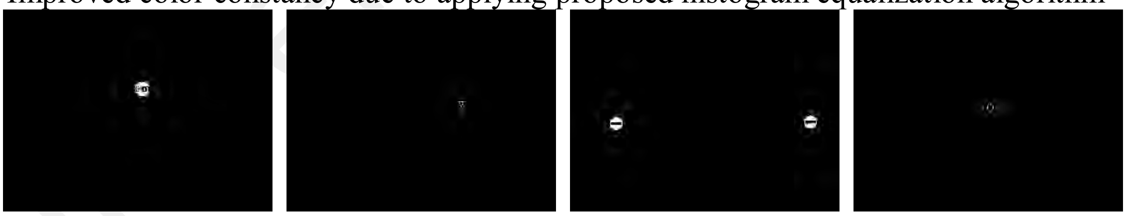


Various poos light condition images



Segmentation outcomes before applying proposed histogram equalization algorithm

Improved color constancy due to applying proposed histogram equalization algorithm



Segmentation outcomes after applying proposed histogram equalization algorithm

Figure 3.5: Results of Applying Histogram Equalization Algorithm

At the intermediate step, an RGB color segmentation algorithm is used for subtracting red (R), green (G) and blue (B) components of that image. In the next step, RGB to grayscale converter algorithm is used to convert subtracted image to grayscale image. Then, a 2-dimensional 3-by-3 median filter is used to remove existing noise from grayscale image. Next, it replaces all the input image pixel value, with luminance is greater than 0.18 to 1 as a white pixel, and all other pixels are replaced to 0 as a black pixel. From this process, a grayscale image converts into the binary image for this proposed system. A threshold level 0.18 is used for this conversion process, because of it gives the best performance for this system.

if the value at the pixel position is greater than 0.18
then the value will be 1(white) else 0 (black)

After that conversion, it removes all the small objects from the binary image which is contained less than 300 pixels and then labels all connected component using 8-connected objects. Next, is measuring of image region properties and then find how many candidates are available on that binary image. This is the target candidate to identify as a road sign. Then from the target candidate, it is determined the position (X, Y- coordinate), height (H) and, width (W) of every single object. For the candidate selection, which candidate has the height (H) and the width (W) ratio closed to 1, is considered as a target candidate. Based on the selected candidates' properties, sign image is cropped from original RGB input frame. It is also high resolution RGB image with target objects, and it is the last process of intermediate step.

At the final step, detected target road sign contain enough pixel information because it is extracted from an original RGB input frame. Initially, it resizes that image to the 128-by-128 pixel, then convert that RGB image to grayscale image according to Equation (1), and remove existing noise by using 3-by-3 (2-dimensional) median filter. Then, the grayscale image is converted to a binary image with grayscale histogram level and the algorithm is below.

if the value at the pixel position is greater than grayscale histogram level
then the value will be 1(white) else 0 (black)

It is the last section of detection of the road sign, Figure 3.6 is shown the overall block diagram and Figure 3.7 is shown the systematic overview of the proposed system.

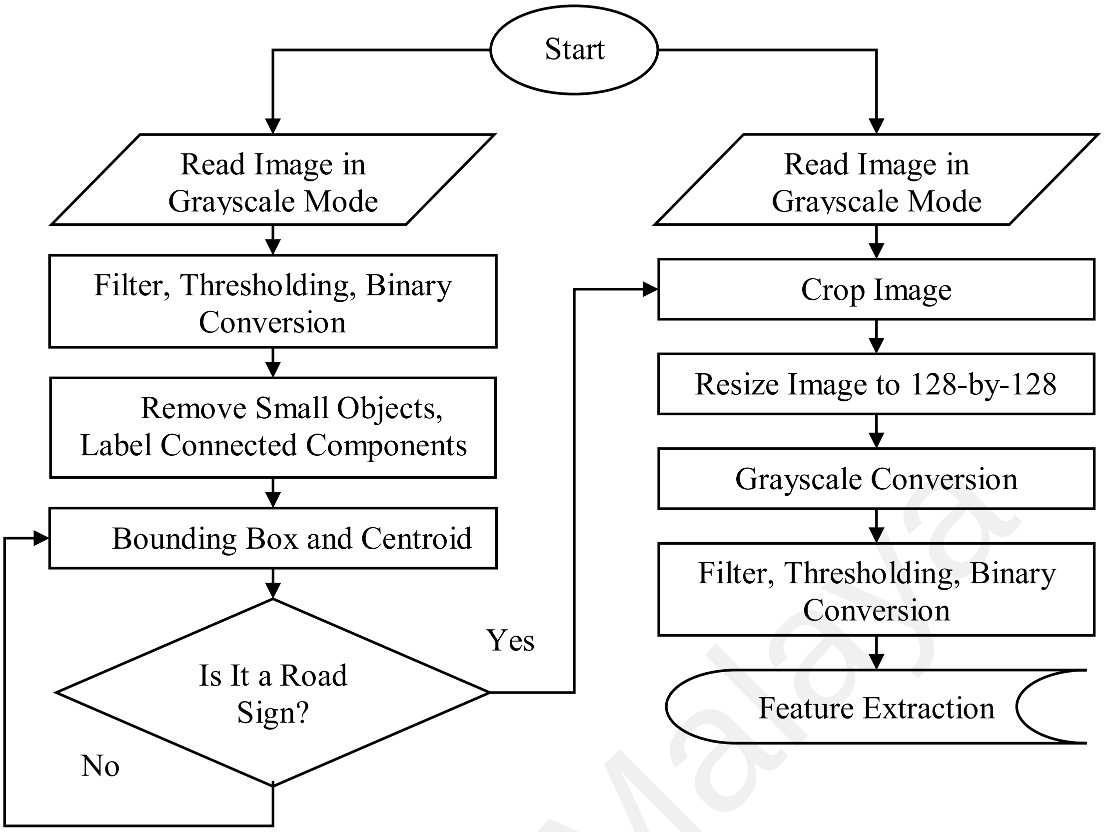


Figure 3.6: The Overall Block Diagram of Road Sign Detection System

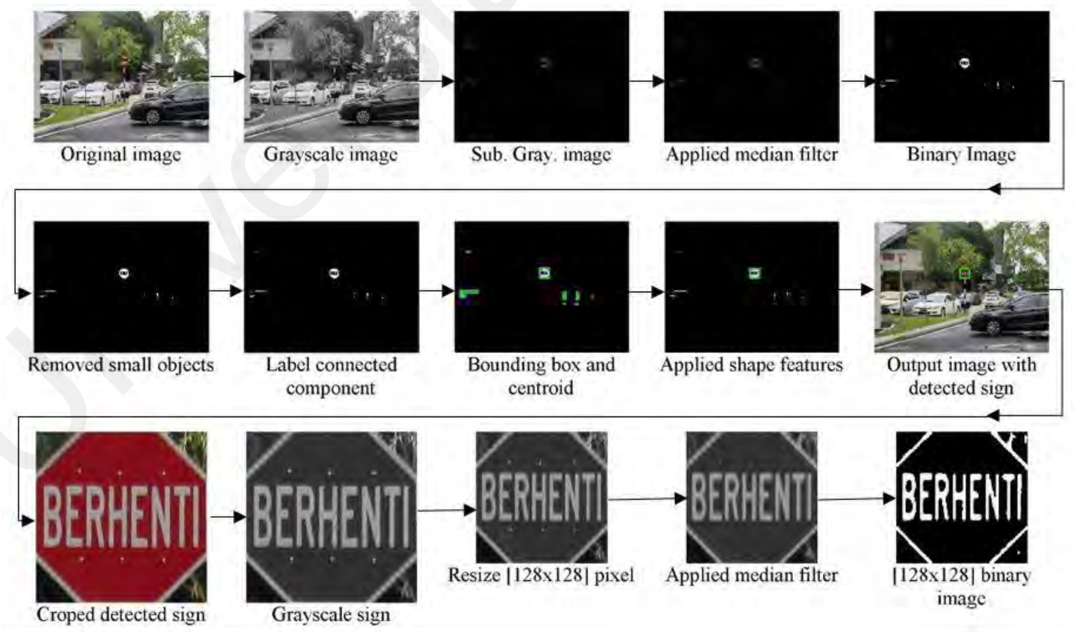


Figure 3.7: A Systematic Overview of the Road Sign Detection Steps

3.6 Feature Extraction

For the first time in a road sign recognition system, a robust custom feature extraction method is introduced to extract multiple features from a single input image. This robust custom feature extraction process is based on a size independent method and obtains 278 features for road signs. Initially, a 128-by-128 pixels binary image is converted to a 128-by-128 binary matrix. The total pixel value is 128-by-128 = 16384 pixels. A matrix 'A' represents a 128-by-128 binary matrix shown in Equation (2) where m = 128 and n = 128.

$$A = \begin{bmatrix} a_{11} & a_{12} & \ldots\ldots & a_{1n} \\ a_{21} & a_{22} & \ldots\ldots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \ldots\ldots & a_{mn} \end{bmatrix} \tag{2}$$

True pixels are the summation of all white pixels using Equation (3):

$$True\ pixel = \sum_{m=1}^{128} \sum_{n=1}^{128} A_{mn} \tag{3}$$

Now, this original matrix A is divided into a submatrix which is S = 4-by-4 matrix by Equation (4) where 1≤ m ≥4 and 1≤ n ≥ 4 and is shown in Figure 3.8. This 4-by-4 sub matrix pixel value needs to be stored in the system database for further processing.

$$S = \begin{bmatrix} s_{11} & s_{12} & \ldots\ldots & s_{1n} \\ s_{21} & s_{22} & \ldots\ldots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{m1} & s_{m2} & \ldots\ldots & s_{mn} \end{bmatrix} \tag{4}$$

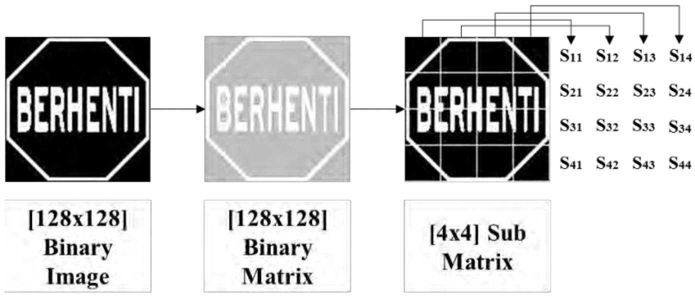


Figure 3.8: Sub Region Segmentation

In this submatrix, each element is the summation of the original matrix's array elements which are defined by Equation (5). The summation conditions are given in Table 3.4.

$$s = \begin{bmatrix} s_{11} & s_{12} & \cdots\cdots & s_{14} \\ s_{21} & s_{22} & \cdots\cdots & s_{24} \\ \vdots & \vdots & \ddots & \vdots \\ s_{41} & s_{42} & \cdots\cdots & s_{44} \end{bmatrix} \tag{5}$$

Table 3.4: Sub Matrix Condition

$S_{11} = \sum_{m=1}^{32}\sum_{n=1}^{32} A_{mn}$	$S_{12} = \sum_{m=1}^{32}\sum_{n=33}^{64} A_{mn}$	$S_{13} = \sum_{m=1}^{32}\sum_{n=65}^{96} A_{mn}$	$S_{14} = \sum_{m=1}^{32}\sum_{n=97}^{128} A_{mn}$
$S_{21} = \sum_{m=33}^{64}\sum_{n=1}^{32} A_{mn}$	$S_{22} = \sum_{m=33}^{64}\sum_{n=33}^{64} A_{mn}$	$S_{23} = \sum_{m=33}^{64}\sum_{n=65}^{96} A_{mn}$	$S_{24} = \sum_{m=33}^{64}\sum_{n=97}^{128} A_{mn}$
$S_{31} = \sum_{m=65}^{96}\sum_{n=1}^{32} A_{mn}$	$S_{32} = \sum_{m=65}^{96}\sum_{n=33}^{64} A_{mn}$	$S_{33} = \sum_{m=65}^{96}\sum_{n=65}^{96} A_{mn}$	$S_{34} = \sum_{m=65}^{96}\sum_{n=97}^{128} A_{mn}$
$S_{41} = \sum_{m97}^{128}\sum_{n=1}^{32} A_{mn}$	$S_{42} = \sum_{m=97}^{128}\sum_{n=33}^{64} A_{mn}$	$S_{43} = \sum_{m=97}^{128}\sum_{n=65}^{96} A_{mn}$	$S_{44} = \sum_{m=97}^{128}\sum_{n=97}^{128} A_{mn}$

Custom features extraction is performed by dividing the 128-by128 binary matrix into multiple submatrices. Road signs are divided into multiple areas such as upper side, down side, left side, right side, upper left side, upper right side, down left side, down right side, four columns side and four rows side which are shown in Figure 3.9. Then the feature extraction algorithm calculates all existing white pixel values in that area.

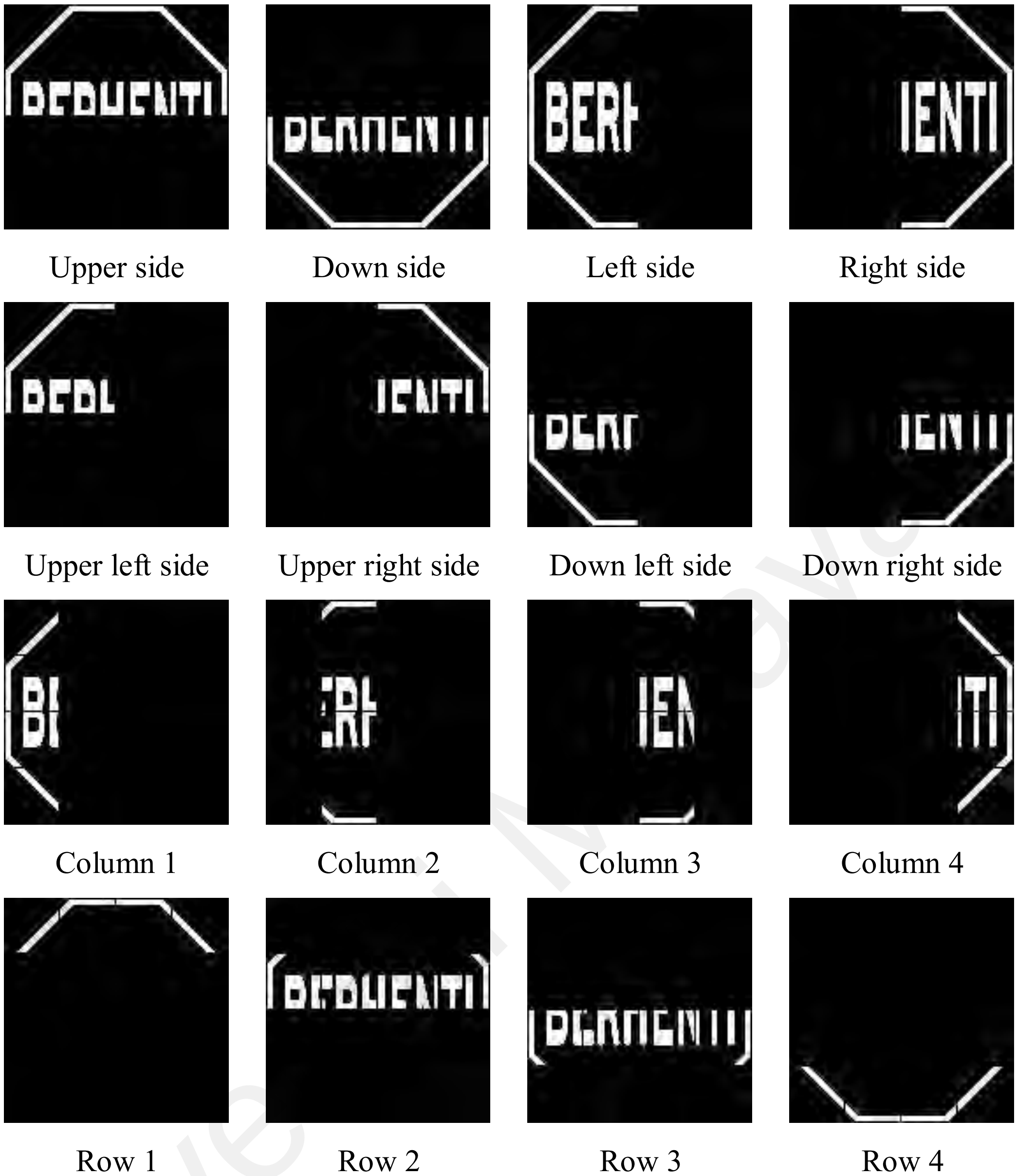
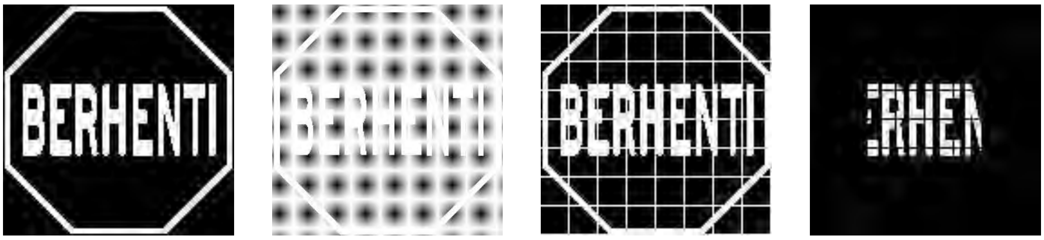


Figure 3.9: Image Sub Region Feature Extraction

Equations (6) and (7) represent the row and the column vectors, respectively, from submatrix S:

$$RV = \sum_{m=1}^{4} S_{mn}; m = 1, \dots, \dots, 4 \qquad (6)$$

$$RV = \sum_{n=1}^{4} S_{mn}; n = 1, \dots, \dots, 4 \qquad (7)$$



Binary image (128-by-128) | Binary matrix (128-by-128) | Sub matrix (8-by-8) | Inner sub matrix (4-by-4)

Figure 3.10: Sub Matrix and Inner Sub Matrix for Pictogram Analysis

Figure 3.10 shows a 4-by-4 inner sub matrix for pictogram pattern analysis. From the 8-by-8 binary matrix a ROI is extracted for pictogram feature analysis which is shown in the Figure 3.11.

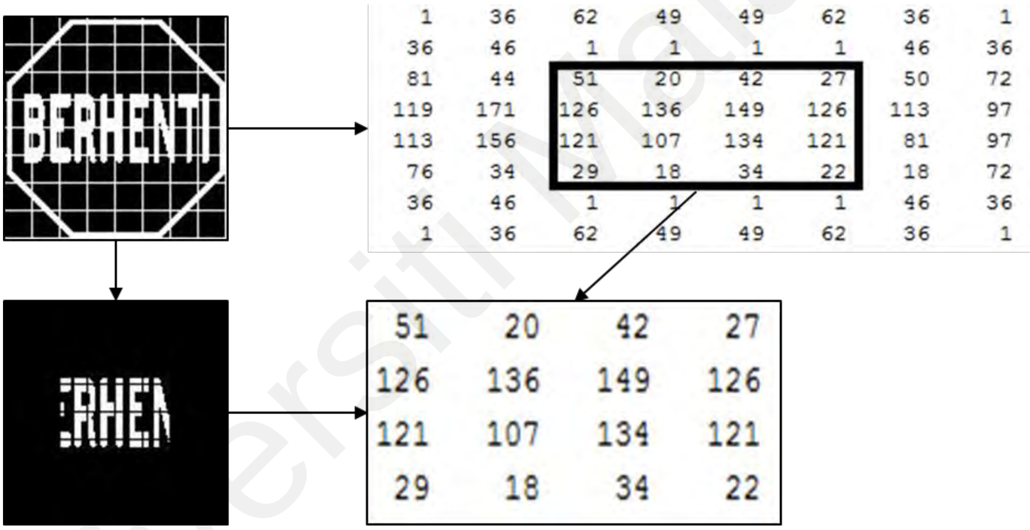


Figure 3.11: An Example of Pictogram Feature Extraction of Stop Sign

3.6.1 Custom feature extraction algorithm

The custom feature extraction algorithm works in several steps (MATLAB code in Appendix B). Every new step is started after finishing the previous step. The process can be represented by the following steps:

1. Read 128-by-128 binary image as A = 128-by-128 matrix.
2. Compute Total Pixels, total_pixels as 128x128 = 16384.
3. Compute True Pixels, true_pixels as the sum of all white pixels of A.

4. Compute 4-by-4 sub matrix of A as sub = 4-by-4 sub matrix of A.
5. Compute 8-by-8 sub matrix of A as S = 8-by-8 sub matrix of A.
6. Compute 4-by-4 sub matrices Rows and Columns as row1 = sub (1) + sub (5) + sub (9) + sub (13); row2 = sub (2) + sub (6) + sub (10) + sub (14); row3 = sub (3) + sub (7) + sub (11) + sub (15); row4 = sub (4) + sub (8) + sub (12) + sub (16); column1 = sub (1) + sub (2) + sub (3) + sub (4); column2 = sub (5) + sub (6) + sub (7) + sub (8); column3 = sub (9) + sub (10) + sub (11) + sub (12); column4 = sub (13) + sub (14) + sub (15) + sub (16);
7. Compute 8-by-8 sub matrices sub Rows and sub Columns as srow1 = s(19) + s(27) + s(35) + s(43); srow2 = s(20) + s(28) + s(36) + s(44); srow3 = s(21) + s(29) + s(37) + s(45); srow4 = s(22) + s(30) + s(38) + s(46); scolumn1 = s (19) + s (20) + s (21) + s (22); scolumn2 = s (27) + s (28) + s (29) +s (30); scolumn3 = s (35) + s (36) + s (37) + s (38); scolumn4 = s (43) + s (44) + s (45) + s (46);
8. Compute Sum of Upper Pixels as up = row1 + row2;
9. Compute Sum of Dows Pixels as dp = row3 + row4;
10. Compute Sum of Left Pixels as lp = column1 + column2;
11. Compute Sum of Right Pixels as rp = column3 + column4;
12. Compute Sum of Upper Left Pixels as ulp = sub (1) + sub (5) + sub (2) + sub (6);
13. Compute Sum of Upper Right Left Pixels as urp = sub (9) + sub (13) + sub (10) + sub (14);
14. Compute Sum of Down Left Pixels as dlp = sub (3) + sub (7) + sub (4) + sub (8);
15. Compute Sum of Down Right Pixels as drp = sub (11) + sub (15) + sub (12) + sub (16);
16. Compute Sum of Upper Left Upper Pixels as ulup = sub (1) + sub (5);
17. Compute Sum of Upper Left Down Pixels as uldp = sub (2) + sub (6);
18. Compute Sum of Upper Left-Left Pixels as ullp = sub (1) + sub (2);

19. Compute Sum of Upper Left Right Pixels as ulrp = sub (5) + sub (6);
20. Compute Sum of Upper Right Upper Pixels as urup = sub (9) + sub (13);
21. Compute Sum of Upper Right Down Pixels as urdp = sub (10) + sub (14);
22. Compute Sum of Upper Right Left Pixels as urlp = sub (9) + sub (10);
23. Compute Sum of Upper Right-Right Pixels as urrp = sub (13) + sub (14);
24. Compute Sum of Down Left Upper Pixels as dlup = sub (3) + sub (7);
25. Compute Sum of Down Left Down Pixels as dldp = sub (4) + sub (8);
26. Compute Sum of Down Left-Left Pixels as dllp = sub (3) + sub (4);
27. Compute Sum of Down Left Right Pixels as dlrp = sub (7) + sub (8);
28. Compute Sum of Down Right Upper Pixels as drup = sub (11) + sub (15);
29. Compute Sum of Down Right Down Pixels as drdp = sub (12) + sub (16);
30. Compute Sum of Down Right Left Pixels as drlp = sub (11) + sub (12);
31. Compute Sum of Down Right-Right Pixels as drrp = sub (15) + sub (16);
32. Compute average 8-by-8 sub matrices as av = (srow1 + srow2 + srow3 + srow4)/16.

The algorithm extracts all the required information by following these 32 steps. This information was used for features extraction. Features 1–12 were defined based on 4-by-4 sub matrix rows. Feature 1 will be the ratio between the first row and the second row and feature 2 will be the ratio between the second row and the first row. This process will continue to the fourth row, and feature 12 will be the ratio between the fourth row and third row. The algorithm is as follows:

f1 = row1/row2; f2 = row2/row1; f3 = row1/row3; f4 = row3/row1; f5 = row1/row4; f6 = row4/row1;

f7 = row2/row3; f8 = row3/row2; f9 = row2/row4; f10 = row4/row2; f11 = row3/row4; f12 = row4/row3;

Features 13–24 were defined based on 4-by-4 sub matrices columns. Features 13–24 will be same as the features 1–12. The only difference is that features 1–12 depend upon rows and features 13–24 depend upon columns. Feature 13 will be the ratio between the first column and the second column. Feature 24 will be the ratio between the fourth column and the third column. The algorithm is as follows:

f13 = column1/column2; f14 = column2/column1; f15 = column1/column3; f16 = column3/column1;

f17 = column1/column4; f18 = column4/column1; f19 = column2/column3; f20 = column3/column2;

f21 = column2/column4; f22 = column4/column2; f23 = column3/column4; f24 = column4/column3;

Features 25–36 were defined based on Upper Pixels, Down Pixels, Left Pixels, and Right Pixels. The 128-by-128 matrix is divided up into horizontally and vertically as upper pixels, down pixels, left pixels, and right pixels. Feature 25 will be the ratio between the upper pixels' value and down pixels' value. Feature 36 will be the ratio between the right pixels' value and left pixels' value. The algorithm is as follows:

f25 = up/dp; f26 = dp/up; f27 = up/lp; f28 = lp/up; f29 = up/rp; f30 = rp/up; f31 = dp/lp; f32 = lp/dp; f33 = dp/rp; f34 = rp/dp; f35 = lp/rp; f36 = rp/lp;

Features 37–48 were defined based on Upper Left Pixels, Upper Right Pixels, Down Left Pixels, and Down Right Pixels which are shown in

Figure 3.9 (2nd row). The 128-by-128 matrix is divided up into four parts which are Upper Left Pixels part is the left top part, Upper Right Pixels part is the top right part, Down Left Pixels part is the bottom left part, and Down Right Pixels part is the bottom right part. Feature 37 will be the ratio between the Upper Left Pixels' value and the upper right pixels' value. Feature 48 will be the ratio between the Down Right Pixels' value and the down left pixels' value. The algorithm is as follows:

f37 = ulp/urp; f38 = urp/ulp; f39 = ulp/dlp; f40 = dlp/ulp; f41 = ulp/drp; f42 = drp/ulp; f43 = urp/dlp; f44 = dlp/urp; f45 = urp/drp; f46 = drp/urp; f47 = dlp/drp; f48 = drp/dlp;

The Upper Left Pixels part is divided into four subparts which are Upper Left Upper Pixels, Upper Left Down Pixels, Upper Left-Left Pixels, and Upper Left Right Pixels. Features 49–60 were defined based on those subparts. Feature 49 will be the ratio between the Upper Left Upper Pixels' values and the upper left down pixels' value. Feature 60 will be the ratio between the Upper Left Right Pixels' value and the upper left-left pixels' value. The algorithm is as follows:

f49 = ulup/uldp; f50 = uldp/ulup; f51 = ulup/ullp; f52 = ullp/ulup; f53 = ulup/ulrp; f54 = ulrp/ulup; f55 = uldp/ullp; f56 = ullp/uldp; f57 = uldp/ulrp; f58 = ulrp/uldp; f59 = ullp/ulrp; f60 = ulrp/ullp;

Upper Right Pixels part is divided into four subparts which are Upper Right Upper Pixels, Upper Right Down Pixels, Upper Right Left Pixels, and Upper Right-Right-Pixels. Features 61–72 were defined based on those subparts. The process is same as earlier, whereby feature 61 will be the ratio between the Upper Right Upper Pixels' value and the upper right down pixels' value. Feature 72 will be the ratio between the upper right-right pixels' value and the upper right left pixels' value. The algorithm is as follows:

f61 = urup/urdp; f62 = urdp/urup; f63 = urup/urlp; f64 = urlp/urup; f65 = urup/urrp; f66 = urrp/urup; f67 = urdp/urlp; f68 = urlp/urdp; f69 = urdp/urrp; f70 = urrp/urdp; f71 = urlp/urrp; f72 = urrp/urlp;

Down Left Pixels part is divided into four subparts which are Down Left Upper Pixels, Down Left Down Pixels, Down Left-Left Pixels, and Down Left Right Pixels and features 73–84 were defined based on those subparts. Feature 73 will be the ratio between the Down Left Upper Pixels' value and the down left down pixels' value. Feature 84 will be the ratio between the down left right pixels' value and the down left-left pixels' value. The algorithm is as follows:

f73 = dlup/dldp; f74 = dldp/dlup; f75 = dlup/dllp; f76 = dllp/dlup; f77 = dlup/dlrp; f78 = dlrp/dlup; f79 = dldp/dllp; f80 = dllp/dldp; f81 = dldp/dlrp; f82 = dlrp/dldp; f83 = dllp/dlrp; f84 = dlrp/dllp;

Down Right Pixels part is divided into four subparts which are Down Right Upper Pixels, Down Right Down Pixels, Down Right Left Pixels, and Down Right-Right Pixels and features 85–96 were defined based on those subparts. Feature 85 will be the ratio between the Down Right Upper Pixels' value and the down right down pixels' value. Feature 96 will be the ratio between the down right-right pixels' value and the down right left pixels' value. The algorithm is as follows:

f85 = drup/drdp; f86 = drdp/drup; f87 = drup/drlp; f88 = drlp/drup; f89 = drup/drrp; f90 = drrp/drup; f91 = drdp/drlp; f92 = drlp/drdp; f93 = drdp/drrp; f94 = drrp/drdp; f95 = drlp/drrp; f96 = drrp/drlp;

Features 97–128 were defined based on the true pixel value. A true pixel value is the sum of all white pixels' value of the image region. All the variables which are declared for defining of feature 1 to feature 96, will be divided by the true pixel value. Feature 97 will be the ratio between the first variable (row1) and the true pixel value. Feature 128 will be the ratio between the last variable (down right-right pixels) and the true pixel value.

Features 129–144 were defined based on the individual elements of the 4-by-4 sub matrix which is shown in Figure 3.8. Feature 129 will be the first element of the 4-by-4 submatrix which is S11. Feature 144, which is S44, will be the 16th element of the 4-by-4 sub matrix because a 4-by-4 submatrix has 16 elements.

Features 145–208 were defined based on the individual elements of the 8-by-8 sub matrix which is shown in Figure 3.10. Feature 145 will be the first element of the 8-by-8 matrix. Feature 208 will be the 64th element of the 8-by-8 sub matrix because a 8-by-8 sub matrix has 64 elements.

Features 209–232 were defined based on the 8-by-8 sub matrix's 4-by-4 inner submatrix which is shown in Figure 3.11. The inner submatrix represents the pictogram pixels' value of a traffic sign. Feature 209 will be the ratio between the inner submatrix's first row and second row and feature 232 will be the ratio between the inner submatrix's forth column and third column. The algorithm is as follows:

f209 = srow1/srow2; f210 = srow2/srow1; f211 = srow1/srow3; f212 = srow3/srow1; f213 = srow1/srow4; f214 = srow4/srow1; f215 = srow2/srow3; f216 = srow3/srow2; f217 = srow2/srow4; f218 = srow4/srow2; f219 = srow3/srow4; f220 = srow4/srow3; f221 = scolumn1/scolumn2; f222 = scolumn2/scolumn1; f223 = scolumn1/scolumn3; f224 = scolumn3/scolumn1; f225 = scolumn1/scolumn4; f226 = scolumn4/scolumn1; f227 = scolumn2/scolumn3; f228 = scolumn3/scolumn2; f229 = scolumn2/scolumn4; f230 = scolumn4/scolumn2; f231 = scolumn3/scolumn4; f232 = scolumn4/scolumn3;

Features 233–244 were defined based on the ratio between every element of the inner submatrix. Feature 233 will be the ratio between the first element and the second element of the inner submatrix. Feature 244 will be the ratio between the last element and the second-last element of that inner sub- matrix. The algorithm is as follows:

f233 = sub(6)/sub(7); f234 = sub(7)/sub(6); f235 = sub(6)/sub(10); f236 = sub(10)/sub(6); f237 = sub(6)/sub(11); f238 = sub(11)/sub(6); f239 = sub(7)/sub(10); f240 = sub(10)/sub(7); f241 = sub(7)/sub(11); f242 = sub(11)/sub(7); f243 = sub(10)/sub(11); f244 = sub(11)/sub(10);

Features 245–260 were defined based on the ratio between every element of the inner submatrix to the true pixels' value. Feature 245 will be the ratio between the first element of that matrix and the true pixels' value and feature 260 will be the ratio between the last element of that matrix and the true pixels' value. The algorithm is as follows:

f245 = sub(1)/tp; f246 = sub(2)/tp; f247 = sub(3)/tp; f248 = sub(4)/tp; f249 = sub(5)/tp; f250 = sub(6)/tp; f251 = sub(7)/tp; f252 = sub(8)/tp; f253 = sub(9)/tp; f254 = sub(10)/tp; f255 = sub(11)/tp; f256 = sub(12)/tp; f257 = sub(13)/tp; f258 = sub(14)/tp; f259 = sub(15)/tp; f260 = sub(16)/tp;

Features 261–276 were defined based on the average value of the 8-by-8 submatrix and every element of the 4-by-4 inner submatrix. Feature 261 will be the ratio between the first element of the inner submatrix and the average value of the 8-by-8 submatrix. Feature 276 will be the ratio between the last element of the inner submatrix and the average value of the 8-by-8 sub matrix. The algorithm is as follows:

f261 = s(19)/av; f262 = s(20)/av; f263 = s(21)/av; f264 = s(22)/av; f265 = s(27)/av; f266 = s(28)/av; f267 = s(29)/av; f268 = s(30)/av; f269 = s(35)/av; f270 = s(36)/av; f271 = s(37)/av; f272 = s(38)/av; f273 = s(43)/av; f274 = s(44)/av; f275 = s(45)/av; f276 = s(46)/av;

The final two features are based on the ratio between the total pixels' value and the true pixels' value. Feature 277 will be the ratio between the total pixels' value and the true pixels' value and feature 278 will be the ratio between the true pixels' value and the total pixels' value. The algorithm is as follows:

f277 = total_pixels/tp; f278 = tp/total_pixels;

The final feature extraction process provides the 278 feature values. All these feature values are needed to build a feature matrix to identify the road signs. The 1-by-278 feature matrix is determined as follows:

F = [feature 1 to feature 278]. Feature extraction overview shows in Figure 3.12.

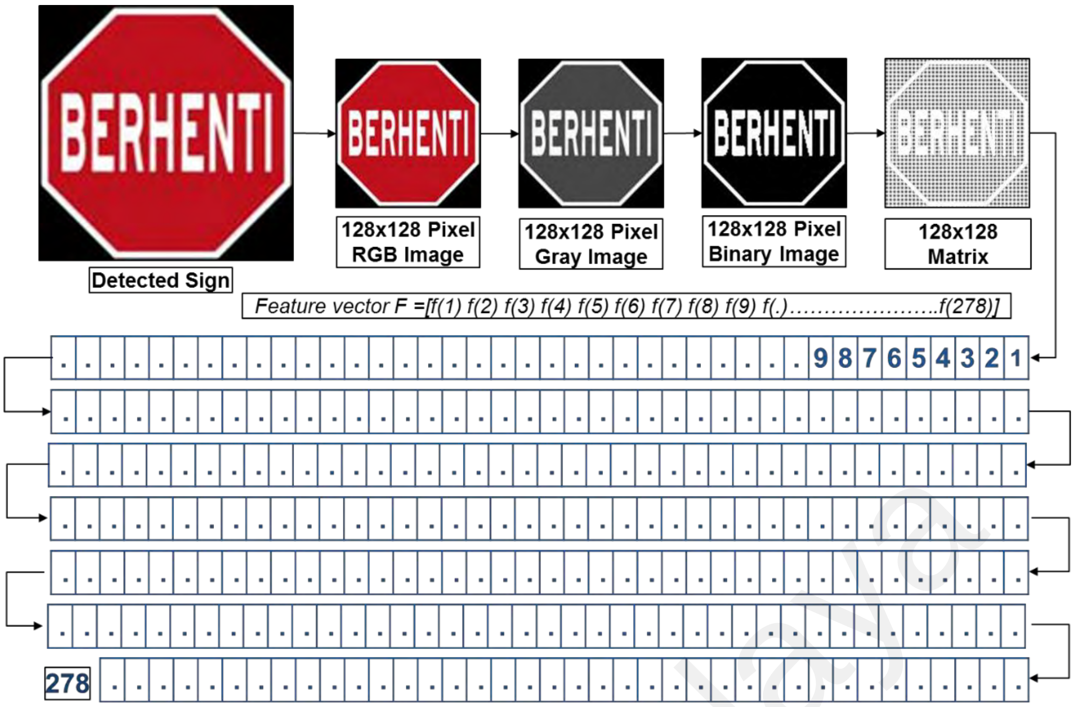


Figure 3.12: An Overview of Feature Extraction Step

For this proposed system number of feature vector is 278 and number of total sign is 1000. A feature vector visualization shown in Figure 3.13 which is 278-by-1000 vector.

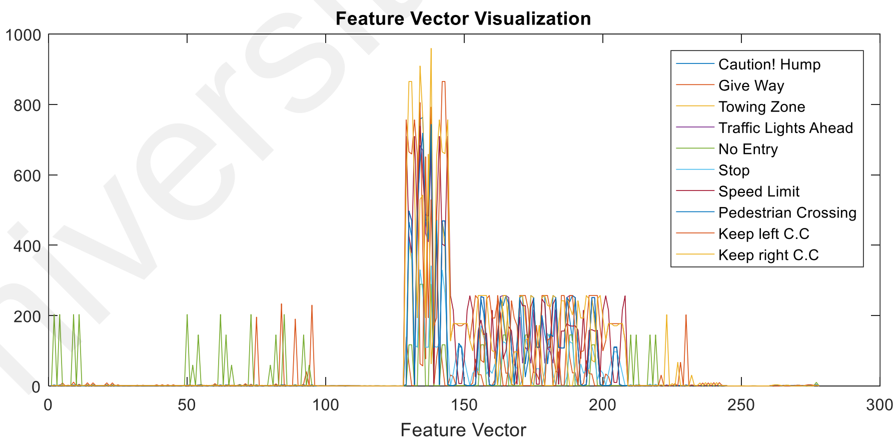


Figure 3.13: Feature Vector Visualization

3.7 Features Extraction Performance Comparison

Features extraction performance is based on the comparison of some other well-known features extraction methods, such as Histogram of Oriented Gradients (HOG) and Speeded Up Robust (SURF) features extraction. The comparison is performed by comparing the computational time of feature extraction and the correct recognition percentage of the extracted features extraction methods. A total of 1000 image samples are used to determine the features extraction performance comparison. Table 3.5 shows the comparison of features extraction method.

Table 3.5: Features Extraction Performance

Method	Processing Time (s)/Image	Recognition Accuracy (%)
HOG	0.45	98.75
SURF	0.79	99.00
Proposed	0.12	99.90

3.8 Recognition of the Road Sign

After the feature extraction, the feature vector passes through to the ANN for the recognition task. The ANN is very reliable and efficient for pattern recognition. The explanation of ANN design, initialization of parameters, training network, validation network, test image and implementation are as follows.

3.8.1 Artificial neural network design

An artificial neural network is implemented by using the Neural Network Pattern Recognition Tool in MATLAB. The standard network that is used for pattern recognition, is a two-layer feed-forward network with a sigmoid transfer function in the hidden layer, and a softmax transfer function in the output layer. For this system, the number of hidden neurons is set to 10, which is more efficient and more reliable for this proposed system. The number of output neurons is set to 10, which is equal to the number of elements in the target vector (the number of sign categories). For the training of the multiple layer ANN, a systematic method is applied with back-propagation-learning algorithm to the network. The main objective of the training is to adjust the weight so that the input produces desired output, and the neural network architecture is shown Figure 3.14.

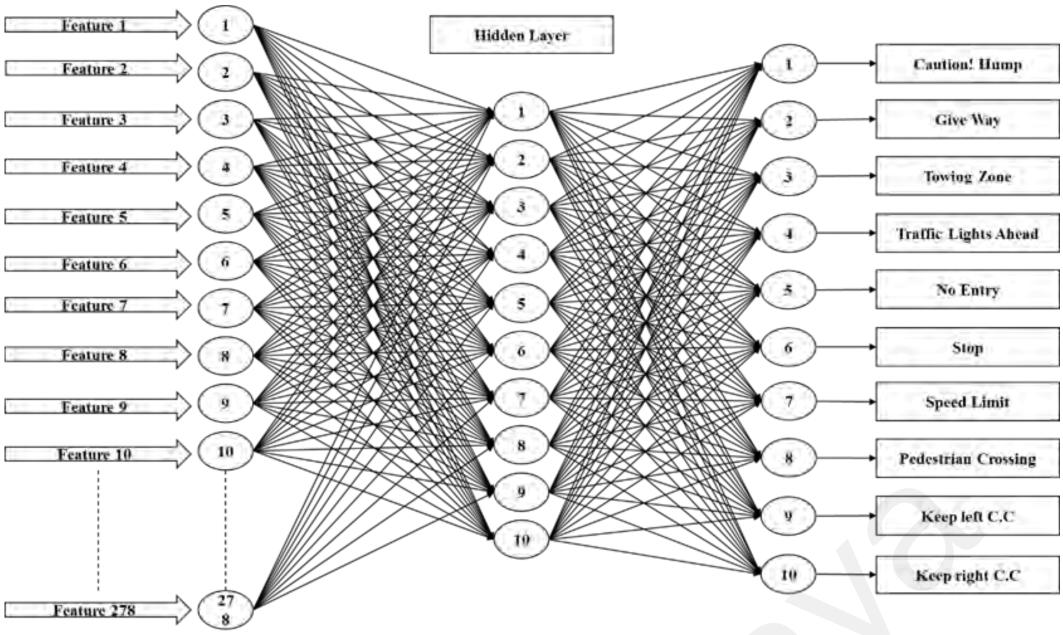


Figure 3.14: Neural Network Architecture

3.8.2 Train Data Set

The proposed system has used ten specific Malaysian road signs and 100 training samples for every class of road-traffic sign to train the neural network to identify those signs properly. Training images are collected by capturing from different roads and highways in Malaysia in a real-time environment from 8:00 a.m. to 6:00 p.m. These ten types of road signs were selected because of the different shapes, colors, and pictograms that were available for those road signs. If this proposed system can correctly classify all those signs, other signs can also be classified. From a total of 2000 samples, the neural network randomly selects 1400 training samples, 300 test and 300 validation samples by default. Examples of training sets, as well as test and validation sets of images, are shown in Figure 3.15.

Figure 3.15: Training Database

CHAPTER 4: EXPERIMENTS RESULTS AND DISCUSSION

4.1 Introduction

This Chapter explains experiments results and discussion with multiple experiments. This Chapter also explores the robustness of this proposed system. There are a number of steps that have to be taken into consideration for this experiment. An Intel Core-i5 2.50 GHz CPU computer with 4 GB of RAM is used to run this program to recognize road signs. The prototype is developed within the MATLAB environment. The image processing toolbox, computer vision toolbox, and neural network toolbox are used to implement this system.

A digital camera was mounted on the dashboard of a moving vehicle to capture video from a real-time environment. This video is segmented frame by frame with 1 s intervals, and it went through a hybrid color segmentation algorithm to identify the available or not road sign candidates. This hybrid color segmentation algorithm contains an RGB histogram equalization, RGB color segmentation, modified grayscale segmentation, binary image segmentation and shape matching algorithm. This hybrid color algorithm determines the exact position and properties of the target road sign. Then, according to that position and properties, the target road sign is extracted. At this point, there is no valuable information loss because the target road sign is extracted from the original image frame. This extracted image is converted into a grayscale image and normalized to 128-by-128 pixels. The normalized image is smoothened by a noise removal algorithm and it is converted into a binary image. This candidate image passes through the feature extraction process to extract the 278-feature vector. This feature vector is used to train the artificial neural network for recognition of the road sign.

4.2 ANN Training Performance

To get an effective response from the neural network, it is necessary to have a reasonable number of training samples. Training is performed with the neural pattern recognition application on MATLAB to solve the pattern recognition problem with a two-layer feed-forward network. The neural network pattern recognition application will help to select data, create, and train a network, and evaluate its performance using cross-entropy and confusion matrices. A two-layer feed-forward network, with sigmoid hidden and softmax output neurons, can classify vectors arbitrarily well, given enough neurons in its hidden layer. The network will be trained with scaled conjugate gradient back-propagation-learning method. For this proposed method, the training input matrix is 2000-by-278 is because of 2000 training samples and every training sample was extracted with 278 features. The output matrix format is a combination of the 2000-by-10 binary matrix as shown in Table 4.1. For the validation and test data, neural network randomly divides up the 2000 samples to, 70% of training data (1400 samples), 15% of validation data (300 samples), and 15% testing data (300 samples). Training data are presented to the network during training, and the network is adjusted according to its error. Validation data are used to measure network generalization, and to halt training when generalization stops improving. Testing data have no effect on training and so provide an independent measure of network performance during and after training. MATLAB coding for ANN training is given in Appendix A.

Table 4.1: Neural Networks Output Format

Rows	**Sign Class**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	1	0	0	0	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0	0
6	0	0	0	0	0	1	0	0	0	0
7	0	0	0	0	0	0	1	0	0	0
8	0	0	0	0	0	0	0	1	0	0
9	0	0	0	0	0	0	0	0	1	0
10	0	0	0	0	0	0	0	0	0	1

Figure 4.1 shows the neural network training performance. The initial stage of neural network training, the cross-entropy was maximum at epoch 1, then neural network optimizes the cross-entropy and gains the best validation performance at epoch 142 which is 7.9427e^{-07}. The neural network halts the training at this point because of generalization stops improving.

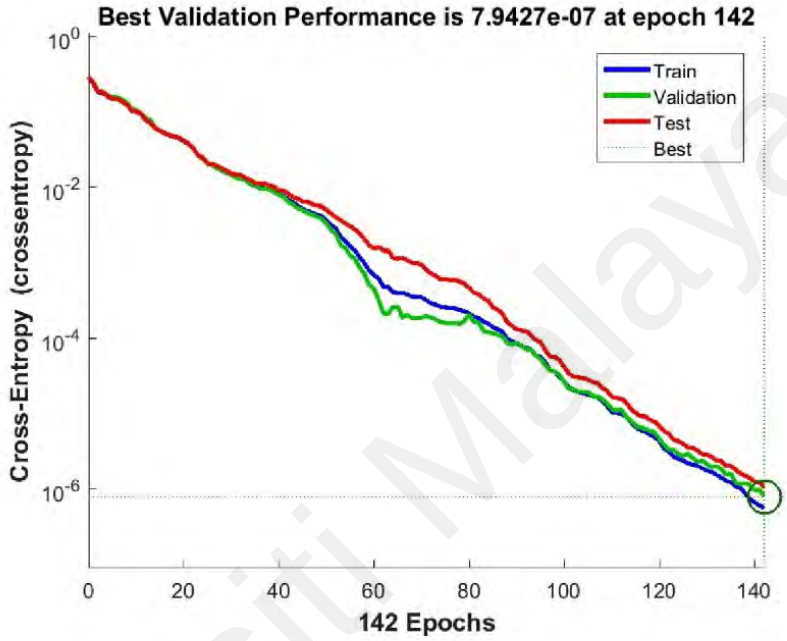


Figure 4.1: Neural Network's Performance

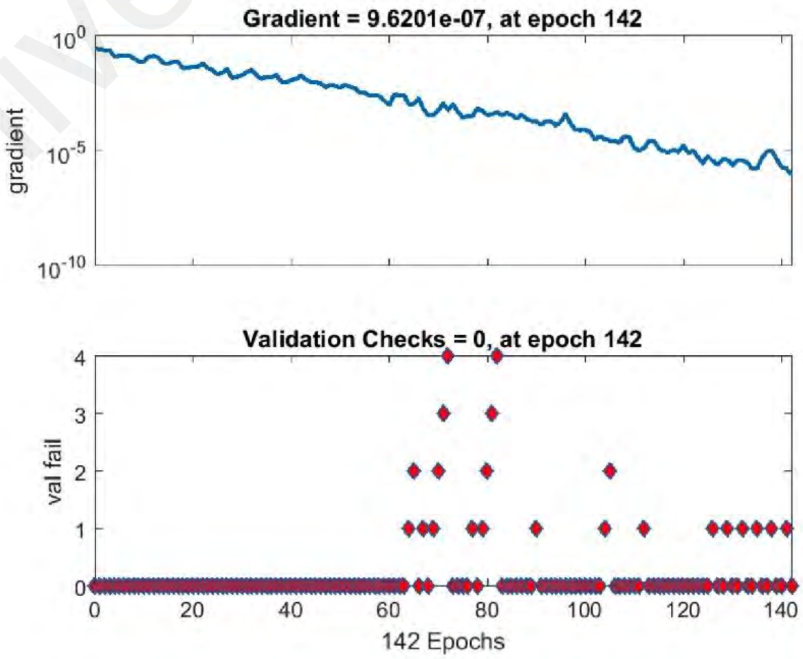


Figure 4.2: Training State

Figure 4.2 shows the network training state. At the epoch 142, gradient is 9.6201e^{-07} and at this point, the network halts the training because it's generalization stops improving.

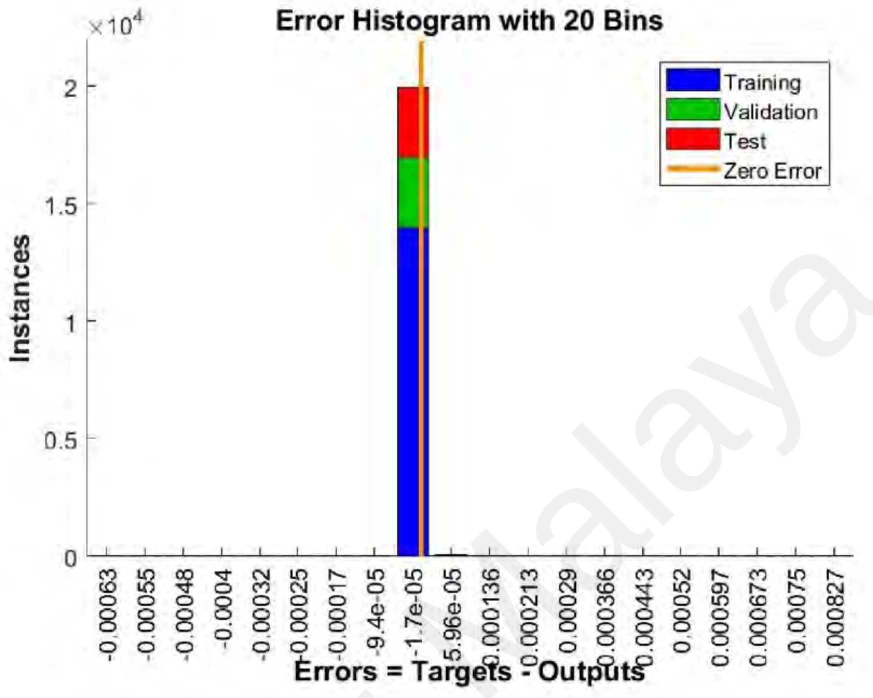


Figure 4.3: Error Histogram

Error histogram shows in Figure 4.3. It represents the training, validation, and testing performance error which are overlapped on the zero-error line. The error histogram plot represents that the error of this proposed system is very close to zero.

On the test confusion matrix plot (Figure 4.4), the rows of the predicted class (output class) correspond, and the columns show the true class (target class). The diagonal cells (green cells) show how many (and what percentage) of the examples the trained network correctly estimates the classes of the observations. That is, it shows what percentage of the true and predicted classes match. The off-diagonal cells show where the classifier made mistakes. The column on the right side of the plot shows the accuracy for each predicted class while the row at the bottom of the plot shows the accuracy for each true class. The cell at the bottom right (blue cell) of the plot shows the total accuracy. This confusion matrix plot shows the overall classification accuracy is 100% correct classification performance. The network gave the best classification performance for this proposed system at the training stage.

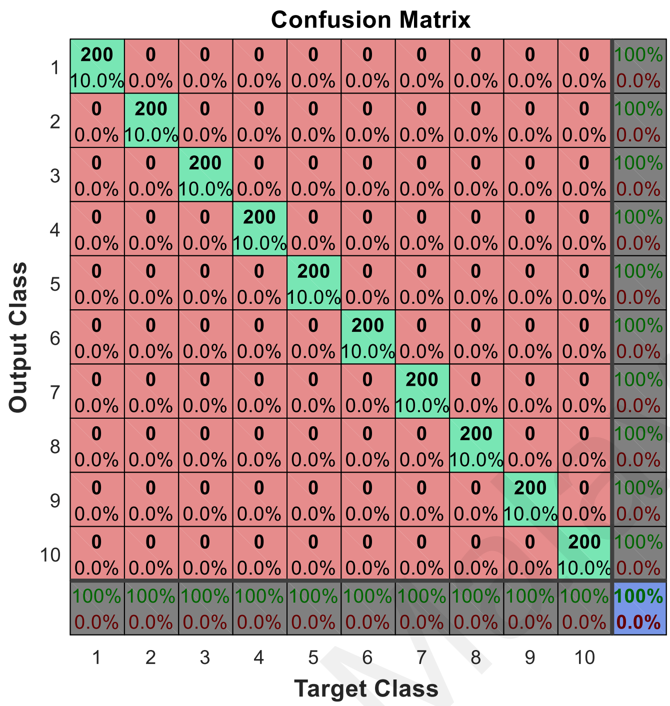


Figure 4.4: Overall Confusion Matrix

Neural network training performance with receiver operating characteristic (ROC) curves are shown in Figure 4.5. The ROC curve shows the graph illustrating the performance of the binary classification system since its discrimination threshold is varied. The curve is formed by plotting the true positive rate (TPR) against the false positive rate (FPR) at numerous threshold settings. From this ROC curve, the neural network is increasing the performance responding the number of iterations. At the iterations 10, the ROC curve shows that there are so many variations on the true positive rate and false positive rate. The perfect classification result is shown on the 142 iterations, it shows that every class is achieved the perfect classification accuracy. Iterations 142 is the optimal iterations for this proposed system where the neural network has given the maximum performance.

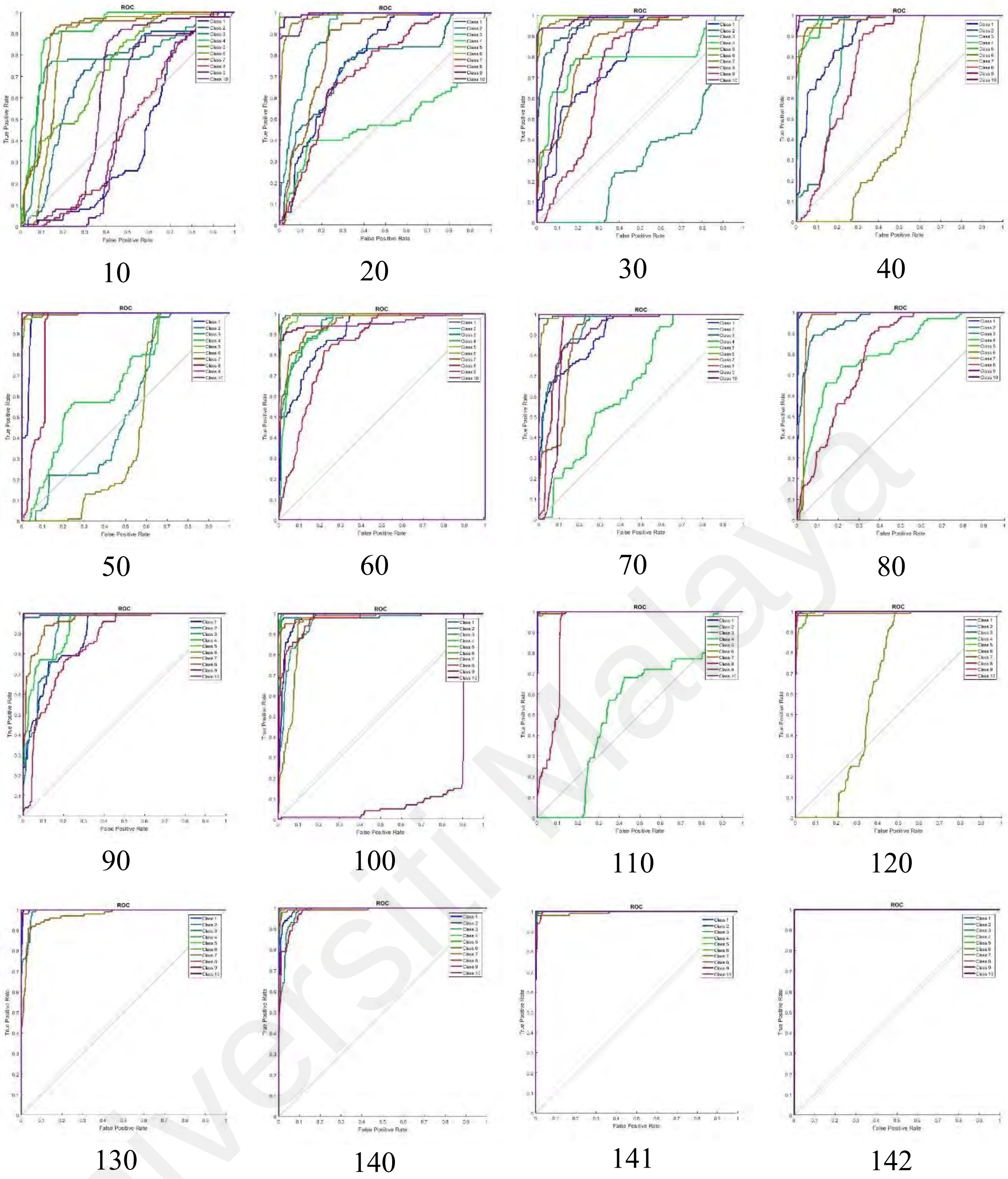


Figure 4.5: Network ROC Curve with 10-142 Iterations

4.3 Experiment with Malaysian Traffic Sign Database

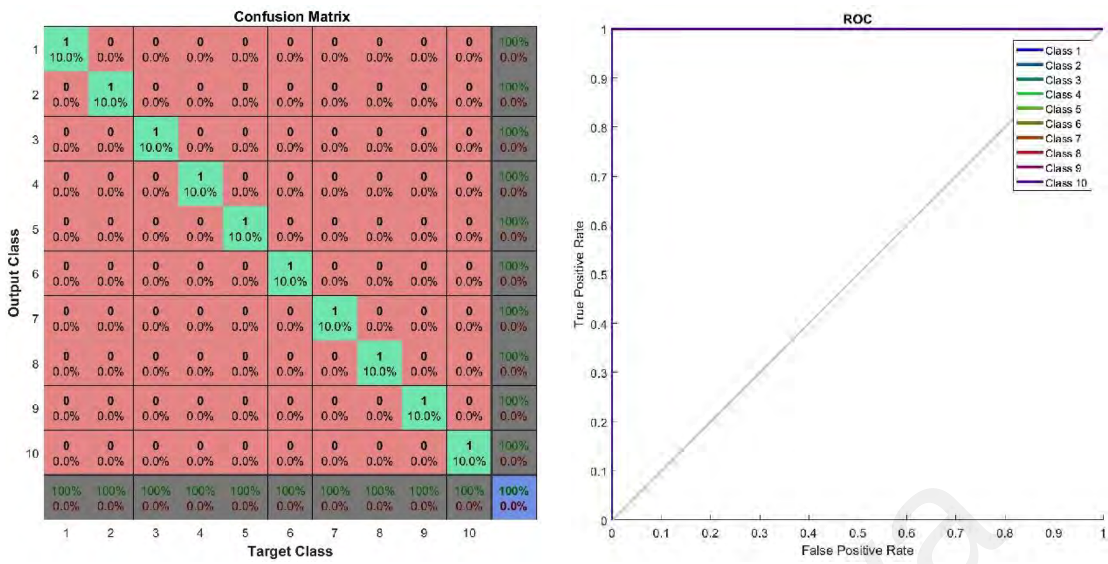
Traffic signs are displayed on the roadside as an indication to instruct a driver to obey a traffic regulation. Some traffic signs are used to indicate a possible danger. There are two different sets of traffic signs in Malaysia: ideogram-based and text-based characters. Ideogram-based traffic signs use simple ideograms to express the meaning, while the text-based traffic-tracing expresses text with other symbols such as arrows.

Figure 4.6: Malaysian Traffic Signs Dataset Example

The Malaysian Traffic Sign Database (Lau et al., 2015; Lim et al., 2012) consists of 100 classes of traffic sign used in Malaysia. Some examples have been shown in Figure 4.6. From this database, ten classes of traffic sign are extracted as proposed for this system are shown in Figure 4.7.

Figure 4.7: Ten Class of Traffic Sign Acquired from the Malaysian Traffic Sign Database

In Figure 4.8 experimental result with Malaysian Traffic Sign Database shows that all ten classes of road signs are correctly classified and there are no misclassifications. Because the database contains only standard signs and in this proposed system standard signs are present in training stage. The ROC curve shows all classes of road signs achieved the maximum area under curve (AUC) and it shows a maximum perfect result for the Malaysian Traffic Sign Database.

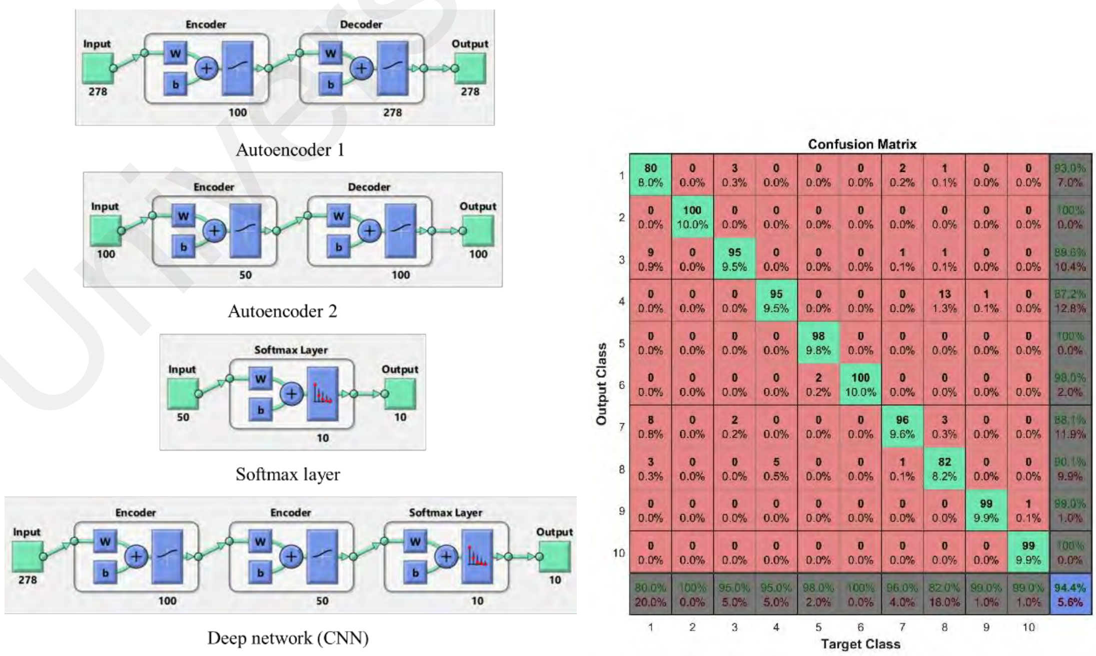


Confusion Matrix ROC curve

Figure 4.8: Test Results with Malaysian Database

4.4 Experiment with Convolution Neural Network (CNN)

The proposed method has been tested with a CNN which has two hidden layers to classify traffic signs. Firstly, the hidden layers have been trained individually in an unsupervised fashion using autoencoders.



(a) **(b)**

Figure 4.9: Experiment with CNN, (A) CNN Architecture and (B) CNN Confusion Matrix

Then a final softmax layer has been trained, and joined with the two hidden layers to form a deep network, which is trained one final time in a supervised fashion. A total of 1000 real-time traffic sign samples are used to get the experimental results with CNN. Figure 4.9(a) shows the architecture of CNN and Figure 4.9(b) shows the CNN confusion matrix. The number in the bottom right-hand square of the confusion matrix gives the overall accuracy, which is 94.40%.

4.5 Experiment with Real-Time

Real-time test images are collected by acquiring targeted frames from a video sequence which is recorded from a real-time environment instantly. For this real-time experiment, ten classes of sign are selected. Every class of the sign contains 100 sample frames which are extracted from the video sequence, and in total 1000 sample frames are used to get real-time experimental results. These selected frames are then passed through the detection process, and the output image is a 128-by-128 binary image. This binary image is converted into a 128-by-128 binary matrix for the feature extraction process, and a 278-feature vector is extracted from each binary image. This feature vector is the input of the ANN to recognize which class of road sign it is. Figure 4.10 shows real-time input signs.

Figure 4.10: Real-Time Input Images

Figure 4.11 shows real-time experimental results of “Stop” sign, “Towing zone” sign, “Yield” sign and “No entry” sign. The first column represents the input frames, the second column is the detected signs, the third column is the recognized signs and the fourth column represents the corresponding output frames.

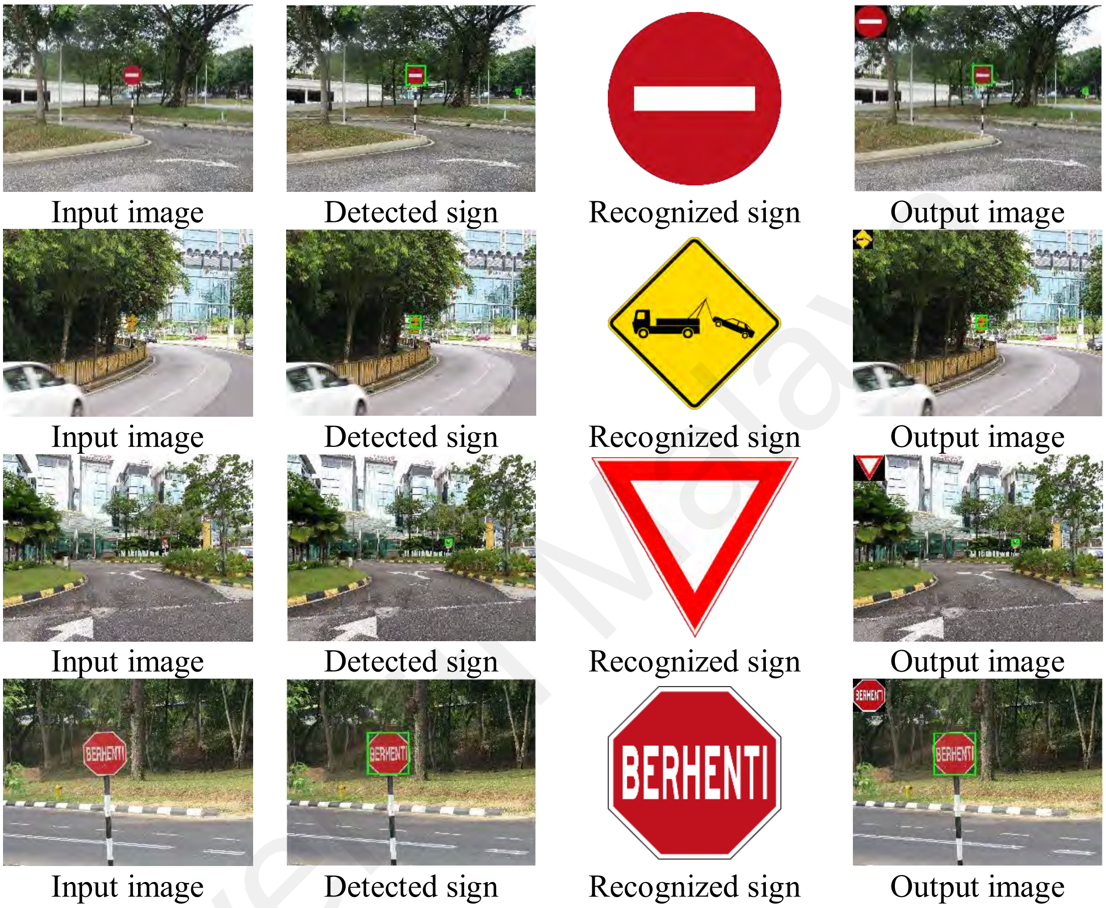
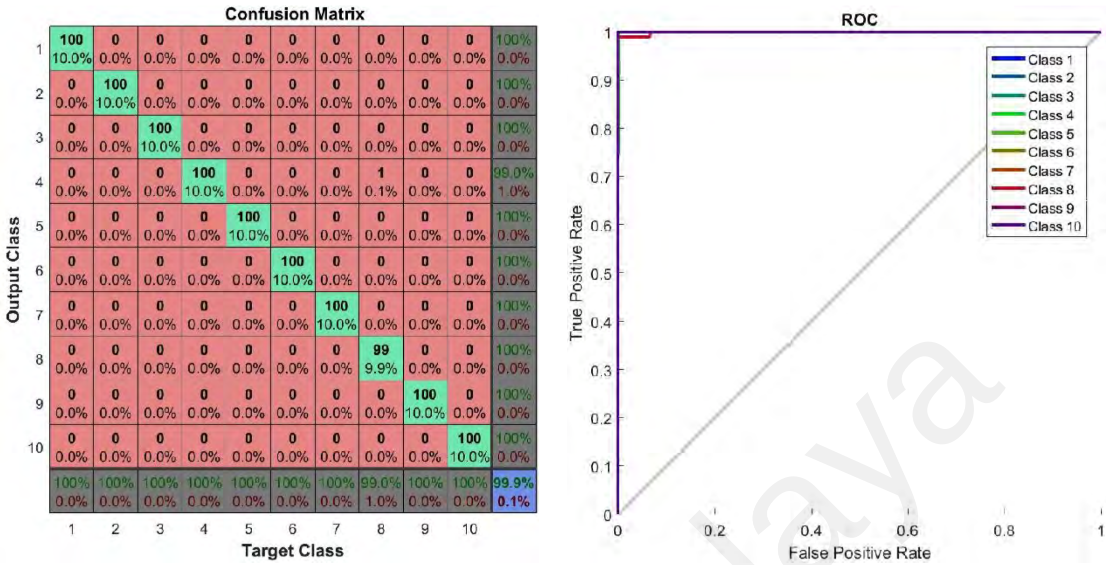


Figure 4.11: Some Experimental Input Frames and the Corresponding Output Frames

The real-time experiment confusion matrix and ROC curve are shown in Figure 4.12. In this confusion matrix, the high numbers of correct responses are shown in the green squares. The low numbers of incorrect responses are shown in the red squares. The lower right blue square illustrates the overall accuracy. A class 8 sign, “Pedestrian Crossing”, was misclassified with a sign class 4, a “Traffic Lights Ahead” sign. The remaining other sign classes are correctly classified. The ROC curve shows that all classes of sign achieved the maximum AUC except class 8. A single misclassification of class 8 occurred due to the numerous (more than 15) non-standard “Pedestrian Crossing” sign formats that exist on actual Malaysian roadsides.



Confusion Matrix ROC curve

Figure 4.12: Real-Time Experiment Result

From the confusion matrix of the real-time experiment data, the evaluation parameters are precision, sensitivity, specificity, F-measure, false positive rate (*FPR*), and accuracy rate (*AR*) which are based on the number of true positive (*TP*), false positive (*FP*), true negative (*TN*), and false negative (*FN*) values as indicated in Table 4.2.

Table 4.2: Evaluation Parameters

Evaluation Parameters	**Mathematical Equation**	**Result**
Precision or Positive Predictive Value PPV	$PPV = \frac{TP}{TP + FP}$	0.999
Sensitivity or Recall or True Positive Rate TPR	$TPR = \frac{TP}{TP + FN}$	0.999
Specificity or True Negative Ratio TNR	$TNR = \frac{TN}{TN + FP}$	0.999
F-measure	$\frac{2 * TP}{2 * TP + FP + FN}$	0.999
False Positive Rate FPR	$\frac{FP}{FP + TN}$	0.001
False Negative Rate FPR	$\frac{FN}{FP + TN}$	0.001
Accuracy	$\frac{TP + TN}{TP + FN + FP + TN}$	0.999

True positive (*TP*) and true negative (*TN*) are defined as the traffic signs that are correctly recognized as the correct class and when other classes of traffic signs are correctly recognized as other class of traffic signs. False positive (*FP*) is defined as the traffic sign that is not recognized correctly. For the *false negative (FN)*, a class of traffic sign is incorrectly recognized as another class of traffic sign.

In Table 4.3, a comparison between the proposed method and other existing methods based on the evaluation parameters is shown. This comparison is based on the precision, Recall, Specificity, F-measure, False positive rate, overall accuracy and finally the processing time.

Table 4.3: Comparison Between Proposed Method and Others Existing Method

Reference	Precision (%)	Recall (%)	Specificity (%)	F-measure (%)	False positive rate	Overall accuracy (%)	Processing time(s)
(Maldonado-Bascon et al., 2007)	41.03	34.15	-	-	0.26	93.60	-
(Garc et al., 2011)	96.51	92.97	-	-	0.13	90.27	0.35
(Greenhalgh & Mirmehdi, 2012)	88.75	81.35	-	-	0.85	97.60	-
(Bui-Minh et al., 2012)	-	-	-	-	1.2	86.70	-
(Wali et al., 2015)	98.21	89.43	-	-	0.009	95.71	0.43
(C.-C. Lin & Wang, 2012)	-	-	-	-	-	92.47	-
(S. Yin, 2015)	-	-	-	-	0.030	98.63	0.36
(Virupakshappa et al., 2015)	-	-	-	-	-	95.20	-
Proposed method	**99.90**	**99.90**	**99.90**	**99.90**	**0.001**	**99.90**	**0.33**

According to the precision percentages, the closest precision percentage was given by Wali *et al.* (Wali et al., 2015) is 98.21% and distant was given by Maldonado-Bascon *et al.* (Maldonado-Bascon et al., 2007) is 41.03%. In this comparison, other researchers do not specify the Specificity percentages and as well as F-measure percentages. Based on the overall accuracy percentages the closest overall accuracy percentage was given by Greenhalgh *et al.* (Greenhalgh & Mirmehdi, 2012) is 97.60% and distant was given by

Bui-Minh *et al.* (Bui-Minh et al., 2012) is 86.70%. In terms of the processing time, 0.35 second processing time was given by (Garc et al., 2011) and 0.43 second processing time was given by Wali *et al.* (Wali et al., 2015) where 0.33 second processing time for this research.

The evaluated proposed system performance based on NN presents in Table 4.4. IDSIA (Cireşan et al., 2012) team used Committee of CNNs method to achieve a 99.46% of correct recognition rate, and this proposed system achieved a 99.90% correct recognition rate. They used different classifier as CNN and different feature extraction method then proposed method has been noticed. A novel neural network based speed limit road sign recognition method which was based on digit recognition was recently investigated by (Hanene Rouabeh, 2016) and achieved 93.45% of correct recognition accuracy.

Table 4.4: Evaluate the System Performance Based on NN

Reference	**Classifier**	**Correct recognition rate**
(Cireşan et al., 2012)	CNN	99.46 %
(Sermanet & LeCun, 2011)	CNN	98.31 %
(Rahman et al., 2008)	ANN	91.48%
(Lau et al., 2015)	CNN	99.00%
(Hanene Rouabeh, 2016)	ANN	93.45%
(Miah, 2015)	ANN	91.50%
(Sanjit Kumar Saha, 2012)	ANN	98.00%
(S. Yin, 2015)	ANN	98.62%
(Luo et al., 2017)	CNN	99.02%
Proposed method	**ANN**	**99.90 %**

4.5.1 Classification algorithm performance

For the classification algorithm performance, the proposed input vector set is applied as an input vector set to the 23 different classification algorithms which are shown in Table 4.5.

Table 4.5: Classification Algorithms Performance

Model Number	**Name of Classifier**	**Accuracy**
1.1	Complex Tree	84.0%
1.2	Medium Tree	84.0%
1.3	Simple Tree	80.0%
1.4	Linear Discriminant	80.5%
1.5	Quadratic Discriminant	87.0%
1.6	Linear SVM	92.0%
1.7	Quadratic SVM	92.0%
1.8	Cubic SVM	92.0%
1.9	Fine Gaussian SVM	82.5%
1.10	Medium Gaussian SVM	92.5%
1.11	Coarse Gaussian SVM	83.0%
1.12	**Fine KNN**	**95.0%**
1.13	Medium KNN	83.0%
1.14	Coarse KNN	52.0%
1.15	Cosine KNN	85.0%
1.16	Cubic KNN	80.5%
1.17	Weighted KNN	89.0%
1.18	**Boosted Trees**	**25.0%**
1.19	Bagged Trees	93.5%
1.20	Subspace Discriminant	93.0%
1.21	Subspace KNN	94.0%
1.22	**RUSBoosted Trees**	**25.0%**
1.23	**ANN**	**99.90%**

In these 23 classification algorithms, model number 1.23, which is the proposed classifier for this system, gives the best accuracy with 99.90%. Model 1.12 gives the nearest accuracy of 95.0% which is given by a Fine KNN classifier. Model 1.18 and model 1.22 which give the worst accuracy of 25%, are produced by the Boosted Trees and RUSBoosted Trees classifiers, respectively. Figure 4.13 shows the classification algorithms performance in terms of accuracy and error percentages.

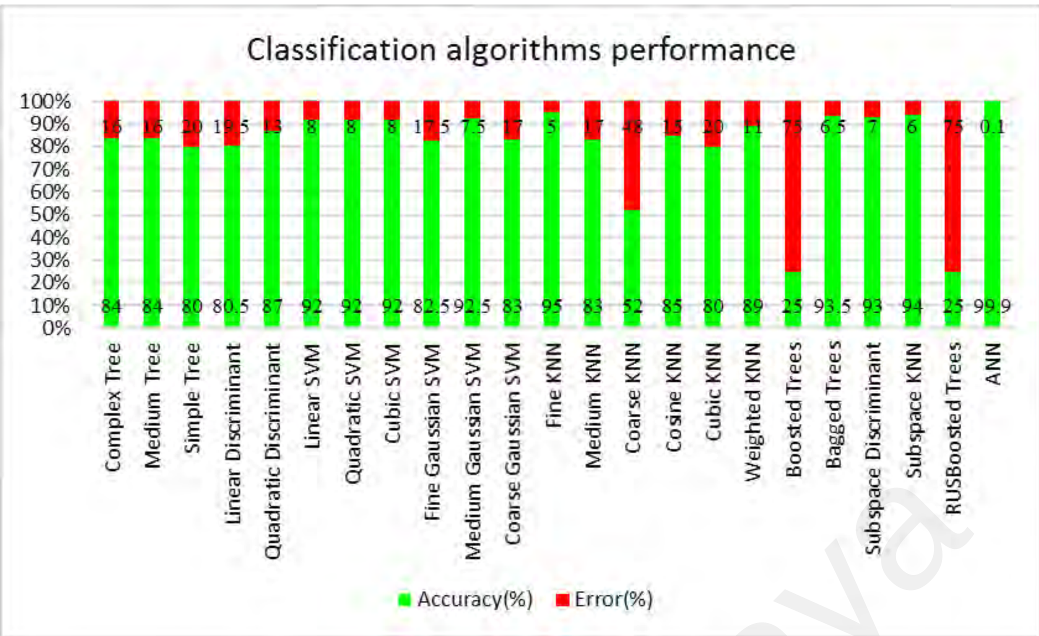


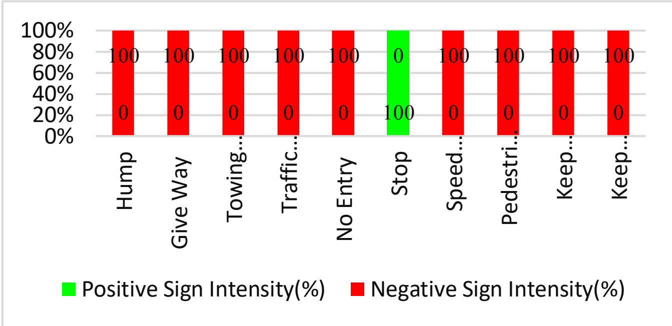
Figure 4.13: Classification Algorithms Performance

4.5.2 Robustness testing

Robustness test is a test method that is used to detect a component's vulnerabilities under unexpected inputs or in a stressful environment. Robustness tests were also used to describe the process of testing the robustness of test cases in a test process. For this proposed system, some of the robustness testing were carried out with natural images and some are synthetic images. Proposed algorithm will consider the highest positive sign intensity value of sign class for recognition of road sign.

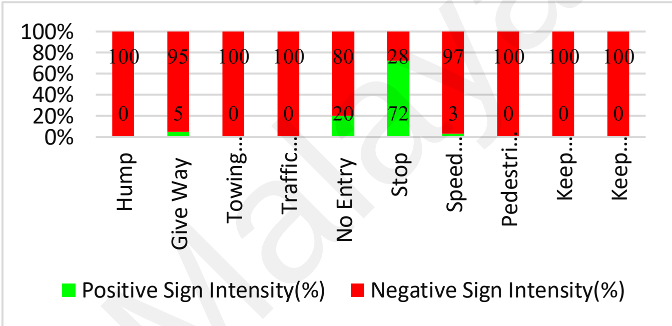
4.5.2.1 Robustness testing based on disorientation angles

A robustness testing based on the disorientation angles showing in the Figure 4.14. For carried out this test, some sign was disoriented by manually because of unavailability of desired disoriented angle. The test result shown that when a traffic sign (Stop) has no disorientation angle then the positive sign intensity is 100% (first picture). For positive 300 disoriented sign, the test results have shown that it has 72% of positive sign intensity. Similarly, when the traffic sign is disoriented by negative 450 the test result shown that it has 95% of positive sign intensity. When a traffic sign angle disoriented by 180° the test result shown that it has also 100% positive sign intensity.



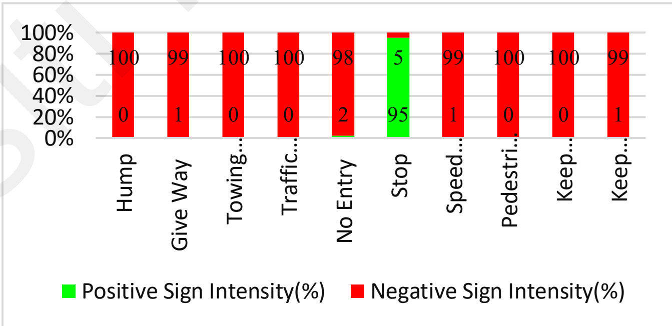
Stop (0 Degree)

Stop 100%



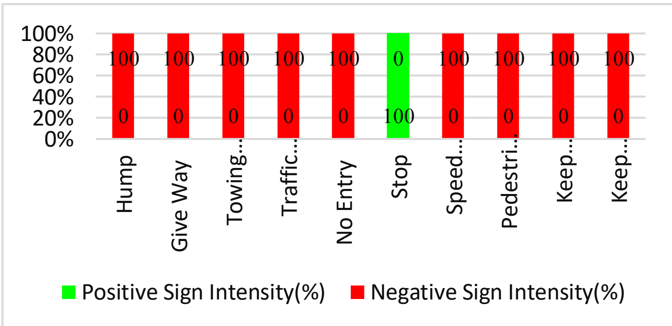
Stop (+30 Degree)

Stop 72%



Stop (-44 Degree)

Stop 95%



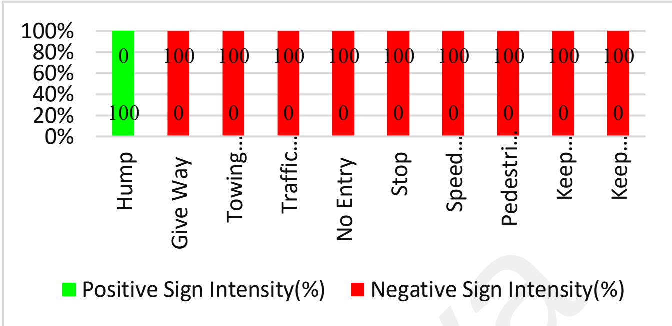
Stop (180 Degree)

Stop 100%

Figure 4.14: Robustness Testing Based on Disorientation Angles

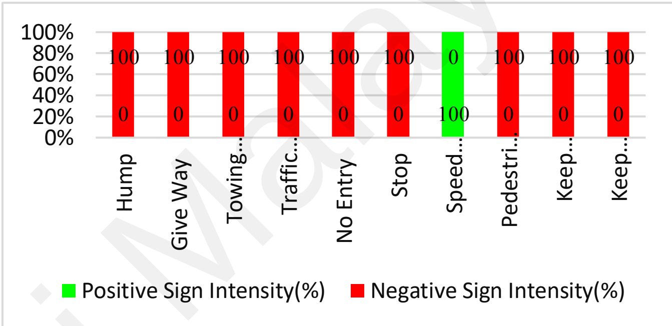
4.5.2.2 Robustness testing based on faded sign

A robustness testing based on the faded sign showing in the Figure 4.15. Test result has shown 100% sign intensity even all signs are faded and non-standard.



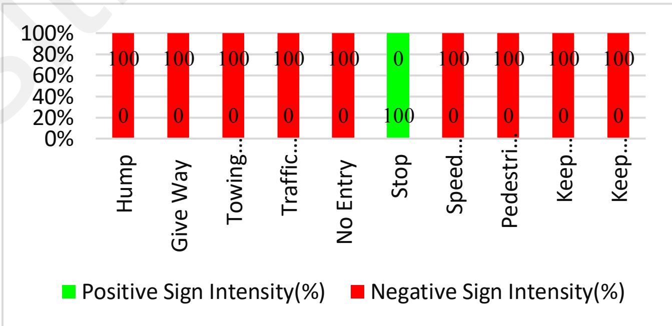
Hump

Hump 100%



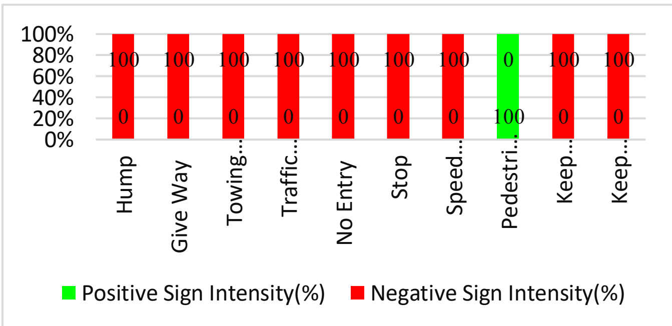
Speed limit

Speed limit 100%



Stop

Stop 100%



Pedestrian crossing

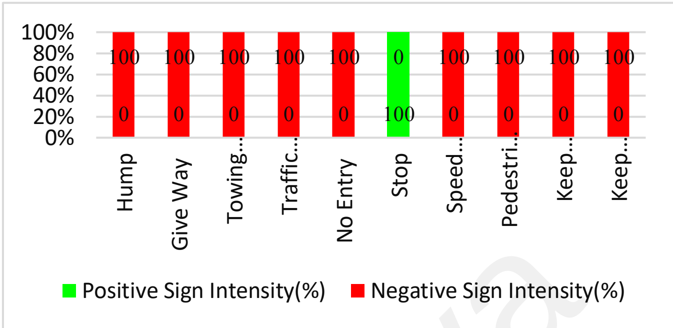
Pedestrian crossing 100%

Figure 4.15: Robustness Testing Based on Faded Sign

4.5.2.3 Robustness testing based on different countries sign

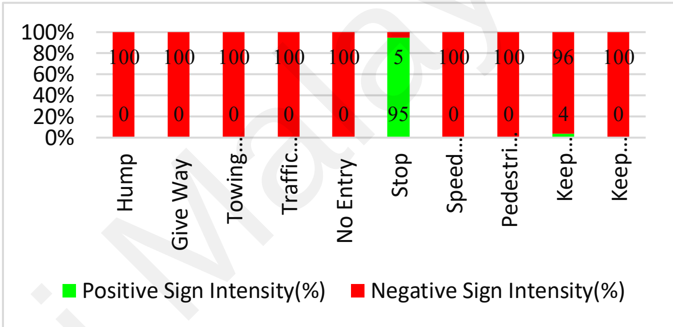
A total 16 different countries stop sign database is created for robustness testing based in different countries sign showing in Figure 4.16 to Figure 4.19.

Stop (AU, CA, USA)



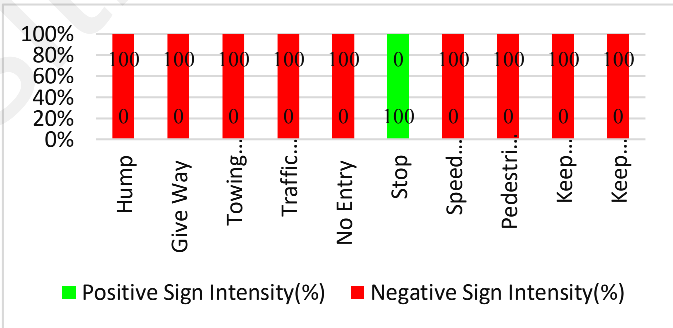
Stop 100%

Stop (Bhutan)



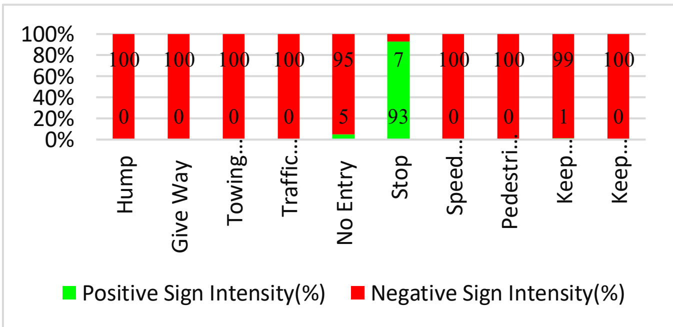
Stop 95%

Stop (Brazil)



Stop 100%

Stop (Brunei)

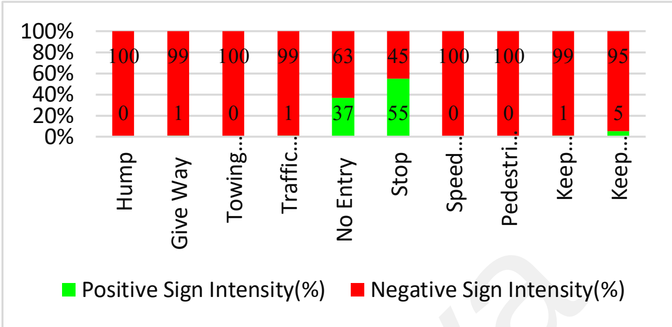


Stop 93%

Figure 4.16: Robustness Testing, Based on Four Different Countries Stop Sign (Test 1)

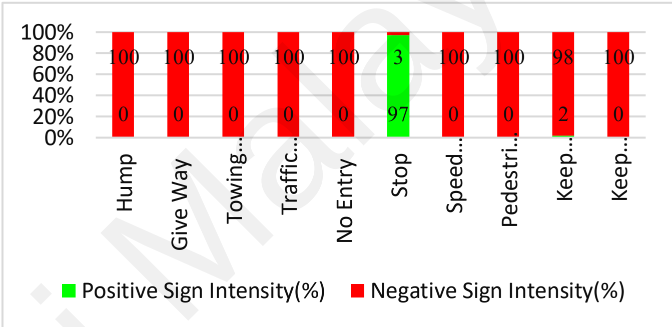
There are four set of tests covering all 16 countries stop sign test, test (1) have 4 countries stop sign, test (2) have 4 countries stop sign, test (3) have 4 countries stop sign, and test (4) have 4 countries stop sign.

Stop (Cambodia)



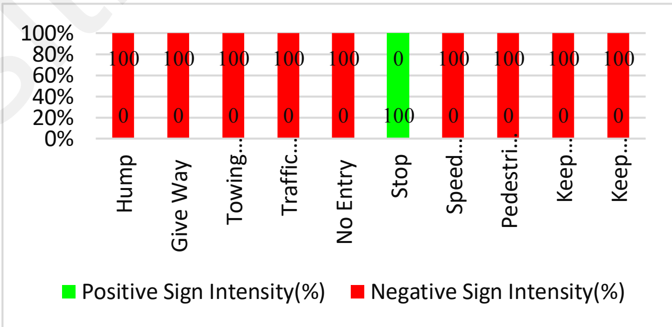
Stop 55%

Stop (Iran)



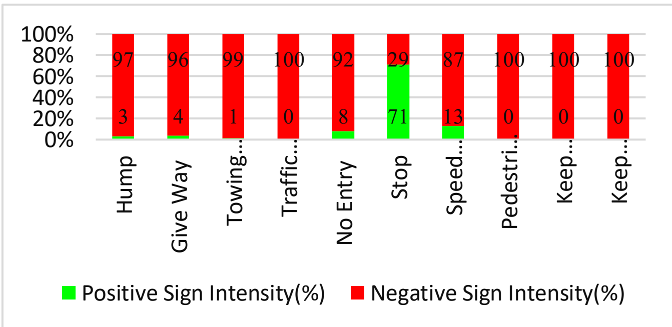
Stop 97%

Stop (Ireland)



Stop 100%

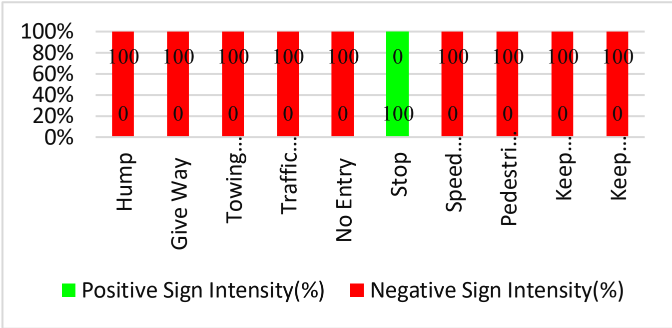
Stop (Laos)



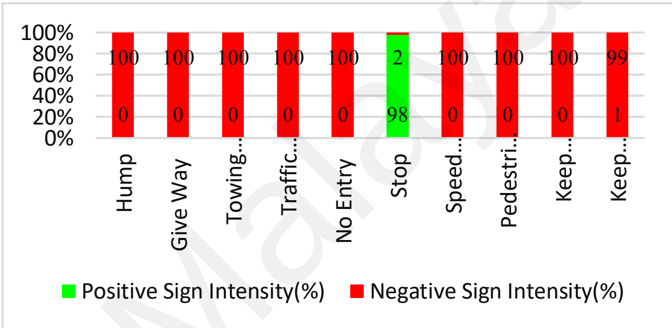
Stop 71%

Figure 4.17: Robustness Testing, Based on Four Different Countries Stop Sign (Test 2)

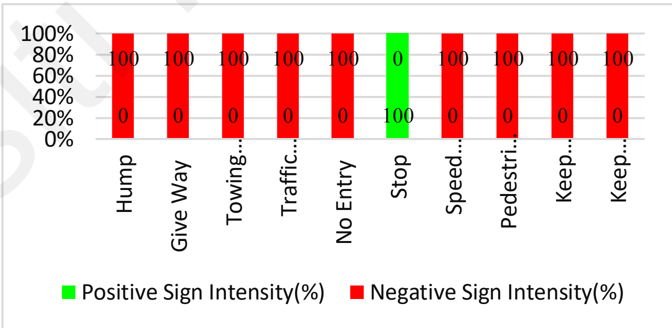
Australia, Canada, and the USA are using same stop sign and this algorithm is given 100% of sign intensity for stop sign which belongs to that countries.



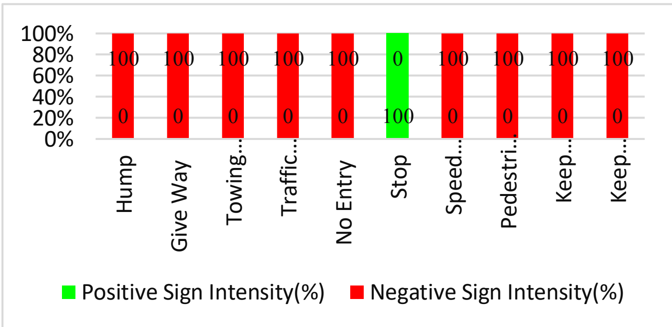
Stop (Mexico) Stop 100%



Stop (Mongolia) Stop 98%



Stop (Singapore) Stop 100%

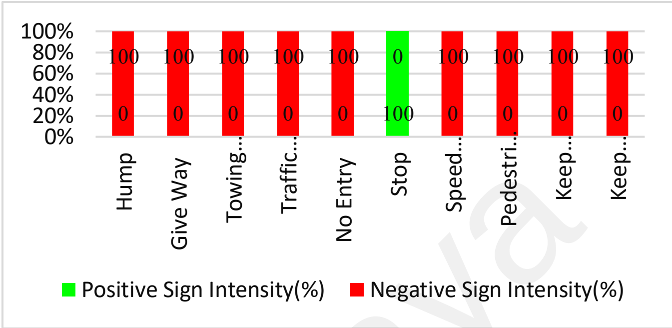


Stop (Thailand) Stop 100%

Figure 4.18: Robustness Testing, Based on Four Different Countries Stop Sign (Test 3)

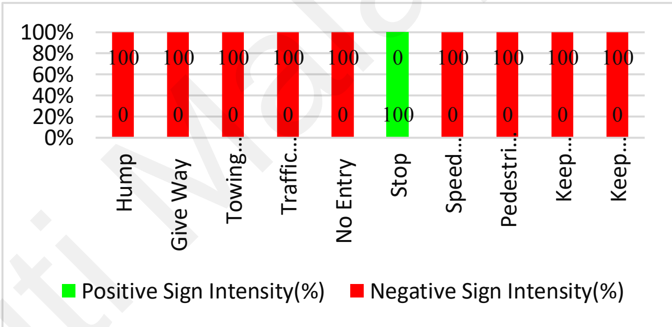
Following countries sign intensity is, Bhutan 95%, Brazil 100%, Brunei 93%, Cambodia 55%, Iran 97%, Ireland 100%, Laos 71%, Mexico 100%, Mongolia 98%, Singapore 100%, Thailand 100%, Turkey 100%, and Vanuatu 100%, Taiwan 93%, Malaysia 100%.

Stop (Turkey)



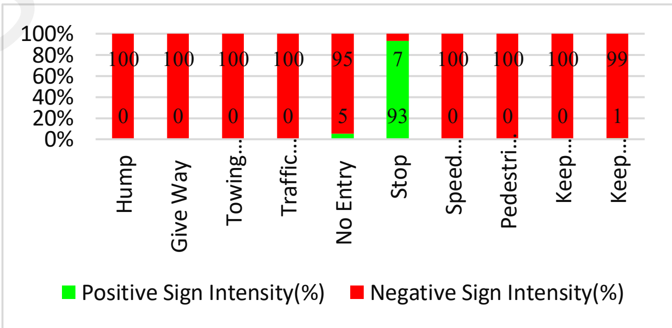
Stop 100%

Stop (Vanuatu)



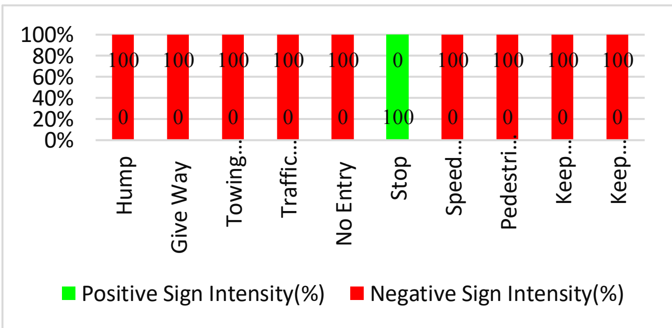
Stop 100%

Stop (Taiwan)



Stop 93%

Stop (Malaysia)

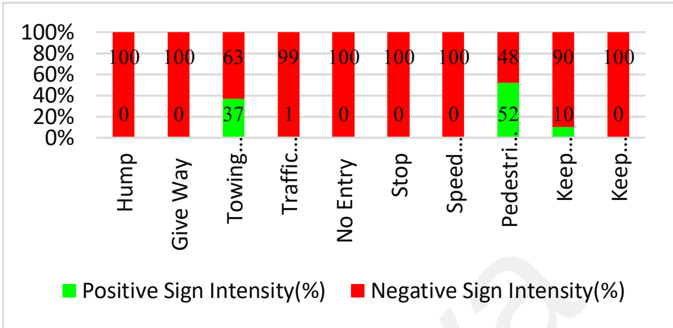


Stop 100%

Figure 4.19: Robustness Testing, Based on Four Different Countries Stop Sign (Test 4)

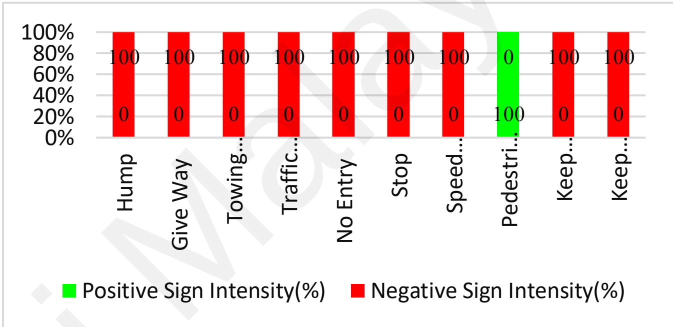
4.5.2.4 Robustness testing based on natural blocked sign

A robustness testing based on naturally blocked sign shown in the Figure 4.20. Pedestrian crossing sign taking place for naturally blocked sign test.



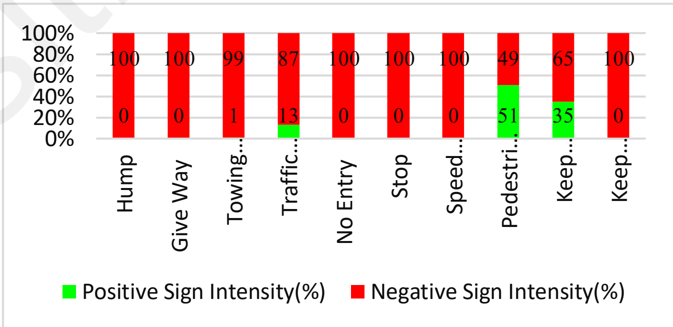
Pedestrian crossing

Pedestrian crossing 52%



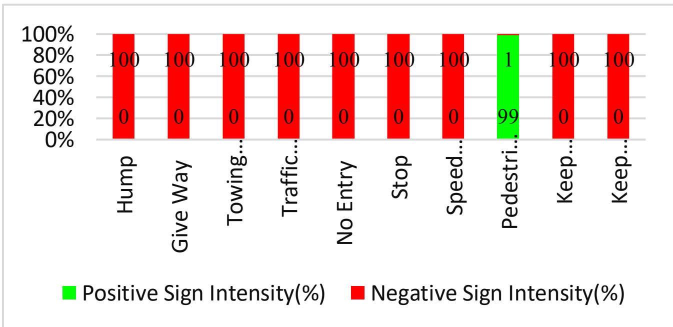
Pedestrian crossing

Pedestrian crossing 100%



Pedestrian crossing

Pedestrian crossing 51%



Pedestrian crossing

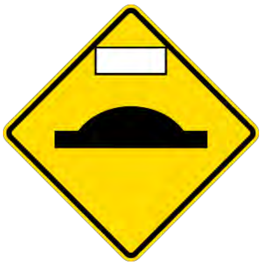
Pedestrian crossing 99%

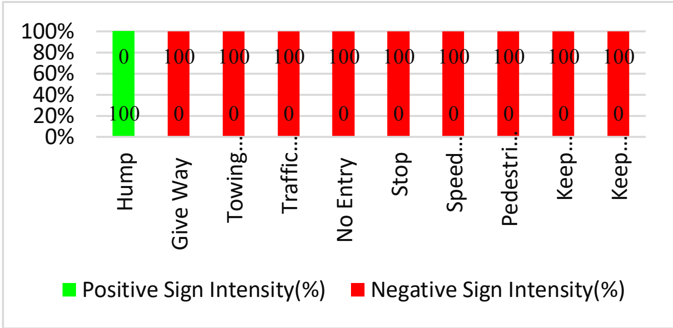
Figure 4.20: Robustness Testing Based on Natural Blocked Sign

From top to bottom, a Pedestrian Crossing sign mostly blocked by trees and the first sign intensity is 52%, the second one is partially blocked and the sign intensity is 100%, the third one is also partially blocked by trees and the sign intensity is 51%, and lastly a pedestrian sign is blocked by trees with similar colored and the sign intensity is 99%.

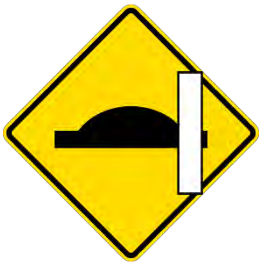
4.5.2.5 Robustness testing based on artificial blocked sign

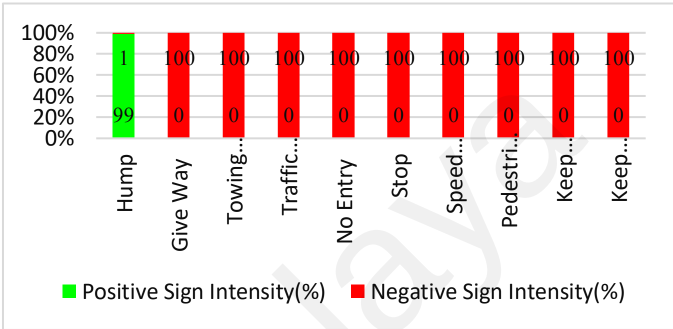
The issues of stickers and banners motivated this artificially blocked sign test as advertising organizations or individual sticks the advertising poster on the traffic sign often. A robustness testing based on artificially blocked sign shown in the Figure 4.21. Artificial blocked sign created in the lab manually for robustness testing. Hump sign taking place for artificially blocked sign test. From top to bottom, a hump sign top part blocked by a sticker and the sign intensity is 100%, second one's right part is partially blocked and the sign intensity is 99%, third one's bottom part is also partially blocked by sticker and the sign intensity is 100%, and lastly a hump sign's left part is blocked by sticker and the sign intensity is 100%.



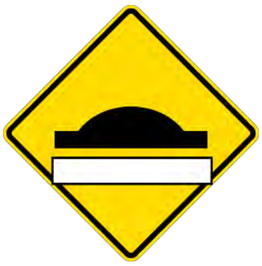


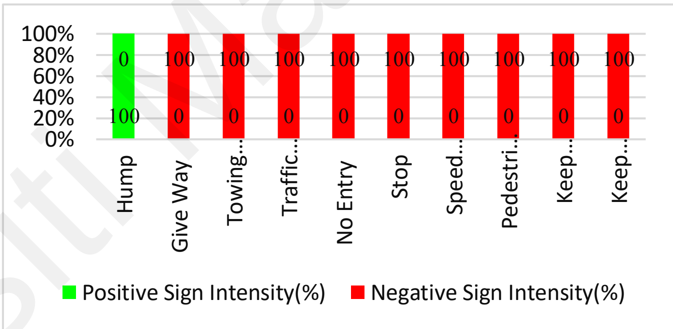
Hump | Hump 100%



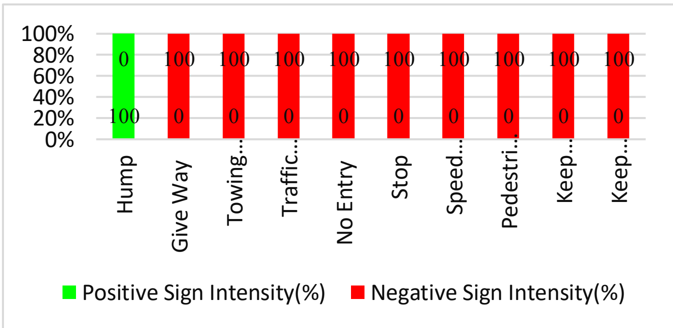


Hump | Hump 99%





Hump | Hump 100%



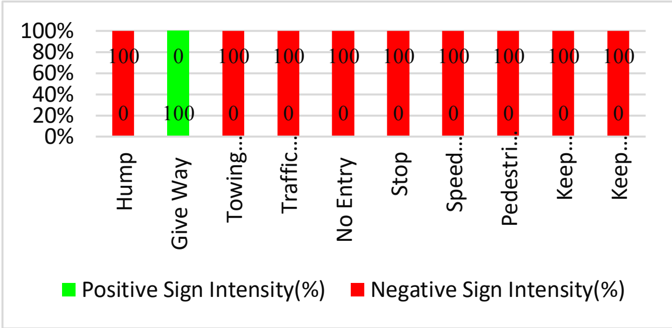
Hump | Hump 100%

Figure 4.21: Robustness Testing Based on Artificial Blocked Sign

4.5.2.6 Robustness testing based on motion blur and speed

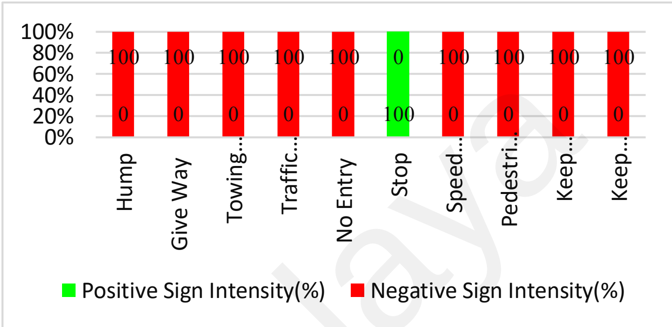
A robustness testing based on motion blur is shown in the Figure 4.22. A motion blurred occurred when the camera is out of focus and sometimes it causes for the speed.

Give Way



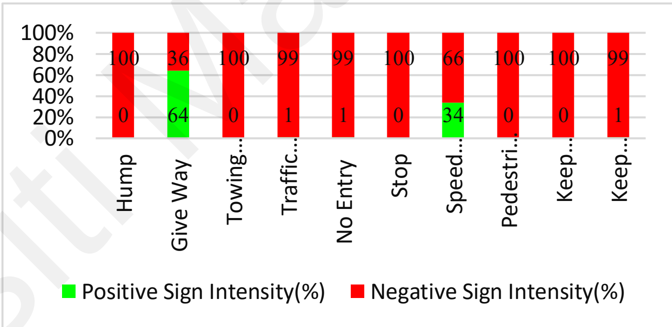
Give Way 100%

Stop



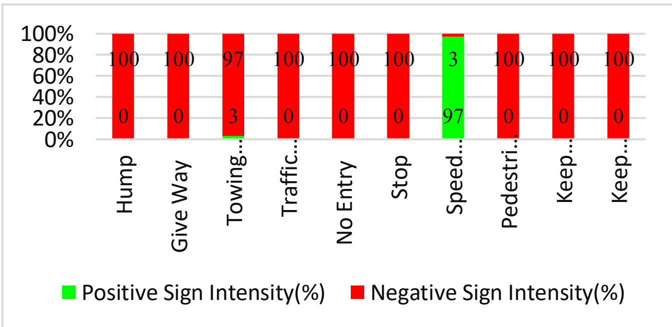
Stop 100%

Give Way



Give Way 64%

Speed limit



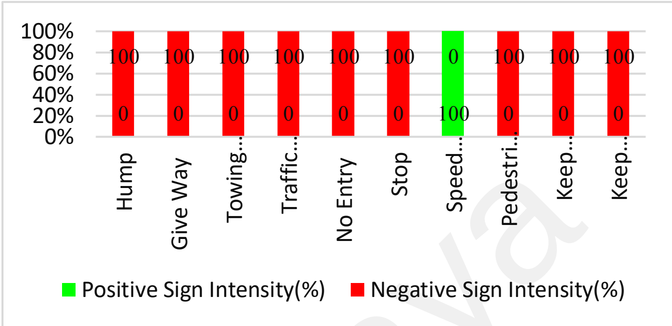
Speed limit 97%

Figure 4.22: Robustness Testing Based on Motion Blur

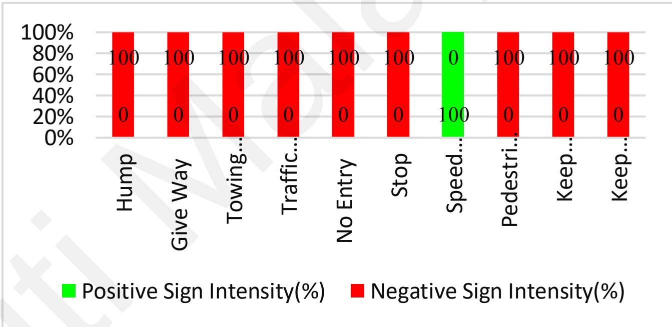
For the motion blur sign from top to bottom, a give way sign intensity is 100%, stop sign intensity is 100%, another give way sign which is blurred and upside down and the sign intensity is 65%, and a speed limit sign intensity is 97%.

4.5.2.7 Robustness testing based on speed

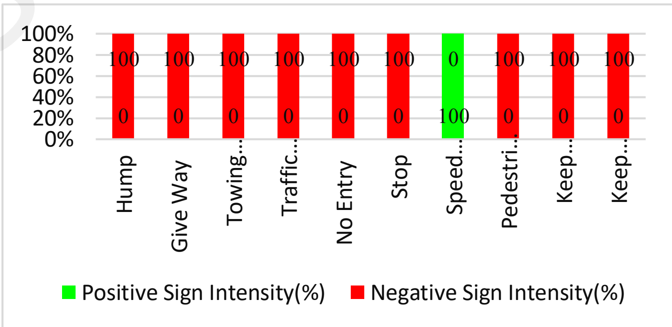
A robustness testing based on speed shown in Figure 4.23. From top to bottom, when the vehicle is approaching with, 60 km/h the sign intensity is 100% and 69% in rainy environment, 50 km/h the sign intensity is 100%, and 35 km/h the sign intensity is 100%.



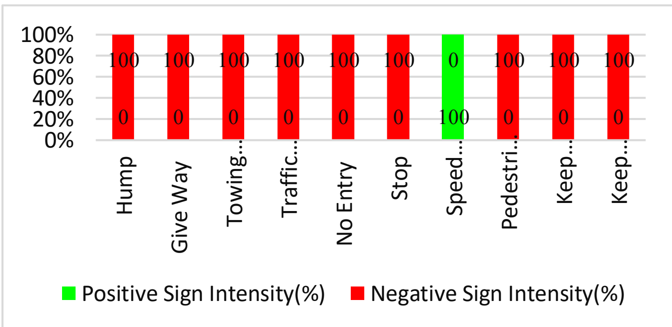
Speed limit (60 km/h) Speed limit 100%



Speed limit (60 km/h Rainy) Speed limit 69%



Speed limit (50 km/h) Speed limit 100%

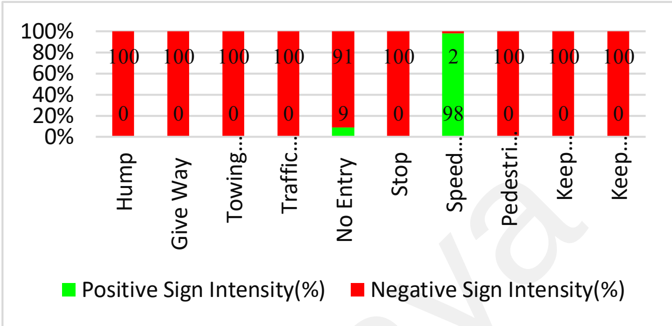


Speed limit (35 km/h) Speed limit 100%

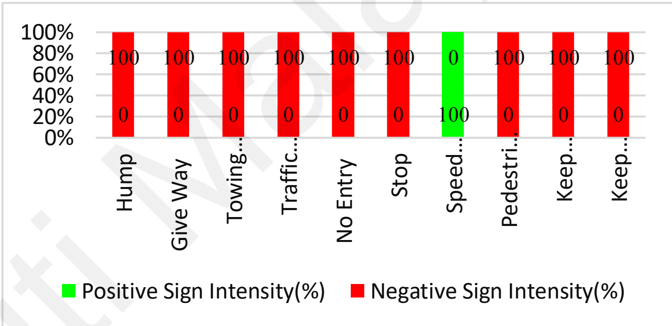
Figure 4.23: Robustness Testing Based on Speed

4.5.2.8 Robustness testing based on capturing distance

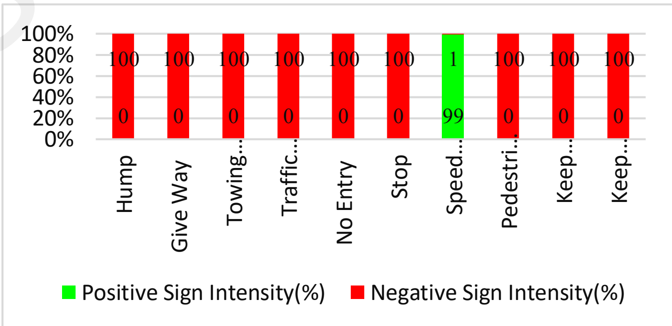
A robustness testing based on capturing distance from vehicle and sign shown in the Figure 4.24. It shown the algorithm performance based on the different capturing distance.



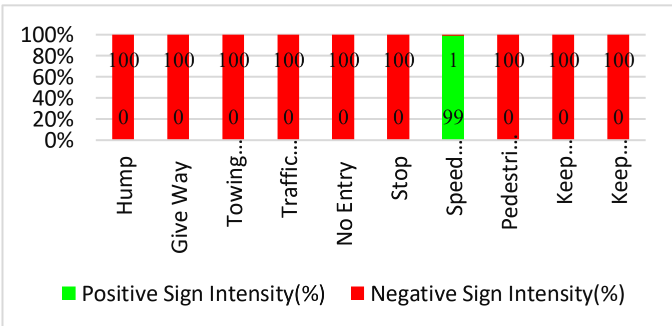
Speed limit (90 m) Speed limit 98%



Speed limit (80 m) Speed limit 98%



Speed limit (70 m) Speed limit 99%



Speed limit (60 m) Speed limit 99%

Figure 4.24: Robustness Testing Based on Capturing Distance

From top to bottom, a speed limit sign captured from 90m distance and the sign intensity is 98%, a speed limit sign captured from 80m distance and the sign intensity is 98%, a speed limit sign captured from 70m distance and the sign intensity is 99%, and a speed limit sign captured from 60m distance and the sign intensity is 99%. From this distance test result, can be concluded that when the vehicle is close to the target sign the sign intensity is increasing subsequently.

4.6 Discussion of Experiment Results

Processing time and the performance is the key consideration for the real-time applications. In this research, a novel custom feature extraction method has been introduced instead of well-known feature extraction methods such as HOG, SIFT, SURF. to consideration of real-time application. A comparison of processing time and the performance of well-known feature extraction methods, and this proposed feature extraction method has been labeled in Table 3.5. This comparison expresses that these proposed feature extraction methods have high performance with less processing time with others. It has happened because well-known feature extraction method extracts huge raw information which may not necessary for this research.

For the object recognition or classification, a classifier or a recognizer is playing the vital role and for the real-time application, a classifier should have given the highest performance with low processing time. Although the performance and processing time of a classifier is depending upon the what type of problem should solve and what type of data have been given to the classifier. Some other classifiers also are given the acceptable results but ANN classifier eventually gives the best desired results for this proposed research shown in the Figure 4.13. The average correct classification accuracy of all Tree classifier is in between (80% - 84%), all SVM classifier is in between (82.5% - 92.5%), all KNN classifier is in between (52% - 95%) and ANN gives the best performance, which is 99.90% of correct classification accuracy. According to the results presented in Table 4.2, the algorithm obtained 99.90% precision, 99.90% sensitivity, 99.90% specificity, 99.90% F-measure, 0.001 false positive rate, 0.001 false negative rate and an overall accuracy is 99.90%. For that reason, this research proposed real-time (Vision-Based) Malaysian Road Sign Recognition Using an ANN. Maldonado-Bascon *et al.* (Maldonado-Bascon et al., 2007) carried out the detection and recognition of traffic sign based on SVMs. They achieved overall recognition accuracy is 93.06% which was almost similar to this present investigation. Garc *et al.* (Garc et al., 2011) also investigated the robust traffic signs detection using the vision and V2I communications. They also used the SVMs. They got the overall recognition accuracy 90.27% with 0.35 second of processing time. The difference of overall recognition accuracy with the present investigation is around 9%. This happens because of using the different method of ANN. Greenhalgh *et al.* (Greenhalgh & Mirmehdi, 2012) performed the real-time road-traffic sign detection and recognition with SVM. They reached the overall recognition accuracy is 97.60% which was consistent with the proposed method. Bui-Minh *et al.* (Bui-Minh et al., 2012) pointed out the robust algorithm for detection and classification of traffic signs in video data with SVM. Their overall recognition accuracy was 86.60%. The difference is noticed around 13% from the result found in ANN. This is also considerable because they used a different classifier from the ANN. Wali *et al.* (Wali et al., 2015) investigated an automatic road-traffic sign identification method based on color segmentation, shape matching with SVM. They achieved overall recognition accuracy is 95.71% with 0.43 second of processing time which is almost similar to this present investigation. Lin *et al.* (C.-C. Lin & Wang, 2012) carried out the road sign recognition with fuzzy adaptive pre-processing models with SVM. They achieved overall recognition accuracy 92.47%. The difference is 7% from the result of ANN, which is also considerable. Yin *et al.* (S. Yin, 2015) found out the fast traffic sign recognition with a rotation invariant binary pattern based feature with ANN. They accomplished overall recognition accuracy 98.62% with 0.36 second of processing time in all cases. Table 4.3 and Table 4.4 are shown that the result of the present investigation is consistent with this literature. Virupakshappa *et al.* (Virupakshappa et al., 2015) investigated traffic sign recognition based on the prevailing bag of visual words representation on feature descriptors. 95.20% overall recognition accuracy had been achieved in their investigation. Their feature extraction method was different with the present study, also classifier difference has been noticed. Because of this reason, the overall recognition accuracy is different from the present study.

As a summary of experimental results, the proposed method has been tested with a Malaysian Traffic Sign Database and a real-time Malaysian database (with CNN and with ANN). Confusion matrices and ROC curves are used to evaluate the classification performance. Different features extraction and their results have also been discussed earlier. Table 4.6 shows the summary of the experimental results.

Table 4.6: Summary of the Experimental Results

Experiment	**Database**	**Number of Test Samples**	**Features Extraction**	**Classifier**	**Classification Accuracy**
1	Malaysian real-time	1000	HOG	ANN	98.75%
2	Malaysian real-time	1000	SURF	ANN	99.00%
3	Malaysian traffic sign	100	Proposed	ANN	100%
4	Malaysian real-time	1000	Proposed	CNN	94.40%
5	Malaysian real-time	1000	Proposed	ANN	99.90%

CHAPTER 5: CONCLUSION AND FUTURE DIRECTION

In this dissertation, a road-traffic sign detection and recognition framework were developed, implemented, and evaluated to contribute in the area of ITS. This system, which includes a combination of computer vision and pattern recognition problems, can extract the road signs from video frames of complex traffic scenes with unpredictable lighting conditions. In the computer vision part, algorithms were developed to segment the image by using a hybrid color segmentation algorithm and to recognize the sign as a priori knowledge by a robust custom feature extraction method. The multilayer ANN classifier was supported in the pattern recognition part to put the unknown sign in one of the road-traffic sign categories depending on the extracted road-traffic sign features. This goal has now been achieved, and the system has shown a high performance as described in Chapter 4 with different experiment results. Section 4.1, 4.2, 4.3, 4.4, and 4.5 described subsequently the ANN training performance, Experiment with Malaysian Traffic Sign Database, Experiment with CNN, Experiment with real-time, and finally Discussion of Experiment Results (Table 4.6). Classification algorithm performance has also been described and illustrated in the sub Section 4.4.1 and represent the superiority of ANN classifier selection for this research (Table 4.5 and Figure 4.13). The robustness testing results as seen in in sub Sections 4.4.2 prove that the developed system has high accuracy even when processing signs in adverse weather conditions as well as signs that are partially obstructed.

The subsequent sections summarize the main findings and contribution of this research, which could be the beginning of a new approach to traffic sign recognition that points to new directions for further research.

5.1 Collection of Traffic Sign Images

A road-traffic images database is developed for the purpose of developing and testing the various algorithms of the traffic sign recognition system. Overall, 3000 standard and non-standard images were captured and collected in Malaysia. All captured images were 4608-by-3456 pixels in size. Another 16 sign images are collected from 16 different countries for robustness testing. Our collected dataset contained the multiple variations of road-traffic sign conditions. There were ten classes of road-traffic sign images, each having 200 sample images for training purpose and 100 sample images for testing purpose.

5.2 Hybrid Color Segmentation Algorithms

In this research, a hybrid color segmentation algorithm has been developed to perform color segmentation to identify the road sign candidate. This hybrid color segmentation algorithm contains an RGB histogram equalization, RGB color segmentation, modified grayscale segmentation, binary image segmentation and shape matching algorithm. Histogram equalization improves the color constancy of all red, green, and blue regions, and RGB color segmentation extracts the red (R) region, green (G) region, and blue (B) region. Figure 3.5 shows the superiority of this algorithm to improving the image for color segmentation.

5.3 A robust image features extraction

For the first time in a road sign recognition system, a robust custom feature extraction method is introduced to extract multiple features from a single input image. This robust custom feature extraction processes are based on a size independent method and obtain 278 features for road signs. Initially, a 128-by-128 pixel binary image is converted to a 128-by-128 binary matrix. The full process was described in Section 3.6 in details.

Features extraction performance has also been presented in Table 3.5. Compared to previous feature extraction methods, the feature extraction approach used in this research allows the ANN classifier to achieve higher accuracy rates with lower processing times.

5.4 ANN for Traffic Sign Recognition

An ANN is implemented by using the Neural Network Pattern Recognition Tool in MATLAB. The standard network that is used for pattern recognition, is a two-layer feed-forward network with a sigmoid transfer function in the hidden layer, and a softmax transfer function in the output layer. For this system, the number of hidden neurons is set to 10, which is more efficient and more reliable for this proposed system. The number of output neurons is set to 10, which is equal to the number of elements in the target vector (the number of sign categories). For the training of the multiple layer ANN, a systematic method is applied with back-propagation-learning algorithm to the network. In addition to normalized images, the ANN classifier is trained and tested using other features extraction process such as HOG, SURF shown in Table 3.5.

The recognition of road and traffic sign is a field of study that can be used to aid the development of ITS or car advisory systems. It continuously monitors the driver, the vehicle and the road in order, for example, to inform the driver in the time of the upcoming decision-making points regarding navigation and potentially driven traffic situations (Yeshodara et al., 2014). The aim of this research was to overcome the current limitations of real-time road sign recognition systems, such as single-color or single-class, specific country, and non-standard road signs. The proposed method is developed with a detection and a recognition stage. Detection is performed by capturing video frames with a dashboard camera in real-time from the highway. That frame goes through a hybrid color segmentation algorithm to identify the availability of the road sign candidates. For the first time in a road sign recognition system, a robust custom features extraction method is introduced to extract multiple features from a single image. This robust custom feature an extraction process is based on a size independent method and obtained 278 features for a single sign. This feature vector goes through a pre-trained ANN for recognition of road signs. ANN learning is performed with 100 sample images for each class of road sign, or a total 1000 sample images for ten classes of the road sign. The recognition performance is evaluated by using confusion matrix analysis, with two different Malaysian traffic sign datasets which are a standard dataset and a real-time dataset. Results show that the algorithm achieved 100% accuracy with the Malaysian traffic sign dataset, and an average of 99.90% accuracy with 99.90% of sensitivity, 0.001 of false positive rate and 0.33 s of processing time, with a real-time Malaysian traffic sign dataset. The experimental results have been compared with existing methods and classifiers, showing the correctness of the proposed method. Additionally, robustness testing shows that this proposed system is robust. The main limitation of this proposed system is that signs obscured by other vehicles or trees may not be recognized.

5.5 Future Directions

Signs are often closed by obstacles and they are usually surrounded by many other objects as shown in Figure 1.3. This kind of situation often occurs when images are taken from different angles. The main problem with these closures is that these signs are unpredictable and the shapes they produce are also unpredictable. A number of researchers have already begun to tackle this problem seriously (De La Escalera et al., 2004), but the amount of work is still below what is necessary. One approach for solving this problem is to use the type of features not affected by the disorder or partial occlusion. As a partial feature extraction process can be a possible solution to this type of problem, if the character is partially hidden, then another part of the character can be performed for recognition. Another future direction is to recognize all type of road-traffic sign in

Malaysia, reduce the processing time and improve the Malaysian traffic database that can also be proposed. The PCA can be used to reduce the computational time.

When such a system is integrated with a global positioning system (GPS), it can be used to provide the driver with useful information about the actual speed limit on a particular road. By comparing the signed limit with the GPS speed measurement, the driver can be warned if the speed limit is exceeded or if the driver does not stop before a Stop signal. Another important future orientation of this proposed system can introduce a road and traffic sign inventory system to develop an inventory of them that can also support the tasks of highway engineers in updating and maintaining.

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