## Appendix 3: Project Proposal Form

**COM748 MSc Research Project Proposal**

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| **Problem Statement (100 words):**  People with visual impairments are less likely to go into an environment they are not familiar with. This can have negative impacts on their health and wellbeing. Obstacle detection and warning can improve the mobility and safety of visually impaired people, particularly in unfamiliar environments. To enable this, obstacles first need to be detected and then localised. Navigation information, to avoid the obstacle, then needs to be communicated to the visually impaired person, using different modalities such as voice, tactile, vibration.  This project proposes the use of machine learning (ML) methods, within an embedded system, to develop a solution which can detect obstacles in the path of a visually impaired user who are navigating within an indoor environment.  Several tasks will need to be completed to determine the system's feasibility. First, an evaluation of different sensor modalities will be undertaken to select the most suitable sensor (or combination of sensors). Then a dataset will be gathered covering a range of obstacle detection and avoidance scenarios. This dataset will then be used to train, test, and validate several Deep Learning (DL) and ML models to understand which is best at detecting and localising obstacles. Development work will then be done to allow this model to be implemented on a constrained device and the performance of the final model will be assessed against key parameters. |
| **Summary of Literature (500 words):**  Many articles have been written on the topic of obstacle detection, some of these, such as [1], uses mobile devices, which also use algorithms to detect the presence of obstacles, which while not being the focus of the proposed project, this work offers interesting insights into the used of potential sensors, such as proximity sensors.  Others, such as [2] offer insights into how machine learning can be used to carry out Real-Time Ranging and Localisation and discusses a few different approaches to labelling data which are interesting and offer useful background to the proposed work. The use two different labelling methods – one is a simple multi-class labelling system, and the other is a grid labelling system. This work also discussed the performance of several classification models which was very insightful – the authors showed that tree-based models along with Stochastic Gradient Boost performed better than linear models. The paper also discussed the which of the labelling methods they investigated showed the best performance. As such, this paper contains a lot of useful information related to the proposed work.  The proposed work’s goal is to access the feasibility of a DL/ML model running on what is referred to as a “constrained device”. Commonly listed constraints would be the availability of onboard memory, and a limited power source. Another common tern for a constrained device would be devices that are on “the edge”. The work presented in [3] offers a discussion on topics like the future of Machine Learning at the edge, as well as a discussion on Machine Learning/Deep Learning algorithms, it also presents a discussion on how Machine Learning can be brought to the edge, discussing architectures and hardware, and wireless standards for Artificial Intelligence-enabled devices. As such, the work in [3] provides a wide ranging and extremely useful background to the topic of Machine Learning and Deep Learning on constrained devices.  The work presented in [4] used a thermal imaging camera and provides some useful insights into data collection as well as a discussion on the system architecture. The work then goes on to discuss the use of a form of CNN and highlighted some of the problems encountered when training on the AlexNet network – specifically lighting, which may be an issue for the work proposed here, depending on sensor type, and as such, is something to keep in mind.  Finally, a slightly older paper is presented in [5]. While this paper is older, it provides a very useful entry point into machine learning at the edge. The work discusses some of the early stages of so-called embeddedML development, looking at work done using smart phones and how non-CPU processors, such as DSPs can play an important role in reducing deep networks to allow them to be used on a constrained device. The paper also discusses methods for overcoming the constraints of an embedded system, which includes a compression model which allow deep neural networks to fit and operate on embedded systems. |
| **Description of Data/ Hardware to be used (100 word) please include links where possible:**  The data will likely have to be gathered during this project, as no suitable, publicly available dataset has been found. A good system for data collection would be the Arduino micro-controller, paired with an ultrasonic sensor, or a similar sensor. The Arduino IDE would be used for code development.  The data will to be gathered for a few situations, such as a hallway with no obstacles in it as well as a hallway with an obstacle placed on the left-hand side of the hallway, more data with an obstacle in the centre of the hallway, and then on the right-hand side of the hallway. Data will also need to be gathered for obstacles of different shapes and sizes, because, while an obstacle is an obstacle, we will want the model to train on as wide a dataset as the timeline will allow us to gather. |
| **Description of development to be undertaken including tools to be used (300 words):**  The hardware used in this project will be an Arduino based micro-controller, such as the Arduino Nano 33 BLE Sensor development kit, along with some type of peripheral devices, for example an ultrasonic sensor, or potentially a microwave sensor, which will be used for data capture. Depending on how the system is set up, there may be a need for some external memory, such as an SD card for data storage – if needed, this extra storage would only be needed in the data collect phase of the project. The code used on the Arduino will be developed in the standard Arduino IDE. Other hardware will be the obstacles. Examples of obstacles could be flowerpots of various sizes, steps or ladders, a chair outside an office or hallway table, and so on.  When the data is ready to be processed. Several models from both the Deep Learning and Machine Learning approaches will be selected and implemented using the data, in TensorFlow. At the end of this process, the best preforming model will be selected, and this will be optimised in TensorFlow Lite. It should be noted that if the results for several models show similar performance, there may be a case to optimise each in TensorFlow Lite. For further evaluation.  Once the model (or models) has been optimised, they will be deployed to the Arduino using the Arduino IDE, with the performance evaluated against a number of metrics. The evaluation metrics could be factors such as correct decision making, latency, memory usage, power consumption and so on. |
| **Risk Factors/Health and Safety Issues/Ethical Issues**:  When gathering the data, I will use an area that members of the public do not have access to, or I will tape off the area I am using for data collection, because the data collection will involve placing obstacles are various points of a hallway.  I will gather the data myself and no University lab setting with volunteers will be used |
| **References (recommended number 3):**  [1] [1] Khairul Azim Bin Za’aba and Lau Bee Theng, “Edge Based Obstacle Detection Model Focused on Indoor Floor-Based Obstacles,” in *2019 IEEE 9th Symposium on Computer Applications & Industrial Electronics (ISCAIE)*, 2019, pp. 202–207. doi: 10.1109/ISCAIE.2019.8743866.  [2] [2] R. Sattiraju, J. Kochems, and H. D. Schotten, “Machine Learning Based Obstacle Detection for Automatic Train Pairing,” Nov. 2018, [Online]. Available: http://arxiv.org/abs/1811.12228  [3] [3] M. Merenda, C. Porcaro, and D. Iero, “Edge machine learning for ai-enabled iot devices: A review,” *Sensors (Switzerland)*, vol. 20, no. 9, May 2020, doi: 10.3390/s20092533.  [4 [4] S. Quinn *et al.*, “A Thermal Imaging Solution for Early Detection of Pre-ulcerative Diabetic Hotspots; A Thermal Imaging Solution for Early Detection of Pre-ulcerative Diabetic Hotspots,” *Annu Int Conf IEEE Eng Med Biol Soc*, pp. 1737–1740, 2019, doi: 10.1109/EMBC.2019.8856900.  [5] N. D. Lane, S. Bhattacharya, A. Mathur, P. Georgiev, C. Forlivesi, and F. Kawsar, “Squeezing Deep Learning into Mobile and Embedded Devices,” *Prevasive Computing*, pp. 82–88, Jul. 2017, doi: 10.1109/MPRV.2017.2940968. |