HUMAN DETECTION FOR SEARCH AND RESCUE OPERATIONS USING EMBEDDED ARTIFICIAL INTELLIGENCE

AHMED ABDULLAH HUSSEIN AL-AZZANI

A project report submitted in fulfilment of the
requirements for the award of the degree of
Master of Engineering (Mechatronic and Automatic Control)

School of Electrical Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

OCTOBER 2022

DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have been that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

ACKNOWLEDGEMENT

Firstly, I would like to thank Allah (God) the most merciful, the most gracious for giving me the strength to complete my thesis, I also would like to thank my supervisor Prof. Madya Ts. Ir. Dr. Mohd Ridzuan for his guidance and motivational and academic support throughout this project. Secondly, I would love to express my thankful and appreciation expressions to my father who always supported me along my academic journey. My wife's support during my study when it was much needed is also appreciated. I am grateful to Allah and my family members.

ABSTRACT

Unmanned aerial vehicles (drones) have been increasingly used in search and rescue operations as a tool to detect humans in an area of disaster where the rescue team is unable to reach them. Human detection is the most important task in a rescue plan. Currently, deep learning and Internet of Things (IoT) technologies are used to automatically detect humans from footage taken from drones, however, the hardware used in such methods consumes high power, requires high processing capability, long computational time, and a constant internet connection which are not effective to be deployed in all scenarios. This project aims to utilize transfer learning to build a human detection model with mean average precision (mAP@0.5) above 90% and compare deep learning models in aspects of the size of the model, computational requirement, and mAP. Furthermore, to compress the final model to be deployed to an edge device for the propose of using edge computing where the computation requirement for the deep learning model is all made on-chip. The development of this project is based on multi-datasets using the TensorFlow v2 framework and virtual machine Google Colaboratory. The dataset used in this project is extracted from two datasets named SARD and SeaDroneSee both are aerial images of humans, and the labeling of the dataset is made using the Roboflow platform. The models used are pre-trained single shot detector models namely MobileNet v2 and EfficientDet-D1, the last shows a better accuracy of 97.3% mAP@0.5 however MobileNet v2 consumes much less GPU for training at around 4.6 GB while maintaining relatively high accuracy of 95.5% mAP@0.5. Lastly, the trained MobileNet v2 model is quantized to 6.4 MB. At the end of this project, a deep learning model for human detection for search and rescue operations is compressed and ready to be deployed to an embedded artificial intelligence device.

ABSTRAK

Kenderaan udara tanpa pemandu (drone) semakin banyak digunakan dalam operasi mencari dan menyelamat sebagai alat untuk mengesan manusia di kawasan bencana di mana pasukan penyelamat tidak dapat mencapai mereka. Pengesanan manusia adalah tugas paling penting dalam rancangan menyelamat. Pada masa ini, pembelajaran mendalam dan teknologi Internet of Things (IoT) digunakan untuk mengesan manusia secara automatik daripada rakaman yang diambil daripada dron, namun, perkakasan yang digunakan dalam kaedah sedemikian menggunakan kuasa tinggi, memerlukan keupayaan pemprosesan yang tinggi, masa pengiraan yang panjang dan sambungan internet yang berterusan yang tidak berkesan untuk digunakan dalam semua senario. Projek ini bertujuan untuk menggunakan pembelajaran pemindahan untuk membina model pengesanan manusia dengan purata ketepatan purata (mAP@0.5) melebihi 90% dan membandingkan model pembelajaran mendalam dalam aspek saiz model, keperluan pengiraan dan mAP. Tambahan pula, untuk memampatkan model akhir yang akan digunakan pada peranti tepi untuk cadangan menggunakan pengkomputeran tepi di mana keperluan pengiraan untuk model pembelajaran mendalam semuanya dibuat pada cip. Pembangunan projek ini adalah berdasarkan berbilang set data menggunakan rangka kerja TensorFlow v2 dan mesin maya Google Colaboratory. Set data yang digunakan dalam projek ini diekstrak daripada dua set data bernama SARD dan SeaDroneSee kedua-duanya adalah imej udara manusia dan pelabelan set data dibuat menggunakan platform Roboflow. Model yang digunakan adalah model pengesan pukulan tunggal terlatih iaitu MobileNet v2 dan EfficientDet-D1, yang terakhir menunjukkan ketepatan yang lebih baik iaitu 97.3% mAP@0.5 namun MobileNet v2 menggunakan lebih sedikit GPU untuk latihan pada sekitar 4.6 GB sambil mengekalkan ketepatan yang agak tinggi 95.5% mAP@0.5. Akhir sekali, model MobileNet v2 terlatih dikuantisasikan kepada 6.4 MB. Pada penghujung projek ini, model pembelajaran mendalam untuk pengesanan manusia untuk operasi mencari dan menyelamat dimampatkan dan sedia untuk digunakan pada peranti kecerdasan buatan terbenam.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

IoT	-	Internet of Things
AI	-	Artificial Intelligence
UAV	-	Unmanned Aerial Vehicle
CV	-	Computer Vision
DL	-	Deep Learning
ML	-	Machine Learning
TF	-	TensorFlow
TinyML	-	Tiny Machine Learning
CNN	-	Convolutional Neural Network
RNN	-	Recurrent Neural Networks
ANN	-	Artificial Neural Network
GPU	-	Graphics Processor Unit
CPU	-	Central Processing Unit
TPU	-	Tensor Processing Unit
YOLO	-	You Only Look Once
FOMO	-	Fast Object More Object
LTE	-	Long Term Evolution
IPSAR	-	Image Processing for Search and Rescue
SAR		Search and Rescue
mAP	-	Mean Average Precision

LIST OF SYMBOLS

mAP@	-	Mean Average Precision at Intersection over Union Threshold

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Problem Background

A search and rescue (SAR) operation is the process of finding and helping those who are in need or immediate danger. Numerous specialized sub-fields fall under the broad category of search and rescue, and these are often decided by the type of terrain the search is done over. These include land and sea search and rescue. The most common disaster in Malaysia is a flood, it is a natural disaster often caused by heavy rainfall, rapid snowmelt, or a storm surge such as the one that occurred more recently in Malaysia in December 2021. It is one of the most destructive events that might happen, causing loss of life, severe damage to properties, and huge economic and environmental impact. Due to global climate change flood events are expected to occur more frequently and more damaging. Therefore, a real-time automated system is needed for disaster rescue planning to analyse, and plan more efficiently.

Conventional rescue plan involves the deployment of helicopters and inflatable boats to search and evacuate people stranded, recently the technology of the internet of things (IoT) and drones have been used to replace the conventional rescue plan but these techniques have many challenges such as the dependence on internet connectivity at all time and data privacy another issue might be facing is when the drone take footage of the affected area the drone needs to send the collected data to the on-ground station so the can be analyzed using machine learning algorithm either on a powerful computer to locate any humans in the area before sending it to the rescue team or using cloud computing.

Internet of things (IoT) sensors are such sensors installed on the ground and are still used in some cases, but it has some disadvantages sensors must always be connected to the internet and they only cover a limited area, that’s what drives AI to be introduced. Artificial intelligence (AI) is a tool used to mimic human intelligence by machines, especially by computers. Recently there has been a continuous study to put AI into use to analyze disasters damages and predict them more specifically using computer vision (CV) which is a system that is used to teach computers to interpret the visual world by mimicking the capability of the human visual system by using deep learning (DL) to resemble human eyes functionality.

Embedded AI is an emerging subfield of AI, it is a technique of using machine learning (ML) and DL at devices such as microcontrollers via software without requiring huge computing ability, in other words, embedded AI is the combination of an embedded system equipped with an application of AI. More recently embedded AI has brought more opportunities to develop a self-reliance application, for instance when using a drone for rescue disaster management, the drone can decide on its own instantly.

TensorFlow (TF) is an open-source library for numerical computation and used for machine learning, it was developed by Google in 2015 since then google and many other companies use it.TF provides the tools needed for developers to build machine learning applications, it is also highly portable to a variety of devices and platforms which makes it one of the keys for building embedded AI.

Tiny machine learning (TinyML) is the most promising type of machine learning due to its capability to compress deep learning networks such CNNs into a 45x18mm microcontroller which brings the sense of embedded AI so when it is attached to a drone, it enables it to become a self-reliance system to detect human stranded in flooded areas without depending on the internet connectivity nor the need for powerful computing equipment.

1.2 Problem Statement

Current rescue operation lacks real-time monitoring due to the requirement of current technology to make inference using cloud and on-ground station inference while delaying the rescue operation response. Furthermore, the current method used is far from being a cost-effective and mainly internet-connection dependency.

1.3 Research Objectives

The objectives of the research are:

(a) To utilize transfer learning for a deep learning model to detect humans in SAR operation

(b) To compare deep learning models for human detection for SAR operation

(c) To evaluate and validate the system.

1.4 Research Scopes

The project begins with data extraction a total of 800 images from SeaDroneSee and SARD datasets to be labelled and used during the development of the deep learning models then research on transfer learning for object detection using TensorFlow version 2 and which will be developed using Python and then quantize to be deployed to embedded artificial intelligence device using TensorFlow Lite. Lastly, validation and comparison of both deep learning models, in this project single shot detector models are used namely MobileNet v2 and EfficientDet-D1 models.

1.5 Project Outlines

This project report contains five chapters. The first chapter provides an overview of the project, including the problem statement, the objective of the project, and the project specification. The second chapter is a literature review of the important components of the project topologies as well as the research gap from previous work done by other researchers. The discussion of the method used in this project is represented in the third chapter of this thesis. The outcome of the project work is represented in the fourth chapter before being concluded in the fifth chapter.

REFERENCES

[1] P. Dalvinder and S. Grewal, "A Critical Conceptual Analysis of Definitions of Artificial Intelligence as Applicable to Computer Engineering," Ver. I. [Online]. Available: www.iosrjournals.org

[2] N. Gupta, "A Literature Survey on Artificial Intelligence." [Online]. Available: www.ijert.org

[3] W. Blewitt, G. Ushaw, and G. Morgan, "Applicability of GPGPU computing to real-time AI solutions in games," *IEEE Trans Comput Intell AI Games*, vol. 5, no. 3, pp. 265–275, 2013, doi: 10.1109/TCIAIG.2013.2258156.

[4] J. R. Hu, J. Chen, B. K. Liew, Y. Wang, L. Shen, and L. Cong, "Systematic co-optimization from chip design, process technology to systems for GPU AI chip," in *2018 International Symposium on VLSI Technology, Systems and Application, VLSI-TSA 2018*, Jul. 2018, pp. 1–2. doi: 10.1109/VLSI-TSA.2018.8403802.

[5] Nvidia, "https://www.nvidia.com/en-us/data-center/dgx-2/," May 2022.

[6] S. S. Gill *et al.*, "Transformative effects of IoT, Blockchain and Artificial Intelligence on cloud computing: Evolution, vision, trends and open challenges," *Internet of Things (Netherlands)*, vol. 8. Elsevier B.V., Dec. 01, 2019. doi: 10.1016/j.iot.2019.100118.

[7] Y. Ampatzidis, V. Partel, and L. Costa, "Agroview: Cloud-based application to process, analyze and visualize UAV-collected data for precision agriculture applications utilizing artificial intelligence," *Comput Electron Agric*, vol. 174, Jul. 2020, doi: 10.1016/j.compag.2020.105457.

[8] F. Saeik *et al.*, "Task offloading in Edge and Cloud Computing: A survey on mathematical, artificial intelligence and control theory solutions," *Computer Networks*, vol. 195. Elsevier B.V., Aug. 04, 2021. doi: 10.1016/j.comnet.2021.108177.

[9] I. H. Sarker, M. M. Hoque, M. K. Uddin, and T. Alsanoosy, "Mobile Data Science and Intelligent Apps: Concepts, AI-Based Modeling and

Research Directions," *Mobile Networks and Applications*, vol. 26, no. 1, pp. 285–303, Feb. 2021, doi: 10.1007/s11036-020-01650-z.

[10] M. del Carmen Rodríguez-Hernández and S. Ilarri, "AI-based mobile context-aware recommender systems from an information management perspective: Progress and directions," *Knowl Based Syst*, vol. 215, Mar. 2021, doi: 10.1016/j.knosys.2021.106740.

[11] S. D'Alfonso, "AI in mental health," *Current Opinion in Psychology*, vol. 36. Elsevier B.V., pp. 112–117, Dec. 01, 2020. doi: 10.1016/j.copsyc.2020.04.005.

[12] Y. C. Jheng *et al.*, "A novelty route for smartphone-based artificial intelligence approach to ophthalmic screening," *Journal of the Chinese Medical Association*, vol. 83, no. 10. Wolters Kluwer Health, pp. 898–899, Oct. 01, 2020. doi: 10.1097/JCMA.0000000000000369.

[13] D. Liu, H. Kong, X. Luo, W. Liu, and R. Subramaniam, "Bringing AI to edge: From deep learning's perspective," *Neurocomputing*, vol. 485, pp. 297–320, May 2022, doi: 10.1016/j.neucom.2021.04.141.

[14] C. Mwase, Y. Jin, T. Westerlund, H. Tenhunen, and Z. Zou, "Communication-efficient distributed AI strategies for the IoT edge," *Future Generation Computer Systems*, vol. 131. Elsevier B.V., pp. 292–308, Jun. 01, 2022. doi: 10.1016/j.future.2022.01.013.

[15] D. Gunduz, P. de Kerret, N. D. Sidiropoulos, D. Gesbert, C. R. Murthy, and M. van der Schaar, "Machine Learning in the Air," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 10, pp. 2184–2199, Oct. 2019, doi: 10.1109/JSAC.2019.2933969.

[16] *2017 IEEE Custom Integrated Circuits Conference (CICC) : April 30 2017-May 3 2017.*

[17] T. Ogino, "Simplified multi-objective optimization for flexible IoT edge computing," in *Proceedings - 2021 4th International Conference on Information and Computer Technologies, ICICT 2021*, Mar. 2021, pp. 168–173. doi: 10.1109/ICICT52872.2021.00035.

[18] W. Bao, C. Wu, S. Guleng, J. Zhang, K.-L. A. Yau, and Y. Ji, "Edge computing-based joint client selection and networking scheme for federated learning in vehicular IoT," *China Communications*, vol. 18, no. 6, pp. 39–52, Jun. 2021, doi: 10.23919/jcc.2021.06.004.

[19] N. Karvonen, J. Nilsson, D. Kleyko, and L. L. Jimenez, "Low-power classification using FPGA - An approach based on cellular automata, neural networks, and hyperdimensional computing," in *Proceedings - 18th IEEE International Conference on Machine Learning and Applications, ICMLA 2019*, Dec. 2019, pp. 370–375. doi: 10.1109/ICMLA.2019.00069.

[20] P. P. Ray, "A review on TinyML: State-of-the-art and prospects," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 4. King Saud bin Abdulaziz University, pp. 1595–1623, Apr. 01, 2022. doi: 10.1016/j.jksuci.2021.11.019.

[21] A. Capotondi, M. Rusci, M. Fariselli, and L. Benini, "CMix-NN: Mixed Low-Precision CNN Library for Memory-Constrained Edge Devices," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 67, no. 5, pp. 871–875, May 2020, doi: 10.1109/TCSII.2020.2983648.

[22] W. Li, W. Deng, R. She, N. Zhang, Y. Wang, and W. Ma, "Edge Computing Offloading Strategy Based on Particle Swarm Algorithm for Power Internet of Things," in *2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering, ICBAIE 2021*, Mar. 2021, pp. 145–150. doi: 10.1109/ICBAIE52039.2021.9389919.

[23] C. Pena-Caballero, D. Kim, A. Gonzalez, O. Castellanos, A. Cantu, and J. Ho, "Real-time road hazard information system," *Infrastructures (Basel)*, vol. 5, no. 9, Sep. 2020, doi: 10.3390/INFRASTRUCTURES5090075.

[24] B. Sudharsan *et al.*, "TinyML Benchmark: Executing Fully Connected Neural Networks on Commodity Microcontrollers," in *7th IEEE World Forum on Internet of Things, WF-IoT 2021*, Jun. 2021, pp. 883–884. doi: 10.1109/WF-IoT51360.2021.9595024.

[25] G. Crocioni, D. Pau, J. M. Delorme, and G. Gruosso, "Li-Ion Batteries Parameter Estimation with Tiny Neural Networks Embedded on Intelligent IoT Microcontrollers," *IEEE Access*, vol. 8, pp. 122135–122146, 2020, doi: 10.1109/ACCESS.2020.3007046.

[26] H. Han and J. Siebert, “TinyML: A Systematic Review and Synthesis of Existing Research,” Mar. 2022, pp. 269–274. doi: 10.1109/icaiic54071.2022.9722636.

[27] R. David *et al.*, “TensorFlow Lite Micro: Embedded Machine Learning on TinyML Systems,” Oct. 2020, [Online]. Available: http://arxiv.org/abs/2010.08678

[28] J. Kwon and D. Park, “Hardware/software co-design for tinyml voice-recognition application on resource frugal edge devices,” *Applied Sciences (Switzerland)*, vol. 11, no. 22, Nov. 2021, doi: 10.3390/app112211073.

[29] Edge Impulse, “Edge Impulse,” *Algorithms for TinyML*, May 20, 2022. https://www.edgeimpulse.com/ (accessed May 20, 2022).

[30] V. Janapa Reddi *et al.*, “Widening Access to Applied Machine Learning with TinyML,” *Harv Data Sci Rev*, Jan. 2022, doi: 10.1162/99608f92.762d171a.

[31] S. Ghamari *et al.*, “Quantization-Guided Training for Compact TinyML Models,” Mar. 2021, [Online]. Available: http://arxiv.org/abs/2103.06231

[32] H. Miao and F. X. Lin, “Enabling Large Neural Networks on Tiny Microcontrollers with Swapping,” Jan. 2021, [Online]. Available: http://arxiv.org/abs/2101.08744

[33] J. D. de Leon and R. Atienza, “Depth Pruning with Auxiliary Networks for TinyML,” Apr. 2022, [Online]. Available: http://arxiv.org/abs/2204.10546

[34] W. Li, W. Deng, R. She, N. Zhang, Y. Wang, and W. Ma, “Edge Computing Offloading Strategy Based on Particle Swarm Algorithm for Power Internet of Things,” in *2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering, ICBAIE 2021*, Mar. 2021, pp. 145–150. doi: 10.1109/ICBAIE52039.2021.9389919.

[35] A. Altan, S. Karasu, and E. Zio, “A new hybrid model for wind speed forecasting combining long short-term memory neural network, decomposition methods and grey wolf optimizer,” *Appl Soft Comput*, vol. 100, Mar. 2021, doi: 10.1016/j.asoc.2020.106996.

[36] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, "Deep learning for visual understanding: A review," *Neurocomputing*, vol. 187, pp. 27–48, Apr. 2016, doi: 10.1016/j.neucom.2015.09.116.

[37] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks." [Online]. Available: http://code.google.com/p/cuda-convnet/

[38] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," Sep. 2014, [Online]. Available: http://arxiv.org/abs/1409.1556

[39] D. S. Breland, S. B. Skriubakken, A. Dayal, A. Jha, P. K. Yalavarthy, and L. R. Cenkeramaddi, "Deep Learning-Based Sign Language Digits Recognition from Thermal Images with Edge Computing System," *IEEE Sens J*, vol. 21, no. 9, pp. 10445–10453, May 2021, doi: 10.1109/JSEN.2021.3061608.

[40] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks." [Online]. Available: https://github.com/liuzhuang13/DenseNet.

[41] A. G. Howard *et al.*, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," Apr. 2017, [Online]. Available: http://arxiv.org/abs/1704.04861

[42] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Dec. 2018, pp. 4510–4520. doi: 10.1109/CVPR.2018.00474.

[43] M. Tan and Q. v Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks."

[44] Institute of Electrical and Electronics Engineers and IEEE Electronics Packaging Society, *IEEE Electrical Design of Advanced Packaging and Systems Symposium (EDAPS 2018) : Hotel TAJ, Chandigarh.*

[45] A. R. Pathak, M. Pandey, and S. Rautaray, "Application of Deep Learning for Object Detection," in *Procedia Computer Science*, 2018, vol. 132, pp. 1706–1717. doi: 10.1016/j.procs.2018.05.144.

[46] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection.” [Online]. Available: http://pjreddie.com/yolo/

[47] X. Long *et al.*, “PP-YOLO: An Effective and Efficient Implementation of Object Detector.” [Online]. Available: https://github.com/PaddlePaddle/

[48] W. Liu *et al.*, “SSD: Single Shot MultiBox Detector.” [Online]. Available: https://github.com/weiliu89/caffe/tree/ssd

[49] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks.” [Online]. Available: https://github.com/

[50] “Image Acquisition.”

[51] E. Karamuz, R. J. Romanowicz, and J. Doroszkiewicz, “The use of unmanned aerial vehicles in flood hazard assessment,” in *Journal of Flood Risk Management*, Dec. 2020, vol. 13, no. 4. doi: 10.1111/jfr3.12622.

[52] D. Hernández, J. M. Cecilia, J. C. Cano, and C. T. Calafate, “Flood Detection Using Real-Time Image Segmentation from Unmanned Aerial Vehicles on Edge-Computing Platform,” *Remote Sens (Basel)*, vol. 14, no. 1, Jan. 2022, doi: 10.3390/rs14010223.

[53] M. M. Hasan *et al.*, “Search and rescue operation in flooded areas: A survey on emerging sensor networking-enabled IoT-oriented technologies and applications,” *Cogn Syst Res*, vol. 67, pp. 104–123, Jun. 2021, doi: 10.1016/j.cogsys.2020.12.008.

[54] V. Wolfe, W. Frobe, V. Shrinivasan, T.-Y. Hsieh, and H. M. Gates, “Feasibility Study of Utilizing 4G LTE Signals in Combination with Unmanned Aerial Vehicles for The Purpose of Search and Rescue of Avalanche Victims (Increment 1) Research Report Team Members.”

[55] A. Arteaga, S. Cespedes, and C. Azurdia-Meza, “Vehicular Communications over TV White Spaces in the Presence of Secondary Users,” *IEEE Access*, vol. 7, pp. 53496–53508, 2019, doi: 10.1109/ACCESS.2019.2912144.

[56] B. Mobedi and G. Nejat, “3-D active sensing in time-critical urban search and rescue missions,” *IEEE/ASME Transactions on*

Mechatronics, vol. 17, no. 6, pp. 1111–1119, 2012, doi: 10.1109/TMECH.2011.2159388.

[57] H. Ren, D. Anicic, and T. A. Runkler, “The synergy of complex event processing and tiny machine learning in industrial IoT,” in *DEBS 2021 - Proceedings of the 15th ACM International Conference on Distributed and Event-Based Systems*, Jun. 2021, pp. 126–135. doi: 10.1145/3465480.3466928.

[58] A. Brasoveanu, M. Moodie, and R. Agrawal, “Textual evidence for the perfunctoriness of independent medical reviews,” in *CEUR Workshop Proceedings*, 2020, vol. 2657, pp. 1–9. doi: 10.1145/nnnnnnn.nnnnnnn.

[59] N. Aldahoul, A. Q. Md Sabri, and A. M. Mansoor, “Real-Time Human Detection for Aerial Captured Video Sequences via Deep Models,” *Comput Intell Neurosci*, vol. 2018, 2018, doi: 10.1155/2018/1639561.

[60] D. Božić-Štulić, Ž. Marušić, and S. Gotovac, “Deep Learning Approach in Aerial Imagery for Supporting Land Search and Rescue Missions,” *Int J Comput Vis*, vol. 127, no. 9, pp. 1256–1278, Sep. 2019, doi: 10.1007/s11263-019-01177-1.

[61] H. M. Mohan, S. Anitha, R. Chai, and S. H. Ling, “Edge Artificial Intelligence: Real-Time Noninvasive Technique for Vital Signs of Myocardial Infarction Recognition Using Jetson Nano,” *Advances in Human-Computer Interaction*, vol. 2021, 2021, doi: 10.1155/2021/6483003.

[62] S. Mantowsky, F. Heuer, S. Saqib Bukhari, M. Keckeisen, and G. Schneider, “ProAI: An Efficient Embedded AI Hardware for Automotive Applications - A Benchmark Study.” [Online]. Available: https://www.raspberrypi.org/

[63] R. Chen and Q. Gu, “YOLO with embedded DenseNet Approach to detect Human Interaction (Computer Vision).”

[64] E. Lygouras, N. Santavas, A. Taitzoglou, K. Tarchanidis, A. Mitropoulos, and A. Gasteratos, “Unsupervised human detection with an embedded vision system on a fully autonomous UAV for search and rescue operations,” *Sensors (Switzerland)*, vol. 19, no. 16, Aug. 2019, doi: 10.3390/s19163542.

[65] N. M. K. Dousai and S. Loncaric, “Detection of humans in drone images for search and rescue operations,” in *ACM International Conference Proceeding Series*, Jan. 2021, vol. PartF168985, pp. 69–75. doi: 10.1145/3449365.3449377.

[66] B. Kiefer, D. Ott, and A. Zell, “Leveraging Synthetic Data in Object Detection on Unmanned Aerial Vehicles,” Dec. 2021, [Online]. Available: http://arxiv.org/abs/2112.12252

[67] W. Rahmaniar and A. Hernawan, “Real-time human detection using deep learning on embedded platforms: A review,” *Journal of Robotics and Control (JRC)*, vol. 2, no. 6. Department of Agribusiness, Universitas Muhammadiyah Yogyakarta, pp. 462-468Y, Nov. 01, 2021. doi: 10.18196/jrc.26123.

[68] L. A. Varga, B. Kiefer, M. Messmer, and A. Zell, “SeaDronesSee: A Maritime Benchmark for Detecting Humans in Open Water.” [Online]. Available: https://seadronessee.cs.uni-tuebingen.de.