DEEP LEARNING FOR MOBILE PHONE DETECTION WHILE DRIVING BY IMAGE RECOGNITION

YEOH MEI HWEI

A project report submitted in partial fulfilment of the
requirements for the award of the degree of
Master of Engineering (Computer and Microelectronic Systems)

School of Electrical Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

JULY 2020

DEDICATION

This thesis is dedicated for all my family and friends who support and encourage me throughout the project. I sincerely thank all of you.

ACKNOWLEDGEMENT

First, I would like to express my sincere gratitude and appreciation to my project supervisor Dr. Usman Ullah Sheikh for his continuous guidance, invaluable words of wisdom and patience throughout the project. I would like to thank him for contributing his time for me out of his hectic schedule. Without his support, my project cannot be completed.

Next, I would like to express my sincere appreciation and gratitude to my sponsorship INTEL MICROELECTRONICS (M) SDN BHD for offering and sponsoring me on this master taught course program.

Lastly, I would like to express my sincere appreciation and gratitude to my family and friends for their continues support and encouragement throughout the project.

ABSTRACT

Majority of the existing works are based on in-car camera system mounted inside the vehicles, which is more suitable to be implemented as driver assistance system. This is because most of the driver assistance systems only are available for advanced cars. Besides that, a large amount of training datasets is required to train the driver monitoring system. However, there are no existing datasets that are captured based on camera system mounted outside the vehicles, thus the total amount of dataset acquired is limited for this project. Therefore, the aim of conducting this thesis is to develop a camera-based automated image recognition system that is mounted outside the vehicles for detecting the driver using mobile phones for calling while driving. Since there are no datasets available for this project, the images are captured and collected using Fujifilm XT 10 with XF 35mm f2 lens at overhead bridge nearby Spice Arena, Penang, Malaysia. The captured time is from 5pm to 7.30 pm. There are a total of 2,340 images are captured and collected. However, about 42 % of the captured images are discarded, left with1,348 images are applicable to be the dataset. The proposed system framework is developed based on Faster R-CNN with Inception-V2 architecture by fine tuning the training configuration parameters. The model is proposed to train up to 20,000 steps with the total loss is less than 0.07. The duration for the training process is about 64 hours. In terms of performance evaluation of the model, it is based on detection evaluation metrics applied by COCO. It shows that the mAP for Intersection Over Union threshold of 0.50 obtained 97.75% for the model in localizing the object along with the classes and the mAR with 10 detections per image obtained 72.03% for the model in classifying the object. In terms of overall detection accuracy, it obtained 88.71% for the accuracy.

ABSTRAK

Kebanyakkan kerja sebelum ini adalah berdasarkan pada sistem kamera yang dipasangkan di dalam kenderaan. Ini adalah lebih sesuai dilaksanakan sebagai sistem bantuan pemandu kerana kebanyakkan sistem bantuan pemandu dipasangkan kepada kereta mewah sahaja. Selain itu, sejumlah besar data latihan perlu dikumpulkan untuk melatih sistem pengawasan pemandu. Namun, tiada data yang disediakan berdasarkan sistem kamera yang dipasangkan di luar kenderaan menyebabkan jumlah data yang dikumpulkan adalah terhad. Oleh itu, tujuan penyelidikan ini adalah untuk membina sistem pengenalan gambar automatik berdasarkan sistem kamera yang dipasangkan di luar kenderaan untuk mengesan pemandu yang menggunakan telefon bimbit untuk membuat panggilan semasa memandu. Gambar dirakam dan dikumpulkan dengan menggunakan Fujifilm XT 10 dengan XF 35mm f2 lens dan dipasangkan di jambatan berdekatan Spice Arena, Pulau Pinang, Malaysia. Waktu yang diambil adalah dari 5 petang hingga 7.30 malam. Terdapat sejumlah 2,340 gambar yang dikumpul. Namun, kira-kira 42% daripada gambar yang terkumpul telah dibuang dan terdapat sejumlah 1,348 gambar sahaja. Sistem yang dicadangkan adalah berdasarkan struktur Faster R-CNN dengan Inception-V2 dan mengemas kini parameter konfigurasi latihan. Model ini dicadangkan untuk melatih sehingga 20.000 langkah dengan jumlah kehilangan kurang daripada 0.07. Tempoh untuk proses latihan adalah sekira-kiranya 64 jam. Dari segi penilaian prestasi model, ia adalah berdasarkan metrik penilaian pengesanan yang diterapkan oleh COCO. Ini menunjukkan bahawa mAP dengan IOU ambang 0.50 memperolehi 97.75% dalam melokalisasi objek dan mAR dengan 10 pengesanan segambar memperolehi 72.03% dalam mengklasifikasikan objek. Dari segi ketepatan pengesanan keseluruhan, ia 88.71% untuk ketepatan.

.

TABLE OF CONTENTS

	TITLE		PAGE
	DECLARATION		**iii**
	DEDICATION		**iv**
	ACKNOWLEDGEMENT		**v**
	ABSTRACT		**vi**
	ABSTRAK		**vii**
	TABLE OF CONTENTS		**viii**
	LIST OF TABLES		**x**
	LIST OF FIGURES		**xi**
	LIST OF ABBREVIATIONS		**xiv**
	LIST OF SYMBOLS		**xv**
	LIST OF APPENDICES		**xvi**
1	**INTRODUCTION**		**1**
	1.1	Background	1
	1.2	Problem Statement	2
	1.3	Objectives	3
	1.4	Scope of Work	4
	1.5	Thesis Organization	4
2	**LITERATURE REVIEW**		**5**
	2.1	Neural Network	5
	2.2	Architecture of Neural Network	5
	2.3	Perceptron	7
	2.4	Convolutional Neural Networks	9
	2.5	Architecture of Convolutional Neural Network	10
	2.6	Architecture of Region-based Convolutional Neural Network Family	14
	2.7	Architecture of YOLO	16

2.8 Network Design of YOLO 19
2.9 YOLO Version 3 20
2.10 Related Works on Distracted Driver Detection System 22

3 METHODOLOGY 27
3.1 Overall Project Methodology 27
3.2 Proposed System Methodology 28
3.2.1 Software Tools Installation and Environment Setup 29
3.2.2 Image Acquisition 30
3.2.3 Data Preprocessing 31
3.2.4 Training Data and Testing Data Generation 33
3.2.5 Proposed Methodologies 33
3.3 Chapter Summary 33

4 RESULTS AND DISCUSSIONS 37
4.1 Discussions for Faster RCNN Model Results 37
4.2 Performance Evaluation between Existing Works and Proposed Work 52

5 CONCLUSION AND RECOMMENDATIONS 57
5.1 Conclusion 57
5.2 Recommendation for Future Works 57

REFERENCES 61

APPENDICES 65

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 2.1	Truth Table for Single Layer Perceptron with 2 Input	9
Table 2.2	Features, Prediction time and limitation for R-CNN Family	15
Table 2.3	Existing Works on Distracted Driver Detection System	23
Table 3.1	Tools Applied in Proposed System Framework	29
Table 3.2	Training and Testing Data Details	15
Table 4.1	Details for Detected Image Results without Passenger	41
Table 4.2	Details for Detected Image Results with Passenger	41
Table 4.3	Performance Evaluation Between The Existing Work And Proposed Work	55

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 2.1	Neural Network with Single Hidden Layer	6
Figure 2.2	Neural Network with Multiple Hidden Layer	6
Figure 2.3	Building Block of single layer perceptron	8
Figure 2.4	Heaviside Step Function	8
Figure 2.5	Architecture of Convolutional Neural Network	11
Figure 2.6	Convolution Operation in Convolutional Layer	11
Figure 2.7	Max and Average Pooling in Pooling Layer	12
Figure 2.8	ReLU in Activation Layer	13
Figure 2.9	Softmax in Fully-connected Layer	14
Figure 2.10	Overview Process in YOLO	16
Figure 2.11	Architecture Design of YOLO	19
Figure 2.12	Architecture Design of Darknet-53	20
Figure 2.13	Architecture Design of YOLOv3	21
Figure 3.1	Flow Chart for Project Flow	28
Figure 3.2	Flow Chart for Proposed Methodology	28
Figure 3.3	Example of Original Captured Image with Multiple Objects	30
Figure 3.4	Example of “Not Call” class - Right-handed Driver Image	32
Figure 3.5	Example of “Not Call” class - Left-handed Driver Image	32
Figure 3.6	Example of “Call” class - Right-handed Driver Image	32
Figure 3.7	Example of “Call” class - Left-handed Driver Image	32
Figure 3.8	Example of “Not Call” class - Right-handed Driver Labeled Image	32
Figure 3.9	Example of “Not Call” class - Right-handed Driver Label Annotation	33
Figure 3.10	High Level Diagram for Faster R-CNN with Inception-V2 Architecture	35

Figure 4.1	RPN Objectness Loss in Training	38
Figure 4.2	RPN Localization Loss in Training	38
Figure 4.3	Box Classifier Classification Loss in Training	39
Figure 4.4	Box Classifier Localization Loss in Training	39
Figure 4.5	Total Loss in Training	39
Figure 4.6	“Not Call” Detected Images: Full Face Right-handed Driver without Passenger	41
Figure 4.7	“Not Call” Detected Images: Full Face Left-handed Driver without Passenger	41
Figure 4.8	“Not Call” Detected Images: Half Face Right-handed Driver without Passenger	42
Figure 4.9	“Not Call” Detected Images: Half Face Left-handed Driver without Passenger	42
Figure 4.10	“Not Call” Detected Images: Only Up to shoulder Right-handed Driver without Passenger	42
Figure 4.11	“Not Call” Detected Images: Only Up to shoulder Left-handed Driver without Passenger	42
Figure 4.12	“Call” Detected Images: Full Face Right-handed Driver without Passenger	43
Figure 4.13	“Call” Detected Images: Full Face Left-handed Driver without Passenger	43
Figure 4.14	“Call” Detected Images: Half Face Right-handed Driver without Passenger	42
Figure 4.15	“Call” Detected Images: Half Face Left-handed Driver without Passenger	43
Figure 4.16	“Call” Detected Images: Only Up to shoulder Right-handed Driver without Passenger	44
Figure 4.17	“Call” Detected Images: Only Up to shoulder Left-handed Driver without Passenger	44
Figure 4.18	“Not Call” Detected Images: Full Face Right-handed Driver with Passenger	44
Figure 4.19	“Not Call” Detected Images: Full Face Left-handed Driver with Passenger	44
Figure 4.20	“Not Call” Detected Images: Half Face Right-handed Driver with Passenger	45

Figure 4.21	"Not Call" Detected Images: Half Face Left-handed Driver with Passenger	45
Figure 4.22	"Not Call" Detected Images: Only Up to shoulder Right-handed Driver with Passenger	45
Figure 4.23	"Not Call" Detected Images: Only Up to shoulder Left-handed Driver with Passenger	45
Figure 4.24	"Call" Detected Images: Only Up to shoulder Right-handed Driver with Passenger	46
Figure 4.25	"Call" Detected Images: Only Up to shoulder Left-handed Driver with Passenger	46
Figure 4.26	False Positive Images: Incorrect Predicted Class "Call"	46
Figure 4.27	False Positive Images: Incorrect Predicted Class "Not Call"	46
Figure 4.28	mAP with IOU Threshold 0.50	48
Figure 4.29	mAP with IOU Threshold 0.75	49
Figure 4.30	mAP with IOU Threshold [0.50, 0.95]	49
Figure 4.31	mAR with 1 Detections Per Image	51
Figure 4.32	mAR with 10 Detections Per Image	51
Figure 4.33	mAR with 100 Detections Per Image	51
Figure 4.34	Usage of Mobile Phone by Driver Detection in [28]	52
Figure 4.35	Hands on Steering Wheel Detection in [28]	53
Figure 4.36	Usage of Mobile Phone by Cyclists and Bikers Detection for [31]	54

LIST OF ABBREVIATIONS

AP	-	Mean Average Precision
AR	-	Mean Average Recall
CNN	-	Convolutional Neural Networks
COCO	-	Common Objects in Context
Fast R-CNN	-	Fast Region-based Convolutional Neural Networks
Faster R-CNN	-	Faster Region-based Convolutional Neural Networks
FPS	-	Frame Per Second
Inception-V2	-	Inception Version 2
mAP	-	Average Precision
mAR	-	Average Recall
mAR	-	Average Recall
MSFRCNN	-	Multiple Scale Faster-RCNN
NMS	-	Non-Maximum Suppression
R-CNN	-	Region-based Convolutional Neural Networks
ReLU	-	Rectified Linear Unit
ROI	-	Region of Interest
RPN	-	Region Proposal Network
TFRecord	-	Tensorflow Record File
YOLO	-	You-Only-Look-Once
YOLOv3	-	YOLO Version 3

LIST OF SYMBOLS

cfd	-	Box Confidence Score
$h(x)$	-	Heaviside Step Function
IOU	-	Intersection Over Union
Pr	-	Probability
x	-	Input Vector
w	-	Weight Vector

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	Config File for Faster R-CNN with Inception V2	65
Appendix B	Label Map for Config File	68
Appendix C	Python Script for Training	69
Appendix D	Python Script for Evaluation	72

CHAPTER 1

INTRODUCTION

1.1 Background

Mobile phones have become a necessity for people nowadays. In year 2000, only 12% of the global population subscribed to mobile phone. In year 2015, the mobile phone subscriptions rate of the global population had increased up to 97%, which is 8 times greater than the mobile phone subscriptions rate in year 2000 [1]. This is because nowadays mobile phone is commonly used by people for their work, entertainment, learning and communication. Based on [2], it stated that the average number of people touching their mobile phones per day can reach up to 2,617 and the average time of an American spending on their mobile phones for browsing per day can reach up to 5 hours. It shows that the prevalence of mobile phone usage has pervasive throughout the world.

With the rapid subscriptions of mobile phone throughout the world, distracted driving has become a critical topic in traffic safety. According to National Highway Traffic Safety Administration Analysis 2018 which carried out by National Safety Council, it stated that the total number of fatal distraction-affected traffic crashes has increased up to 2,628 where 349 traffic crashes are caused by the mobile phone usage while driving, which contributes about 13.3% of the total number of fatal distraction-affected traffic crashes. Mobile phones are always the main cause for driver distraction, which is defined as deviation of driver concentration from the driving task. In other words, it means that the driver conducted other activities while driving which leads to loss of attentions to the driving condition. Basically, the driver distraction can be classified into 3 types which are visual, manual and cognitive distractions. For visual distraction, it is occurred when the drivers take their eyes off the road. While, for manual distraction, it is occurred when the drivers take off their hands from the steering wheel. The driver is considered involving in the cognitive distraction when their minds are out of focusing to the driving conditions. Obviously, the acts of using a mobile phone while driving involved in all types of distraction, which may lead to property damages, severe injuries or loss of lives [3, 4].

In order to improve safety and responsible behavior among drivers, many countries enforce the law banning for usage of mobile phone while driving, such as Malaysia, Singapore and Australia. However, about 1% to 11% of drivers still use their mobile phones while driving [5]. Although, the traffic police officers are often to be the authority who being assigned for the traffic enforcement on highways and roads, the process is laborious and inefficient for them to monitor the driving behavioral for each driver visually. This is because it is often required a large amount of police traffic officers for setting several checkpoints at different location, which might facing a problem of lacking sufficient officer for the inspection operation. At the same time, it is often to be the dominant factor for causing traffic jam at the road as it consumed time for the officers to track car by car. Thus, a camera-based automated image recognition system for detecting the driver using their mobile phones for talking while driving is highly required by the traffic safety agencies, which is a highly efficient and inexpensive solution to the problems. With the automated enforcement system, it is used to track whether the driver making a phone call while driving and provide the tracking information to the traffic safety agencies. The system acts as a precaution in traffic safety by government with the purpose of reducing the total number of crashes that involving the usage of mobile phones while driving. At the same time, it acts as a reminder for drivers to be alert and attentive while driving for preventing unintentional property-damaged, injury and death.

1.2 Problem Statement

Majority of the prior works are based on the in-car camera system mounted inside the vehicles. The captured input data images are not suitable to be used for this project, it will be more suitable for driver assistance system. This is because it is not easy for government to enforce a law for all drivers to install the camera monitor system into the driver assistance system, impossible to expect all the cars have the driver assistance system which only available for highly advanced cars. Therefore, in order to monitor the driver behavioural on traffic, a driver monitoring system is required to be designed with camera system mounted outside the vehicles.

In order to implement Convolutional Neural Network in the system, it requires a large amount of training datasets for training the system to extract the same feature space and distribution. However, total amount of dataset acquired is limited for this project. Besides that, different researchers implement different image recognition system to detect for the usage of mobile phone while driving. But, the accuracy and computation time for the system varies with the complexity of the problem.

1.3 Objectives

The objective of this project is to develop a camera-based automated image recognition system for detecting the driver using mobile phones for calling while driving. Expected achievements in order to fulfill the objectives are:

i. To collect datasets for driving conditions of car driver in Malaysia.
ii. To design and develop a Convolutional Neural Network based approach deep learning system with high overall detection accuracy.
iii. To provide performance evaluation between the prior work with the proposed framework.

1.4 Scope of Work

The details of scope work for this project are described as follow:

i. The camera system is set at the overhead bridge for capturing the car driver's driving conditions from front view and captured during daylight.
ii. Datasets with excessive amount of reflection on windscreen and unclear are filtered.
iii. The detecting system limited to single object in an image for car drivers using their mobile phone for calling or not calling only, other distractions are not included.
iv. Assumption on bending driver's hand toward their head will be consider as an action for holding a mobile phone for calling while driving.

1.5 Thesis Organization

This project report consists of 5 chapters. Chapter 1 includes the background, problem statement, objectives and scope of work of the project. Chapter 2 discusses about the studies on the architecture of CNN and the related works on the driver distracted system. The software tools applied and proposed methods are discussed in chapter 3, the results and discussions are discussed in chapter 4. Lastly, chapter 5 discusses about the conclusion, future works and recommendations.

REFERENCES

[1] World Bank Blogs. (2019). Are cell phones becoming more popular than toilets?. [online] Available at: http://blogs.worldbank.org/opendata/are-cell-phones-becoming-more-popular-toilets [Accessed 16 Dec. 2019].

[2] King University Online. (2019). Cell Phone Addiction: Stats and Signs | King University Online. [online] Available at: https://online.king.edu/news/cell-phone-addiction/ [Accessed 16 Dec. 2019].

[3] Injury Facts. (2019). Distracted driving - Injury Facts. [online] Available at: https://injuryfacts.nsc.org/motor-vehicle/motor-vehicle-safety-issues/distracted-driving/ [Accessed 16 Dec. 2019].

[4] Insurance, F. (2019). Types of distracted driving: Visual, manual and cognitive. [online] Home. Available at: https://www.fmins.com/blog/types-of-distracted-driving/ [Accessed 17 Dec. 2019].

[5] Alkan, B., Balci, B., Elihos, A., & Artan, Y. (2019). Driver Cell Phone Usage Violation Detection using License Plate Recognition Camera Images. Proceedings of the 5th International Conference on Vehicle Technology and Intelligent Transport Systems. doi: 10.5220/0007725804680474

[6] Investopedia. (2019). Neural Network Definition. [online] Available at: https://www.investopedia.com/terms/n/neuralnetwork.asp [Accessed 20 Dec. 2019].

[7] Fong, S. F. Object Classification using Deep Learning. Master Thesis. Universiti Teknologi Malaysia, 2015.

[8] Radzi, S. A. Convolutional Neural Networks for Eace Recogntiton and Finger-Vein Biometric Identification. Ph.D dissertation. Universiti Teknologi Malaysia, 2014.

[9] Medium. (2019). Neural Networks for Beginners: Popular Types and Applications. [online] Available at: https://blog.statsbot.co/neural-networks-for-beginners-d99f2235efca [Accessed 20 Dec. 2019].

[10] GitHub. (2019). Multilayer Perceptron Example. [online] Available at: https://github.com/rcassani/mlp-example [Accessed 26 Dec. 2019].

[11] Medium. (2019). What the Hell is Perceptron?. [online] Available at: https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53 [Accessed 20 Dec. 2019].

[12] Nielsen, M. (2019). Neural Networks and Deep Learning. [online]. Available at: http://neuralnetworksanddeeplearning.com/chap1.html [Accessed 20 Dec. 2019].

[13] Rudzuan, M. F. A Fruit Sorting System Using HSV Colour Space and Deep Learning Technique. Bachelor of Degree Thesis. Universiti Teknologi Malaysia, 2019.

[14] Yeoh, H. P. Characterization of Ventricular Tachycardia and Ventricular Fibrillation Based On Convolutional Neural Network Deep Learning Algorithm. Master Thesis. Universiti Teknologi Malaysia, 2019.

[15] Ong, J. Y. Sentiment Analysis of Informal Malay's Tweet Using Deep Learning Method (Convolutional Neural Network). Master Thesis. Universiti Teknologi Malaysia, 2019.

[16] Medium. (2019). Understanding of Convolutional Neural Network (CNN) Deep Learning. [online] Available at: https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148 [Accessed 22 Dec. 2019].

[17] Medium. (2019). A Comprehensive Guide to Convolutional Neural Networks— the ELI5 way. [online] Available at: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53 [Accessed 22 Dec. 2019].

[18] AILEPHANT. (2019). ReLU function - AILEPHANT. [online] Available at: https://ailephant.com/glossary/relu-function/ [Accessed 24 Dec. 2019].

[19] Medium. (2019). Understand the Softmax Function in Minutes. [online] Available at: https://medium.com/data-science-bootcamp/understand-the-softmax-function-in-minutes-f3a59641e86d? [Accessed 24 Dec. 2019].

[20] Tan, L. F. An Automatic Malaysian Car Plate Recognition based on Deep Learning Approach. Bachelor of Degree Thesis. Universiti Teknologi Malaysia, 2019.

[21] Choo, Y. K. A DEEP LEARNING APPROACH USING DARKNET IN CAR PLATE DETECTION. Bachelor of Degree Thesis. Universiti Teknologi Malaysia, 2018.

[22] Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection", arXiv.org, 2019. [Online]. Available: https://arxiv.org/abs/1506.02640. [Accessed: 25- Dec- 2019].

[23] Medium. (2019). YOLO v3 theory explained. [Online]. Available: https://medium.com/analytics-vidhya/yolo-v3-theory-explained-33100f6d193. [Accessed: 26- Dec- 2019].

[24] Tsang, S. H. (2019). YOLOv3 — You Only Look Once (Object Detection). [online] Available at: https://towardsdatascience.com/review-yolov3-you-only-look-once-object-detection-eab75d7a1ba6 [Accessed 26 Dec. 2019].

[25] Artan, Y., Bulan, O., Loce, R. P.,Paul, P., (2014) Driver Cell Phone Usage Detection From HOV/HOTNIR Images, In IEEE Conf. on Comp. Vis. Pat. Rec.

[26] Berri, R. A., Silva, A. G., Parpinelli, R. S.., Girardi, E., Arthur, R., (2014). A Pattern Recognition System for Detecting Use of Mobile Phones While Driving, In arXiv:1408.0680v1.

[27] Seshadri, K., Juefei-Xu, F., Pal, D. K., Savvides, M., Thor, C., (2015). Driver Cell Phone Usage Detection on Strategic Highway Research Program (shrp2) Face View Videos, In Proc. IEEE Conf. CVPRW, pp. 35-4.

[28] Le, T. H. N., Zheng,Y., Zhu, C., Luu, K. and Savvides, M., (2016). Multiple Scale Faster-RCNN Approach to Driver's Cell-phone Usage and Hands on Steering Wheel Detection, in CVPR.

[29] Elqattan, Y., Moustafa M. N. and El-Shafey M. H., "System for Detecting and Reporting Cell Phone Distracted Drivers," 2019 11th International Symposium on Image and Signal Processing and Analysis (ISPA), Dubrovnik, Croatia, 2019, pp. 215-221. doi: 10.1109/ISPA.2019.8868481

[30] Nair A., Mansoori S., Moghe R., Shah P. and Talele K., "Driver Assistant System using Haar Cascade and Convolution Neural Networks(CNN)," 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2019, pp. 1261-1263. doi: 10.1109/ICOEI.2019.8862779

[31] Ulhaq A., He J. and Zhang Y., "Deep actionlet proposals for driver's behavior monitoring," 2017 International Conference on Image and Vision Computing New Zealand (IVCNZ), Christchurch, 2017, pp. 1-6. doi: 10.1109/IVCNZ.2017.8402447

[32] Singh Chandel, V. (2019). Selective Search For Object Detection (C++ / Python). [online] Learnopencv. Available at: <https://www.learnopencv.com/selective-search-for-object-detection-cpp-python/> [Accessed 13 June 2020].

[33] Ren, S., He, K., Girshick, R. and Sun, J., 2017. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(6), pp.1137-1149.

[34] Sharma, P. (2018). A Practical Implementation Of The Faster R-CNN Algorithm For Object Detection (Part 2 – With Python Codes). [online] Analytics Vidhya. Available at: <https://www.analyticsvidhya.com/blog/2018/11/implementation-faster-r-cnn-python-object-detection/?fbclid=IwAR3lmnq6mI7MwMr2WRfzejIzXzZHmtYjnI0LS3eF0O3ENWdzmVjhXIIoQbk> [Accessed 13 June 2020].

[35] MissingLink.ai. n.d. Building Faster R-CNN On Tensorflow: Introduction And Examples - Missinglink.Ai. [online] Available at: <https://missinglink.ai/guides/tensorflow/building-faster-r-cnn-on-tensorflow-introduction-and-examples/?fbclid=IwAR2ofMP5x0eW4J1niIBXLhXef634Ygny2pQS6pR4JfY00F9z7Z7VAKT9FDI> [Accessed 13 June 2020].

[36] Goswami, S. (2018). A Deeper Look At How Faster-RCNN Works. [online] Medium. Available at: <https://medium.com/@whatdhack/a-deeper-look-at-how-faster-rcnn-works-84081284e1cd> [Accessed 14 June 2020].

[37] KHAZRI, A. (2019). Faster RCNN Object Detection. [online] Medium. Available at: <https://towardsdatascience.com/faster-rcnn-object-detection-f865e5ed7fc4> [Accessed 14 June 2020].

[38] Gandhi, R. (2018). R-CNN, Fast R-CNN, Faster R-CNN, YOLO — Object Detection Algorithms. [online] Medium. Available at: <https://towardsdatascience.com/r-cnn-fast-r-cnn-faster-r-cnn-yolo-object-detection-algorithms-36d53571365e> [Accessed 14 June 2020].