VEHICLE MAKE AND MODEL RECOGNITION SYSTEM FOR OCCLUSION AND BAD LIGHTING IMAGES

AYMEN FADHIL ABBAS

UNIVERSITI TEKNOLOGI MALAYSIA

VEHICLE MAKE AND MODEL RECOGNITION SYSTEM FOR OCCLUSION AND BAD LIGHTING IMAGES

AYMEN FADHIL ABBAS

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy

School of Electrical Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

DECEMBER 2021

DEDICATION

Dedicated to my beloved family especially my parents, and my supportive supervisor – DR. USMAN ULLAH SHEIKH. Thank you very much for being positive, helpful and understanding.

ACKNOWLEDGEMENT

Praise Be to Allah S.W.T, the Lord of the World

Foremost, I would like to express my sincere gratitude to my supervisor Dr. Usman Ullah Sheikh for the continuous support of my study and research, for his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my study.

My sincere thanks also go to all staff, lectures, and individuals who directly or indirectly support me throughout completing this study. I am deeply thankful to my friends and officemates who always support and motivate me during ups and down.

ABSTRACT

Intelligent transportation system (ITS) is a massive and very significant sector in the socio-economic context of contemporary society. The need to use roads continues to increase, and this comes with the need to establish more efficient vehicle detection methods. Vehicle Make and Model Recognition (VMMR) has become an important aspect of vision-based systems, since it is applied to access control systems, traffic control, surveillance, and security systems, among others. However, the use of VMMR is challenging due to numerous factors, such as camera angle, poor lighting, and occlusion. Most of the existing works are focused on designing a VMMR system in a normal scenario, where the dataset is set for an ideal scenario, a scenario without illumination, or occlusion. Recent studies have used certain methods to extract the features by extracting the region of interest (ROI) of the front or the rear view of the vehicle to detect and recognize the vehicle. However, the aforementioned methods would fail with poor lighting or occlusion cases. In this thesis, a VMMR system is introduced, which begins by building the dataset, a combination of a benchmark dataset (dataset1) and a self-collected dataset (dataset2). A new approach of image enhancement method was applied to improve the low-light dataset. Then, the enhanced geographical feature extraction techniques were applied to extract the headlight and license plate. For occlusion cases, a new grid-based Speeded-Up Robust Features (SURF) was presented to extract the ROI even in the presence of an occluded object. Two classification approaches were used to recognize the make and model of the vehicle. The first approach is based on the Decision Tree, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) algorithms, where they are called ensemble classifiers, which can predict the VMM accurately. This is because the Decision Tree classifier predicts instances by sorting them based on feature values, while for SVM, the precision of classifying can be enhanced by employing suitable factors. As such, Radial basis function (RBF) kernel and optimized factors were chosen for SVM and KNN, where the testing data was classified by comparison to the k nearest training data based on a distance function. The second approach is the PCANet-II classifier, an approach with second-order pooling and binary feature variance with promising accuracy. The overall performance of the work in this thesis demonstrates a promising outcome, where the overall accuracy reached 96.08% by adopting an ensemble classifier and two datasets (dataset1, dataset2), while the PCANet-II classifier achieved 97.56% using both datasets (dataset1, dataset2). In conclusion, this approach proposed in this thesis showed higher performance than existing methods when bad lighting and occlusion are considered.

ABSTRAK

Sistem pengangkutan pintar (ITS) adalah sektor yang besar dan sangat penting dalam konteks sosio-ekonomi masyarakat kontemporari. Keperluan untuk menggunakan jalan raya terus meningkat, dan ini datang dengan keperluan untuk mewujudkan kaedah pengesanan kenderaan yang lebih cekap. Pengecaman Model dan Buatan Kenderaan (VMMR) telah menjadi aspek penting dalam sistem berasaskan penglihatan kerana ia digunakan untuk sistem kawalan akses, kawalan trafik, pengawasan dan sistem keselamatan, antara lainnya. Walau bagaimanapun, penggunaan VMMR adalah mencabar kerana pelbagai faktor, seperti sudut kamera, pencahayaan yang kurang baik, dan oklusi. Kebanyakan kerja sedia ada tertumpu pada mereka bentuk sistem VMMR dalam senario biasa, di mana set data ditetapkan untuk senario yang ideal, senario tanpa pencahayaan atau oklusi. Kajian terkini telah menggunakan kaedah tertentu untuk mengekstrak ciri dengan mengekstrak kawasan yang penting (ROI) bahagian hadapan atau pandangan belakang kenderaan untuk mengesan dan mengecam kenderaan. Namun begitu, kaedah yang disebutkan di atas akan gagal di bawah pencahayaan yang lemah atau kes oklusi. Dalam tesis ini, sistem VMMR diperkenalkan, bermula dengan membina set data, gabungan set data penanda aras (dataset1) dan set data terkumpul sendiri (dataset2). Pendekatan baharu kaedah peningkatan imej telah digunakan untuk menambah baik set data dalam keadaan cahaya malap. Kemudian, teknik pengekstrakan ciri geografi yang dipertingkatkan digunakan untuk mengekstrak lampu depan dan plat lesen. Untuk kes oklusi, Ciri-ciri yang Teguh Dipercepatkan (SURF) berasaskan grid baharu telah dibentangkan untuk mengekstrak ROI walaupun dengan kehadiran objek oklusi. Dua pendekatan klasifikasi telah digunakan untuk mengenali jenama dan model kenderaan. Yang pertama adalah berdasarkan algoritma Pohon Keputusan, Mesin Vektor Sokongan (SVM), dan K Jiran Terdekat (KNN), di mana ia dipanggil pengelas ensembel yang mampu meramalkan VMM dengan tepat. Ini kerana pengelas Pokok Keputusan meramalkan keadaan dengan mengisihnya berdasarkan nilai ciri, manakala bagi SVM, ketepatan pengelasan boleh dipertingkatkan dengan menggunakan faktor yang sesuai. Oleh itu, kernel fungsi basis radial (RBF) dan faktor yang dioptimumkan telah dipilih untuk SVM dan KNN, di mana data ujian dikelaskan dengan perbandingan kepada k data latihan terdekat berdasarkan fungsi jarak. Yang kedua dipanggil pengelas PCANet-II, iaitu pendekatan dengan pengumpulan tertib kedua dan varians ciri binari dengan ketepatan yang menjanjikan. Prestasi keseluruhan kerja dalam tesis ini menunjukkan hasil yang menjanjikan, di mana ketepatan keseluruhan mencapai 96.08% dengan mengguna pakai pengelas ensembel dan dua set data (dataset1, dataset2), manakala pengelas PCANet-II mencapai 97.56% menggunakan kedua-dua set data (dataset1, dataset2). Kesimpulannya, kerja yang dicadangkan dalam tesis ini menunjukkan prestasi yang lebih tinggi berbanding kaedah sedia ada apabila pencahayaan dan oklusi yang buruk dipertimbangkan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
BFD	-	Binary Feature Difference
BHE	-	Bi-Histogram Equalization
BME	-	Bayesian Minimum Error
BMR	-	Bayesian Minimum Risk
BoSURF	-	Bag-of-SURF
CAPOA	-	Content Adaptive Progressive Occlusion Analysis
CNN	-	Convolutional Neural Network
CR	-	Candidate Region
CV	-	Coefficient of Variation
ELM	-	Extreme Learning Machine
FID	-	Full Inside Division
GDM	-	Generalized Deformable Model
GMM	-	Gaussian Mixture models
HE	-	Histogram Equalization
HOG	-	Histograms of Orientated Gradients
ITS	-	Intelligent Transportation System
KDE	-	Kernel Density Estimation
KNN	-	K- Nearest Neighbors
LBP	-	Local Binary Patterns
LBSP	-	Local Binary Similarity Pattern
LIPA	-	Low-cost Image Processing Algorithm
LLC	-	Locality-Constraint Linear Coding Method
NDD	-	Narrow Direct Division
PCA	-	Principal Component Analysis
PKDE	-	Pattern Kernel Density Estimation
RBF	-	Radial Basis Function
RBMs	-	Restricted Boltzmann Machines
ReLu	-	Rectified Linear unit
ROI	-	Region of Interest

SAGMM	-	Self-Adaptive Gaussian Mixture Model
SE	-	Structure Element
SID	-	Symmetrical Inside Division
SIFT	-	Shift-Invariant Feature transform
SILTP	-	Scale Invariant Local Ternary Pattern
SURF	-	Speeded Up Robust Features
SVM	-	Support Vector Machine
VLR	-	Vehicle Logo Recognition
VMTM	-	Vector Mask Template Matching
VTR	-	Vehicle Type Recognition
WDD	-	Wide Direct Division

LIST OF SYMBOLS

u, v	-	Angle Measurement Parameters
R_{area}	-	Area Ratio
AS	-	Area (Size) Symmetry Score of Pair P_k
$\frac{W_1}{H_1}$	-	Aspect Ratio of Headlight
$ARS(P_k)$	-	Aspect Ratio Symmetry Score of Pair P_k
t_s	-	Average of $G_s\left(I_t(p)\right)$
l_s	-	Bottom Boundary of ROI
C_i	-	Candidate Multi-Paired
ρ	-	Chrominance Ratio
Γ_C	-	Convex Hull
C	-	Convexity Metric
$\{\mathrm{f}_k^i\}_{k=1}^{k_i}$	-	Convolutional Outputs
CovM_m^i	-	Covariance Between Feature Maps
$\mathrm{DT_{pred}}$	-	Decision Tree Prediction
$DoH(x, y, \sigma)$	-	Determination of Hessian Matrix
θ_n	-	Deviation Angle
$\left\lvert\nabla_\mathrm{p}\right\rvert, \theta_p$	-	Direction and Magnitude of the Gradient
$\nabla y, \nabla x$	-	Directional Gradients
DS (p_k)	-	Direction Symmetry Score of the Pair
M_d	-	Distance Between Two CPs
$V_1 \in \mathbb{R}^{l_1 l_2 \times K_1}$	-	Eigenvectors Calculation
f_{BFD}^i	-	Encode BFD
$\mathrm{B}_k^i(x, y)$	-	Feature Map
$G_s(I_t(p))$	-	Gaussian Shadow Model
σ^2	-	Gaussian Variance
G_t	-	Gradient Total
HL pair	-	Headlight Pair
h_1	-	Height of the Vehicle

ra	-	Height to Width Ratio
Ag(y)	-	Histogram By the accumulation of the horizontal edge
I	-	Intensity
$\propto$	-	Intensity Factor
NN_{pred}	-	KNN Prediction
l_l	-	Left Boundary of ROI
BL	-	Limit of Object Length
$\mathrm{G} \in \mathbb{R}^{l_1 l_2 \times NP,}$	-	Local Patch Set Creation
M_s	-	Match Score
γ_1, γ_2	-	Maximum Intensity Region
I_{max}	-	Maximum Value of Intensity
μ	-	Mean
μ_s, σ_s	-	Mean and Variance of the Shadow
M_o	-	Measures the Alignment of Two CD Areas
Φ	-	Numerical Value of Three Classifier predictions
X^t	-	Objective Plate-Box Coordinates
p_k	-	Obtained Paired
IDR	-	Occlusion Detection
W_m	-	Optimal Weight
Δh_1	-	Proposed Candidate Region
f	-	Regularization Factor
l_r	-	Right Boundary of ROI
R	-	Searching Area
$\Delta h1_{low}, \Delta h1_{up}$	-	Searching Area Regions
K_i	-	Set of Filter Kernels
l_1, l_2	-	Size of the Patches
σ	-	Standard Deviation
$\mathrm{SVM}_{\mathrm{pred}}$	-	SVM Prediction
μ_k^i	-	The Average Feature of the Feature Map $\mathrm{B}_k^i(x, y)$
C_V	-	The New ROI
P	-	Total Number of Local Patches

u_s	-	Upper Boundary
$C_{x,y}$	-	Values of Translated Pixel

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Research Background

The transportation system is one of the massive industries in contemporary society. The need to use of roads is, therefore, ever-increasing, and this comes with the need to have better ways to detect and identify vehicles. Among the critical applications that have been used for video systems in traffic surveillance, studies have been done on visual-based intelligent transportation systems for traffic planning to develop accurate traffic information, planning and traffic flow. In the past few years, video cameras have been widely utilized to monitor traffic as it is viewed as an efficient means of collecting information on traffic in general and its flow in particular. Furthermore, the rapid advances in computer vision, computational and camera knowledge and skills, tin tandem with advances in automated video applications for analyzing and processing information have significantly raised interest in the use of video systems to monitor traffic [1].

The use of computer vision approaches in monitoring traffic is currently considered crucial for an intelligent transportation system (ITS). ITS employs visual appearance to detect and identify vehicles and for tracking that is significantly beneficial in analyzing and understanding traffic incidents, and human behavior. Besides, it provides traffic flow details such as vehicle class, count, trajectory etc. However, despite the level of work done to enhance the effectiveness of video-based traffic monitoring systems, and the application of ITS continues to face some practical challenges [2].

A camera-based approach to monitor traffic is an essential aspect of an ITS, which essentially involves automatic surveillance of digital cameras to capture snapshots of passing vehicles and other moving objects. The captured images are of high-resolution and static in nature, and from which police and other security authorities can obtain crucial information pertaining to a vehicle plate number, the precise moment it passed, its movement path and even the driver's face, etc. In the past, the very substantial number of captured images were manually processed, which took time besides being inefficient [2].

Traffic environments varies and comprises of straight highways, parts of urban roads, intersections, corners as well as tunnels, which give rise to a number of challenges of varying magnitudes such as congested traffic, and the unpredictability of weather and illumination circumstances. However, the diversity in vehicle types, including size, shape and color among other factors, poses constraints on vehicle identification and tracking to specific scenes [1].

In recent years, there has been increasing emphasis on road safety and security by ensuring roads are adequate and safe, but transportation systems still face problems that have motivated researchers to be more concerned about road safety and made them consider the development of novel algorithms to address these issues.

Due to the extensive applications of vehicle detection and recognition, challenges have become real concerns and need to be resolved to enhance security and to avoid any mistakes on the urban roads or in traffic systems. One of these problems is occlusion. Occlusion is typically a significant challenge in vehicle detection, and which can significantly affect the vehicle identification process and make the vehicle identification impossible [53][55].

The failure to identify a vehicle due to bad lighting is another challenge faced in any ITS. Color is among the significant factors to describe the entire image of the object that is included. On the contrary, the color of the object can be substantially different because of the variations of intensity, source of illumination, weather, among other factors. Besides, capturing an image of the same object can produce different results because of a color change brought about by the surface reflection or camera angles [53][55].

Currently, such challenges have become obstacles in the field of ITS when it comes to the detection or recognition of a vehicle. One question often asked is: What if the researchers want to build a system to detect and recognize the make and the model of a vehicle? Vehicle make and model recognition (VMMR) has become an important aspect of vision-based systems as it is applied in access control systems, traffic control and surveillance and security systems among others. The rationale behind VMMR is the extraction of the desired features of an image to identify the make and model of a vehicle.

The majority of research begins with the detection of a vehicle, which yields regions of interest (ROIs) that contain the vehicles' face (front) distinguished from the background. The vehicle classification systems then work on the ROIs, and Figure 1.1 shows the general architecture of the VMMR system.

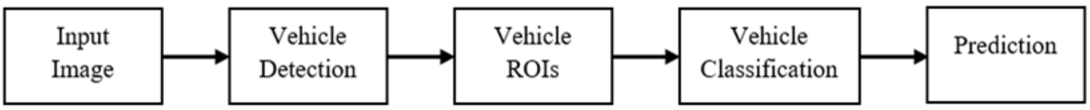

Figure 1.1 The general architecture of the VMMR system

Depending on the granular quality of the classification, vehicle classification systems can be grouped into three categories: Type, make (Logo), or make and model recognition, as shown in Figure 1.2.

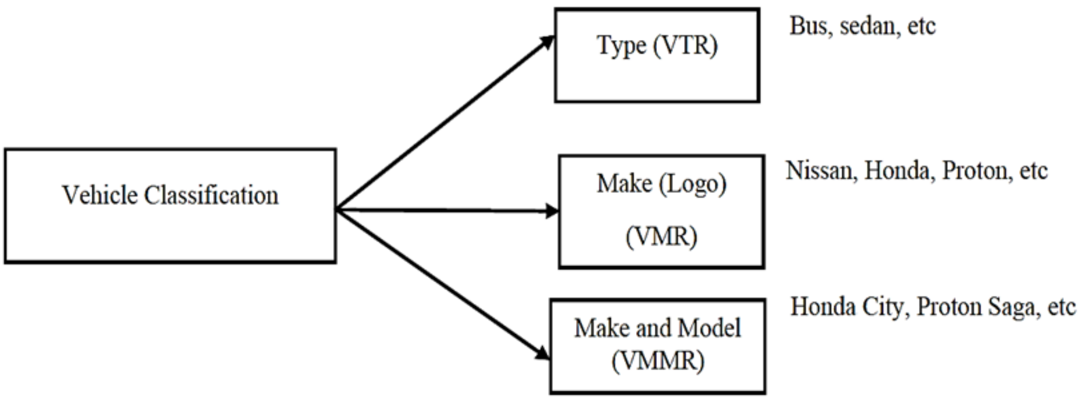

Figure 1.2 Vehicle classification showing Vehicle Type Recognition (VTR), Vehicle Make (logo) Recognition (VMR or VLR), and Vehicle Make and Model Recognition (VMMR)

1.2 Problem Statement

Recently, much work has been done focusing on the use of video cameras for traffic monitoring applications, which are viewed as rich sources of useful information regarding traffic flow. Applying computer vision approaches to monitor traffic has come to be viewed as crucial for ITS, which employs observable images in detecting vehicles, identification, and tracking that is beneficial for detecting incidents, analyzing, and understanding human behavior. Besides, it provides traffic flow information such as number of vehicles, trajectory, etc.

Despite concerted efforts being made for the improvement of video-based traffic monitoring systems, several issues still remain that challenge the practical application of ITS and researchers. If these issues are addressed, the ITS will be more secure, efficient, and powerful in enhancing security in urban roads and facilitate society in detecting all possible vehicles and identifying them. Some issues also need to be looked into, including vehicle occlusion with other objects, so it is going to be difficult to detect and identify the vehicle. Another interesting challenge is lighting and illumination that arise due to inadequate lighting. Hence, this thesis will describe these problems in detail.

- The roads today have hundreds of vehicles passing through. The question is whether the VMMR systems would be able to detect all vehicles without missing any. Occlusion is one of the main problems in video surveillance systems. In this thesis, there is a need to detect and recognize vehicles efficiently. Still, the challenge is when the detected object in a scene is behind another object, whereby some parts in the object are undetected due to occlusion. The camera needs a clear vision of the vehicle but will fail due to occlusion. In this case, the occlusion is caused by human activity or another vehicle. Recently some researches tried to address the problem of occlusion by applying certain samples of occlusion dataset to VMMR system like in [53][106] the authors proposed a new symmetrical SURF descriptor to extract the make and model of the vehicle, but it fails when it comes to occlusion samples due to the missing parts of symmetrical pairs. The author in [55] applied real-time automated VMMR according to a collection of expedited robust features (BoSURF), as it claims that can handle the occlusion scenario, this work did not take enough samples of the occlusion dataset. The author in [107] proposed Random Forest-based VMMR system while in [109], a new cascaded part-based system was suggested for VMMR. Ghassemi, S [112] suggested a deep convolutional structure based on multi-scale attention windows to address the problem of VMMR classification system. In [113] suggested a novel configurable on-road VMMR framework and took advantage of the unsupervised feature learning approaches and employed Locality-constraint Linear Coding (LLC) technique as a fast feature encoder to encode the input SIFT. In conclusion, most of these works failed to address and solve the occlusion problem. Figure 1.3 below shows a sample of an occlusion case.

(a) (b)

Figure 1.3 Occlusion scenario (a) From [53] and (b) Self-collected dataset

- The dataset must be of good visual quality. On the other hand, due to variances in illumination and camera distortions, various cameras could give quite substantially different visual qualities. Hence, detecting and recognizing a targeted object that moves across the cameras can be a challenge. Police also needs to be able to detect different vehicles by camera confidently. Not many studies focused on low light scenarios because it requires a lot of work, robust tools and classifiers to extract the ROI and image enhancement techniques to make a still image with a better contrast. Chen, L [106] and Hsieh, J.W [53] used the symmetrical SURF descriptor for vehicle detection on roads and tried to apply it on low light dataset, the system failed to detect the symmetrical pairs due to low light and weak contrast. However, [55] used some samples for low light cases and managed to extract the make and model of the vehicle but as mentioned earlier, the author used only a few samples to test the system. The works done in [109],[111],[112],[113], came up with an ideal VMMR system, but none of them dealt with the low light scenario. Figure 1.4 shows samples of bad lighting case.

(a) (b)

Figure 1.4 Bad lighting scenario (a) From [53] and (b) From self-collected dataset

1.3 Research Objectives

Due to the problems mentioned in the previous section, the main goal of this work is to design a vehicle make and model recognition system with the ability to perform well under the low light condition and in the presence of occlusion. The main objectives are listed below:

a) To propose an image enhancement technique to enhance vehicle images in poor lighting for VMMR system.

b) To improve geographical feature extraction technique for vehicle frontal view feature extraction.

c) To propose a novel scheme to extract the region of interest (ROI) using SURF features in the presence of occlusion.

d) To build an image dataset for low lighting and occlusion for the purpose of training and testing.

1.4 Scope of Work

The following is the scope of this work:

a) Collect a suitable database for the research. This database should contain all possible vehicles under different conditions and different types of cars used for this work. The database collected using a camera on the local road, and the databases used in previous works are also used for comparison.

b) The benchmark dataset contains 5,610 samples with twenty vehicle makes and models. While the self- collected dataset contains 680 samples with six vehicle makes and models.

c) In this thesis, only the front view of the vehicle was considered.

d) This thesis will focus on occlusion and bad lighting as main issues in recognition systems.

e) Experimental work was performed offline using software implementation on MATLAB. The simulation was performed on Intel Core i7 CPU (2.4 GHz), 8GB of RAM and Windows 10 64-bit operating system.

1.5 List of Contributions

a) Built an image database of self- collected dataset and existing benchmark dataset.

b) This thesis introduced a new approach to enhance vehicle images in low light using a multiple exposure technique.

c) In this work, existing geographical feature extraction has been improved that can be applied on frontal view of vehicle images and able to extract headlight pairs.

d) To overcome the occlusion, in this thesis, an improved and modified method has been shown that is based on SURF. The method can handle occlusion more accurately than existing approaches.

1.6 Thesis Organization

This thesis is presented in five chapters. This chapter presents a brief research background of the investigated topic, identifying the motivations which have led to this research. The scientific objectives and the scope of work are outlined and highlighted with a clear identification of the research goals. The remaining chapters of this thesis organized as follows:

Chapter 2 presents a literature review of the whole VMMR system starting from the detection stage to describe the latest VMMR works. Algorithms of recognition processes, classifiers, feature selection techniques and classification performance evaluations were presented. Also, this chapter presents and discusses the problems that face VMMR algorithm such as bad lighting and occlusion in detail.

Chapter 3 describes the whole VMMR system of this study and presents every stage in detail. A suitable database for the research is collected and the dataset contained all possible vehicles under different conditions and different types of cars used for this work.

In Chapter 4, the experimental results are presented in detail. The results from both classifiers (ensemble classifier and PCANet-II) were evaluated and then compared with the state of art works to check the accuracy and the validity of this study.

In Chapter 5, results obtained in Chapter 4 discussed along with theoretical expectations. The chapter then gives a conclusion by summarizing the work done in this thesis and presents future directions of research for VMMR works.

REFERENCES

1. Tian, B., Morris, B.T., Tang, M., Liu, Y., Yao, Y., Gou, C., Shen, D., and Tang, S. (2017) ‘Hierarchical and Networked Vehicle Surveillance in ITS: A Survey’, *IEEE Transaction on Intelligent Transportation Systems,* 18(1), pp. 25–48.
2. Ghosh, R., Pragathi, R., Ullas, S. and Borra, S. (2017) ‘Intelligent transportation systems: A survey’, *2017 International Conference on Circuits, Controls, and Communications (CCUBE)*, pp. 160–165.
3. Song, H., Liang, H., Li, H., Dai, Z and Yun, X. (2019) ‘Vision-based vehicle detection and counting system using deep learning in highway scenes’, *European Transport Research Review*, 11(51), pp. 1–16.
4. Antony, J. J. and Suchetha, Dr. M. (2016) ‘Vision based vehicle detection: a literature review’, *International Journal of Applied Engineering Research*, 11, pp. 3128–3133.
5. Seenouvong, N., Watchareeruetai, U., Nuthong, C., Khongsomboon, K. and Ohnishi, N. (2016) ‘A computer vision-based vehicle detection and counting system’, *2016 8th International Conference on Knowledge and Smart Technology (KST)*, pp. 224–227.
6. Tian, B., Morris, B.T., Tang, M., Liu, Y., Yao, Y., Gou, C., Shen, D. and Tang, S. (2017) ‘Hierarchical and networked vehicle surveillance in ITS: a survey’, *IEEE Transactions on Intelligent Transportation Systems*, 18(1), pp. 25–48.
7. Khurana, P., Sharma, A., Singh, S. N. and Singh, P. K. (2016) ‘A survey on object recognition and segmentation techniques’, *2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom),* pp. 3822–3826.
8. Kumar, S. and Yadav, J. S. (2016) ‘Video object extraction and its tracking using background subtraction in complex environments’, *Perspective in Science*, 8, pp. 317–322.
9. Madhan, R. and Banu, S. (2015) ‘Intelligent video surveillance system using background subtraction technique and its analysis’, *International Journal of Applied Engineering Research*, 10(2), pp. 4849–4863.

10. Takhar, G., Prakash, C., Mittal, N. and Kumar, R. (2016) ‘Comparative analysis of Background Subtraction techniques and applications’, *2016 International Conference on Recent Advances and Innovations in Engineering (ICRAIE)*, pp. 1–8.
11. Cuevas, C. and García, N. (2013)’ Improved background modeling for real time spatio-temporal non-parametric moving object detection strategies’, *Image and Vision Computing*, 31(9), pp. 616–630.
12. Li, X., Chen, L., Yang, Z. and Zhang, W. (2016) ‘A novel object detection technique for dynamic scene and static object’, *2016 7th International Conference on Mechanical, Industrial, and Manufacturing Technologies (MIMT 2016)*, 54, pp. 1–7.
13. Zhu, T. and Zeng, P. (2015) ‘Background subtraction based on non-parametric model’, *4th International Conference on Computer Science and Network Technology (ICCSNT)*, pp. 1379–1382.
14. Liao, S., Zhao, G., Kellokumpu, V., Pietik¨ainen, M. and Li, S.Z. (2010) ‘Modeling pixel process with scale invariant local patterns for background subtraction in complex scenes, *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 1301–1306.
15. Narayana, M. Hanson, A. and Learned-Miller, E. (2012) ‘Improvements in joint domain-range modeling for background subtraction’, *in Proceedings of the British Machine Vision Conference (BMVC)*, pp. 1–11.
16. Khilar, R. and Chitrakala, S. (2016) ’A novel method for effective vehicle detection and tracking eliminating occlusion’, *Asian Journal of Research in Social Sciences and Humanities*, 6(1), pp. 714–727.
17. Noh, S. and Jeon, M. (2013)’A new framework for background subtraction using multiple cues’, Asian Conference on Computer Vision (ACCV),7726, pp. 493–506.
18. Suganya Shri,S.P. and Latha, Dr.L. (2016)’ Non-parametric background modeling for foreground extraction using detection theory and object tracking’, *International Journal on Applications in Information and Communication Engineering*, 2(4), pp. 57–61.
19. Xue, Z. -M., Li, Z. -C., Qin, M. and Qiao, G.-Y. (2015) ‘Vehicle detection algorithm based on codebook and local binary patterns algorithms’ *Journal of Central South University*, 22, pp. 593–600.

20. Manzanera, A. (2007) ‘Σ-Δ Background subtraction and the zipf law’, *Progress in Pattern Recognition, Image Analysis and Applications (CIARP)*, pp. 42–51.
21. Toral, S., Vargas, M., Barrero, F. and Ortega, M.G. (2009) ‘Improved sigma–delta background estimation for vehicle detection’, *Electronics Letters*, 45, pp. 32–34.
22. Milla, J.M., Toral, S.L., Vargas, M. and Barrero, F.J. (2013) ‘Dual-rate background subtraction approach for estimating traffic queue parameters in urban scenes’, *Intelligent Transport Systems journal (IET)*,7(1), pp. 122–130.
23. Stauffer, C. and Grimson, W.E.L. (1999) ‘Adaptive background mixture models for real-time tracking’, *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2, pp. 246 - 252.
24. Nurhadiyatna, A., Jatmiko, W., Hardjono, B., Wibisono, A., Sina, I. and Mursanto,P. (2013) ‘Background subtraction using gaussian mixture model enhanced by hole filling algorithm (GMMHF)’, *2013 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 4006–4011.
25. Bhaskar, P.K. and Yong, S.P. (2014) ‘Image processing-based vehicle detection and tracking method’ *2014 International Conference on Computer and Information Sciences (ICCOINS)*, pp. 1–5.
26. Indrabayu, R., Bakti, Y., Areni, I.S. and Prayogi, A.A. (2016) ‘Vehicle detection and tracking using gaussian mixture model and kalman filter’, *2016 International Conference on Computational Intelligence and Cybernetics*, pp. 115–119.
27. Huang, Z., Qin, H. and Liu, Q. (2017) ‘Vehicle ROI extraction based on area estimation gaussian mixture model’, *2017 3rd IEEE International Conference on Cybernetics (CYBCONF)*, pp. 1–7.
28. Kalman, R. E. (1960) ‘A new approach to linear filtering and prediction problems’, *ASME Journal of Basic Engineering*, 82(1), pp. 35–45.
29. Oliver, N.M., Rosario, B. and Pentland, A.P. (2000) ‘A bayesian computer vision system for modeling human interactions’, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(8), pp. 831–843.
30. Wang, X., Sun, J. and Peng, H.Y. (2013) ‘Foreground object detecting algorithm based on mixture of gaussian and kalman filter in video surveillance’, *Journal of Computers*, 8(3), pp. 693–700.

31. Rin, V. and Nuthong, C. (2019) ‘Front moving vehicle detection and tracking with kalman filter’, *2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS),* pp. 304–310.
32. Srilekha, S., Swamy, G.N. and Krishna, A.A. (2015) ‘A novel approach for detection and tracking of vehicles using kalman filter’, *2015 International Conference on Computational Intelligence and Communication Networks,* pp. 234–236.
33. Tah, A., Roy, S., Das, P. and Mitra, A. (2017) ‘Moving object detection and segmentation using background subtraction by kalman filter’, *Indian Journal of Science and Technology,* 10(19), pp. 1–11.
34. Hu, Z., Ye, G., Jia, G., Chen, X., Hu, Q., Jiang, K., Wang, Y., Qing, L., Tian, Y., Wu, X. and Gaoa, W. (2009) ‘Pku@trecvid2009: Single-actor and pair-activity event detection in surveillance video’, *in Proceeding of TRECVID Workshop,* pp. 1–10.
35. Gunawan, A.A.S., Tanjung, D.A. and Gunawan, F.E. (2019) ‘Detection of vehicle position and speed using camera calibration and image projection methods’, *Procedia Computer Science,* 157, pp. 255–265.
36. Tian, Y., Wang, Y., Hu, Z. and Huang, T. (2013) ‘Selective eigenbackground for background modeling and subtraction in crowded scenes’, *IEEE Transactions on Circuits and Systems for Video Technology,* 23(11), pp. 1849–1864.
37. Chen, Y. and Wu, Q. (2015) ‘Moving vehicle detection based on optical flow estimation of edge’, *2015 11th International Conference on Natural Computation (ICNC),* pp. 754–758.
38. Agarwal, A., Gupta, S. and Singh, D.K. (2016) ‘Review of optical flow technique for moving object detection’, *2016 2nd International Conference on Contemporary Computing and Informatics (IC3I),* pp. 409–413.
39. Liu, Y., Lu, Y., Shi, Q. and Ding, J. (2013) ‘Optical flow based urban road vehicle tracking’, *2013 IEEE 9th International Conference Computational Intelligence and Security (CIS),* pp. 391–395.
40. Bhaskar, P.K., Yong,S.P. and Jung, L.T. (2015) ‘Enhanced and effective parallel optical flow method for vehicle detection and tracking’, *2015 IEEE International Symposium on Mathematical Sciences and Computing Research (ISMSC),* pp. 138–143.

41. Sreedevi, I., Gupta, M. and Bhattacharyya, Prof. A. (2011) ‘Vehicle tracking and speed estimation using optical flow method, *International Journal of Engineering Science and Technology (IJEST),* 3(1), pp. 429–434.
42. Lowe, D.G. (1999) ‘Object recognition from local scale-invariant features’, *in proceeding of 7th International Conference on Computer Vision*, pp. 1150–1157.
43. Agarwal S., Awan A., and Roth D. (2004) ‘Learning to detect objects in images via a sparse part-based representation’, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 26(11), pp. 1475–1490.
44. Ma, X. and Grimson, W.E.L. (2005) ‘Edge-based rich representation for vehicle classification’, *2005 IEEE 10th International Conference on Computer Vision (ICCV'05),* 2, pp. 1185–1192.
45. Yawen, T. and Jinxu, G. (2018) ‘Research on vehicle detection technology based on SIFT feature’, *2018 8th International Conference on Electronics Information and Emergency Communication (ICEIEC),* pp. 274–278.
46. Chen, X. and Meng, Q. (2013) ‘Vehicle detection from UAVs by using SIFT with implicit shape model’, *2013 IEEE International Conference on Systems Man and Cybernetics (SMC)*, pp. 3139–3144.
47. Juan, L. and Gwun, O. (2009) ’A comparison of SIFT, PCA-SIFT and SURF’, *International Journal of Image Processing (IJIP),* 3(4), pp. 143–152.
48. Cai, Y., Li, L., Ni, S., Lv, J., Zeng, W. and Yuanlong, Y. (2015) ‘Moving vehicle detection based on dense SIFT and Extreme Learning Machine for visual surveillance’, *2015 IEEE International Conference on Robotics and Biomimetics (ROBIO),* pp. 1614–1618.
49. Lazebnik, S., Schmid, C. and Ponce, J. (2006) ’Beyond bags of features: spatial pyramid matching for recognizing natural scene categories’, *2006 IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 2169–2178.
50. Lowe, D. (2004) ‘Distinctive image features from scale-invariant keypoints’, *International Journal of Computer Vision,* 60(2), pp. 91–110.
51. Mu, K., Hui, F. and Zhao, X. (2016) ‘Multiple vehicle detection and tracking in highway traffic surveillance video based on SIFT feature matching’, *Journal of Information Processing Systems,* 12(2), pp. 183–195.

52. Bay, H., Tuytelaars, T. and Van Gool, L. (2006) ‘Surf: speeded up robust features’*, in Proceeding of Computer vision (ECCV*), pp. 404–417.
53. Hsieh, J.W., Chen, L.C. and Chen, D.Y. (2014) ’Symmetrical SURF and its applications to vehicle detection and vehicle make and model recognition’, *IEEE Transactions on Intelligent Transportation Systems*, 15(1), pp. 6–20.
54. Shujuan, S., Zhize, X., Xingang, W., Guan, H., Wenqi, W. and De, X. (2015) ‘Real-time vehicle detection using Haar-SURF mixed features and gentle AdaBoost classifier’, *2015 IEEE 27th Control and Decision Conference*, pp. 1888–1894.
55. Siddiqui, A.J., Mammeri, A. and Boukerche, A. (2016) ’Real-time vehicle make and model recognition based on a bag of SURF features’, *IEEE Transactions on Intelligent Transportation Systems*, 17(11), pp. 3205–3219.
56. Sivic, J. and Zisserman, A. (2003) ‘Video google: a text retrieval approach to object matching in videos’, *2003 9th IEEE International Conference in Computer Vision*, 2, pp. 1470–1477.
57. Csurka,G, Dance, C.R., Fan, L., Willamowski, J. and Bray, C. (2004) ’Visual categorization with bags of keypoints’, *in Workshop on statistical learning in computer vision, ECCV* , pp. 1–22.
58. Navneet, D. and Bill, T. (2005) ’Histograms of oriented gradients for human detection’, *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, l, pp. 886–893.
59. Mammeri, A., Zhou, D., Boukerche, A. and Almulla, M. (2014) ‘An efficient animal detection system for smart cars using cascaded classifiers’, *2014 IEEE International Conference on Communications (ICC)* pp. 1854–1859.
60. Mammeri, A., Boukerche, A., Feng, J. and Wang, R. (2013) ‘North-American speed limit sign detection and recognition for smart cars’, *2013 IEEE 38th Conference on Local Computer Networks Workshops (LCN Workshops)*, pp. 154–161.
61. Mao, L., Xie, M., Huang, Y. and Zhang, Y. (2010) ‘Preceding vehicle detection using Histograms of Oriented Gradients’, *2010 International Conference on Communications, Circuits and Systems (ICCCAS)*, pp. 354–358.
62. Yan, G., Yu, M., Yu, Y. and Fan, L. (2016) ‘Real-time vehicle detection using histograms of oriented gradients and AdaBoost classification’, *Optik*, 127(19), pp. 7941–7951.

63. Irhebhude, M.E., Nawahda,A. and Edirisinghe,E.A. (2016) ‘View invariant vehicle type recognition and counting system using multiple features’, *International Journal of Computer Vision and Signal Processing*, 6(1), pp. 20–32.
64. Chen, Z., Ellis, T. and Velastin, S.A. (2012) ’Vehicle detection, tracking and classification in urban traffic’, *2012 15th International IEEE Conference on Intelligent Transportation Systems*, pp. 951–956.
65. Wang, R., Zhang, L., Xiao, K., Sun, R. and Cui, L. (2014) ‘EasiSee: real-time vehicle classification and counting via low-cost collaborative sensing’, *IEEE Transactions on Intelligent Transportation Systems*, 15(1), pp. 414–424.
66. Dong, Z., Pei, M., He, Y., Liu, T., Dong, Y. and Jia, Y. (2014) ‘Vehicle type classification using unsupervised convolutional neural network’, *2014 22nd International Conference on Pattern Recognition*, pp. 172–177.
67. Wang, S., Liu, F., Gan, Z. and Cui, Z. (2016) ‘Vehicle type classification via adaptive feature clustering for traffic surveillance video’, *2016 8th International Conference on Wireless Communications & Signal Processing (WCSP)*, pp. 1–5.
68. Kim, P. and Lim, K. (2017) ‘Vehicle type classification using bagging and convolutional neural network on multi view surveillance image’, *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp. 914–919.
69. Xiao, J., Xiang, W. and Liu, Y. (2015) ‘Vehicle logo recognition by weighted multi-class support vector machine ensembles based on sharpness histogram features’, *IET Image Processing*, 9(7), pp. 527–534.
70. Boser, B.E., Guyon,I.M. and Vapnik,V.N. (1992) ‘A training algorithm for optimal margin classifiers’, *in Proceedings of the Fifth Annual Workshop of Computational Learning Theory*, pp. 144–152.
71. Breiman, L. (2001) ‘Random forests’, *Machine Learning*, 45(1), pp. 5–32.
72. Ho, T.K. (1995) ‘Random decision forests’, *1995 3rd International Conference on Document Analysis and Recognition*, pp. 278–282.
73. Bosch, A., Zisserman, A. and Munoz, X. (2007) ‘Image classification using random forests and ferns’, *2007 IEEE 11th International Conference on Computer Vision*, pp. 1–8.

74. Fei-Fei, L., Fergus, R. and Perona, P. (2004) ‘Learning generative visual models from few training examples: an incremental bayesian approach tested on 101 object categories’, *2004 IEEE CVPR Workshop of Generative Model Based Vision*, pp. 178–178.
75. Griffin, G., Holub, A. and Perona, P. (2007) ‘Caltech 256 object category dataset’, *Technical Report UCB/CSD-04-1366, California Institute of Technology*, pp. 1–20.
76. Zaklouta, F., Stanciulescu,B. and Hamdoun,O. (2011) ‘Traffic sign classification using K-d trees and random forests’, *2011 International Joint Conference on Neural Networks*, pp. 2151–2155.
77. Ali, S.M., Joshi, N., George, B. and Vanajakshi, L. (2012) ‘Application of random forest algorithm to classify vehicles detected by a multiple inductive loop system’, *2012 IEEE Conference on Intelligent Transportation Systems*, pp. 491–495.
78. Wright, J., Ma, Y., Mairal, J., Sapiro, G., Huang, T. and Yan, S. (2010) ‘Sparse representation for computer vision and pattern recognition’, *in Proceedings of IEEE*, 98(6), pp. 1031–1044.
79. Liu, T., Mi, J.X., Liu, Y. and Li, C. (2016) ‘Robust face recognition via sparse boosting representation’, *Neurocomputing*, 214, pp. 944–957.
80. Zhang, Z., Liang, Y., Bai, L. and Hancock, E.R. (2015) ‘Discriminative sparse representation for face recognition’, *Multimedia Tools and Applications*, 75(7), pp. 3973–3992.
81. Alskeini, N., Nguyen, K., Chandran, V. and Boles, W. (2018) ‘Face recognition: Sparse Representation vs. Deep Learning’, *2018 2nd International Conference on Graphics and Signal Processing (ICGSP)*, pp. 31–37.
82. Charfi, N., Trichili, H., Alimi, A. M. and Solaiman, B (2017) ‘Bimodal biometric system for hand shape and palmprint recognition based on sift sparse representation’, *Multimed Tools and Appl*ications, 76(20), pp. 20457–20482.
83. Wang, W., Tang, C., Wang, X., Luo, Y., Hu, Y. and Li, J. (2019) ‘Image object recognition via deep feature-based adaptive joint sparse representation’, *Journal of Computational Intelligence and Neuroscience*, pp. 1–9.

84. Moayedi, F., Azimifar, Z. and Boostani, R. (2015) 'Structured sparse representation for human action recognition', *Neurocomputing*, 161, pp. 38–46.

85. Sarkar, R. (2017) 'Dictionary learning and sparse representation for image analysis with application to segmentation, classification and event detection', *PhD Thesis, University of Virginia*.

86. Yue, C., Liang, J., Qu, B., Lu, Z., Li, B. and Han, Y. (2017) 'Sparse representation feature for facial expression recognition', *in Proceeding International Conference on Extreme Learning Machine*, pp. 12–21.

87. Bhateja, A.K., Sharma, S., Chaudhury, S. and Agrawal, N. (2015) 'Iris recognition based on sparse representation and k-nearest subspace with genetic algorithm', *in Pattern Recognition Letters*,73, pp.13–18.

88. Nalla, P.R. and Chalavadi, K.M. (2015) 'Iris classification based on sparse representations using on-line dictionary learning for large-scale de-duplication applications', *Springer Plus*, 4(1), pp. 1–10.

89. Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., LiuT., Wang, X. and Wang, G., Cai, J. and Chen, T. (2018) 'Recent advances in convolutional neural networks', *Pattern Recognition*, pp. 354–377.

90. Alom, M.Z., Taha, T.M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M.S., Hasan, M., Van Essen, B.C., Awwal, A.A. and Asari, V.K. (2019) 'A state-of-the-art survey on deep learning theory and architectures', *Electronics*, 8(3), pp. 1–67.

91. Indolia, S., Goswami, A., Mishra, S.P. and Asopa, P. (2018) 'Conceptual understanding of convolutional neural network- a deep learning approach', *International Conference on Computational Intelligence and Data Science (ICCIDS 2018), Procedia Computer Science*, 132, pp. 679–688.

92. Agarap, A.F. (2018) 'Deep learning using rectified linear units (relu)', *arXiv Priprint*, 1803.08375.

93. Liu, Y.H. (2018) 'Feature extraction and image recognition with convolutional neural networks', *In Journal of Physics: Conference Series* ,1087(6), pp. 1–7.

94. Abiyev, R.H. and Ma'aitah, M.K. S. (2018) 'Deep convolutional neural networks for chest diseases detection', *Journal of Healthcare Engineering, Hindawi*, pp. 1–11.

95. Scherer, D., Muller, A. and Behnke, S. (2010) ‘Evaluation of pooling operations in convolutional architectures for object recognition’, *2010 20th International Conference on Artificial Neural Networks (ICANN)*, pp. 92–101.

96. Basha, S.H.S., Dubey, S.R., Pulabaigari, V. and Mukherjee, S. (2019) ‘Impact of fully connected layers on performance of convolutional neural networks for image classification, *Neurocmputing*, 378, pp. 112–119.

97. Alamgeer, Z. Selvaperumal, S.K. Prum, S. and Fei, T.K. (2018) ‘Review of car make and model recognition systems’, *Journal of Applied Technology and Innovation*, 2(2), pp. 9–16.

98. Manzoor, M.A., Morgan, Y. and Bais, A. (2019) ‘Real-time vehicle make and model recognition system’, *MDPI: machine learning and knowledge extraction*, 1, pp. 611–629.

99. Manzoor, M.A. and Morgan, Y. (2017) ‘Vehicle make and model classification system using bag of SIFT features’, *In Proceedings of the 7th Annual IEEE Computing and Communication Workshop and Conference (CCWC)*, pp. 9–11.

100. AbdelMaseeh, M., Badreldin, I., Abdelkader, M.F. and El Saban, M. (2012) ‘Car make and model recognition combining global and local cues’ *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)*, pp. 910–913.

101. Pearce, G. and Pears, N. (2011) ‘Automatic make and model recognition from frontal images of cars’, *2011 8th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*, pp. 373–378.

102. Clady, X., Negri, P., Milgram, M., and Poulenard, R. (2008) ‘Multiclass vehicle type recognition system’, *In Artificial Neural Networks in Pattern Recognition (ANNPR)*, 5064, pp. 228–239.

103. Baran, R., Glowacz, A. and Matiolanski, A. (2015) ‘The efficient real-and non-real-time make and model recognition of cars’, *Multimedia Tools and Applications*, 74(12), pp. 4269–4288.

104. Lee, S., Gwak, J. and Jeon, M. (2013) ‘Vehicle model recognition in video’, *International Journal of Signal Processing, Image Processing and Pattern Recognition*, 6(2), pp. 175–184.

105. Zhang, B. (2013) Reliable classification of vehicle types based on cascade classifier ensembles', *IEEE Transactions on Intelligent Transportation Systems*, 14(1), pp. 322–332.

106. Chen, L., Hsieh, J-W., Yan, Y. and Chen, D. (2013) 'Vehicle make and model recognition using sparse representation and symmetrical SURFs', *2013 IEEE 16th International Conference on Intelligent Transportation Systems (ITSC)*, pp. 1143–1148.

107. Manzoor, M.A. and Morgan, Y. (2018) 'Vehicle make and model recognition using random forest classification for intelligent transportation systems', *2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 148–154.

108. [Online]. Available: http://mmplab.cs.ntou.edu.tw/MMR/.

109. Biglari, M., Soleimani, A. and Hassanpour, H. (2018) 'A cascaded part-based system for fine-grained vehicle classification', *IEEE Transaction on Intelligent Transportation Systems*,19(1), pp. 273–283.

110. Yang, L., Luo, P., Loy, C.C. and Tang, X. (2015) 'A large-scale car dataset for fine-grained categorization and verification', *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3973–3981.

111. Lu, L. and Huang, H. (2019) 'A Hierarchical scheme for vehicle make and model recognition from frontal images of vehicles', *IEEE Transactions on Intelligent Transportation Systems*, 20(5), pp. 1774–1786.

112. Ghassemi, S., Fiandrotti, A., Caimotti, E., Francini, G. and Magli, E. (2019) 'Vehicle joint make and model recognition with multiscale attention windows', *Signal Processing: Image Communication,*72, pp. 69–79.

113. Nazemi, A., Azimifar, Z., Shafiee, M.J. and Wong, A. (2020) 'Real-time vehicle make and model recognition using unsupervised feature learning', *IEEE Transactions on Intelligent Transportation Systems*, 21(7), pp. 1–11.

114. Iwanami, T., Goto, T., Hirano, S. and Sakurai, M. (2012) 'An adaptive contrast enhancement using regional dynamic histogram equalization," *2012 IEEE International Conference on Consumer Electronics (ICCE)*, pp. 719–722.

115. Bae, T.W., Ahn, S.H. and Altunbasak, Y. (2017) 'Automatic contrast enhancement by transfer function modification', *ETRI Journal*, 39(1), pp.76–86.

116. Kaur, M., Kaur, J. and Kaur, J. (2011) ‘Survey of contrast enhancement techniques based on histogram equalization’, *International Journal of Advanced Computer Science and Applications (IJACSA)*, 2(7), pp.137–141.
117. Chen, S.-D. and Ramli, A.R. (2003) ‘Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation, *IEEE Transactions on Consumer Electronics*, 49(4), pp. 1301–1309.
118. Sim, K.S., Tso, C.P. and Tan, Y.Y. (2007) ‘Recursive sub-image histogram equalization applied to gray scale images, *Pattern Recognition Letter*, 28, pp. 1209–1221.
119. Wang, C., Fang, Y., Zhao, H., Guo, C., Mita, S. and Zha, H. (2016) ‘Probabilistic Inference for Occluded and Multiview On-road Vehicle Detection’, *IEEE Transactions on Intelligent Transportation Systems*, 17(1), pp. 215–229.
120. S. R. E. Datondji, Y. Dupuis, P. Subirats and P. Vasseur, "A Survey of Vision-Based Traffic Monitoring of Road Intersections," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 10, pp. 2681-2698.
121. Velazquez-Pupo R, Sierra-Romero A, Torres-Roman D, Shkvarko YV, Santiago-Paz J, Gómez-Gutiérrez D, Robles-Valdez D, Hermosillo-Reynoso F, Romero-Delgado M. Vehicle Detection with Occlusion Handling, Tracking, and OC-SVM Classification: A High Performance Vision-Based System. *Sensors*. 2018.
122. Van Pham, H. and Lee, B.-R. (2015) ‘Front-view car detection and counting with occlusion in dense traffic flow’, *International Journal of Control, Automation and Systems*, 13**,** pp**.** 1150–1160.
123. Heidari, V. and Ahmadzadeh, M.R. (2013) ‘A method for vehicle classification and resolving vehicle occlusion in traffic images’, *In Pattern Recognition and Image Analysis (PRIA), 2013 First Iranian Conference on*, pp. 1–6.
124. Bertozzi, M., Broggi, A., Fascioli, A. and Nichele, S. (2000) ‘Stereo vision-based vehicle detection’, *Proceedings of the IEEE Intelligent Vehicles Symposium 2000 (Cat. No.00TH8511)*, pp. 39–44.
125. Chandel, H., Vatta, S. (2015) ‘Occlusion detection and handling: a review’, International Journal of Computer Applications, 120(10), pp. 33–38.

126. Perera, A.GA., Srinivas, C., Hoogs, A., Brooksby, G. and Hu, W. (2006) 'Multi object tracking through simultaneous long occlusions and split-merge conditions', *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, pp. 666–673.
127. Faro, A., Giordano, D. and Spampinato, C. (2011) 'Adaptive background modeling integrated with luminosity sensors and occlusion processing for reliable vehicle detection', in *IEEE Transactions on Intelligent Transportation Systems*, 12(4), pp. 1398–1412.
128. Gupte, S., Masoud, O., Martin, R.FK. and Papanikolopoulos, N.P. (2002) 'Detection and classification of vehicles', *IEEE Transactions on Intelligent Transportation Systems*, 3(1), pp. 37–47.
129. Huang, C.L. and Liao, W.C. (2004) 'A vision-based vehicle identification system', *Proceedings of the 17th International Conference on Pattern Recognition (ICPR) 2004*, 4, pp. 364–367.
130. Zhang, W., Jonathan Wu, Q.M., Yang, X. and Fang, X. (2008) 'Multilevel framework to detect and handle vehicle occlusion', *IEEE Transactions on Intelligent Transportation Systems,* 9(1), pp. 161–174.
131. Baş, E., Tekalp, A.M. and Salman, F.S. (2007) 'Automatic vehicle counting from video for traffic flow analysis', *2007 IEEE Intelligent Vehicles Symposium*, pp. 392–397.
132. Yang, T., Pan, Q., Li, J. and Li, S.Z. (2005) 'Real-time multiple objects tracking with occlusion handling in dynamic scenes', *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, 1, pp. 970–975.
133. Yung, N.H.C. and Lai, A.H.S. (1998) 'Detection of vehicle occlusion using a generalized deformable model', *Proceedings of the 1998 IEEE International Symposium on Circuits and Systems (Cat. No.98CH36187)*, 4, pp. 154–157.
134. Senior, A., Hampapur, A., Tian, Y.-L., Brown, L., Pankanti, S. and Bolle, R. (2006) 'Appearance models for occlusion handling', *Image and Vision Computing*, 24(11), pp. 1233–1243.
135. Li, Y., Tian, B., Li, B., Xiong, G., Zhu, F. and Wang, K. (2013) 'Vehicle detection with a part-based model for complex traffic conditions', *Proceedings of 2013 IEEE International Conference on Vehicular Electronics and Safety*, pp. 110–113.

136. Wu, B.-F., Kao, C.-C., Jen, C.-L., Li, Y.-F., Chen, Y.-H. and Juang, J.-H. (2014) 'A relative-discriminative-histogram-of-oriented gradients-based particle filter approach to vehicle occlusion handling and tracking', *IEEE Transactions on Industrial Electronics,* 61(8), pp. 4228–4237.

137. Pan, J. and Hu, B. (2007) 'Robust occlusion handling in object tracking', *2007 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8.

138. Ma, Y. and Chen, Q. (2010) 'Depth Assisted Occlusion Handling in Video Object Tracking*', Advances in Visual Computing (ISVC),* pp. 449–460.

139. Song, X. and Nevatia, R. (2005) 'A model-based vehicle segmentation method for tracking', *Tenth IEEE International Conference on Computer Vision (ICCV'05),* 1, pp. 1124–1131.

140. Pang, C.C.C., Lam, W.W.L. and Yung, N.H.C. (2004) 'A novel method for resolving vehicle occlusion in a monocular traffic image sequence', *IEEE Transactions on Intelligent Transportation Systems*, 5(3), pp. 129–141.

141. Rad, R. and Jamzad, M. (2005) 'Real time classification and tracking of multiple vehicles in highways', *Pattern Recognition Letters,* 26(10), pp. 1597–1607.

142. Pang, C.C.C., Lam, W.W.L. and Yung, N.H.C. (2007) 'A method for vehicle count in the presence of multiple-vehicle occlusions in traffic images', *IEEE Transactions on Intelligent Transportation Systems*, 8(3), pp. 441–459.

143. Shu, G., Dehghan, A., Oreifej, O., Hand, E. and Shah, M. (2012) 'Part-based multiple-person tracking with partial occlusion handling', *2012 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1815–1821.

144. ÜLKER, B. (2015) 'Automatic vehicle detection and occlusion handling at road intersections', *PhD Thesis, Middle East Technical University*.

145. Goyette, N., Jodoin, P.-M., Porikli, F., Konrad, J. and Ishwar, P. (2012) 'Change detection. net: a new change detection benchmark dataset', *2012 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, pp. 1–8.

146. Chen, Z. and Ellis, T. (2011) 'Self-adaptive gaussian mixture model for urban traffic monitoring system', *2011 IEEE International Conference on Computer Vision Workshops (ICCV Workshops)*, pp. 1769–1776.

147. St-Charles, P., Bilodeau, G.-A. and Bergevin, R. (2015) ‘Subsense: a universal change detection method with local adaptive sensitivity’, *IEEE Transactions on Image Processing*, 24(1), pp. 359–373.

148. Sanin, A., Sanderson, C. and Lovell, B.C. (2010) ‘Improved shadow removal for robust person tracking in surveillance scenarios’, *2010 20th International Conference on Pattern Recognition*, pp. 141–144.

149. Prati, A., Mikic, I., Trivedi, M.M. and Cucchiara, R. (2003) ‘Detecting moving shadows: algorithms and evaluation’, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(7), pp. 918–923.

150. Sklansky, J. (1982) ‘Finding the convex hull of a simple polygon’, *Pattern Recognition Letters,* 1(2), pp. 79–83.

151. Heidari, V. and Ahmadzadeh, M.R. (2013) ‘A method for vehicle classification and resolving vehicle occlusion in traffic images’, *2013 First Iranian Conference on Pattern Recognition and Image Analysis (PRIA)*, pp. 1–6.

152. Zhang, W., Wu, Q. M. J., Yang, X and Fang, X. (2008) ‘Multilevel framework to detect and handle vehicle occlusion’, *IEEE Transactions on Intelligent Transportation Systems*, 9(1), pp. 161–174.

153. Kumar, R., Arthanariee, A.M. (2013) ‘A Comparative Study of Image Segmentation using Edge-Based Approach’, *International Journal of Mathematical and Computational Sciences*, 7(3), pp. 510–514.

154. Liu, S. and Zhang, Y. (2019) ‘Detail-preserving underexposed image enhancement via optimal weighted multi-exposure fusion’, *IEEE Transactions on Consumer Electronics,* 65(3), pp. 303–311.

155. Felzenszwalb, P., McAllester, D. and Ramanan, D. (2008) ‘A discriminatively trained, multiscale, deformable part model’, *2008 26th IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* pp. 115–129.

156. Forsyth, D. (2014) ‘Object detection with discriminatively trained part-based models’, *IEEE Computer Society Press,* 47(2), pp. 6–7.

157. Boonsim, N. (2016) ‘Car make and model recognition under limited lighting conditions at night’, *PhD Thesis, University of Bedfordshire*.

158. Mendes, P. R., Neves, J. M., Tavares, A. and Menotti, D. (2011) ‘Towards an automatic vehicle access control system: license plate location’, *2011 IEEE International Conference on Systems, Man, and Cybernetics,* pp. 2916–2921.

159. Bai, H. and Changping, L. (2004) ‘A hybrid license plate extraction method based on edge statistics and morphology’, *in Proceedings of the 17th IEEE International Conference on Pattern Recognition (ICPR),* pp. 831–834.

160. Otsu, N. (1979) ‘A threshold selection method from gray-level histograms’, *IEEE Transactions on Systems, Man, and Cybernetics,* 9(1), pp. 62–66.

161. Jaderberg, M., Simonyan, K. and Zisserman, A. (2015) ‘Spatial transformer networks’, *in: Advances in Neural Information Processing Systems,* pp. 2017–2025.

162. Gritsch, G., Donath, N., Kohn, B. and Litzenberger, M. (2009) ‘Night-time vehicle classification with an embedded, vision system’, *2009 12th IEEE International Conference on Intelligent Transportation Systems (ITSC),* pp. 1–6.

163. Boonsim, N. and Prakoonwit, S. (2014) ‘An algorithm for accurate taillight detection at night’, *International Journal of Computer Applications,* 100(12), pp. 31–35.

164. Matas, J., Chum, O., Urban, M. and Pajdla, T. (2004) ‘Robust wide-baseline stereo from maximally stable extremal regions’, *Image and Vision Computing,* 22(10), pp. 761–767.

165. O’Malley, R., Glavin, M. and Jones, E. (2008) ‘Vehicle detection at night based on tail-light detection’, *In Proceedings of the First International Symposium on Vehicular Computing Systems*, pp. 1–5.

166. Gang, L., Zhang, M., Zhao, X. and Wang, S. (2015) ‘Improved genetic algorithm optimization for forward vehicle detection problems’, *Information 2015,* 6(3), 339–360.

167. Zhang, D. and Lu, G. (2004) ‘Review of shape representation and description techniques’, *Pattern Recognition*, 37(1), pp. 1–19.

168. Sajjanhar, A. and Lu, G. (1997) ‘A grid-based shape indexing and retrieval method’, *Australian Computer Journal,* 29(4), pp. 131–140.

169. Parte, R. S., Supriya, S., Ashwini, G., Pooja, G. and Kajal, k. (2016) ‘Carbohydrate contents detection in food using bag of feature’, *International Research Journal of Engineering and Technology (IRJET)*, 3(10), pp. 1–4.

170. Chougule, A. and Halkarnikar, P. (2011) ‘Building gaussian mixture shadow model for removing shadows in surveillance videos’, *information Technology and Mobile Communication, AIM 2011,* 147, pp. 190–195.

171. Amancio, D. R., Comin, C. H., Casanova, D., Travieso, G., Bruno, O. M., Rodrigues, F. A. and Costa, L. D. F. (2014) ‘A systematic comparison of supervised classifiers’, *PloS One 2014,* 9(4), pp. 1–14.

172. Li, X., Wang, L. and Sung, E. (2008) ‘AdaBoost with SVM-based component classifiers’, *Engineering Applications of Artificial Intelligence,* 21(5), pp. 785–795.

173. Valentini, G. and Dietterich, T. G. (2004) ‘Bias-variance analysis of support vector machines for the development of SVM-based ensemble methods’, *The Journal of Machine Learning Research,* 5, pp. 725–775.

174. Kotsiantis, S. B. (2007) ‘Supervised machine learning: a review of classification techniques’, *Informatica,* 31, pp. 249–268.

175. Domingos, P. (2012) ‘A few useful things to know about machine learning’, *Communications of the ACM,* 55(10), pp.78–87.

176. Hinton, G.E., Srivastava, N., Krizhevsky, A., Sutskever, I. and Salakhutdinov, R.R., 2012. Improving neural networks by preventing co-adaptation of feature detectors. *arXiv preprint arXiv:1207.0580*.

177. Chan, T.H., Jia, K., Gao, S., Lu, J., Zeng, Z. and Ma, Y., (2015) ‘PCANet: A simple deep learning baseline for image classification’, *IEEE transactions on image processing*, 24(12), pp. 5017–5032.

178. Lin, T.Y., RoyChowdhury, A. and Maji, S., (2015) ‘Bilinear CNN models for fine-grained visual recognition’, *2015 IEEE international conference on computer vision*, pp. 1449–1457.

179. Tian, L., Hong, X., Zhao, G., Fan, C., Ming, Y. and Pietikäinen, M. (2017) ‘PCANet-II: when PCANet meets the second order pooling’, *Eprint ArXiv171000166.*

180. Hong, X., Zhao, G., Pietikäinen, M. and Chen, X. (2014) ‘Combining LBP difference and feature correlation for texture description’, *IEEE Transactions on Image Processing*, 23(6), pp. 2557–2568.

181. Soon, F.C., Khaw, H.J. and Kanesan, J. (2019) ‘PCANet-based convolutional neural network architecture for a vehicle model recognition system’, *IEEE Transactions on Intelligent Transportation Systems, 20(2), pp. 749-759.*

APPENDIX A

LIST OF PUBLICATIONS

A.1 List of Journals

1. A.F.Abbas, U.U. Sheikh and M.H. Haji Mohd., ’Recognition of vehicle make and model in low light conditions’, *Bulletin of Electrical Engineering and Informatics*, 9(2),pp.550-557, 2020.

2. A.F.Abbas, U.U. Sheikh , F.T. Al-Dhief and M.H. Haji Mohd,’ A Comprehensive review of vehicle detection using computer vision’, *TELKOMNIKA Telecommunication, Computing, Electronics and Control,* 19(3), pp. 838-850, 2021.