MESH Literature Review

Low-Cost Sonobuoy for Passive Acoustic Detection and Classification of Marine Vessels

Jonathan Walsh, 7678721, Bachelor of Mechatronic Engineering

Date: 12/07/2026

Nomenclature and Abbreviations

Symbol	Description	Units
f	Frequency	Hz
P	Power	W
V	Voltage	V
I	Current	A
T	Temperature	°C
t	Time	s
λ	Acoustic wavelength	m
c	Speed of sound in water	m/s
dB	Sound pressure level (decibel)	dB
kHz	Kilohertz	Hz × 10^3
MHz	Megahertz	Hz × 10^6

ABBREVIATION	MEANING
AE	Autoencoder
AI	Artificial Intelligence
ANN	Artificial Neural Network
ASW	Anti-Submarine Warfare
BMS	Battery Management System

CAPSE-VIT	Channel Attention Pyramid Squeeze-Excitation Vision Transformer
CATFISH	Classification Algorithm with Trainable Filter-banks
CNN	Convolutional Neural Network
CMOE	Conditional Mixture of Experts
CTD	Conductivity, Temperature and Depth
DEMON	Detection of Envelope Modulation on Noise
DSP	Digital Signal Processing
EVMD	Enhanced Variational Mode Decomposition
FFT	Fast Fourier Transform
GMM	Gaussian Mixture Model
GPS	Global Positioning System
GRU	Gated Recurrent Unit
HMM	Hidden Markov Model
IMF	Intrinsic Mode Function
ICL	Interpretable Contrastive Learning
IOT	Internet of Things
KNN	K-Nearest Neighbours
LDA	Linear Discriminant Analysis
LI-ION	Lithium-ion
LOFAR	Low Frequency Analysis and Recording
LSTM	Long Short-Term Memory
MCU	Microcontroller Unit
MESH	Modular Economical Sonobuoy Heuristic
ML	Machine Learning
MVP	Minimum Viable Product
NCSLSC	Nowra Culburra Surf Life Saving Club
PCB	Printed Circuit Board
PPE	Personal Protective Equipment
PWM	Pulse Width Modulation

R&D	Research and Development
RF	Radio Frequency
RNN	Recurrent Neural Network
SCAE	Separable Convolution-Based Autoencoder
SNR	Signal-to-Noise Ratio
SOP	Standard Operating Procedure
SPL	Sound Pressure Level
SVM	Support Vector Machine
SWSS	Shallow Water Surveillance Systems
TRL	Technology Readiness Level
UATR	Underwater Acoustic Target Recognition
UOW	University of Wollongong
USB	Universal Serial Bus
VIT	Vision Transformer
WIL	Work Integrated Learning
WI-FI	Wireless Fidelity
XGBOOST	Extreme Gradient Boosting

Acknowledgements

Son Lam Phung as Academic Supervisor

Col Lawrence as Operational Supervisor

Brad Stappenbelt as Discipline Coordinator

Faisel Tubbal as Discipline Coordinator

Burak Turfanda as Administrative Support

Mates at UOW Mechatronic Society and UOW Motorsport Society

Contents

Introduction

This document reports the feasibility of the 420-hour professional experience project known as MESH (Modular Economical Sonobuoy Heuristic). This project aims to design and evaluate a low-cost, embedded hydrophone system for passive acoustic detection and classification of marine vessels. The research focuses on instrumentation design, embedded digital signal processing, and acoustic feature-based classification under realistic deployment conditions to satisfy the Professional Experience Requirements for an Undergraduate Engineering Degree as stipulated by Engineers Australia [1]. More information can be found at the project website [2]. Assessing the feasibility of this project is necessary to ensure technical, operational, schedule, safety, ethical, environmental, regulatory, and stakeholder satisfaction. This has been completed by identifying the required tasks and their resources to satisfy them.

This 420-hour professional experience project proposes the design and evaluation of a low-cost, embedded hydrophone system for passive acoustic detection and classification of marine vessels. The research focuses on instrumentation design, embedded digital signal processing, and acoustic feature-based classification under realistic deployment conditions.

Aligned with Defence Innovation, Science and Technology priorities in Trusted Autonomous Systems and Information Warfare [3], this project proposes a Modular Economical Sonobuoy Heuristic (MESH). The system adopts a software-first, hardware-second design philosophy [4]. It emphasises hydrophone instrumentation, embedded digital signal processing (DSP), and autonomous interpretation, targeting deployment via low-cost, commercially available aerial platforms. Budget has been calculated with focus on achieving the objectives with minimal hardware cost.

Literature Review

The purpose of this literature review is to detail marine vessel acoustic signature classification methods, their usage contexts, and their implementation in hardware. Understanding this background is crucial to characterising marine vessel acoustic signature classification methods performance in a prototype system.

Strategic Context

The significance of this research is informed by the MESH's potential littoral surveillance impact in the strategic context of Anti-Submarine Warfare, Illegal fishing, and Search and Rescue. This research addresses these areas through controlled laboratory and field experiments assessing detection reliability and vessel discrimination performance in realistic coastal conditions.

Anti-Submarine Warfare

The Australian Maritime Strategy 2035 [5] and the 2024 National Defence Strategy [6] prioritises the defence of Australia's coastline, with particular emphasis on uncrewed systems supporting Anti-Submarine Warfare (ASW). Surface and subsurface vessels generate acoustic signatures through propulsion, which can be exploited for detection and classification [7]. In littoral environments, submarines exploit cluttered terrain and mask passive signatures within ambient noise, reducing the effectiveness of active and passive sonar. A development goal of Shallow Water Surveillance Systems (SWSS) is to counteract acoustic masking of submarines [8].

Surveillance of Illegal fishing

Commonwealth Scientific and Industrial Research Organisation (CSIRO), in partnership with Microsoft [9], has developed isolated and networked remote surveillance systems. Upon the detection of illegal, unreported and unregulated (IUU) fishing activities by local machine learning models, border and fisheries authorities are alerted in real-time via satellite or mobile networks [10]. A development goal is a cost-effective alternative to traditional monitoring methods like vessel inspections and satellite tracking, which are often too expensive or logistically impossible at large scale.

Surveillance for Search and Rescue

The effectiveness of passive sonobuoys in surveillance for search and rescue is constrained by the negligible or inherently weak acoustic signatures of targets such as submerged flight data recorders and their underwater locator beacons (ULBs). Developments advances in weak signal detection, such as stochastic resonance-based methods and signal enhancement techniques like mixing and normalising stochastic resonance (MNSR) [11], suggest potential pathways to improve detectability when active sonar isn't viable.

Sonobuoy Systems

The operational requirements of each application determine the selection of sonobuoy architecture, influencing design parameters such as manufacturability, cost, communication method, sensing capability, endurance, and deployment strategy. Existing sonobuoy and shallow water surveillance systems provide valuable design insights into low-power operation, modular hardware architectures, and distributed sensing networks. Building upon these principles, MESH applies recent advances in embedded digital signal processing, edge-based machine learning inference, and low-power wireless communications to develop a low-cost, autonomous passive acoustic sensing platform for coastal vessel detection and classification. While not intended to replicate the capability of military surveillance systems, MESH demonstrates how modern embedded technologies can enable scalable and affordable maritime surveillance algorithm prototyping for research, environmental monitoring, and future defence applications.

Military sonobuoys and SWSS

Conventional Military sonobuoy systems and emerging Shallow Water Surveillance Systems (SWSS) form complementary components of modern anti-submarine warfare (ASW) architectures, enabling distributed acoustic sensing across littoral and open-ocean environments [8]. Air-deployed A-size sonobuoys, such as the AN/SSQ-53D(3) [12] Directional Frequency Analysis and Recording (DIFAR) sonobuoy, are launched from maritime patrol aircraft or helicopters [13] using cartridge-assisted deployment mechanisms, allowing rapid establishment of configurable acoustic surveillance fields. Following water entry, the sonobuoy deploys a surface float containing a 1 W VHF telemetry transmitter (136-173.5 MHz) while a directional hydrophone array descends to a programmable operating depth of 30, 60, 120 or 300 m, stabilising within approximately 100-240 s depending on deployment depth. The hydrophone provides both omnidirectional and directional acoustic sensing over a 5 Hz-2.4 kHz frequency range, enabling the detection of narrowband, broadband and transient acoustic emissions generated by submarines and surface vessels for a maximum of 8 hours. Comparable sonobuoys have been developed by Elbit Systems [14] and the Barra Sonobuoy [15].

In contrast, SWSS concepts extend persistent undersea monitoring through semi-fixed or seabed-deployed sensor networks designed for long-duration surveillance in shallow water environments where acoustic clutter and multipath effects reduce detection reliability. Systems such as the Advanced Deployable System (ADS), Autonomous Off-Board Surveillance Sensor (AOSS), Deployable Autonomous Distributed System (DADS), Seaweb, and PLUSNet demonstrate evolving approaches to distributed passive acoustic sensing, often integrating hydrophones, magnetometers, and communication nodes to enable cooperative or networked detection. These architectures prioritise persistence, multistatic fusion, and wide-area situational awareness over the expendability and rapid deployment characteristics of sonobuoys.

Compared with conventional military sonobuoys and SWSS, MESH adopts a fundamentally different design philosophy. Rather than functioning as an expendable, aircraft-deployed sensor integrated into large-scale ASW networks, MESH is designed as a low-cost, reusable floating sensing platform incorporating embedded digital signal processing, onboard machine learning inference, and LoRa-based telemetry to enable autonomous vessel detection and classification.

The lightweight and modular design of MESH provides the potential for rapid deployment using small unmanned aerial systems (UAS), vessels, or manual deployment methods, reducing the logistical requirements and operational costs associated with conventional airborne launch platforms such as helicopters or maritime patrol aircraft. Although MESH currently lacks the directional sensing capability and cooperative localisation performance of systems such as DIFAR sonobuoys, its modular architecture provides a pathway towards future multi-node deployment and distributed acoustic localisation. This approach enables scalable maritime monitoring capabilities while reducing acquisition and deployment costs by several orders of magnitude. A comparison between existing SWSS architectures detailed in the Emerging Disruptive Assessment Symposium [8] and MESH is presented for each system in Table (i) and generally in Table (ii).

System	*Developer / Program*	*Deployment Method*	*Sensor Configuration*	*Communication*	*Primary Purpose*	*Endurance*	*Operational Status*	*Estimated Cost*
Advanced Deployable System (ADS) (AN/WQR-5)	US Navy	Rapidly deployable seabed line arrays	Multiple passive acoustic line arrays	Connected surveillance network	Wide-area surveillance of submarines, ships and mine-laying operations	Extended duration	Reached operational testing but not adopted into service	>$50 million
Autonomous Off-Board Surveillance Sensor (AOSS)	SPAWAR / ONR	Aircraft or surface ship deployed sonobuoy	14 hydrophones, 3 magnetometers, 1 electric field sensor	Acoustic link to receiver buoy, RF uplink to aircraft/satellite	ASW and ISR barrier surveillance	Up to 90 days	Development program (mid-1990s)	Not publicly available
Deployable Autonomous Distributed System (DADS)	ONR	Distributed seabed sensor nodes	Acoustic and magnetic sensors connected by serial cables	Cooperative wired network	Cooperative detection and tracking of submarines and surface vessels	Long-term seabed deployment	Experimental sea trials (2005-2009)	Not publicly available

Seaweb	SPAWAR & Naval Postgraduate School	Distributed underwater sensor network	Various underwater sensors and autonomous vehicles	Underwater acoustic networking	Underwater communication, networking and command of distributed assets	Long-term network operation	Ongoing research and experimentation	Research platform
Persistent Littoral Undersea Surveillance Network (PLUSNet)	ONR & research partners	Fixed seabed and mobile sensor network	Acoustic and mobile underwater sensors	Semi-autonomous sensor network	Persistent littoral undersea surveillance	Long-duration deployment	Research program (2005-2016+)	Research platform
MESH Modular Economical Sonobuoy Heuristic (Proposed)	University of Wollongong	Rapid deployment, floating sonobuoy	Single passive hydrophone (expandable to multi-node array)	LoRa (AU915 MHz) to shore base station	Autonomous detection and classification of marine vessels with future localisation capability	Hours (dependant on power consumption of AI and battery capacity)	Prototype research system	~AUD $300 per node

Table (i) sonobuoy system-by-system comparison to MESH.

CHARACTERISTIC	SWSS	MESH
COST	Millions to tens of millions of dollars	Approximately AUD $300 per node
PLATFORM	Seabed arrays or specialised sonobuoys	Floating passive sonobuoy
DEPLOYMENT	Military vessels, aircraft, specialist operators	Small vessel or drone
COMMUNICATIONS	Acoustic networks, RF relay, satellite	LoRa to local base station
AI CLASSIFICATION	Limited public information	Embedded DSP and machine learning classification
LOCALISATION	Multi-sensor cooperative tracking	Future Time-of-Arrival (ToA) multi-node extension
PRIMARY USERS	Defence organisations	Research, maritime surveillance, search and rescue, future defence applications
SCALABILITY	High capability, high cost	High scalability through low-cost distributed deployment

Table (ii). General sonobuoy system comparison to MESH.

Together, sonobuoy and SWSS approaches underpin multi-platform ASW sensor fusion, where airborne, surface, and seabed systems are combined to improve classification performance of marine vessel acoustic signatures under varying environmental conditions. Current areas of development in SWSS include rapid deployment, local real-time processing, and cost-effective manufacture. Existing rapid-deployment sonobuoys, while effective for deep water ASW, are typically high-cost, heavy, and single-use, with limited suitability for littoral surveillance [13]. Deployment often requires crewed aircraft or specialised rotary-wing uncrewed aerial systems, creating logistical and economic barriers to coast-wide coverage [16].

Commercial and Research Buoys

This study is significant as it advances the practical deployment of economical, autonomous underwater acoustic surveillance systems for littoral environments. From an applied perspective, it supports scalable and reusable monitoring solutions relevant to coastal security, maritime safety, and environmental awareness, reducing reliance on high-cost, single-use sonobuoys. From a theoretical perspective, the research contributes to understanding trade-offs between hydrophone instrumentation quality, embedded processing complexity, power consumption, and classification accuracy within resource-constrained systems. These insights inform the design of future low-cost passive acoustic sensing architectures that balance performance with deployability and endurance.

Recent developments in low-cost Internet of Things (IoT) [17] aquatic sensing have demonstrated the feasibility of deploying distributed floating sensor networks for persistent environmental monitoring. Unlike conventional military sonobuoys and SWSS architectures, these systems are designed primarily for oceanographic data collection, coastal monitoring, and scientific observation rather than acoustic detection of vessels. However, their emphasis on low-cost hardware, autonomous operation, wireless communication, and scalable deployment provides relevant design parallels for MESH.

The LoRaWAN-based marine monitoring buoy developed by Majumder *et al.* [18] integrates environmental sensors with long-range low-power wireless communication to enable remote monitoring of marine conditions. The platform is designed around the limitations of conventional ocean monitoring systems, which often rely on expensive fixed infrastructure, research vessels, or satellite-connected buoys. By incorporating LoRaWAN telemetry, the system enables low-cost transmission of environmental measurements such as water quality parameters, reducing deployment and operational costs. However, the platform is primarily focused on passive environmental data acquisition and does not incorporate acoustic sensing, onboard signal processing, or machine-learning-based classification.

Similarly, the Open LoRa Buoy (OLB) developed by Dreyer *et al* [19]. demonstrates an open-source approach for coastal water measurement using inexpensive commercial hardware and LoRa communication. The OLB architecture prioritises accessibility, reproducibility, and community-driven development by providing a modular platform for collecting coastal environmental measurements. The system demonstrates that reliable maritime sensing can be achieved using low-cost embedded electronics rather than specialised oceanographic instrumentation. Compared with MESH, OLB shares the concept of a modular floating sensing node with long-range low-power communication; however, its sensing objectives are limited to physical ocean parameters rather than acoustic vessel detection.

Trevathan and Schmidtke's [20] open-source IoT aquatic environmental sensing platform further demonstrates the potential of distributed low-cost aquatic sensor networks. Developed within an Australian research context, the platform explores the use of open hardware, IoT connectivity, and community-accessible technologies for aquatic monitoring applications. Similar to MESH, this approach focuses on reducing barriers to deployment through inexpensive, scalable sensor nodes. However, the platform is intended for environmental monitoring applications and does not incorporate acoustic signal processing, autonomous target detection, or maritime situational awareness capabilities.

Compared with these environmental monitoring platforms, MESH adopts a different operational objective by applying low-cost IoT principles to maritime acoustic surveillance.

Rather than measuring water conditions, MESH uses a passive hydrophone, embedded digital signal processing, and machine-learning inference to identify and classify marine vessel signatures. The use of LoRa communication provides a comparable low-power telemetry approach, enabling distributed deployment without requiring expensive satellite communication or dedicated RF infrastructure.

The primary advantage of MESH compared with existing IoT aquatic platforms is the integration of intelligent edge processing. Environmental monitoring buoys generally transmit sensor measurements for later analysis, whereas MESH performs onboard acoustic feature extraction and classification, reducing communication requirements and enabling near-real-time detection. While the environmental platforms demonstrate proven approaches for low-cost marine deployment, MESH extends these concepts towards autonomous maritime awareness applications with full utilisation of computational resources.

A comparison between existing IoT aquatic sensing platforms and MESH is presented in Table (iii) and Table (iv).

System	**Developer / Program**	**Deployment Method**	**Sensor Configuration**	**Communication**	**Primary Purpose**	**Endurance**	**Operational Status**	**Estimated Cost**
LoRaWAN Marine Monitoring Buoy	Majumder *et al.*, University of Cagliari	Floating marine buoy deployment	Environmental sensors for marine condition monitoring	LoRaWAN long-range wireless communication	Remote ocean environmental monitoring	Long-duration dependent on battery/solar configuration	Research prototype	Low-cost prototype (<$1000 estimated)
Open LoRa Buoy (OLB)	Dreyer *et al.*, University of Oslo / Norwegian Meteorological Institute	Floating coastal buoy	Modular environmental sensors for coastal water measurements	LoRa communication	Open-source coastal environmental monitoring	Long-duration deployment	Open-source research platform	Low-cost commercial components
Open-source IoT Aquatic Environmental Sensing Platform	Trevathan & Schmidtke, Griffith University / Substation33	Distributed aquatic sensor nodes	Environmental monitoring sensors	IoT wireless communication	Accessible aquatic environmental monitoring	Application dependent	Research prototype / open-source platform	Low-cost

MESH Modular Economical Sonobuoy Heuristic (Proposed)	University of Wollongong	Rapid deployment floating sonobuoy	Passive hydrophone with expandable multi-node acoustic array	LoRa AU915 MHz telemetry to shore station	Autonomous marine vessel detection and classification	Hours (battery and processing dependent)	Prototype research system	~AUD $300 per node

Table (iii) Commercial and Research Buoy system-by-system comparison to MESH.

CHARACTERISTIC	IOT AQUATIC MONITORING PLATFORMS	MESH (PROPOSED)
PRIMARY OBJECTIVE	Environmental monitoring and oceanographic data collection	Autonomous vessel detection and acoustic surveillance
COST	Low-cost compared with traditional oceanographic buoys	Approximately AUD $300 per node
PLATFORM	Floating environmental monitoring buoy	Floating passive acoustic sonobuoy
DEPLOYMENT	Research vessels, coastal stations, manual deployment	Small vessels, UAS, or manual deployment
SENSORS	Temperature, water quality, environmental parameters	Passive hydrophone, expandable acoustic array
COMMUNICATION	LoRa/LoRaWAN/IoT wireless telemetry	LoRa AU915 MHz telemetry
DATA PROCESSING	Primarily remote data collection and analysis	Embedded DSP and machine-learning classification
AI CLASSIFICATION	Generally not implemented	Onboard acoustic classification
LOCALISATION CAPABILITY	Geographic measurement location only	Future multi-node ToA-based localisation
SCALABILITY	High through inexpensive distributed nodes	High through inexpensive distributed nodes
MAIN USERS	Environmental researchers, coastal monitoring agencies	Research, maritime surveillance, SAR, future defence applications

Table (iv). General Commercial and Research Buoy system comparison to MESH.

Low-Cost Hydrophone Design

Recent advances in low-cost embedded computing have enabled autonomous acoustic sensing for marine applications. However, several challenges remain, including achieving an adequate signal-to-noise ratio using inexpensive hydrophones, maintaining signal integrity in harsh underwater environments, and performing reliable real-time detection and classification on resource-constrained embedded platforms.

The MESH hydrophone subsystem is designed to satisfy the acoustic performance requirements for passive monitoring of marine vessels. The design is based on two established low-cost hydrophone implementations: the CoPiDi hydrophone developed by CoPiDi [21] and the Ryckebusch hydrophone designs [22], including both the *Elaborate* “Let's Build Some World Class Hydrophones” and *Condensed* “Hydrophone Drop Rigs versions”.

The hydrophone is intended to operate over an effective frequency range suitable for marine vessel monitoring. Vessel radiated noise is typically concentrated below several tens of kilohertz and includes low-frequency machinery noise together with higher-frequency propeller cavitation and turbulence components [23]. This frequency content provides the spectral features required for vessel detection and classification. See further in Characteristics of Underwater Acoustic Signals.

Two transducer configurations were considered for MESH:

- CoPiDi design: two 27 mm piezoelectric discs connected in a balanced differential configuration. Volume of 91.763 ml due to 37 mm × 37 mm × 67 mm dimensions.
- Ryckebusch design: a cylindrical piezoelectric element providing near-omnidirectional sensitivity with a mechanically simple construction. Volume of 50ml.

Both designs require signal conditioning to amplify the weak piezoelectric output before analogue-to-digital conversion. Suitable preamplifier implementations include the OPA1642 low-noise operational amplifier used in the Ryckebusch design or the 2N3819 JFET differential preamplifier used in the CoPiDi design. Both circuits provide approximately 15 dB of voltage gain while maintaining low noise performance.

Power supply requirements represent the primary difference between the two designs. The CoPiDi hydrophone is intended for laboratory applications and requires 48 V phantom power, making integration into a compact battery-powered sonobuoy considerably more complex. In contrast, the Ryckebusch design operates from a 9 V supply, which can be readily provided by a small battery or generated from the MESH 3.7-5 V lithium-ion power system using a compact DC-DC boost converter. An additional 9 V battery shall be used because this substantially simplifies power system integration while preserving portability.

Since the Raspberry Pi 4 does not provide a 3.5 mm audio input, either hydrophone design requires an external USB audio interface (or equivalent analogue-to-digital converter) to digitise the acoustic signal. Both hydrophone assemblies are sufficiently compact to fit within a reasonable volume, making either design physically compatible with the MESH platform.

Overall, both hydrophone designs satisfy the physical and acoustic requirements of the MESH system. However, the Ryckebusch design was selected because it provides an excellent balance of performance, simplicity, and cost. Its lower supply voltage eliminates the need for 48 V phantom power, reducing system complexity, improving battery compatibility, and making it a more practical solution for a low-cost, portable sonobuoy.

Underwater Acoustic Signal Processing

Passive underwater acoustic target recognition (UATR) has evolved significantly over the past three decades. Early systems relied on manually engineered acoustic features extracted from hydrophone recordings, whereas modern approaches increasingly utilise deep learning architectures capable of automatically learning discriminative representations directly from spectrograms. Despite these advances, underwater acoustic classification remains challenging due to multipath propagation, ambient noise, reverberation, Doppler effects, and limited labelled datasets. Consequently, current research combines advanced signal processing techniques with machine learning to maximise classification performance while remaining computationally feasible for embedded deployment.

Prior to machine learning, underwater acoustic recognition relied almost entirely upon signal processing. 24 bit Wav, 96Khz . The objective was to of ship-radiated noise while suppressing environmental interference. Typical processing stages include:

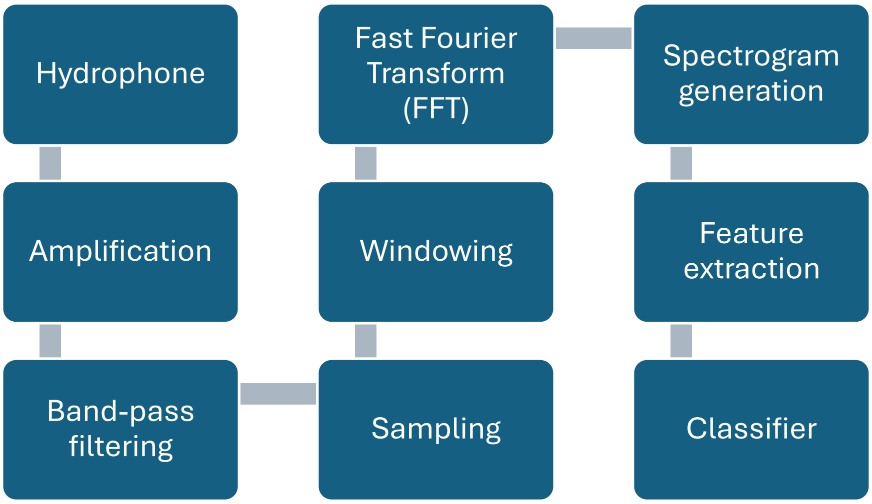

Figure (i) DSP

Characteristics of Underwater Acoustic Signals

The acoustic signal characteristics utilised to detect and classify between different marine vessels is cavitation (narrowband components), propeller harmonics (broadband components), motor noise, and water surface disturbance from the hull bouncing on the water (source level: SL). These form the global dependent sound profile to be analysed. Small boats, a primary focus for MESH, produce harmonic signatures related to engine speed and shaft rotation, with critical discriminative information often concentrated below 1 kHz.

Unlike airborne sound, underwater acoustic propagation is strongly influenced by environmental conditions including water temperature, salinity, depth, seabed composition, and surface reflections. This propagation loss (PL) is described by Snell’s law. Multiple propagation paths introduce constructive and destructive interference while frequency-dependent attenuation causes higher frequencies to diminish rapidly with range.

These effects produce highly variable received signals, even for identical vessels operating under similar conditions. Consequently, preprocessing is essential before classification can be attempted. Obstruction interference with terrain, surface, marine creatures, and non-target vessels includes absorption and scattering in each multipath reflection. Generation interference includes wave noise, rain marine animals, and non-target vessels. This motivates sophisticated signal conditioning techniques prior to feature extraction.

Upon identification of the instrumentations processing band (NL) and array gain (AG) properties, a measured decibels comparison to the environmental conditions yields the basic passive sonar equation:

$SNR_{Passive} = SL - PL - NL + AG.$ (((21)))

Pre-processing

Effective pre-processing is essential to suppress background noise and enhance isolate distinctive acoustic signature characteristics. Once an appropriate sampling frequency resolution has been applied to the audio stream, spatial filtering (beamforming) to isolate signals from target directions and noise whitening via algorithms like the two-pass split window (TPSW). Signal enhancement frameworks such as Coherently Averaged Power Spectral Estimation (CAPSE) [24] improve the signal-to-noise ratio (SNR) by preserving phase coherence across multiple observations. This provides a substantial improvement in SNR for detecting tonal machinery signatures in noisy littoral environments.

For non-linear signals, Enhanced Variational Mode Decomposition (EVMD) [25] can be used to decompose complex noise into finite intrinsic mode functions.

The Fast Fourier Transform remains the foundation of underwater spectral analysis because it converts time-domain recordings into frequency-domain representations where harmonic engine signatures become visible. However, simple FFTs often fail to separate closely spaced harmonics in noisy environments [26].

Representation

Underwater acoustic data is often transformed from the time domain into two-dimensional time-frequency representations for better feature visualization. Spectrograms based on the Short-Time Fourier Transform (STFT) are standard, but fixed window widths limit their simultaneous resolution in time and frequency.

LOFAR (Low Frequency Analysis and Recording) [27] grams are widely used for identifying sustained engine noise. LOFAR produces long-duration spectrograms that reveal persistent narrowband tonal components generated by engines, generators, reduction gearboxes, and shaft rotation in a computationally inexpensive method. The result is a 50 x 4000 interpretable set of characteristic spectral lines to emphasise sustained engine sounds and mechanical spectral components. Its principal limitation is sensitivity to background noise and changing environmental conditions. To maintain a classification accuracy above 50% even at low signal-to-noise ratios (5 dB), focus shall be targeted on distinguishable vessel-specific global features.

DEMON (Detection of Envelope Modulation on Noise) [28] spectra highlight periodic modulations from propellers and shafts. Rather than analysing overall frequency content, DEMON estimates blade passing frequency and shaft rotation. This enables estimation of propeller blade count, shaft RPM and vessel speed, which can be matched to probable vessle type.

Other representations include Cepstrograms [26], which are time-varying graphical representations of the cepstrum. They're used to analyse periodic patterns by plotting time on the horizontal axis and "quefrency" on the vertical axis, with signal power or magnitude displayed via a heatmap. Quefrency measures the rate at which the spectral components (harmonics) of a signal repeat and is measured in seconds. Unlike a standard spectrogram, which visualizes raw frequency content, a cepstrogram undergoes an additional mathematical step (taking the inverse Fourier transform of the logarithmic spectrum).

These techniques improve signal quality before classification by separating mixed acoustic components into intrinsic mode functions.

Feature Extraction

Feature extraction serves to reduce data dimensionality while retaining essential target information to prevent model overfitting. Mel-frequency cepstral coefficients (MFCCs) and Gammatone frequency cepstral coefficients (GFCCs) are borrowed from speech processing to mimic non-linear human auditory perception [23] [29]. While MFCCs are effective for identifying specific features in clean signals, GFCCs often demonstrate superior robustness and recognition accuracy under low signal-to-noise ratio (SNR) or interference conditions. The Constant Q Transform (CQT) is increasingly favoured for vessel classification because it utilizes a bank of geometrically-spaced filters to provide higher frequency resolution at low frequencies, where discriminative machinery tonals and propeller signatures are most prevalent. Unlike standard Fourier transforms, CQT provides a constant relative bandwidth that helps solve the problem of fundamental frequency identification.

For non-stationary and complex underwater signals, Wavelet Transforms and the Hilbert-Huang Transform (HHT) [25]are employed to capture local instantaneous characteristics and variable time-frequency patterns. HHT is particularly useful for decomposing non-linear complex signals into Intrinsic Mode Functions (IMFs) to accurately describe instantaneous frequency components. Hybrid approaches, such as combining MFCCs with Spectral Dynamic Features (SDF), aim to capture the temporal evolution of spectral patterns by analysing changes between successive frames over extended segments. This combination can enhance the correct classification rate by adding statistically uncorrelated features that leverage the non-homogeneous nature of vessel-generated noise.

Recent advancements have introduced trainable spectral front-ends, such as Sinc-Net or LEAF [30], that learn Gabor-based filterbanks directly from raw waveforms rather than using fixed descriptors. These models can dynamically emphasise different frequency components to discover stable, propagation-invariant cues, making them more robust to signal distortion caused by varying source-sensor distances. Additionally, Weighted Permutation Entropy (WPE) is utilised to measure signal complexity, as it is more sensitive to signal mutations and fluctuations than traditional permutation entropy. Integrating multiple feature sets through multi-feature learning or fusion strategies (e.g., combining CQT, Mel, and Bark spectrograms) is often employed to increase the robustness and generalisation ability of the recognition process.

Underwater Acoustic Datasets

The development of automated vessel classification systems is significantly hindered by a scarcity of publicly available, annotated datasets. This shortage stems from two primary barriers: military secrecy, which restricts access to vast amounts of data collected for naval purposes, and the prohibitive costs of conducting underwater experiments. Furthermore, the high variability of the underwater environment, influenced by depth, temperature, and salinity, means that a model trained on one dataset may not generalise to another. Consequently, researchers often rely on self-constructed or proprietary datasets that lack the scale needed for deep learning, or they turn to data augmentation and transfer learning to bypass these data gaps.

ShipsEar [31] is one of the most widely cited open-source databases for vessel classification. It consists of 90 recordings representing 11 vessel types, totaling approximately 3 hours of audio recorded off the Spanish Atlantic coast. For experimental purposes, these 11 types are frequently merged into four size-based classes (Class A: fishing/tugs, Class B: motorboats, Class C: passenger ferries, Class D: ocean liners) plus a fifth class for background noise. While its relatively small scale can lead to overfitting in deep learning models, it remains a critical baseline for benchmarking new algorithms.

To address the need for larger datasets, DeepShip [32] was introduced as a real-world, large-scale benchmark. It contains 47 hours and 4 minutes of recordings from 265 different ships across four commercial classes: Cargo, Tanker, Tug, and Passenger ships. Unlike earlier datasets, DeepShip provides recordings from throughout the year, encompassing diverse sea states and noise levels. However, it primarily focuses on signals where a single vessel is within 2 km of the hydrophone, and its background noise class was added from a distinct source, which can create a "domain shift" that allows models to learn sensor quirks rather than actual acoustic signatures.

The QiandaoEar22 [33] dataset addresses the limitation of single-target datasets by providing multi-target ship noise signals collected in Qiandao Lake, China. It contains nearly 22 hours of background noise and 9.5 hours of ship signals, including speedboats, "KaiYuan" vessels, and Uncrewed Underwater Vehicles (UUVs). By capturing multi-target scenarios, this dataset serves as a high-quality resource for benchmarking Underwater Acoustic Target Detection (UATD) and recognition (UATR) systems in complex, real-world underwater environments.

Research Gap and the MESH Context Current datasets often fail to represent the complexity of multi-target scenarios or the impact of varying source-sensor range in realistic littoral environments. The MESH project leverages these existing benchmarks, specifically VTUAD for its distance-based scenarios, to evaluate the trade-offs between low-cost hardware and classification reliability. This focus addresses the critical gap in moving from high-cost, single-use military systems to modular, economical sonobuoys that can accurately detect small vessels like jet skis and inflatable rescue boats in shallow waters.

Machine Learning

Following signal conditioning, spectral representation, and feature extraction, the final stage of the underwater acoustic processing pipeline is marine vessel detection and classification. Artificial Intelligence (AI) techniques enable autonomous interpretation of extracted acoustic features, allowing embedded systems to distinguish between vessel types without human intervention. Within underwater acoustic target recognition, these techniques have progressed from conventional statistical learning algorithms to modern deep learning architectures capable of learning discriminative representations directly from spectrograms.

Machine Learning (ML), as a subset of Artificial Intelligence, enables classifiers to infer relationships between acoustic features and vessel classes from labelled training data rather than relying on manually defined decision rules. The literature broadly categorises underwater acoustic classification methods into three groups: Statistical Learning Methods, Deep Learning Architectures, and Hybrid or Feature-Based Techniques. Each represents a trade-off between classification accuracy, computational complexity, training data requirements, interpretability, and suitability for embedded deployment.

Whilst prior skills in computer vision development have been demonstrated in the 2025 Triple I QUACK project [34], formal development of Machine Learning and Deep Learning has not occurred. Consequently, skill gaps of the research student shall be addressed via the Andrew NG Machine Learning Specialization course on Coursera [35] and the Deep Learning Specialization on Coursera [36] for the necessary concepts at the appropriate time.

Statistical Machine Learning

As detailed by Luo et al. [25] and da Silva et al. [26], traditional statistical classifiers serve as excellent baselines for resource-constrained platforms due to their low computational overhead and small training data requirements. The primary statistical algorithms under evaluation include:

- Support Vector Machines (SVM) [28]: Utilized for constructing optimal separating hyperplanes on compact acoustic feature vectors.
- Hidden Markov Models (HMM) [28]: Applied to exploit temporal dependencies and model the sequential evolution of vessel signatures..
- Gaussian Mixture Models (GMM) [28]: Deployed to estimate the underlying probability distributions of acoustic features for distinct vessel classes.
- Linear Discriminant Analysis (LDA) [37] & K-Nearest Neighbors (KNN): Low-memory, computationally efficient baseline classifiers.

- XGBoost [37]: An ensemble gradient-boosting method capable of achieving classification accuracies approaching 99.7% with computational demands low enough for real-time edge processing.

Although statistical learning methods remain highly interpretable and computationally efficient, their performance is fundamentally constrained by the quality of handcrafted feature extraction and often degrades when operating conditions differ significantly from the training environment.

Deep Learning

Deep learning models bypass handcrafted feature dependency by automatically learning hierarchical representations directly from two-dimensional time-frequency representations (such as LOFARgrams or CQT spectrograms) [21]. This significantly improves robustness to environmental variability while reducing reliance on domain-specific feature design.

Convolutional Neural Networks

Lucas C. F. Domingos et al [26] has detailed that Convolutional Neural Networks (CNNs) remain the dominant architecture for underwater acoustic target recognition because they effectively identify harmonic structures, modulation patterns, and broadband spectral characteristics. Common variants include VGGNet, ResNet, DenseNet, and MobileNet, with MobileNet particularly suited to embedded deployment due to its reduced computational complexity and lower memory requirements.

Vision Transformers

Recent research has increasingly adopted transformer-based architectures such as Vision Transformers (ViT), which employ self-attention mechanisms to capture long-range relationships across an entire spectrogram. Lightweight implementations including CAPSE-ViT [24] combine coherent spectral estimation with transformer-based inference to achieve maximum classification accuracy while remaining computationally lite for edge computing platforms. Sequential architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) continue to provide advantages when modelling temporal evolution within ship-radiated noise.

Hybrid Learning Approaches

Rather than replacing traditional signal processing, many recent approaches combine established acoustic feature extraction techniques with machine learning to improve robustness under challenging environmental conditions. Hybrid methods integrate physical knowledge of underwater acoustics with data-driven learning, improving generalisation across varying propagation conditions.

Representative techniques include CATFISH [30], which learns adaptive filterbanks directly from waveforms; Interpretable Contrastive Learning (ICL) [38], which jointly analyses low-frequency machinery tonals and high-frequency modulation; Separable Convolution Autoencoders (SCAE), designed for denoising high-background-noise recordings; and Convolution-based Mixture of Experts (CMoE), which dynamically selects specialised neural networks according to the operating environment. Other approaches integrate DSP methods such as DEMON [39], LOFAR, and Enhanced Variational Mode Decomposition (EVMD) [25] as preprocessing stages before neural inference, combining interpretable acoustic features with modern classification algorithms.

Embedded Deployment

The minimum viable product (MVP) for MESH is the comparative evaluation of representative statistical, deep learning, and hybrid classification methods using simulated underwater acoustic propagation [40] and detection [41] models within MATLAB before deployment on embedded hardware. Once successfully simulated, the top-performing models shall be employed into the sonobuoy prototype.

Classification performance will be assessed using publicly available underwater acoustic datasets and evaluated according to accuracy, inference latency, computational complexity, memory utilisation, and power consumption.

The embedded implementation adopts a hybrid computing architecture comprising a Raspberry Pi 4 operating under Raspberry Pi OS Lite (64-bit Linux) for digital signal processing, machine learning inference, and high-level system management incorporating deterministic sensor acquisition and hardware. Due to the computational requirements of the ML inferences, the Raspberry Pi's 4 GB of RAM with low power consumption are two primary factors for selecting it. Acoustic recordings sampled at 24-bit, 96 kHz will be processed primarily within the 0-1600 Hz frequency band, where the dominant machinery harmonics and propulsion signatures of small marine vessels are concentrated. This adheres to the Nyquist Theorem. To maximize battery life, the system implements a two-stage "Detect and Classify" workflow [21]. This architecture provides deterministic real-time sampling while supporting modern machine learning frameworks including Python and TensorFlow Lite. These software design decisions are made to facilitate the ML inference on the Raspberry Pi.

Research Gap and Relevance to MESH

Although numerous studies have demonstrated high classification accuracy using statistical learning, convolutional neural networks, and transformer-based architectures [42], comparatively little work has examined the practical trade-offs between instrumentation quality, hardware cost, embedded computational requirements, energy consumption, and classification performance for low-cost autonomous sonobuoys. Consequently, the MESH project evaluates representative algorithms across these criteria to identify a computationally efficient classification pipeline suitable for autonomous edge deployment while maintaining reliable vessel detection and classification performance.

Surface communications

Surface communication systems enable autonomous sonobuoys to transmit detection results, system health information, and positioning data from the deployment area to operators. Unlike traditional military sonobuoys that utilise VHF radio links to aircraft or surface combatants, recent low-cost autonomous platforms increasingly employ low-power Internet of Things (IoT) [20]communication technologies such as LoRa [17], LoRaWAN, cellular networks, and satellite communications. These technologies offer a trade-off between communication range, bandwidth, power consumption, and deployment cost, making them well suited to persistent environmental monitoring and coastal surveillance applications.

Positioning and Timing

Reliable positioning and precise time synchronisation are fundamental requirements for distributed underwater acoustic sensing systems. Global Navigation Satellite System (GNSS) receivers provide continuous estimates of buoy position [19] while simultaneously supplying highly accurate Coordinated Universal Time (UTC) references for timestamping acoustic detections. Accurate timing enables future implementation of Time of Arrival (ToA) localisation [43], where detections recorded by multiple sonobuoys can be correlated to estimate the position of an acoustic source through trilateration.

For the MESH system, positioning is provided using the u-blox NEO-6M GPS [44] receiver, a mature embedded GNSS module widely adopted within low-power autonomous systems. The receiver communicates via a standard UART interface and provides continuous position, velocity and UTC time information with a typical positioning accuracy of approximately 2.5 m CEP under open-sky conditions while supporting update rates of up to 5 Hz. These characteristics are sufficient for monitoring the relatively slow drift of a free-floating sonobuoy. Platform attitude and motion are further characterised using a GY-85 Inertial Measurement Unit (IMU) [45] to provide orientation and stability measurements during deployment.

LoRa Communication

Long Range (LoRa) radio has emerged as an attractive communication technology for distributed maritime sensing due to its combination of low power consumption, long communication range and modest bandwidth requirements. Rather than continuously streaming acoustic recordings, LoRa is typically employed to transmit event-driven notifications containing processed detection results, reducing communication energy requirements while extending deployment endurance.

The Open-Source LoRa Buoy (OLB) [19] architecture provides the principal reference implementation for the communication framework adopted within the MESH project. Operating within the Australian AU915 (915-928 MHz) Industrial, Scientific and Medical (ISM) band, the system utilises the SX1262 LoRa transceiver configured with 125 kHz bandwidth, Spreading Factor 8, Coding Rate 4/6, and transmit powers up to 20 dBm. Under typical marine operating conditions, communication ranges of approximately 2-5 km can be achieved, with greater distances possible under favourable line-of-sight conditions.

Communication follows a lightweight point-to-point protocol designed to minimise transmission time and energy consumption. A shore-based base station periodically broadcasts its identity and listening status. Upon detecting this beacon, the sonobuoy initiates a handshake containing both device identifiers before transmitting a compact binary payload containing only processed information rather than raw acoustic recordings. The transmitted payload includes:

- Vessel detection and classification results
- GPS coordinates and timestamps
- IMU measurements
- System diagnostic information
- Communication status and performance metrics

Following successful transmission, the base station may return configuration updates, modified operating parameters or remote reset commands over the same communication link.

Communication Hardware

The proposed communication hardware utilises the RP2040-LoRa-HF [46] development board, integrating the RP2040 dual-core Arm Cortex-M0+ microcontroller with the Semtech SX1262 LoRa transceiver [47]. Compared with the Wio-E5 Mini employed by the Open-Source LoRa Buoy platform, the RP2040 provides greater processing capability while maintaining low-power operation suitable for embedded sensing applications.

The SX1262 supports LoRa, FSK and GFSK modulation schemes, provides receiver sensitivities approaching -148 dBm, and configurable transmit powers up to +22 dBm. The High Frequency (HF) variant operates within the Australian 915-928 MHz ISM band, making it directly compatible with the proposed communication architecture.

A shore-based monitoring station employs a corresponding USB-to-LoRa-HF interface using the same SX1262 transceiver. The interface functions as a transparent USB serial modem, forwarding telemetry packets received from deployed sonobuoys to the monitoring application running on the host computer.

Communication Architecture

The MESH communication architecture follows an edge-computing paradigm in which all computationally intensive digital signal processing and machine learning inference are performed onboard the sonobuoy. Consequently, only high-level detection events, vessel classifications, positioning information and system diagnostics are transmitted to the shore-based base station. This approach significantly reduces communication bandwidth and energy consumption while improving deployment endurance compared with systems that continuously transmit raw hydrophone recordings.

The technical parameters adopted for the proposed AU915 LoRa implementation are summarised in Table (v).

Parameter	Specification	Notes

Upstream Channels (200 kHz spacing)	64 channels from 915.2 MHz to 927.8 MHz	Linear spacing of 200 kHz.
Upstream Channels (1.6 MHz spacing)	8 channels from 915.9 MHz to 927.1 MHz	Linear spacing of 1.6 MHz.
Downstream Channels	8 channels from 923.3 MHz to 927.5 MHz	Linear spacing of 600 kHz.
Operating Band	915-928 MHz ISM Band	Suitable for regions supporting the 915 MHz LoRaWAN band (e.g., AU915/US915).
Default Bandwidth	125 kHz	Standard for high-sensitivity LoRa links.
Spreading Factor	8	Configurable integer between 5 and 12.
Coding Rate\	6	Range: 5 to 8 (commonly represented as 4/6).
LoRa Output Power	20 dBm	Configurable from -9 dBm to 22 dBm.
Transmission Range	~2 km to 5.4 km	Up to 2 km in ocean water; up to 10 km under ideal line-of-sight conditions.
Data Format	Raw byte array	Minimizes payload size for improved energy efficiency.

Table (v) Technical parameters adopted for the proposed AU915 LoRa implementation.

Data Acquisition

The MESH project records only the technical information required to evaluate system performance during laboratory and field trials. Data collected include:

- Underwater hydrophone recordings
- Vessel acoustic signatures
- Sonobuoy GPS position
- IMU measurements
- Battery voltage and system diagnostics
- Processor utilisation
- LoRa communication performance metrics
- Environmental conditions during testing
- Controlled vessel operating scenarios

Systems Engineering Considerations

The MESH project primarily integrates mature technologies rather than developing novel hardware components. The selected sensing, embedded computing, positioning, communication, and machine learning technologies have all demonstrated successful operation in comparable applications and possess high Technology Readiness Levels (TRLs) [48]. Consequently, the principal engineering challenge lies not in individual component development, but in the integration of these technologies into a reliable autonomous sensing platform.

Emphasis is therefore placed on defining interfaces between the hydrophone, embedded processing hardware, communication subsystem, power management, and software architecture. Systems engineering principles including modularity, interface standardisation, staged verification, and incremental testing are adopted throughout the project to minimise integration risk and simplify future system expansion. This approach enables individual subsystems to be independently validated before full system integration and supports future enhancements such as distributed multi-node localisation and additional sensing capabilities.

Research Gap

Existing literature demonstrates significant advances in underwater acoustic signal processing, embedded machine learning, low-power communication, and autonomous maritime sensing [27] [49]. Publicly available datasets and modern deep learning architectures have enabled increasingly accurate vessel classification, while low-cost hardware platforms have made autonomous passive acoustic sensing more accessible [30] [32].

However, comparatively little research has investigated the integration of these mature technologies into a complete low-cost autonomous sonobuoy specialised for littoral vessel surveillance. In particular, few studies evaluate the trade-offs between hydrophone performance, embedded computational capability, power consumption, communication bandwidth, deployment method, and classification accuracy within a single integrated platform [30].

Furthermore, existing military sonobuoys and shallow water surveillance systems prioritise operational capability over affordability, while environmental monitoring buoys generally lack onboard acoustic intelligence [26]. This creates a gap for a reusable, low-cost sonobuoy capable of performing onboard digital signal processing, embedded machine learning inference, and long-range wireless telemetry using commercially available components.

The MESH project addresses this gap by evaluating the feasibility of integrating passive acoustic sensing, embedded artificial intelligence, GNSS positioning, and LoRa communication into a modular autonomous sonobuoy designed for coastal vessel detection and classification.

References

[1] Engineers Australia, “Stage 1 competency standard for professional engineers,” November 2019. [Online]. Available: https://www.engineersaustralia.org.au/sites/default/files/2022-07/stage-1-competency-standard-professional-engineer.pdf. [Accessed 4 February 2026].

[2] J. Walsh, “MESH - Modular Economical Sonobuoy Heuristic,” Jonathan Walsh, 9 February 2026. [Online]. Available: https://jonowalsh.net/projects/MESH.html. [Accessed 26 June 2026].

[3] Australian Department of Defence, “Defence Innovation, Science and Technology Priorities,” Australian Department of Defence, Canberra, 2024.

[4] R. Laird, “How to Ramp Up ADF Capabilities in the Near Term? A Perspective from Anduril Australia,” Second Line of Defence, 21 October 2022. [Online]. Available: https://sldinfo.com/2022/10/how-to-ramp-up-adf-capabilities-in-the-near-term-a-perspective-from-anduril-australia/. [Accessed 01 January 2026].

[5] P. Jones and J. Parker, A Maritime Strategy for Australia: AMS 2035, University of New South Wales (Canberra), 2025.

[6] Commonwealth of Australia, “2024 National Defence Strategy,” 2024. [Online]. Available: https://www.defence.gov.au/about/strategic-planning/2024-national-defence-strategy-2024-integrated-investment-program. [Accessed 26 June 2026].

[7] R. J. Urick, Principles of Underwater Sound, Third ed., Westport, Connecticut: Peninsula Publishing, 1983.

[8] EDTAS, “Remote Undersea Surveillance: Insights Paper,” 2022.

[9] F. Brown, “Artificial and human intelligence used to tackle illegal fishing,” 21 August 2020. [Online]. Available: https://www.csiro.au/en/news/All/Articles/2020/August/tackling-illegal-fishing. [Accessed 4 July 2026].

[10] Australian Defence, “Covert Tech Deployed in the Torres Strait,” 24 November 2020. [Online]. Available: https://www.australiandefence.com.au/defence/sea/covert-tech-deployed-in-the-torres-strait. [Accessed 6 June 2026].

[11] Guolong Liang, Guangming Wan, Jinjin Wang, Xue Wang, “A Novel Underwater Location Beacon Signal Detection Method Based on Mixing and Normalizing Stochastic Resonance,” 27 February 2020. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC7085629/. [Accessed 4 July 2026].

[12] Cobham Ultra, “Passive Directional Sonobuoy AN/SSQ-53D(3),” [Online]. Available: https://www.cobhamultra.com/media/2448/anssq-53d3-datasheet_final.pdf. [Accessed 7 July 2026].

[13] The Navy League, “THE RAN’S 725 SQUADRON SEAHAWK ‘ROMEO’,” *THE NAVY,* vol. 75, no. 3, p. 36, 2013.

[14] Elbit Systems, “Anti-Submarine Sonobuoys,” Elbit Systems, [Online]. Available: https://www.elbitsystems.com/naval/underwater-warfare/anti-submarine-sonobuoys. [Accessed 26 June 2026].

[15] Commonwealth of Australia Defence Science and Technology Group, “Barra Sonobuoy,” [Online]. Available: https://www.dst.defence.gov.au/innovation/barra-sonobuoy. [Accessed 26 June 2026].

[16] Militär Aktuell, “Schiebel: S-100 dropped sonobuoys at “Repmus”,” 16 October 2024. [Online]. Available: https://militaeraktuell.at/en/schiebel-s-100-dropped-sonobuoys-at-repmus/. [Accessed 01 January 2026].

[17] L. Leonardi, “LoRa Communication Technology for IoT Applications,” 2025. [Online]. Available: https://mdpi-res.com/bookfiles/book/11172/LoRa_Communication_Technology_for_IoT_Applications.pdf?v=1751906779. [Accessed 7 July 2026].

[18] M. L. ,. S. P. ,. A. K. Arnas Majumder, “Buoys for marine weather data monitoring and LoRaWAN communication,” 1 December 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0029801824028592?via%3Dihub. [Accessed 26 June 2026].

[19] A. P. U. o. O. R. S. J. R. Lars Willas Dreyer, “OLB: An Open Lora Buoy for Coastal Water Measurements,” January 2026. [Online]. Available: https://www.researchgate.net/publication/399667295_OLB_An_Open_Lora_Buoy_for_Coastal_Water_Measurements. [Accessed 26 June 2026].

[20] S. S. Jarrod Trevathan, “Open-source Internet of Things remote aquatic environmental sensing,,” October 2022. [Online]. Available: https://doi.org/10.1016/j.ohx.2022.e00336.. [Accessed 25 06 2026].

[21] “The Development of a Low-Cost Hydrophone for Passive Acoustic Monitoring of Dolphins Vocalizations,” *Remote Sensing,* vol. 15, p. 1946, 2023.

[22] J. Ryckebusch, “Hydrophone Drop Rigs,” 2022. [Online]. Available: https://www.instructables.com/Hydrophone-Drop-Rigs/. [Accessed 20 June 2026].

[23] G. A. a. M. Karlsson, “Classify Different Types of Boat Engine Sounds with Machine Learning,” KTH ROYAL INSTITUTE OF TECHNOLOGY, SWEDEN, 2019.

[24] U. U. S. A. Z. S. NAJAMUDDIN, "CAPSE-ViT: A Lightweight Framework for Underwater Acoustic Vessel Classification Using Coherent Spectral Estimation and Modified Vision Transformer," *Archives of Acoustics,* vol. 50, pp. 161-171, 2025.

[25] D. X. Z. A. H. Q. H. S. 1. J. Q. a. J. W. Hamada Esmaiel, "Multi-Stage Feature Extraction and Classification for Ship-Radiated Noise," *Sensors,* vol. 22, p. 112, 2022.

[26] L. C. F. DOMINGOS, "An Investigation of Preprocessing Filters and Deep Learning Methods for Vessel Type Classification With Underwater Acoustic Data," *IEEE Access,* vol. 10, pp. 117582-117596, 2022.

[27] P. E. S. P. S. M. S. R. S. A. B. a. K. S. Lucas C. F. Domingos, "A Survey of Underwater Acoustic Data Classification Methods Using Deep Learning for Shoreline Surveillance," *Sensors,* vol. 22, p. 2181, 2022.

[28] L. C. H. Z. a. H. C. Xinwei Luo, "A Survey of Underwater Acoustic Target Recognition Methods Based on Machine Learning," *Journal of Marine Science and Engineering,* vol. 11, no. https://www.mdpi.com/2077-1312/11/2/384, p. 384, 2023.

[29] M. d. B. S. a. R. d. M. Calazan, "Improved Spectral Dynamic Features Extracted from Audio Data for Classification of Marine Vessels," *Intelligent Marine Technology Systems,* vol. 2, p. 18, 2024.

[30] T. V. a. A. B. Jonas Elsborg, "Acoustic Classification of Maritime Vessels using Learnable Filterbanks," 2025.

[31] S. T.-G. A. C.-L. A. P.-G. David Santos-Domínguez, "ShipsEar: An Underwater Vessel Noise Database," *Applied Acoustics,* vol. 113, pp. 64-69, 2016.

[32] M. e. a. Irfan, "DeepShip: An Underwater Acoustic Benchmark Dataset and a Separable Convolution Based Autoencoder for Classification," *Expert Systems with Applications,* vol. 183, p. 115270, 2021.

[33] X. Du, "QiandaoEar22: A high quality noise dataset for identifying specific ship from multiple underwater acoustic targets using ship-radiated noise," [Online]. Available: https://arxiv.org/html/2406.04354v1. [Accessed 6 July 2026].

[34] University of Wollongong, "QUACK Demonstration Video," 23 October 2025. [Online]. Available: https://www.youtube.com/watch?v=g4BwJXTqhwU. [Accessed 2 July 2026].

[35] greyhatguy007, "Machine-Learning-Specialization-Coursera," 2 November 2023. [Online]. Available: https://github.com/greyhatguy007/Machine-Learning-Specialization-Coursera. [Accessed 2 July 2026].

[36] amanchadha, "Deep Learning Specialization on Coursera (offered by deeplearning.ai)," 2 July 2021. [Online]. Available: https://github.com/amanchadha/coursera-deep-learning-specialization. [Accessed 2 June 2026].

[37] L. L. T. N. F. Allyson A. da Silva, "Machine Learning Ship Classifiers for Signals from Passive Sonars," *Applied Sciences,* vol. 15, p. 6952, 2025.

[38] J. R. J. X. Yuan Xie, "Guiding the Underwater Acoustic Target Recognition with Interpretable Contrastive Learning," Institute of Acoustics, Chinese Academy of Sciences, Beijing, 2024.

[39] R. H. R. Muhammad Abdur Rehman Hashmi, "Novel DEMON Spectra Analysis Techniques and Empirical Knowledge Based Reference Criterion for Acoustic Signal Classification," *Journal of Electrical Engineering & Technology,* vol. 18, pp. 561-578, 2023.

[40] CENTRE FOR MARINE SCIENCE AND TECHNOLOGY (CMST), "Underwater acoustic propagation modelling software – AcTUP V2.2L," [Online]. Available: https://cmst.curtin.edu.au/products/underwater/. [Accessed 1 June 2026].

[41] MATLAB, "underwaterChannel - Propagated and reflected sonar signals - MATLAB," [Online]. Available: https://au.mathworks.com/help/fusion/ref/underwaterchannel.html. [Accessed 1 June 2026].

[42] T. Meir, M. Tsionskiy, A. Sutin and H. Salloum, "Decision Learning Algorithm for Acoustic Vessel Classification," vol. Supplement 4, no. Article 3, April 2012.

[43] U-Blox, "GPS-based Timing - Application Note," 3 March 2011. [Online]. Available: https://content.u-blox.com/sites/default/files/products/documents/Timing_AppNote_%28GPS.G6-X-11007%29.pdf. [Accessed 2 June 2026].

[44] U-blox, "NEO-6 u-blox 6 GPS Module," 19 October 2011. [Online]. Available: https://content.u-blox.com/sites/default/files/products/documents/NEO-6_DataSheet_%28GPS.G6-HW-09005%29.pdf. [Accessed 2 June 2026].

[45] J3, "GY-85 A quick datasheet study," 6 June 2017. [Online]. Available: https://medium.com/jungletronics/gy-85-a-quick-datasheet-study-79019bb36fbf. [Accessed 6 July 2026].

[46] SpotPear Electronics, "Raspberry Pi PICO RP2040 LoRa Development Board Integrates SX1262," [Online]. Available: https://www.aliexpress.com/item/1005006539361701.html#nav-description. [Accessed 2 July 2026].

[47] Shenzhen Gintech Electronics, "USB to LoRa Module SX1262 HF XTAL," [Online]. Available: https://www.aliexpress.com/item/1005010333249217.html#nav-description. [Accessed 2 July 2026].

[48] DSTG, "TRL Explanations_1.pdf," [Online]. Available: https://www.dst.defence.gov.au/sites/default/files/basic_pages/documents/TRL%20Explanations_1.pdf. [Accessed 25 June 2026].

[49] "Unraveling Complex Data Diversity in Underwater Acoustic Target Recognition through Convolution-based Mixture of Experts," 2024.

[50] "Transfer Learning for Distance Classification of Marine Vessels Using Underwater Sound," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 18, 2025.

[51] "Extraction of Small Boat Harmonic Signatures from Passive Sonar," *Journal of the Acoustical Society of America,* 2011.

[52] "Collision Evasive Action Timing for MASS Using CNNLSTMBased Ship Trajectory Prediction in Restricted Area," *Ocean Engineering,* vol. 294, p. 116766, 2024.

[57] "Underwater Acoustic Target Recognition Based on Smoothness-Inducing Regularization and Spectrogram-Based Data Augmentation," 2023.

[58] UOW, "PROFESSIONAL EXPERIENCE REQUIREMENTS ENGG454," 2026. [Online]. Available: https://documents.uow.edu.au/content/groups/public/@web/@eis/documents/doc/uow274700.pdf. [Accessed 26 June 2026].

[59] A. D. R. a. D. P. R. N. Sa'Adah, "Tracking Position on GPS Smart Buoy System Using LoRa Communication," 14 October 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10348269. [Accessed 26 June 2026].

[60] RFWireless-World, "LoRa Frequency Bands in Australia: AU915-928 Details," [Online]. Available: https://www.rfwireless-world.com/terminology/lora-frequency-australia. [Accessed 02 June 2026].

[61] University of Wollongong - Faculty of Engineering and Information Sciences, "Laboratory Safety Manual," 22 March 2016. [Online]. Available: https://documents.uow.edu.au/content/groups/public/@web/@eis/documents/doc/uow262966.pdf. [Accessed 2 June 2026].

[62] University of Wollongong - Faculty of Engineering and Information Sciences, "UOW MakerSpace Student Induction and Teaching Resources (TCHR053_22)," [Online]. Available: https://moodle.uowplatform.edu.au/course/view.php?id=34397. [Accessed 2 June 2026].

[63] Surf Life Saving NSW, "Public Safety Standard Operating Procedures - October 2025," 7 October 2025. [Online]. Available: https://www.surflifesaving.com.au/wp-content/uploads/sites/2/2023/09/Public-Safety-Standard-Operating-Procedures-October-2025.pdf. [Accessed 2 June 2026].

Appendices

Appendix A - Bill of Materials

TOTAL	Est Cost (AUD)	Est Weight (g)	Est Delivery Time (Days)
System and setup	$305.73	983	60
System (excluding Makerspace parts)	$277.83	-	-

Component	Est Cost (AUD)	Est Weight (g)	Est Delivery Time (Days)	URL
Raspberry Pi 4 (4GB)	$80.00	50	10	https://core-electronics.com.au/raspberry-pi-4-model-b-2gb.html?staticblockpopup=rpi_mixed
USB To 3.5mm Jack	$1.93	13	14	https://www.aliexpress.com/item/1005011581054350.html
Hydrophone transducer (PZT)	$30.00	15	15	https://www.aliexpress.com/item/1005005532825972.html
Power supply adapter (USB-C 5V 3A)	$2.14	60	11	https://www.aliexpress.com/item/1005005703532263.html
LoRa module (node)	$16.29	15	15	https://www.aliexpress.com/item/1005006539361701.html

Li-ion battery pack (1260110)	$10.89	60	60	https://www.aliexpress.com/item/1005007611232592.html
Microphone cable (5m)	$34.98	50	2	https://www.amazon.com.au/Outdoor-Lights-Waterproof-Connectors-Extension/dp/B07SZPZ769
32–128 GB high-end SD card	$19.00	5	0	https://www.cheapchips.com.au/sandisk-ultra-microsdxc-uhs-i-64gb
Mogami W2524 Unbalanced Instrument Cable	$4.60	50	30	https://toughaudio.com.au/product/mogami-w2524-bulk-gold-guitar-instrument-cable-black
MOGAMI W2964 Double Shield Coax Cable	$3.38	20	30	https://toughaudio.com.au/product/mogami-w2964-double-shield-coax-cable-4-8mm-od-per-m/

Mogami W2697 Miniature Balanced Mic Cable	$1.75	10	30	https://toughaudio.com.au/product/mogami-w2697-mini-balanced-microphone-cable-per-m
3.5mm Jack Male Terminal	$1.46	5	14	https://www.aliexpress.com/item/1005005812715035.html
GY-85	$5.23	10	14	https://www.aliexpress.com/item/1005012143179868.html
ClearWeld 5 Minute Epoxy	8.5	20		https://www.amazon.com/J-B-Weld-ClearWeld-Syringe-25mL/dp/B09C6R4VSQ/?th=1
Hydrophone buffer PCB	$30.00	56	14	https://www.jlielectronics.com/diy-accessories/dual-hydrophone-pcb/
Urethane resin (small kit)	$12.00	500	14	https://www.temu.com/au/-16-9oz--kit-clear-and-non-yellowing--self-leveling--1-1-casting-and--for--making-art-n-and-epoxy--g-601100807235659.html
Battery BMS / protection board	$5.05	12	12	https://www.temu.com/au/18650-battery-charging-module-type-c-port-charging-circuit-board-charging-board-suitable-for-3-6-3-7v-lithium-batteries-and-polymer-lithium-battery-charge--protection-featuring--functions-g-605811124354884.html

Stereo Aux Cable 3.5mm length 3m	$1.46	12	12	https://www.aliexpress.com/item/1005007286786952.html
GPS module (external)	$7.69	10	10	https://www.temu.com/au/-gy-neo6mv2-neo-6m-module-featuring-an--kit-for-with--and--in-robotics-g-601103014730725.html
On/off switch	$1.48	10	10	https://www.temu.com/au/one-piece-of-on-off-stop-switch-for-chainsaws-4500-5200-5800-and-45-52-58cc-suitable-for-replacement-of-spare-parts-g-601100220306963.html
USB to LoRa Data Transfer Module, Based On SX1262, Suitable For Data Acquisition In Industry And Agriculture	$19.79	30	14	https://www.aliexpress.com/item/1005010333249217.html
Hydrophone mold / misc	$1.00	50	14	Makerspace
9V Connector	$1.46	5	10	Makerspace
Silicone Grease	$2.00	5	1	Makerspace

Misc wiring/connectors/heat shrink	$0.50	20	1	Makerspace
Enclosure / buoy housing	$3.00	200	1	Makerspace
Fasteners (Rubber Band)	$0.05	5	1	Makerspace
Sealants / grommets	$0.10	50	1	Makerspace
Not counted in system weight.				

Appendix B - Risk Assessment RSK2600460

The published risk assessment [2]

Appendix C - Testing Strategy

The MESH Operational Testing Strategy [2].

Appendix D - Project Schedule

Date	Day	Start	Finish	Total	Running Total	Phase	Plan
29/06/2026 00:00:00	Monday	8:00:00	17:00:00	9:00:00	9:00:00	Literature Review & Requirements Definition	Research existing systems. Project Requirements: Passive sonar, Shallow water acoustics, Marine Vessel Acoustic Signatures Databases, Vessel acoustic features, Range (frequency & distance), Minimum SNR, classification methods (neural networks, K-nearest neighbours, Gaussian, and decision tree techniques) System Constraints and Success: Power budget, Computation budget, Cost & Weight, Deployment (storage duration, time until active), Environmental (waterproofing, material degradation), Sampling Frequency, Processing Latency.
30/06/2026 00:00:00	Tuesday	8:00:00	17:00:00	9:00:00	18:00:00		
01/07/2026 00:00:00	Wednesday	8:00:00	17:00:00	9:00:00	27:00:00		
02/07/2026 00:00:00	Thursday	8:00:00	17:00:00	9:00:00	36:00:00		
03/07/2026 00:00:00	Friday	8:00:00	17:00:00	9:00:00	45:00:00		
04/07/2026 00:00:00	Saturday	8:00:00	17:00:00	9:00:00	54:00:00		
05/07/2026 00:00:00	Sunday	0:00:00	0:00:00	0:00:00	54:00:00	Break	
06/07/2026 00:00:00	Monday	8:00:00	17:00:00	9:00:00	63:00:00		Selecting hydrophone type

07/07/2026 00:00:00	Tuesday	8:00:00	17:00:00	9:00:00	72:00:00	System Architecture & Trade Study	(piezo vs electret) Designing analogue front-end: Gain staging, Filtering (anti-aliasing, band-pass), ADC selection and sampling rate justification. DSP prototyping of classification methods using TensorFlow Lite for Microcontrollers. Validate algorithms
08/07/2026 00:00:00	Wednesday	8:00:00	17:00:00	9:00:00	81:00:00		
09/07/2026 00:00:00	Thursday	8:00:00	17:00:00	9:00:00	90:00:00		
10/07/2026 00:00:00	Friday	8:00:00	17:00:00	9:00:00	99:00:00		
11/07/2026 00:00:00	Saturday	8:00:00	17:00:00	9:00:00	108:00:00		
12/07/2026 00:00:00	Sunday	0:00:00	0:00:00	0:00:00	108:00:00	Break	
13/07/2026 00:00:00	Monday	8:00:00	17:00:00	9:00:00	117:00:00	Data Acquisition	Timestamping, buffering, logging, sample integrity, clipping behaviour, synchronization.
14/07/2026 00:00:00	Tuesday	8:00:00	17:00:00	9:00:00	126:00:00		
15/07/2026 00:00:00	Wednesday	8:00:00	17:00:00	9:00:00	135:00:00	DSP Fundamentals	Time-domain detection FFT-based spectral analysis Feature extraction (band energy, harmonics, spectral centroid) Detection and catagorisation via different techniques
16/07/2026 00:00:00	Thursday	8:00:00	17:00:00	9:00:00	144:00:00		
17/07/2026 00:00:00	Friday	8:00:00	17:00:00	9:00:00	153:00:00		
18/07/2026 00:00:00	Saturday	8:00:00	17:00:00	9:00:00	162:00:00		
19/07/2026 00:00:00	Sunday	0:00:00	0:00:00	0:00:00	162:00:00	Break	
20/07/2026 00:00:00	Monday	8:00:00	17:00:00	9:00:00	171:00:00	Analogue Front-End & Instrumentation Design	Raspberry Pi Optimisation Algorithms: CPU load, Memory, Power, Performance, Documenting trade-offs.
21/07/2026 00:00:00	Tuesday	8:00:00	17:00:00	9:00:00	180:00:00		
22/07/2026 00:00:00	Wednesday	8:00:00	17:00:00	9:00:00	189:00:00	3D print Prototype	Test (buoyancy, instability, water ingress, vibration issues). Enclosure fabrication. Use both Makerspace and Fluids Lab.
23/07/2026 00:00:00	Thursday	8:00:00	17:00:00	9:00:00	198:00:00	Embedded Software	Configure RTOS with all local

24/07/2026 00:00:00	Friday	8:00:00	17:00:00	9:00:00	207:00:00		dependencies to be developed
25/07/2026 00:00:00	Saturday	8:00:00	17:00:00	9:00:00	216:00:00	Design Test	Evaluating test methodology: detection accuracy, false positives, compliance (risk, safety and ethics)
26/07/2026 00:00:00	Sunday	0:00:00	0:00:00	0:00:00	216:00:00	Break	
27/07/2026 00:00:00	Monday	8:00:00	17:00:00	9:00:00	225:00:00	Order parts	Order all online parts and continue buoyancy tests.
Total Mid Year Hours. Recommence in Summer Break					**225:00:00**	**Break**	
14/12/2026	Monday	8:00:00	17:00:00	9:00:00	234:00:00	Assemble System	Use both 8G22 and Makerspace. Bench testing: Noise floor measurement, Frequency response testing
15/12/2026	Tuesday	8:00:00	17:00:00	9:00:00	243:00:00		
16/12/2026	Wednesday	9:00:00	18:00:00	9:00:00	252:00:00	Controlled Experimental Testing	Running pool experiments with controlled sound sources, collecting and labelling data Evaluating detection accuracy and false positives Refining algorithms based on results, Calibration (sensitivity, System gain, Frequency response, Self-noise, Environmental noise).
17/12/2026	Thursday	8:00:00	17:00:00	9:00:00	261:00:00		
18/12/2026	Friday	8:00:00	17:00:00	9:00:00	270:00:00		
19/12/2026	Saturday	8:00:00	17:00:00	9:00:00	279:00:00		
20/12/2026	Sunday	0:00:00	0:00:00	0:00:00	279:00:00	Break	
21/12/2026	Monday	8:00:00	17:00:00	9:00:00	288:00:00	Controlled Experimental Testing	Iterate improvements in the testing regime according to performance requirements. Pilot testing regime in harbour to verify: waterproofing, logging, battery life, recovery procedure
22/12/2026	Tuesday	8:00:00	17:00:00	9:00:00	297:00:00		
23/12/2026	Wednesday	9:00:00	18:00:00	9:00:00	306:00:00		
Recommence in after New Years					**306:00:00**	Break	
02/01/2027	Saturday	8:00:00	17:00:00	9:00:00	315:00:00		

03/01/2027	Sunday	8:00:00	17:00:00	9:00:00	324:00:00	Full Deployment Verification	Deploying system in real coastal conditions, Recording acoustic data from RWCs and IRBs, Break for operators. Implementation of the recordings into classification data, Conduct testing of the system to detect and classify
04/01/2027	Monday	8:00:00	17:00:00	9:00:00	333:00:00	Full Deployment Verification (Backup)	Conduct intended Full Deployment Verification in Wollongong harbour instead. If this is not required because the Deployment Verification was successfully completed at NCSLSC, then skip onto the next section.
05/01/2027	Tuesday	8:00:00	17:00:00	9:00:00	342:00:00		
06/01/2027	Wednesday	8:00:00	17:00:00	9:00:00	351:00:00		
07/01/2027	Thursday	8:00:00	17:00:00	9:00:00	360:00:00		
08/01/2027	Friday	8:00:00	17:00:00	9:00:00	369:00:00	Analysis	Compilation of the data to conduct analysis of results. Evaluating real-world performance vs lab results
09/01/2027	Saturday	8:00:00	17:00:00	9:00:00	378:00:00		
10/01/2027	Sunday	0:00:00	0:00:00	0:00:00	378:00:00	Break	
11/01/2027	Monday	8:00:00	17:00:00	9:00:00	387:00:00	Documentation & Professional Reflection	Comparing performance vs requirements Identifying limitations and future improvements Writing technical documentation and reflection
12/01/2027	Tuesday	8:00:00	17:00:00	9:00:00	396:00:00		
13/01/2027	Wednesday	8:00:00	17:00:00	9:00:00	405:00:00		
14/01/2027	Thursday	8:00:00	17:00:00	9:00:00	414:00:00		
15/01/2027	Friday	8:00:00	17:00:00	9:00:00	423:00:00		
16/01/2027	Saturday	8:00:00	17:00:00	9:00:00	432:00:00		
17/01/2027	Sunday	0:00:00	0:00:00	0:00:00	432:00:00	Break	
18/01/2027	Monday	8:00:00	14:00:00	6:00:00	**438:00:00**	Finalisation and submission	Formatting, references and styling.
PEX Hours Obtained							

Appendix E - List of Tables

END OF DOCUMENT