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APPETITE FOR CREATIVE DESTRUCTION – MACHINE LEARNING FOR ACOUSTIC SENSOR OPERATION IN ANTI-SUBMARINE WARFARE

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JCSP 46

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PCEMI 46

Maîtrise en études de la défense

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CANADIAN FORCES COLLEGE ~ COLLÈGE DES FORCES CANADIENNES
JCSP 46 ~ PCEMI 46
6 MAY 2020

DEFENCE RESEARCH PAPER

**APPETITE FOR CREATIVE DESTRUCTION – MACHINE LEARNING FOR
ACOUSTIC SENSOR OPERATION IN ANTI-SUBMARINE WARFARE**

By / Par le Major Corey Taylor

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ABSTRACT

Anti Submarine Warfare (ASW) over the last century has consisted of a balance between cutting-edge technology and an affinity for maintaining the status quo. Machine Learning (ML) has been a relatively recent transformative technology that has been applied to countless industries and products and has been successfully applied in research settings to classify ships, submarines and marine life. This paper explores whether ML could potentially make the leap from the research laboratory to Canadian ships, aircraft and submarines to execute the individual tasks currently carried out by acoustic sensor operators.

The analysis in this paper covers efforts by the Government of Canada and the CAF/DND to lay a policy groundwork for the adoption of data management and Artificial Intelligence (AI), looks at the status of the planned acquisition of new ASW naval vessels and aircraft of Canada, allied nations and our adversaries and explores the tasks of sensor operators through all phases of the ASW mission, from pre-mission information gathering and mission planning, through to the detection and tracking of a submarine in real time, to post-mission data extraction and intelligence production. The potential to enhance the performance of ASW units, execute more tasks concurrently and reduce costs in terms of manning and number of platforms required is examined through a review of the tasks of the operators and current research in AI/ML with direct ASW applications, as well as how it is used in other industries.

This paper concludes that ML has massive potential for augmenting, and ultimately replacing, human sensor operators in ASW that leveraging this technology on future platforms will contribute significantly to our national interests and help to ensure Canada remains a relevant and capable ASW partner among our allies.

CHAPTER 1: INTRODUCTION

It was one thing to use computers as a tool, quite another to let them do your thinking for you.

- Tom Clancy, *The Hunt for Red October*

Anti-Submarine Warfare (ASW) is widely recognized by experts within the Canadian Armed Forces (CAF) and among our allies as a “cat and mouse game” of one-upmanship and technological advancement which seeks to achieve and maintain any advantage over one’s adversary, whether in real time at the tactical level, or in a broader sense using improvements in technology on submarines and the platforms that hunt them.¹ This art of chasing an evasive submarine in its own element requires a set of skills honed over decades and inculcated into the current generation of ASW warriors. It is a perishable capability that if not regularly practiced deteriorates quickly, and Canada is at risk of being left behind in the next advancement of ASW capabilities.

With the end of the Cold War, and the subsequent reduced Soviet submarine patrols throughout the 1990s and early 2000s, some Canadian commanders questioned the need to maintain Canada’s ASW expertise in the face of a diminished adversary threat. From the mid 2000s onward, conflicts in Afghanistan and Iraq refocused the CAF’s efforts on “counterinsurgency, counter-terrorism, counterpiracy and peace support operations” and further away from over-water roles, including hunting for submarines.² The Canadian CP-140 community, for example, transferred responsibility for Acoustic Sensor Operator duties from Air Navigators, who were traditionally officers, to Airborne Electronic Sensor Operators (AES Op)

¹Gareth Evans, “Cat and Mouse: The Art of Submarine Detection,” *Naval-Technology.com*, 13 June 2011 <https://www.naval-technology.com/features/feature121453/>

²Chris Thatcher, “Submarine Hunter,” *RCAF Today 2018*, 49 <https://army.ca/forums/index.php?action=dlattach;topic=66394.0;attach=57166>

and cut the number of positions for this duty significantly while the Navy retained SONAR Operators (SONAR Ops), but also saw less ASW training take place.

Through the last decade, submarine deployments have risen to levels not seen since the end of the Cold War, with many nations growing their submarine fleets.³ Achieving an edge over one's underwater adversaries requires operational units sufficiently manned with capable, experienced operators to not only carry out their own difficult missions, but also to concurrently train the next generation of warriors. Canadian ASW sensor operators (AES Ops and SONAR Ops, particularly), however, have been challenged to build their manning and expertise back to levels present during the height of Cold War ASW operations.

The author of this paper was one of the aforementioned CP-140 Air Navigators Acoustic Sensor Officer, with follow-on postings to units that continued to train AES Ops and SONAR Ops in underwater acoustics, including most recently back at an ASW-focused operational unit through the recent period of heightened submarine operations. These experiences have all been tied in some way to the challenge of retaining and enhancing ASW sensor operators' expertise, and have informed this paper.

Technologically, Canadian acoustic processing systems and other sensors used in ASW are recognized as among the best in the world.⁴ These systems, however, are beginning to age and as we look at the timelines that will be required for procurement of the next generation of ASW ships and aircraft to counter future generations of adversary submarines, which will no doubt be more stealthy and whose movements will be harder to detect and track, it is apparent that the time is now to consider how to achieve the next bound in ASW sensor technology.

³Commander William Perkins, "Alliance Airborne Anti-Submarine Warfare – A Forecast for Maritime Air ASW in the Future Operational Environment," *NATO Joint Air Power Competence Centre*, June 2016; Thatcher, "Submarine Hunter. . .", 49

⁴Thatcher, "Submarine Hunter. . .", 49

This paper's title alludes to "creative destruction," a concept borrowed from Eric Topol's 2012 book on how technology was on the verge of revolutionizing medicine and which he, in turn, had borrowed from Joseph Schumpeter, an Austrian economist, who used the term to "denote transformation that accompanies radical innovation."⁵

Likewise, the aim of this paper is to outline how advances in Machine Learning (ML) could radically change the field of ASW through application to the sensor operator tasks currently carried out by human sensor operators in ASW, as well as to demonstrate how Canada's manning challenges, position as a technology leader and current stages in the acquisition process of new ASW platforms represent an ideal time to consider making what amounts to an essential technological leap for Canada's next generation of ASW platforms in order to maintain our position as a capable ASW partner. This leap will entail tearing down, or 'creatively destroying,' current structures and mindsets within the CAF, but will be a necessary step to keep pace with advancements that are currently underway.

Chapter 2 takes the reader through an overview of the basic principles of ASW, AI and ML concepts and some of the policies of the CAF as they relate to the military adoption of AI. While some readers may find the contents of this chapter quite basic, for those without a background in either ASW or AI/ML, this chapter lays the groundwork for the discussions to follow. Chapter 3 gives an overview of the ASW sensor operator occupations and the tasks carried out by these highly trained personnel, as well as frames some of the challenges inherent in dealing with the massive amounts of data generated by modern acoustic sensors. Chapter 4 examines some recent research into the application of ML to acoustic analysis, as well as many of the current applications of ML in other fields and how they could potentially be applied to

⁵Eric Topol, *The Creative Destruction of Medicine; How the Digital Revolution Will Create Better Health Care* (New York: Basic Books, 2012), v

tasks carried out by operators through the phases of ASW. While this paper does not contain a traditional literature review, as references to current research and articles appear across several chapters, readers seeking current research and articles related to AI/ML and ASW will find the majority of them discussed in Chapter 4. Chapter 5 outlines some tactical considerations that will need to be taken into account if ML is to transition from laboratory and research settings to a real-world application in an operational environment. Chapters 6, 7 and 8 outline, respectively, initiatives of adversaries, allies and Canadian-specific initiatives, as they relate to ASW, as well as current and future platforms. Chapter 9 looks at some initiatives in other fields and cutting-edge research that could one day be transferrable to ASW. Chapter 10 recommends a sequence of steps or stages that would be required for Canada to take ML from a laboratory research setting to full application on real-time tactical platforms.

Before outlining some basic concepts in the next chapter, two caveats need to be addressed. The first is that this paper relies strictly on unclassified sources. A well-known axiom in ASW circles, and one that is completely untrue, is that “submariners never cheat and seldom lie.”⁶ Through the use of unclassified sources, there is a danger that capabilities of systems in existence or under development have been either under or over-reported, with the potential impact of the arguments and conclusions in this paper potentially being coloured by disinformation or by the hiding of the true capabilities of one’s systems or platforms.

A second caveat is that while there is significant discussion on ethics within military applications of Artificial Intelligence (AI) and ML, such as with Google’s Project Maven⁷ and

⁶Note: This expression comes from the ‘dolphin code’ which, as described on several websites, (such as <https://www.submarinesaustralia.com/upperiscope2/dolphin-code.html>) “was a method of encrypted communications designed to enable submarines, submariners, ship captains, helicopter pilots, anti-submarine aircraft to speak to each other in areas of submarine operations or in many cases, social and domestic activities surrounding people of *“The Trade.”*”

⁷Global News, “What is Project Maven? The Pentagon AI project Google employees want out of,” *GlobalNews.ca*, 5 April 2018 <https://globalnews.ca/news/4125382/google-pentagon-ai-project-maven/>

the ethics of allowing autonomous systems to make lethal decisions without a human in the loop, this paper will concentrate more narrowly on the ability of a system to derive information from sensors and provide it to human decision makers. The ethics of autonomous weapon delivery and the more general implementation of ML to carry out military tasks are important topic areas that certainly require further attention and research, but are beyond the scope of this study.

CHAPTER 2: BACKGROUND/BASICS

ASW – “AWFULLY SLOW WARFARE” NO MORE

Anti-Submarine Warfare was once thought of as slow, as it involved platforms sometimes only doing a few knots at sea. It now could be considered to occur at the “speed of information,” specifically the speed at which human crews aboard the platforms can process the vast amounts of information arriving through their sensors.⁸ However, before addressing how Machine Learning could play a role in managing this deluge of information in the chapters that follow, this chapter will provide an overview of what ASW, AI and ML are and will highlight some of the policies around the use of AI and ML in a military context.

Regardless of the level of hostilities, an unlocated adversary submarine can threaten freedom of movement through maritime choke points or across areas of open ocean. In times of conflict, a submarine can stealthily position itself close enough to a task group to shoot at, and potentially sink, high value ships, such as aircraft carriers or resupply ships. Positioned closely enough to an allied shoreline undetected, submarines with modern cruise missiles could attack inland targets. As Commander William Perkins writes in his Alliance Airborne ASW document, “a lone submarine can do more damage in both a military and a political sense than probably any other single conventional platform, naval or military.”⁹ In order to mitigate or avoid these effects, ASW co-ordinated among multiple nations is used to keep tabs on the locations and, to the extent possible, the intentions of adversary submarines. Admiral James Stavridis, in likening submarines to sharks, with both constructed to silently hunt and kill their prey, wrote

⁸The Technium, “The Speed of Information,” *kk.org*, accessed 2 May 2020, <https://kk.org/thetechnium/the-speed-of-in/>

⁹William Perkins, “Alliance Airborne Anti-Submarine Warfare. . .”, 78. Chapter 2 of Perkins’ JPACC document has a very good primer on ASW and sound sources. It also provides one of the few unclassified sources for this type of information compiled in one place and as such is heavily referenced in this paper. For further reading beyond what is summarized here, that document provides a great overview and is highly recommended.

“occasionally, it becomes necessary to find and destroy them – to keep open sea lanes of communication, to sweep an area and make it safe for allied shipping. Destroying a submarine, I think, is the hardest task in naval warfare.”¹⁰

ASW, as the name implies, is the method by which these tasks are carried out. It can be a single platform or a co-ordinated effort among subsurface, surface, air and shore-based assets attempting to search for, detect, localize, track and, when necessary, attack one or more submarines. These stages of ASW rely on a suite of sensors, which are generally referred to as passive or active.

Historically, the primary sensor used for ASW was Sound Navigation and Ranging (SONAR), with passive systems, which “detect emissions from a target or its influence on the environment without the emission of energy from the sensor” used beginning in 1916 and active systems adopted by the close of WWI.¹¹ These systems have over time become augmented by many others, including radio direction finding, Electro-Optical/Infra-Red (EO/IR), night vision goggles, visual observation using gyro-stabilized binoculars, digital photography, electronic warfare (anti-radar, anti-radio, intelligence gathering and direction finding), communications intelligence, magnetic anomaly detection and broad range of RADAR capabilities, including imaging modes to classify vessels.

Passive SONAR, which “listens to the sound in the ocean and tries to find the noise that the submarine makes in the water”, was the sensor of choice for ASW throughout the Cold War, in particular against earlier generations of noisier nuclear-powered submarines.¹² These systems,

¹⁰James Stavridis, *Destroyer Captain: Lessons of a First Command*, (Naval Institute Press, 2008), 48

¹¹NATO Maritime Multi-Mission Aircraft (M3A) Statement of Operational Requirement (SOR) – 2nd Draft 2 March 2018, 12; Encyclopedia Britannica Online <https://www.britannica.com/technology/SONAR>

¹²Canada. Department of National Defence and Canadian Armed Forces. Royal Canadian Navy, website accessed 27 March 2020 <http://www.navy-marine.forces.gc.ca/en/innovation/innovation-view.page?doc=underwater-warfare-suite-upgrade-protects-sailors-from-quieter-submarines-and-torpedoes/jwfmfy3sc>

which were effective for “long range detection of noisy targets in large bodies of water,” are still in use, albeit against ever-quieter submarine targets.¹³

Sounds produced by submarines which can be exploited by adversaries can generally be traced back to three different categories of sources: propulsion plant noise, propeller noise, and noise generated as water moves over the hull.¹⁴ The propulsion and propeller categories are made up of “rotating machineries that are unique to the class of the vessel so the frequency and the magnitude of these machinery tonals should be able to uniquely characterise them.”¹⁵ The third category consists of “broadband component because of cavitation and other effects.”¹⁶

Advances in submarine quieting technologies have included designs to lessen the radiation of noise of individual systems, anechoic coatings to reduce attenuation of noises and the addition of technologies like Air Independent Propulsion (AIP), which reduces how often conventional submarines need to make themselves vulnerable by surfacing and generate engine noise, to recharge batteries. Operations have also shifted, in some cases, into “acoustically-noisy littoral regions,” meaning quieter submarine sources are masked by busy shipping and other maritime traffic close to shore.¹⁷ These challenges to the use of passive acoustic sensors have put more emphasis on active acoustic systems, which “employ emissions to detect a target or its influence on the environment and are typically overt sensors.”¹⁸ Active sensors can be subdivided into further classes, monostatic, bi-static or multi-static, depending on whether the transmitters and receivers are located on the same platform or in two or more locations working together and can include hull-mounted SONARs on ships and submarines, aircraft-deployed

¹³Ibid

¹⁴William Perkins, “Alliance Airborne Anti-Submarine Warfare. . .”, 36

¹⁵A. Das, A. Kumar, and R. Bahl, “Marine vessel classification based on passive SONAR data: the cepstrum-based approach,” *IET Radar, SONAR & Navigation*, 2013, 7(1):87-93.

¹⁶Ibid

¹⁷NATO M3A SOR. . ., A-10

¹⁸NATO M3A SOR. . ., 12

sonobuoy fields which relay the sounds in the ocean back to the aircraft via radio transmitter, and dipping active SONARs streamed from hovering helicopters.

While active SONAR has typically been limited by an inability to classify a submarine or other contact by the sound returned to the receiver, “future development not only in the use of multi-statics for initial submarine detection but also for target classification via active SONAR” is a significant area of research.¹⁹

NATO has expressed concern of a “growing risk the Alliance will find itself unprepared to capably respond to a potential increase in non-NATO submarine operations.”²⁰ Many countries are working to develop ASW technology and tactics, including AI and ML, in order to ensure they are prepared when the need arises. There will be wide-ranging changes to ASW as a result of applying these technologies to sensors as diverse as RADAR, Magnetic Anomaly Detection, Electronic Support Measures, Electrical/Optical and many others, and the implementation of ML to operate those sensors should definitely be pursued. Since passive and active acoustics are arguably the more difficult tasks to offload to a computer system, however, the scope of this paper is limited to the conduct of those tasks.

AI and ML – the Future of ASW

“With its promise of automating mundane tasks as well as offering creative insight, industries in every sector from banking to healthcare and manufacturing are reaping the benefits” of ML, AI and other technologies that have become buzzwords in recent years.²¹ Before

¹⁹William Perkins, “Alliance Airborne Anti-Submarine Warfare. . .”, 41

²⁰NATO M3A SOR. . ., 1

²¹Bernard Marr, “What is the Difference Between Artificial Intelligence and Machine Learning?”, *Forbes.com* December 6, 2016, <https://www.forbes.com/sites/bernardmarr/2016/12/06/what-is-the-difference-between-artificial-intelligence-and-machine-learning/#78971af32742> website accessed 27 Mar 2020

addressing the platforms and the tasks of the operators, a primer on Machine Learning, Artificial Intelligence, Deep Learning and other concepts is appropriate.

Artificial Intelligence is “a system, or component of a system, which emulates aspects of human cognition such as perception, reasoning, planning, and learning such that it can enable actions either digitally or through the powering of physical systems.”²² Basically, AI can be described as “a system that makes autonomous decisions.”²³ AI can recognize sounds and objects, solve problems, understand language, and use strategy to meet goals and is a term that typically is applied to “machines being able to carry out tasks in a way that we would consider ‘smart’”²⁴ The techniques it uses to carry out these tasks will be discussed in Chapter 4.

Machine Learning (ML) is a subset or application of AI, which uses algorithms to analyse large datasets to make predictions about relationships in the data and eventually “teach themselves to learn and act.”²⁵ A key player in the development of ML was Geoff Hinton, a professor at the University of Toronto, who “imagined a new kind of neural net, one made up of multiple layers that each extracted different information until it recognized what it was looking for.”²⁶ By the mid-2000s, this development of neural networks had become a turning point in teaching computers to train themselves, rather than having all of their actions programmed. Through establishing “successive layers where each layer is connected to a small number of local units below,” and having each layer check “for slightly more complicated features by combining the features below” computers manage to, in a way, classify “information in the same way a

²²Canada - DND/CAF Data Strategy. . . , C-32

²³Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*, (New York: Public Affairs, 2019), 14

²⁴Bernard Marr, “What is the Difference Between Artificial Intelligence and Machine Learning?”

²⁵Canada - DND/CAF Data Strategy – C-32

²⁶Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . , 41

human brain does.”²⁷ This process also acknowledges that while there may be many raw attributes of data, there are a much more limited number of important attributes that can be extracted from the data and often there are hidden or unknown relationships between them.²⁸ In identifying, and assigning weights to, these relationships, the system “works on a system of probability based on data fed to it,” and makes statements, decisions or predictions with an associated degree of certainty.²⁹ A feedback loop, where the system is told whether its outputs are right or wrong, allows the system to modify its algorithms and adjust future predictions.

Deep Neural Networks (DNN) were an offshoot of the original neural networks and applied what is called ‘deep learning,’ learning only from the data, without the need for human supervision, to train computers to perform tasks.³⁰ Since being implemented, deep learning networks have “performed efficiently in classification or recognition tasks” particularly when fed very large datasets.³¹ Part of the appeal of these networks is that they do not require as much labeled data and computing power, or supervision, and can be done much faster with the learning algorithm able to “discover all that is necessary by itself.”³² Whereas earlier methods required using the whole data set to train the system, modern systems can do “small updates on the connection weights as we see training instances one at a time,” which is ideal because it can learn by using a few examples at a time and adapt to changes in underlying characteristics of the data. As will be discussed later in this paper, this is relevant to acoustic analysis, because as new

²⁷Ethem Alpaydin, *Machine Learning, the New AI*, (The MIT Press, 2016). ISBN 9780262529518, 102; Bernard Marr, “What is the Difference Between Artificial Intelligence and Machine Learning?”

²⁸Ethem Alpaydin, *Machine Learning, the New AI*. . ., 102

²⁹Bernard Marr, “What is the Difference Between Artificial Intelligence and Machine Learning?”

³⁰Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . ., 41

³¹Guanghao Jin, Fan Liu, Hao Wu & Quinzeng Song (2020) “Deep Learning based Framework for expansion, recognition and classification of underwater acoustic signal,” *Journal of Experimental & Theoretical Artificial Intelligence*, 32:2, 205-218, DOI: 10.1080/0952813X.2019.1647560

³²Ethem Alpaydin, *Machine Learning, the New AI*. . ., 108

or updated naval platforms come online, new information is gathered over time and a system that “can adapt seamlessly, without needing to stop, collect new data, and retrain” is needed.³³

National and CAF Policies

In the Chief of Force Development’s assessment of the future security environment, it is acknowledged that “advances in sensing technologies will increase the ability to detect, characterize, and engage platforms, systems and individuals.”³⁴ These new and more widespread sensing capabilities will expand the amount of data being collected and being able to deal with this ‘big data’ will be as important to maintenance of timely intelligence and support to military decision makers as it is in the rest of society. Referencing unmanned systems, but in a comment that could equally apply to platforms where people’s tasks are augmented with machine assistance, this document forecasts that “artificial intelligence may one day make combat decisions.”³⁵

In 2019, the DND/CAF Data Strategy was released. It also acknowledged the challenges inherent in dealing with data and data-driven approaches, concluding that without being able to fully exploit our data, “the Defence Team will fall behind, and risks facing better-informed, more agile adversaries in conflict situations.”³⁶ Possible areas where this could be applicable include “exploring how to use data-driven technologies such as artificial intelligence...to improve the efficiency and effectiveness of Defence programs.”³⁷ The document acknowledges that “future military platforms will have tremendous data requirements to enable the full capability of the platform’s offensive and defensive weapon systems” and refers to enhanced intelligence to allow

³³Ethem Alpaydin, *Machine Learning, the New AI*. . . , 91

³⁴Canada, Chief of Force Development, “The Future Security Environment 2013-2040,” 73

³⁵Ibid, 75

³⁶Canada - DND/CAF Data Strategy, 2019, i

³⁷Ibid

platforms to detect, identify, evade, and engage the enemy.³⁸ Initiatives relating to collection, storage, and sharing of data on foreign threat systems, and our own platforms, those of friendly countries or non-combatants are also discussed “in order to optimize the performance of our future systems.”³⁹

Strong Secure Engaged (SSE), released in 2017, characterizes the future of defence as “expected to be vastly different than today, with a greater emphasis on information technologies, data analytics, deep learning, autonomous systems, advancements in the electromagnetic and cyber domains.”⁴⁰ It also refers to “transformative technologies,” such as quantum computing, which will briefly be touched on in Chapter 9. In the area of ASW platforms, SSE outlines the recapitalization of the naval fleet through the acquisition of 15 Canadian Surface Combatants, modernization of the four Victoria-class submarines and the replacement of the CP-140 Aurora. While SSE looks to “acquire new or enhanced naval intelligence, surveillance, and reconnaissance systems...and additional systems for current and future platforms allowing for more effective offensive and defensive naval capabilities,” there is no specific allocation in the defense policy for applying AI or ML to ASW.⁴¹ A broad interpretation of its discussion of a network-centric approach to Joint Intelligence, Surveillance and Reconnaissance, consisting of “interconnected intelligence collection platforms – including aircraft, remotely piloted systems, land vehicles, ships, submarines, people, and satellites” and the capture of information and exchange of data in near real-time, could be applicable to ASW.⁴² Additionally, SSE outlines the Innovation for Defence Excellence and Security (IDEaS) programme, which seeks to “bring

³⁸Canada - DND/CAF Data Strategy, C-33

³⁹Ibid

⁴⁰Canada, *Strong Secure Engaged*, Canada’s Defense Policy, 2017, 55

⁴¹Ibid, 64

⁴²Ibid

together academics, industry and other partners to form collaborative innovation networks” and emphasizes that “areas for advanced research and development include surveillance” and data analytics.⁴³ In short, these policies are certainly forward-looking and lay the foundation for the adoption of ML/AI on ASW platforms.

The mandate letter from the Prime Minister to the Minister of National Defence after the last election emphasized the importance ensuring the CAF “have the capabilities and equipment required to uphold their responsibilities through continued implementation of SSE, including new procurements and planned funding increases.”⁴⁴ This letter reiterated the intent to renew the Royal Canadian Navy (RCN) Fleet, “ensuring Canada’s Navy has the modern ships that it needs” and working “to develop better surveillance. . . in the North and in the maritime and air approaches to Canada, to strengthen continental defence, protect Canada’s rights and sovereignty and demonstrate international leadership with respect to the navigation of Arctic waters.”⁴⁵

As an aggregate, these documents outline a vision of the CAF operating in a high-tech future where “DND/CAF explores and implements data-driven approaches to expand and enhance operational capabilities.”⁴⁶ The contention of this paper is that much more advanced tasks, such as those carried out by sensor operators on ASW platforms, should also be considered for application of AI/ML, in order to remain competitive with our adversaries in the coming decades. The DND/CAF Data Strategy states that “the GC has released, or plans to release, new and updated policies and directives around” areas including “automated decision approaches

⁴³Canada. Strong Secure, Engaged, Canada’s Defense Policy, 77

⁴⁴Office of the Prime Minister of Canada. Minister of National Defence Mandate Letter, December 13, 2019 <https://pm.gc.ca/en/mandate-letters/2019/12/13/minister-national-defence-mandate-letter>

⁴⁵Ibid

⁴⁶Canada. DND/CAF Data Strategy. . . , 9

such as artificial intelligence.”⁴⁷ In the next chapter, rationale for the implementation AI/ML in ASW, and the specific shortfalls it would address, will be expanded upon.

⁴⁷Ibid, 30

CHAPTER 3: PROBLEM FRAMING

As previously mentioned, ASW sensor operator skills are perishable and require regular refreshing through training exercises or operations. After nearly twenty years of reduced submarine activity, allied ASW forces are growing their experience levels back, and recognize that re-building the proficiency of acoustic operators and ASW crews could take a whole generation.⁴⁸ This chapter outlines who Canada's acoustic sensor operators are, the tasks they carry out and some of the challenges they face that could be offset by the adoption of ML.

In Canada, passive and active acoustic sensors are operated by SONAR Operators (SONAR Ops) in the Navy and by Airborne Electronic Sensor Operators (AES Ops) in the Air Force. Other sensors used by the Navy in ASW are operated by Naval Electronic Sensor Operators (NES Ops), who “operate radar and radio detection devices, radar jamming systems and decoys” and Naval Combat Information Operators (NCI Ops), who “are responsible for the operation of all shipboard surveillance radars and associated equipment of the shipboard intelligence, surveillance and recognizance systems.”⁴⁹ In the RCAF, AES Ops also operate suites of non-acoustic sensors on the CH-148 Cyclone Maritime Helicopter and the CP-140 Aurora Long Range Patrol aircraft, including RADAR, electro-optic/infrared (EO/IR) systems, magnetic anomaly detection (MAD), and electronic warfare equipment”⁵⁰

While significant to the conduct of ASW on their platforms, and although NES Ops, NCI Ops and non-acoustic AES Ops' sensors could equally be subject to augmentation or

⁴⁸William Perkins, “Alliance Airborne Anti-Submarine Warfare. . .”, 58

⁴⁹Canada, Department of National Defence, “Naval Electronic Sensor Operator,” <https://forces.ca/en/career/naval-electronic-sensor-operator/>; Canada, Department of National Defence, “Naval Combat Information Operator,” <https://forces.ca/en/career/naval-combat-information-operator/>

⁵⁰Canada, Department of National Defence, <https://forces.ca/en/career/airborne-electronic-sensor-operator/>

replacement by ML systems, this paper focuses on the operation of acoustic sensors by ML systems as a starting point for the ‘creative destruction’ of ASW alluded to earlier.

The primary role of SONAR Ops is to “compile and analyze acoustic intelligence information.”⁵¹ They listen to sounds in the ocean and use processing systems to “interpret what they hear to determine what is occupying the surrounding waters,” primarily with the purpose of finding enemy submarines.⁵² SONAR Operators’ tasks, almost all of which would need to be carried out by an ML system, include:

- “evaluating and identifying significant features from oceanographic data;
- performing function checks on equipment, using built-in and integrated test equipment and basic fault diagnostic procedures;
- Operating all active and passive SONARs, bathythermograph equipment and sonobuoys;
- analyzing SONAR and intelligence data, interpreting the tactical picture and implications and assisting in the development of command decisions;
- providing oceanographic and acoustic data to post-mission analysis facilities; and
- maintaining watchkeeping records, geographical, operational and tactical plots”⁵³

The SONAR Op medical standards specify the need to “concentrate on extremely fine visually represented data for up to 7 hours in brightly lit windowless areas,” as well as physical seamanship tasks not related to their sensor duties, such as standing for extended periods, carrying loads and firefighting duties, which will be assumed to not apply to an ML system.⁵⁴ Likewise, AES Ops carry out physical tasks, such as inspections of aircraft spaces and ordnance duties like loading sonobuoys onto aircraft, which would not be expected of an ML-trained system. Both occupations perform duties “exposed to all weather and climatic conditions” and

⁵¹Canada, Department of National Defence, <https://forces.ca/en/career/SONAR-operator/>

⁵²Jenn Jackson, “Junior SONAR Operators Learn How to Hear and Track a Submarine,” *Navy-Marine.forces.gc.ca*, <http://www.navy-marine.forces.gc.ca/en/news-operations/news-view.page?doc=junior-SONAR-operators-learn-how-to-hear-and-track-a-submarine%2Fk42zftfp>

⁵³Canada, Department of National Defence, <https://forces.ca/en/career/SONAR-operator/>

⁵⁴Canada, Department of National Defence, “Task Statement for Military Occupational Structure Identification - 00324 Sonar Operator,” <https://www.canada.ca/en/department-national-defence/corporate/policies-standards/medical-standards-military-occupations/military-occupational-structure-id-task-statements/non-commissioned-members/mosid-00324-SONAR-op.html>

exposed to fumes, chemicals, radio frequency radiation and high noise levels.⁵⁵ Motion of the platform, amplified by heavy sea state or poor weather conditions and fatigue from working from a computer screen in a dark room at any time of day further degrade physiological limits on how many sensors an operator can cycle through to identify “short-duration contact on a modern quiet submarine.”⁵⁶ As Perkins points out, many operators use a correction factor, called Directivity Index, which accounts for the sensitivity of the acoustic system, but also factors in “on station performance reduction due to fatigue and offset any lack of operator proficiency or ASW currency.”⁵⁷ ML systems are not limited by these physiological factors and would have a lower probability of missing a submarine contact due to these factors that can degrade human operators’ performance.

AES Ops “employ leading-edge technologies to detect and track submarines,” among several roles.⁵⁸ As such, the training for these highly skilled specialists takes a significant amount of time. After 10 weeks of Basic Training, AES Ops attend six months of basic occupational and flying training in Winnipeg, MB.⁵⁹ Whether selected for CP-140 or the CH-148 Cyclone, they then undergo a 6-month operational flight training course.⁶⁰ CP-140 ASOs undergo a further 18-month upgrade process on squadron, upon completion of which they become independently employable on a crew and become responsible for training the next generation of ASOs. Not accounting for gaps or breaks between training, it currently takes approximately 33 months of training to produce a top-category acoustic sensor AES Op. Recent statistics indicate that of 228 total positions, only a portion of which carry out acoustic duties, the

⁵⁵Ibid

⁵⁶William Perkins, *Alliance Airborne Anti-Submarine Warfare* . . . , 40

⁵⁷Ibid, 115

⁵⁸Courier News and Publishing, 4 Wing Cold Lake. “Become an Airborne Electronic Sensor Operator,” April 30, 2019. <http://couriernews.ca/2019/04/30/become-an-airborne-electronic-sensor-operator/>

⁵⁹Canada, Department of National Defence, <https://forces.ca/en/career/airborne-electronic-sensor-operator/>

⁶⁰Ibid

AES Op occupation has a Trained Effective Strength (TES) of only 78% of its established positions.⁶¹

After Basic Training, RCN SONAR Ops attend a five-week basic naval operations course in either Halifax, NS, or Esquimalt, BC, followed by a 25-week course in Esquimalt to learn the basics of the SONAR Op occupation. Once they have completed this course, they can begin to be employed, under supervision on surface ships, submarines, or Integrated Undersea Surveillance, with additional acoustic and supervisory courses are offered as they progress through ascending ranks.⁶² Overall 352 of 401 SONAR Op positions or 89% have achieved TES, with shortages most notable at the most junior ranks, which would typically be the system operators.⁶³ SONAR Ops are noted as “in demand” and as of May 2020 were being offered signing bonuses in order to boost their recruitment.⁶⁴ Additionally, the competition for talented people with skillsets to operate advanced systems is so high that some nations are tailoring their ship designs to make Navy service appealing to the “type of people” they want to recruit.⁶⁵

Likewise, AES Ops can be employed on an air platform or at post-mission acoustic processing facilities, referred to in some publications as the “Ground Segment,” and which “includes fixed and deployable mission support centres and Processing, Exploitation and Dissemination (PED) entities.”⁶⁶ The Ground Segment is, like operations on the platforms themselves, reliant on large amounts of data and, in respect to ASW, exists in order to facilitate

⁶¹D Mil C 4-6-2 2020 Career Manager Briefing Accessed 4 Feb 2020. All figures in this paper are rounded to the nearest percentage for ease of reading.

⁶²Canada, Department of National Defence, “SONAR Operator,” <https://forces.ca/en/career/SONAR-operator/>

⁶³MCS Establishment data as of 3 Dec 19

⁶⁴Ibid

⁶⁵Christopher Woody, “The military's 'war for talent' is affecting what the Navy's future ships will look like,” *Business Insider*, 23 February 2020. <https://www.businessinsider.com/military-recruiting-efforts-affecting-future-navy-ship-designs-2020-2>

⁶⁶NATO M3A SOR. . . , 9

the collection, analysis and dissemination of data in order to enable ASW operators on various platforms to successfully carry out their missions.

Initiatives to enhance ASW operations in the future and optimize sensor performance are all reliant on managing ever-increasing amounts of data more effectively. For example, a future development in ASW “will be the ability of a Maritime Multi-Mission Aircraft (M3A) to cooperate with other SONAR-equipped platforms in a network-enabled, multi-platform system, using each other’s SONAR transmissions to improve the overall ensonification of a threat area.”⁶⁷ This would involve a massive amount of data exchange and to manage the complexity and amount of data inherent in these systems they are being designed with tools to reduce operator workload, such as “new automated detection methods to improve search techniques and situation awareness.”⁶⁸ Incorporation of satellites, uninhabited aerial vehicles (UAVs), uninhabited underwater vehicles (UUVs), and other sensor systems into these networks of ASW assets will contribute to maritime situational awareness and will result in ASW data growing at an extreme rate, although perhaps paling in comparison to the information generated on the internet and through smart devices.

The non-military sector has long recognized the overwhelming amounts of data being produced and collected. We are now talking in terms of producing multiple zettabytes (each of which represents one trillion gigabytes) every year.⁶⁹ Much of this originates from what has been called “a sea of sensors,” in which “devices, everyday things and particularly humans-can become a sensor, gathering and transmitting information about the real world.”⁷⁰ The

⁶⁷Ibid, A-11

⁶⁸Ibid

⁶⁹Eric Topol, *The Creative Destruction of Medicine*. . . , ix

⁷⁰Ibid, 16

subsequent “Big Data” consists of “extremely large data sets that may be analysed computationally to reveal patterns, trends, and associations.”⁷¹

The “sea of data” from military sensors needs to be processed but, as with Big Data in other fields, cannot all be processed by humans. Peter Layton, in discussing fifth-generation fighter aircraft, but in themes that can be applied to any number of future, highly networked platforms fitted with numerous sensors, describes warfare that is “data hungry.”⁷² This hunger, he says, also applies to command centres, which use the data in the planning and execution of missions.⁷³ With humans unable to “reliably and quickly process the amount of data collected by the fleet and its respective environment’s many sensors” there can be resulting operational constraints which need to be resolved.⁷⁴

Future ASW platforms’ systems are expected to evolve within the next decade to become more capable, ultimately resulting in smaller crews “covering much larger areas more quickly and more cheaply.”⁷⁵ This ultimately begs the question of whether a human operator, limited by “metabolic and chemical thresholds, which limit the processing power of the wet computers inside our heads,” can possibly keep up with the number of concurrent tasks and the overwhelming amount of information coming in to next-generation platforms.⁷⁶

In many other fields attempting to leverage ML and AI tools to harness the value of Big Data, “engineers realized that rather than teaching computers and machines how to do everything, it would be far more efficient to code them to think like human beings.”⁷⁷

⁷¹Peter Layton, “Working Paper 43 - Fifth Generation Air Warfare,” *Royal Australian Air Force Air Power Development Centre*, 2017, 9

⁷²Ibid

⁷³Ibid

⁷⁴E. Artusi, F. Chaillan, “Automatic Recognition of Underwater Acoustic Signature for Naval Applications.” *1st Maritime Situational Awareness Workshop (MSAW) 2019*

⁷⁵Ibid, A-9

⁷⁶Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . , 42

⁷⁷Bernard Marr, “What is the Difference Between Artificial Intelligence and Machine Learning?”

Given the amount of data inherent in acoustic sound signatures in the ocean collected from many platforms and the shortages of SONAR Ops and AES Ops, who take a relatively long time to train, the tasks of filtering all of the data, turning it into knowledge and intelligence and feeding it back to front line operators are perfectly suited to the use of augmentation, automation and ultimately Machine Learning and Artificial Intelligence.

The next chapter will outline how ML has been implemented across many initiatives to leverage the vast amounts of data being generated and will explore how those techniques could be applied to the tasks of acoustic sensor operators through the phases of ASW.

CHAPTER 4: RELATION TO ML TECHNIQUES IN OTHER FIELDS

Perhaps fittingly for the topic of ASW, data is often referred to in as bodies of water, with terms such as “data lakes,” “data oceans,” “information tidal waves” and “tsunami of data” denoting not only a vastness, but an ease of flowing from one location to another.⁷⁸ Countless industries and fields of study have leveraged AI and ML to streamline their operations, market their products and deal with the vast volumes of data being generated by ever-growing networks of sensors. From toys that can carry on a conversation with a child, to recognizing images captured by a camera, to self-driving cars, these technologies process vast volumes of data to create models which ‘learn’ by identifying hidden patterns in this data and forming correlations between them in order to make highly accurate predictions.⁷⁹

As mentioned in the introduction, ASW is often compared to a game between a stealthy submarine and those trying to find and track them. Some of the better-known applications of AI and ML come from their application to games and hold valuable lessons to be learned for ASW, as they both adhere to certain rules, pit one side against the other and ultimately aim to have a winner.

Games

From the 1994 victory of an AI against the then world champion in checkers, to 1997’s defeat of the world chess champion by IBM’s Deep Blue supercomputer, to IBM’s Watson defeating Jeopardy’s longest-reigning champion Ken Jennings (who had won 74 consecutive

⁷⁸Dmitriy Stepanenko, “Data Warehouse vs. Data Lake, Which is Right for Your Enterprise App Development Effort?”, *The Medium.com*, February 19, 2019 <https://medium.com/@distillerytech/data-warehouse-vs-data-lake-which-is-right-for-your-enterprise-app-development-effort-fa9f046d47ca>; Eric Topol, *The Creative Destruction of Medicine*. . . , 18; The Guardian., “Tsunami of data could consume fifth of global electricity by 2025,” *The Guardian.com*, 11 December 2017, <https://www.theguardian.com/environment/2017/dec/11/tsunami-of-data-could-consume-fifth-global-electricity-by-2025>.

⁷⁹Bernard Marr, “27 Incredible Examples Of AI And Machine Learning In Practice,” *Forbes*, 30 April 2018, <https://www.forbes.com/sites/bernardmarr/2018/04/30/27-incredible-examples-of-ai-and-machine-learning-in-practice/2/#4348a6424a36>; Ethem Alpaydin, *Machine Learning, the New AI*. . . , 14

games against human opponents) to the 2014 defeat of the world Go champion by an AI system, several high-profile cases of the dominance of machines in the realm of games have been recorded.⁸⁰ In almost all of these examples, there are instances of the human player losing confidence, being affected by their personality, patience, and “overall state of mind,” or succumbing to stress while the AI was unaffected by any of these factors.⁸¹ As outlined in the previous chapter, human operators on ASW platforms are equally subject to fatigue, motion sickness and stress while machines can learn and be employed day and night, with no degradation in performance.

Open-source information suggests that the realm of ASW is also focusing on games “that include social networking, performance collection, big data analysis and Machine Learning” to “provide for high-velocity learning” and teach critical skills to humans and eventually integrate derived information into advanced systems, such as “the AN/SQQ-89A (V) 15 Surface Ship Undersea Warfare Combat System.”⁸²

With echoes of how Go programmers initially trained their system using “humans in the loop and an initial set of 100,000 Go games in order to learn how to play,”⁸³ in the U.S. DARPA recently asked thousands of anonymous players to “come up with ways to track elusive subs” by playing a modified version of the ‘Dangerous Waters’ video game.⁸⁴ In the crowd-sourced instance, “the best players broke the rules and in the process may have discovered a better way to track subs from the surface.”⁸⁵ What goes unpublished in these open-source accounts is that the

⁸⁰Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . , 39-40

⁸¹Ibid, 44-45

⁸²SBIR, “Multiplayer Serious Game for Anti-Submarine Warfare SONAR Operator Training,” *SBIR.gov*, accessed 21 April 2020, <https://www.sbir.gov/node/1606287>,

⁸³Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . ,45-46

⁸⁴Adam L. Penenberg, “The Anti-Sub Game,” *Fast Company*, 17 October 2011, <https://www.fastcompany.com/1788339/anti-sub-game>

⁸⁵Ibid

designers of these ASW game initiatives collect data on thousands of game scenarios and serials, which is likely a sufficient amount of data to teach a system how to play the game of ASW.

How far advanced any of these initiatives might be in developing a system that is powerful enough to win at ASW, with either supervised or unsupervised learning, is open to speculation.

What is known in the realm of games is that developers have been able to transition from programming systems with specific rules and feed them data consisting of thousands of sets of games in order to learn how to play to a “system that could train itself to become just as powerful, without having to rely on humans.”⁸⁶ Without humans holding the systems back, ML systems when applied to games have been able to evolve “into both a better student than the world’s greatest Go masters and a better teacher than its human trainers.”⁸⁷

Through feedback loops of playing a game and then self-optimizing based on what it had learned in the game, AI systems quickly evolved to the point of surpassing humans in terms of thinking “in an entirely new way and to make its own choices.”⁸⁸ Without the constraints of human knowledge, the Zero program, for example, “developed creative strategies that no one had ever seen before, suggesting that maybe machines were already thinking in ways that are both recognizable and alien to us.”⁸⁹

In reviewing some of the existing applications of ML and some areas of research specific to ASW, connections will be made between what a machine could ‘learn’ from these operators (supervised learning) and areas where a ML algorithm may be able to learn deeper rules and possibly outperform human operators solely by learning from the data (unsupervised learning). The following section will describe some of the current research around underwater acoustics, as

⁸⁶Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . , 45

⁸⁷Ibid, 46

⁸⁸Ibid, 47

⁸⁹Ibid

well as initiatives outside of military settings, in order to highlight current capabilities and the status of research in the ASW field.

As previously established, the CAF has highly trained ASW operators on platforms and shore-based processing facilities who know many of the relationships between pieces of acoustic information and what they mean to the tactical picture. This section will be organized according to the phases of an ASW mission: Search; Detect; Localize; Track; and Attack and will also highlight aspects of pre-mission and post-mission activities which could incorporate ML.

Search

In the search phase, sensor operators are typically cued to the type of target they are looking for and given an operating area to cover. They are given or derive likely speeds and direction of travel for the target, oceanographic information and expected sound sources and come up with a plan to search their assigned area using the best sensor to achieve their mission. Often, multiple platforms will coordinate, sometimes in conjunction with shore-based sensors to carry out ASW, leveraging the strengths of each platform (persistence of surface ships and shore-based sensors, speed and reach of aircraft, stealth of submarines) to maximize the probability of detecting opposing force submarines.

In discussing ‘temporal difference learning,’ Alpaydin describes that “in certain applications, the environment is partially observable, and the agent does not know the state exactly. It is equipped with sensors that return an observation, which it uses to estimate the state of the environment.”⁹⁰ This description can be related both working in a new operating area, where operators must determine the parameters of the ocean environment, as well as the tactical running state of a submarine.

⁹⁰Ethem Alpaydin, *Machine Learning, the New AI* . . .,135

One of the more complex “routine” tasks that sensor operators must continually carry out is to assess and understand the oceanographic conditions in which they are operating.⁹¹ Acoustic analysis starts with first gaining a basic understanding of oceanography, as operators must know how sound travels through water and how factors such as composition of the ocean floor, water depth and temperature affect sound propagation.⁹² When an ASW platform arrives on-scene, it carries out an initial measurements of the local water mass, including bathymetry, sound speed profile and measurements of the background noise of the ocean to update estimates of the probable detection ranges for a submarine.

Once these calculations are made, the platform deploys its sensors to attempt to gain contact on the target submarine, attempting to optimize for the predicted operating state and expected amount of radiated noise from the target. As computer engineering professor Ethem Alpaydin points out, a system would have to predict “the probability that it is in each state given the observation and then does the update for all probable states weighted by their probabilities.”⁹³ Given the amount of uncertainty inherent not only in oceanographic conditions, but also submarine noise emission, the search phase consists of a series of very complex tasks with high uncertainty, which “makes the task much more difficult and the problem harder to learn.”⁹⁴

Successful implementation of an ML system for the search phase tasks could ensure optimum search tactics and sensor settings. One area where this could be an advantage lies in Directivity Index, which is the amount of ‘gain’ applied to “detection probability based on the

⁹¹Patrick Tucker, “How AI Will Transform Anti-Submarine Warfare,” *Defense One*, 1 July 2019, <https://www.defenseone.com/technology/2019/07/how-ai-will-transform-anti-submarine-warfare/158121/>

⁹²Jenn Jackson, “Junior SONAR Operators Learn How To Hear and Track a Submarine,” *navy-marine.forces.gc.ca*, 19 December 2019 <http://www.navy-marine.forces.gc.ca/en/news-operations/news-view.page?doc=junior-SONAR-operators-learn-how-to-hear-and-track-a-submarine%2Fk42zftfp>

⁹³Ethem Alpaydin, *Machine Learning, the New AI*. . .,135

⁹⁴Ibid

sensitivity of the acoustic detection system in use. . . and whether the system is used in Directional or non-directional (360 degrees) search mode.”⁹⁵ Through optimization of a system which could thoroughly monitor multiple channels at once and carry out simultaneous processing of multiple modes, something a human operator is unable to do, some newer systems “allow planners to use as much as 10dB gain.”⁹⁶ A 10 dB gain is equivalent to a ten-fold increase in submarine noise, which would give significantly extended detection ranges.

Detect

One of the most difficult tasks of the acoustic operator is determining which returns among all of the sound sources in the ocean are of interest and which are simply background noise. When describing the task of figuring out which of the many signals that exceed the ambient ocean noise may be submarine related, this task is often summed up by operators as determining “which of these things is not like the others.”⁹⁷

A further challenge in this stage of ASW is that operators adjust the settings on their systems, based on their knowledge of the oceanography in the area and the anticipated sound sources of the target. When these settings are made incorrectly, as pointed out by Seo et al in reference to active systems, low signal to noise ratio “signals do not yield enough feature information to distinguish them from clutter,” and human operators, and the ML systems that would replace them, will be unable to detect the target.⁹⁸

When the position of the submarine is unknown, its sound sources can reach the receiver through any number of propagation paths, which is made even more complicated by the target’s

⁹⁵ William Perkins, “Alliance Airborne Anti-Submarine Warfare. . .”,115

⁹⁶ Ibid

⁹⁷ <https://www.youtube.com/watch?v=rsRjQDrDnY8>

⁹⁸ Iksu Seo, Seongweon Kim, Youngwoo Ryu, Jungyong Park and Dong Seog Han, “Underwater Moving Target Classification Using Multilayer Processing,” *Appl. Sci.* 2019, 9, 4617; doi:10.3390/app9214617 www.mdpi.com/journal/applsci

relative motion. “Acoustic signal waveform distortion, loss of signal information, and incomplete received acoustic signals” due to target motion and propagation of sound through complex water profiles are challenges of the underwater environment that have undergone significant study and to which “many algorithms have been applied.”⁹⁹ Algorithms to “significantly reduce the multipath distortion effects of shallow underwater channel” could be generated strictly from oceanographic research or could leverage research carried out on RADAR and other sensors in optimizing systems to model variability in propagation paths, avoiding missed contact due to “the weakest target signal returns being often buried by the clutter floor induced by these dominant paths.”¹⁰⁰ Any ML acoustic system will need sufficient data to account for these factors in the detection of targets, either passively or actively.

Alpaydin discusses commercial ML systems using outliers from the norm to detect “an abnormal behavior of the system” and gives examples of fraudulent credit card transactions, intrusion attempts by hackers to get into a network traffic and in health-care deviations from a patient’s normal behavior as potential symptoms of the onset of disease.¹⁰¹ In the case of ASW, the “normal” could be seen as the regular ambient noise of the ocean with biological sounds and shipping activity, and outliers from those sounds being filtered and analyzed as having a higher probability of originating from a submarine.

Such an approach was used by Yang et al, in attempting to create a model replicating the functions of the human auditory system.¹⁰² Based on the premise that “underwater acoustic

⁹⁹Ibid

¹⁰⁰A. Das, A. Kumar, and R. Bahl, “Marine vessel classification based on passive SONAR data: the cepstrum-based approach,” *IET Radar, SONAR & Navigation*, 2013, 7(1):87-93.; Gilles Chabriel, Jean Barrère. “Adaptive Target Detection Techniques for OFDM-Based Passive Radar Exploiting Spatial Diversity.” *IEEE Transactions on Signal Processing*, Institute of Electrical and Electronics Engineers, 2017, 65 (22), pp.5873 - 5884. 10.1109/TSP.2017.2742980. hal-01790695

¹⁰¹Ethem Alpaydin, *Machine Learning, the New AI. . .*, 72

¹⁰²Honghui Yang, Junhao Li, Sheng Shen and Guanghui Xu, “A Deep Convolutional Neural Network Inspired by Auditory Perception for Underwater Acoustic Target Recognition,” *Sensors: Sensors 2019*, 19, 1104

target recognition still mainly relies on well-trained SONAR man,” who identifies objects of interest using the “powerful information processing ability of the auditory system,” they constructed a model “composed of a series of deep filter sub-networks, fusion layers and decision layer” and applied it to the recognition of underwater acoustic targets.¹⁰³ Their approach relied on training their model to “learn discriminative features from frequency distribution of different ship types” and use that information to classify ships by type.¹⁰⁴

While potentially of some use in discriminating targets of interest from background noise, their method assumed SONAR operators primarily use their auditory system to classify targets. While operators can differentiate between natural and man-made sources and can do rudimentary classification based on sound characteristics of components like propeller fitment, on most modern platforms submarine classification to specific type or beyond is carried out using processed information to identify patterns and relationships between specific components and the sounds they emit. While they claimed their results “show that auditory perception inspired deep learning method has encouraging potential to improve the classification performance of UATR,” an 82% accuracy rate in classifying among a limited set of 55 targets, consisting of cargo ships, passenger ships and tankers would be insufficient in an ASW environment where the use of torpedoes would have strategic impacts.¹⁰⁵ They also acknowledge that for recognition of tankers, the accuracy was only 69%, possibly due to the tanker having “similar dynamical system and similar size with cargo.”¹⁰⁶ Much like the results with advanced performance in games such as Go based on attempting to replicate human thought

¹⁰³Ibid

¹⁰⁴Ibid

¹⁰⁵Ibid

¹⁰⁶Ibid

processes, trying to mimic human physiological capabilities may provide more limited results than other ML approaches.

The Yang study does have the use of Convolutional Neural Networks (CNN) in common with many other studies of acoustic applications, as well as with many of the commercial applications of ML. CNNs have been applied to auditory functions like speech recognition, musical information retrieval, and acoustic scene classification, as well as non-auditory tasks such as handwriting recognition, facial recognition, natural language processing and “visual recognition tasks on large collections of labelled images,” and have “surpassed human levels of performance” in certain classification tasks.¹⁰⁷ This method works by constructing multiple layers within the data, with each layer having input and output connections to preceding or subsequent layers. The system then identifies which dependencies between specific inputs and outputs are statistically relevant and gives those connections, or operations, a convolution, or a matching, “of its input with its weight”¹⁰⁸ One study attempting to use CNNs for object detection and classification was carried out by Thomas et al, who applied CNNs to detecting and classifying marine mammals through passive acoustic recordings, but which also could have applications to detecting and classifying marine vessels. Their method proved “capable of classifying the vocalizations of three species of whales, nonbiological sources of noise, and a fifth class pertaining to ambient noise.”¹⁰⁹

In many ways, the classification of marine mammal sounds is more difficult than that of classifying surface vessels, as they tend to be short-duration, they move across frequencies and

¹⁰⁷Hao Yue, Lilun Zhang, Dezhi Wang, Yongxian Wang and Zengquan Lu, “The Classification of Underwater Acoustic Targets Based on Deep Learning Methods,” *Advances in Intelligent Systems Research*, volume 134, Atlantis Press; Mark Thomas, Bruce Martin, Katie Kowarski, Briand Gaudet and Stan Matwin – “Marine Mammal Species Classification using Convolutional Neural Networks and a Novel Acoustic Representation,” July 2019, 1

¹⁰⁸Ethem Alpaydin, *Machine Learning, the New AI. . .*, 101

¹⁰⁹Mark Thomas et al, Marine Mammal Species Classification using Convolutional Neural Networks. . . , 1

one species of mammal does not always generate sounds at the exact same frequency. Often, their acoustic signatures are masked by loud shipping noise occurring in the same portion of the frequency spectrum. Techniques to overcome these characteristics would be useful for an ML system in the detection and classification of submarines, which share many of the above characteristics with marine mammals. Some short-duration sounds have key tactical meanings and a real-time ASW mission would need to minimize the chances of being misled by (or not reacting appropriately to) a significant submarine or warship tactical action. Thomas et al acknowledge that “while the results focused on in this paper are centred on detection and classification of marine mammals, the framework outlined ... can be adapted to other tasks such as acoustic scene classification.”¹¹⁰

Contrary to the Yang study, Thomas et al correctly recognized that “human analysis of acoustic data is often carried out visually using spectrograms, as it is faster to visually identify signals of interest without having to listen to the entire recording.”¹¹¹ Visual representations of acoustic information also allows “for the analysis and interpretation of sounds outside of the human hearing range.”¹¹² Ultimately, the classifier presented in the paper was “capable of detecting the presence and absence of whale vocalizations in an acoustic recording” and, notably, was capable of generalizing to additional species through transfer learning.¹¹³ This last point is promising for the realm of ASW, since if the system is “capable of learning generalizable representations for the purpose of including additional species...with very little annotated data” the training process could be faster for additional species, or in the case of ASW, classes of

¹¹⁰Ibid

¹¹¹Ibid

¹¹²Ibid

¹¹³Ibid

submarines, “through transfer learning.”¹¹⁴ In the case of a new submarine type or one with a small number of detections after a refit or other change to its acoustic signature, transfer learning should be equally applicable. Given the broad variety in acoustic sources across platforms, it could be expected that a system that has “learned” how to carry out basic analysis could subsequently learn subsequent steps faster and make more accurate assessments.

A challenge identified by the authors, which is applicable to the ASW realm is “that ground truth labelled data is difficult to obtain due to the required expertise and training of the labeller. As a result, only a very small fraction of the large collections of acoustic data is suitable for supervised learning.”¹¹⁵ This would apply equally to the use of an annotated library of submarine and other marine vessel signatures, most of which would be classified and subject to limited release to companies or researchers attempting to teach an ML how to carry out passive acoustic analysis. Akin to a marine mammal emitting different types of vocalizations, marine vessels do not always operate in the same speed regime or equipment running states, further challenging the algorithms to “learn” the signature of a vessel when there is significant variety in examples from which to learn.

The authors also note that in the analysis of acoustic recordings, researchers often alter the parameters used, such as time sampling and other settings, to generate a variety of spectrograms with different time and frequency resolutions, in order to optimize for varying durations and frequency ranges of vocalizations. This re-processing can either amplify a detection or can cause one to “misclassify a vocalization as a different species or miss the vocalization entirely.”¹¹⁶ They proposed generating several spectrograms using multiple a

¹¹⁴Ibid

¹¹⁵Ibid

¹¹⁶Ibid

variety of parameters. This mirrors the processes used during post-mission analysis, where a trained operator will carry out several iterations of processing to achieve the best-looking LOFAR ‘cut’ of a contact, in order to provide feedback or use the example for training other operators.¹¹⁷ This point could be important for mimicking the tasks of operators on an ASW platform, as well. While searching for submarine sources, and trying to optimize their systems once a source is detected, operators will adjust the processing parameters of their systems to try to get the best picture. Much like the discussion of Directivity Index and having a system able to simultaneously process multiple modes, an ML system that could concurrently process multiple settings on an incoming signal could potentially increase its chances of detecting a target significantly.

While Thomas et al’s work focused on using spectrograms or visual representations of sound data, they point out that “recent work into neural network architectures that operate directly on the waveform of an acoustic signal have shown great promise” as “through learning from the waveform directly we avoid any information loss that takes place during a Fourier transform.”¹¹⁸ Jin et al found in their work, however, that their “neural network can achieve higher performance on LOFAR spectrum samples [76%] than the audio format ones [53%],” so there is some discrepancy in research on which method is more accurate.¹¹⁹ Ultimately, for the purposes of this paper, a deciding factor may be which solution could be capable of real-time acoustic analysis. In an ML system replacing a human operator, there would be no need for a

¹¹⁷LOFAR is an acronym for “Low Frequency Analysis and Ranging”

¹¹⁸Mark Thomas et al, “Marine Mammal Species Classification using Convolutional Neural Networks. . .”, 15

¹¹⁹Guanghao Jin, Fan Liu, Hao Wu & Quinzeng Song (2020) Deep Learning based Framework for expansion, recognition and classification of underwater acoustic signal, *Journal of Experimental & Theoretical Artificial Intelligence*, 32:2, 205-218, DOI: 10.1080/0952813X.2019.1647560

representation of data for human eyes, so a key criterion may be avoiding information loss to ensure optimal performance by the system.

Yue et al reported higher accuracy in their 2017 classification study when using a generative Deep Belief Network (DBN), essentially a combination of deep learning methods including a system originally developed to classify whale calls. Their method, which they concluded could “extract more stable and more expressive features of the target than the schemes based on expert knowledge of underwater acoustic signal processing,” while based on a limited target set of 16 noisy World War II recordings, showed that a combination of methods to classify targets, rather than using a single method could be more effective in classification.¹²⁰ They concluded that a larger dataset of targets would be necessary to drive future deep learning studies in this field. Interestingly, in 2019, Artusi and Chaillan used a similar dataset and came to similar conclusions.¹²¹

Jin et al have echoed that datasets for training are difficult to use because of security and other restrictions, “which affects the performance of the deep learning methods as those need a big dataset to ensure high accuracy.”¹²² This has the potential effect of limiting “features that can be captured by samples.”¹²³ They comment that the expansion of a limited database by mathematical methods, which has been used in many of the studies reviewed in the research for this paper, creates a limitation, as there is still a “lack of diversity” in the data.

¹²⁰Hao Yue, Lilun Zhang, Dezhi Wang, Yongxian Wang and Zengquan Lu, “The Classification of Underwater Acoustic Targets Based on Deep Learning Methods,” *Advances in Intelligent Systems Research*, volume 134, Atlantis Press, January 2017

¹²¹E. Artusi, F. Chaillan, “Automatic Recognition of Underwater Acoustic Signature for Naval Applications.” *1st Maritime Situational Awareness Workshop (MSAW) 2019*

¹²²Guanghao Jin, Fan Liu, Hao Wu & Quinzeng Song (2020) “Deep Learning based Framework for expansion, recognition and classification of underwater acoustic signal,” *Journal of Experimental & Theoretical Artificial Intelligence*, 32:2, 205-218, DOI: 10.1080/0952813X.2019.1647560

¹²³Ibid

Another source of lack of diversity in submarine signature databases is that subs change operating modes to control the amount of noise given off or their aspect relative to an active sensor to attempt to hide from search sensors and presumably do not show their vulnerabilities when they suspect an ASW platform is trying to detect or collect information on them. In facial recognition, where “the input is the image captured by a camera and the classes are the people to be recognized,” the program has to first determine what is a face and what is background and then match the detected images of faces to an individual identity, while overcoming challenges related to incomplete information such as differences in angles and lighting, creating significant variations in a two-dimensional images and subjects trying to cover parts of their faces or disguise their identities.¹²⁴

Facial recognition must deal with two factors, “features that define the identity,” and “features that have no effect on the identity but affect appearance, such as a hairstyle; or expression.”¹²⁵ As outlined earlier, submarines produce sounds from propulsion plant noise, propeller noise, and noise generated as water moves over the hull.¹²⁶ Some of these sources are fixed and can be used to classify or define the identity of a submarine, while others affect the overall appearance of the sound signature, but do not directly relate to the classification.

With facial recognition, the system takes the inputs of pixels, which do not, themselves “carry discriminative information,” and through application of DNNs, generates and analyzes features and combinations of features to define a face, which it does by “feature extraction.”¹²⁷ Though people recognize faces easily, it is an unconscious process that is difficult to explain and,

¹²⁴Ethem Alpaydin, *Machine Learning, the New AI* . . . , 65

¹²⁵Ibid

¹²⁶William Perkins, “Alliance Airborne Anti-Submarine Warfare” . . . , 36

¹²⁷Ethem Alpaydin, *Machine Learning, the New AI* . . . ,76

as such, we cannot write the corresponding computer program.”¹²⁸ A learning program, on the other hand, can identify the unchanging hidden patterns specific to an individual and use them to identify that person.

Similarly, acoustic operators already know many of the formulas and relationships between systems on a submarine or ship, so these known patterns among the data could be fed into the system to train the AI. However, since we have already established the potential of ML systems to conduct deep learning to discover hidden or unseen relationships, there is potential to give the system a head start, much as the designers of the initial ML Go champions did.

Another area where humans and AI systems are working together to detect anomalies and identify whether a sensed item is of interest is in the medical field. The first use of the Watson computer that beat Jeopardy champions was at Columbia University and the University of Maryland medical centers “to provide a cybernetic assistant service to doctors.”¹²⁹ AI systems have proven as effective as doctors in finding and classifying tumours in patients’ mammograms and other scans.¹³⁰ AI systems have also been enlisted in the fight against the COVID-19 pandemic, examining X-rays or CT scans of the lungs to try to identify signs of the virus, as an alternative to tests looking for genetic materials of the virus itself.¹³¹ This initiative has run into the challenge of limited data about the virus and the data that exists being spread around the world, making it difficult to access and utilize to its full potential. Like the medical field, acoustic analysis of submarines, with its limited data catalogues and restrictions on information sharing between nations, must be cautious not to skew or corrupt the data and subsequent

¹²⁸Ibid, 23-24

¹²⁹Eric Topol, *The Creative Destruction of Medicine*. . . , ix

¹³⁰Fergus Walsh, “AI ‘Outperforms’ Doctors Diagnosing Breast Cancer,” *BBC News*, 2 January 2020 <https://www.bbc.com/news/health-50857759>

¹³¹Ray Tiernan, “AI Runs Smack Up Against a Big Data Problem in COVID-19 Diagnosis,” *ZD Net*, 4 April 2020, <https://www.newsbreak.com/news/00erkFRZ/ai-runs-smack-up-against-a-big-data-problem-in-covid-19-diagnosis>

learning. Some research is suggesting that purely supervised learning, or even Deep Learning methods with insufficient data sets, are not the optimum way of creating ML systems and that Self-Supervised systems could be more effective even with limited data sets.¹³² For detection of acoustic sources from out of the background noise of the ocean, these algorithms would need to be optimized to provide the best learning from limited amounts of data.

Localize

Once a signal has been detected and deemed a possible target of interest, its position, course and speed are refined and further analysis of classification occurs concurrently during the localize phase of ASW. If the initial detection is on one of multiple sensors, such as a sonobuoy within a deployed pattern or distributed field, other nearby sensors are checked to see if they also hold contact and bearing information is correlated to refine the position of the contact. This job of correlating initial contact between sensors would need to be performed by an ML system.

If the initial detection was via passive acoustic sensors, such as a sonobuoy, further tactical information is typically collected as the contact passes through the closest point of approach (CPA). The probability of the contact being a submarine, and specifically the submarine being hunted, can be further refined through the use of additional sensors, such as MAD, or RADAR to correlate known information. The narrowing of classification relies on the knowledge and experience of the operator, as well as the specific information being given off by the target, whether acoustic signature, or tactical information such as speed.

The passive acoustic signature typically consists of discrete (small bandwidth) lines representing specific frequencies on a LOFAR display depicting frequency over time.

¹³²Ben Dickson, “Self-Supervised Learning is the Future of AI,” *The Next Web*, 5 April 2020 <https://thenextweb.com/neural/2020/04/05/self-supervised-learning-is-the-future-of-ai-syndication/>

Fluctuations in these lines depict changes in frequency and the analysis of these “line features of LOFAR spectrum images” is how passive analysis of submarine targets is typically achieved.¹³³

The analysis of these frequency lines can be related to applications such as text recognition, where a computer examines several layers of information to determine what information is being perceived. For example, small groupings of pixels will be identified by their characteristics and classified according to their properties. These combinations are made iteratively until the system can recognize them and based on the absence or presence of other clusters around them, predict which letters and words are most likely present. This relates to a display of acoustic information, in that there are stable and unstable lines at particular frequencies associated with various mechanical sources and individual lines can be related to other lines elsewhere in the frequency spectrum, via mathematical relationships, to derive tactical and classification information.

The shift in a frequency due to changes in relative aspect of a sound source (the Doppler effect) is another area in which a sensor operator needs to recognize what is happening tactically. A very short-duration, steep-angled, change in frequency could reflect a very close-range pass by a sonobuoy, whereas a more gradual shift usually indicates a longer-range approach. Human operators discriminate between fluctuations in frequency due to a change in the sound source and events perceived due to a change in Doppler due to maneuvering of the target and an AI system could use techniques such as those used in text recognition to similarly be able to differentiate between these scenarios in order to determine tactically significant information in ASW.

¹³³Guanghao Jin, Fan Liu, Hao Wu & Quinzeng Song, “Deep Learning based Framework for expansion, recognition and classification of underwater acoustic signal,” *Journal of Experimental & Theoretical Artificial Intelligence*, (2020) 32:2, 205-218, DOI: 10.1080/0952813X.2019.1647560

With handwriting image analysis, “we know that because the visual scene changes smoothly, nearby pixels tend to belong to the same object, and where there is sudden change-an edge-is informative because it is rare.”¹³⁴ Lines in a LOFAR gram are similar, in that lines are typically continuous, with minimal sudden shifts and a sudden change, or edge, usually indicates an abrupt tactical change, like a turn, speed change or other abrupt change to the operating characteristics of the target.

Another ASW sensor example, albeit one not currently carried out by acousticians, is the analysis of MAD traces, where a human operator must differentiate between interference generated by maneuvering of the aircraft and an actual disturbance to the magnetic field that the system senses from a metal object in the ocean. The MAD trace consists of a vertical line with constant sharp and shallow horizontal deviations. An AI could be trained to interpret these traces, arguably with more accuracy and more focus on the returns at all times. The data for this could be collected (and the AI trained) by flying an aircraft over various sized ships or known items. While current systems are automated to recognize and identify when a deviation occurs, they are programmed, not learned through deep learning networks, leaving an opportunity for this system to be optimized.

The task of extracting processing multiple layers of information to interpret the structure of a line, or in the case of passive acoustics the relationships between all of the sources associated with a contact, and associating that structure with learned tactical implications, has proven to be achievable by ML methods in handwriting analysis, speech recognition and other areas of research and could be promising for application to the conduct the ASW tasks in the localization phase. In one example, Yue et al applied the Mel Frequency Cepstral Coefficient

¹³⁴Ethem Alpaydin, *Machine Learning, the New AI* . . . , 101

(MFCC), which is usually “used to extract the characteristics of speech signals,” as a feature extraction technique prior to categorizing targets using CNNs and DBNs, with reported accuracies over 16 target types of up to 97%, using unsupervised learning.¹³⁵

The detect and localize phases have centred primarily around passive sensors, as they are often used tactically to try to avoid alerting the target submarine to the presence of ASW assets. With the quieting of submarines, active SONAR techniques for detecting and localizing submarines may become more prominent. Since an individual submarine’s size, material of construction and surface composition do not vary over time, ML systems to detect them over background clutter and to potentially even classify them based on specific distributions of energy patterns of target echoes are promising area of research.¹³⁶ A system would need sufficient data and training to correlate known aspect and positional information relative to sensors to variations in the return echoes. For example, Seo et al claim that return strengths of active pings can differ by over at least 10 dB “according to the aspect angle of a submarine,” a challenge that would have to be overcome.¹³⁷ Classification via active SONAR is an area not typically carried out by human operators and presents an opportunity for ML systems to exceed the capability of the humans currently carrying out the tasks in the Detect and Localize phases.

Track

The tracking phase of ASW typically involves maintaining acoustic contact on a target, having a relatively high confidence in the classification of the submarine and its position, course and speed and reporting this information back to higher command authorities. In the case of an

¹³⁵Hao Yue, Lilun Zhang, Dezhi Wang, Yongxian Wang and Zengquan Lu, “The Classification of Underwater Acoustic Targets Based on Deep Learning Methods,” *Advances in Intelligent Systems Research*, volume 134, Atlantis Press, January 2017

¹³⁶Iksu Seo, Seongweon Kim, Youngwoo Ryu, Jungyong Park and Dong Seog Han, “Underwater Moving Target Classification Using Multilayer Processing.”

¹³⁷Ibid

evasive submarine, this phase would arguably have the most parallels to games like chess or Go, with tacticians on each platform trying to outmaneuver each other. In earlier phases of ASW, there is a parallel to playing chess against an opponent without being able to directly observe the board, as the ASW platform doesn't know which pieces the opponent has in the game or where they are located. By tracking phase, however, there is a good estimate of where the submarine is and where it is going, yet there still must be deductions made about what the opponent's intentions are, perhaps more akin to poker, another game where AI has learned to dominate human opponents.¹³⁸ For sensor operators, this phase offers the opportunity to collect the highest-fidelity acoustic data on a contact and make the best estimate of its tactical operating state.

Tracking is not carried out solely by passive or active acoustic sensor operators. Information is fused from non-acoustic sensors like MAD, RADAR and EO/IR, as well as information coming in to the platform from co-operating units. The more information that is brought together, the better the tactical picture and the harder it becomes for the submarine to deceive or evade its hunters. Current AI systems use biometrics in the same way to ensure computer system users are who they claim to be, integrating "inputs from different modalities," such as voice recognition, fingerprints, keystroke patterns and gait of typing to defeat spoofing and verify a user's identity.¹³⁹ Mastercard, for example, claims to authenticate transactions "using billions of data points, biometrics, and artificial intelligence to recognize the uniqueness of every individual."¹⁴⁰

¹³⁸Will Knight, "China's AI Awakening," *Technology Review.com*, 10 October 2017
<https://www.technologyreview.com/2017/10/10/148284/chinas-ai-awakening/>

¹³⁹Ethem Alpaydin, *Machine Learning, the New AI. . .*, 66

¹⁴⁰<https://www.mastercard.ca/en-ca/merchants/safety-security/authentication-services.html>

The tracking phase has a temporal aspect, as well. Much of the current research on acoustic classification takes a snapshot in time and compares it against a database. ASW tracking builds new information on top of old. If a target can be classified by an acoustic source one moment, and then changes its operating parameters such that it no longer displays those classification sources the next moment, a human crew is able to connect those two states to logically deduce that the classification of the target has not changed. This would seemingly pose a challenge to a system trained on ‘snippets’ of information lasting only a portion of a second. An approach, used in other applications such as speech or language processing and music genre classification, could be to use recurrent neural connections, which “allow the current state to depend not only on the current input but also on the network state in the previous time steps calculated from the previous inputs.”¹⁴¹ Choi describes the combination of CNNs with Recurrent Neural Networks (RNN) to classify music and proposes that RNNs and CNNs differ in their ability to summarize features over time, with the conclusion that a model that “captures local time-frequency relationships, is more effective than the others, which ignores local frequency relationships.”¹⁴² R. Yang et al attempt to apply parallel recurrent convolutional neural networks (PRCNN), to overcome similar neglect of “sequential relationships found in the time-series data, which are significant for time-series data classification.”¹⁴³ When extrapolated from music to submarine acoustic signatures, an ML needs to have an “understanding” of how a signature is created over time, in the same way a human acoustician is taught to relate frequencies back to sound sources and how they relate to each other concurrently and over time.

¹⁴¹Ethem Alpaydin, *Machine Learning, the New AI* . . . , 93

¹⁴²Choi, K., Fazekas, G., Sandler, M., Cho, K.: “Convolutional recurrent neural networks for music classification.” *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. pp. 2392–2396. IEEE (2017)

¹⁴³Rui Yang, Lin Feng, Huibing Wang, Jianing Yao and Sen Luo, “Parallel Recurrent Convolutional Neural Networks-Based Music Genre Classification Method for Mobile Devices,” *IEEE Access*, Volume 8 2020, 20 January 2020

In addition to identifying and classifying a target during the tracking phase, having an ML system that could continually use the information the system was collecting to examine the oceanographic features and model them against the sound sources actually being emitted by the submarine would allow for optimum sensor placement, both for tracking and data collection. As Perkins points out when describing air ASW operations, “less experienced aircrew...are often hesitant and overly conservative when employing sonobuoys,” which he claims “has led to lost contact during dynamic phases of the prosecution.”¹⁴⁴ While these decisions are typically made by the human Tactical Coordinator on the platform, they are heavily influenced by the information passed by the sensor operators. Having an AI/ML trained system capable of optimizing sensor usage recommendations, based on historical data as well as in-depth analysis of oceanographic conditions in real-time, could optimize sonobuoy usage rates, maximize on-station time of air assets, expand stand-off ranges for platforms and minimize the chances of lost contact.

Attack

In the case of a deliberately planned launch of a torpedo, acousticians will have classified the target to the maximum possible extent and authorization based on this information is given by the force commander. For an ML to contribute to this phase, it could rely on techniques used in ‘voice authentication’ prior to deploying a weapon. Advanced voice applications use speech and consider “each word sound to be composed of two sets of factors, those that relate to the word and those that relate to the speaker.”¹⁴⁵ The first is used by speech recognition software, which similarly to the example of facial recognition discussed earlier would be related to types of systems that create sounds on a submarine, such as propellers or engines. Speaker

¹⁴⁴William Perkins, “Alliance Airborne Anti-Submarine Warfare” . . . , 40

¹⁴⁵Ethem Alpaydin, *Machine Learning, the New AI* . . . , 67

authentication uses the second type of factors, which could be related to the specific characteristics of the sounds generated by that equipment to fingerprint a specific hull of a submarine type. Similar to how a human could recognize a voice to a certain degree, but could not be relied on to absolutely authenticate based on it, AI could extract features that the human never could to provide certainty about the target, and ideally, alleviate any concerns of use of AI in military kinetic activity.

In the case of an urgent response to an enemy attack, such as the firing of torpedoes, an ML system taught to identify torpedo acoustic signatures could provide high-fidelity information on the type of weapon being used, its origin and the best evasive maneuvers based on its running profile and position, all without being degraded by the natural stress that a human operator would feel when a torpedo is detected in the ocean.

Pre-Mission

Prior to executing a mission, human acoustic operators are provided information about the watermasses in the operating area and the latest information about the potential target, including recent acoustic information gained by other prosecuting platforms. Likewise, an ML system would need to be uploaded with the most up-to-date information on bathymetry and target signatures prior to the mission. For ML, careful consideration of how this would occur must take place.

In the field of Natural Language Processing, it was found that using predefined databases to represent relationships between words in a language had some success, but that it was better to have the system “learn hierarchies at different levels of abstraction” directly from relationships within the data was more effective than simply uploading a database.¹⁴⁶ An ML system for

¹⁴⁶Ethem Alpaydin, *Machine Learning, the New AI* . . . , 108

acoustics would need to balance optimum performance with the ability to turn new information around quickly.

Post-Mission

This phase of the mission, from an operator point of view, entails reporting of anomalies and malfunctions to maintenance personnel and the transfer of recorded mission data from various sub-systems being delivered to mission support personnel for extraction and analysis. This stage typically includes aircrew debriefing mission support personnel on significant events and completing post-mission reports. An ML system would need to be capable of transferring all mission information to post-mission facilities.

Post-mission analysis of acoustic data is currently a labour-intensive process and is carried out to confirm the operators' assessment of their target, or to detect missed contact that operators could have exploited. Were an ML system to replace human operators on ASW platforms, and given the sheer amount of information expected to be collected by sensors on all future platforms, it would be logical to expect that the tasks of personnel at ground segments, such as extraction and analysis of mission data, could also be augmented or replaced by ML systems. Confirmation of tactics, including the effectiveness or search and tracking methods, could in the future be carried out by ML systems and could rapidly screen mission information and feed back intelligence more quickly to follow on events to maximize the chances of success on subsequent missions.

This chapter drew parallels between the application of ML to several fields unrelated to ASW, as well as investigated recent research into ML for ocean acoustic specific tasks. In recognizing that the adoption of ML techniques to the tasks of acoustic sensor operators, both at

ground stations and on the tactical platforms is achievable, either in terms of existing or emerging capability, as well as the ability to fit sufficient processing power on relatively small operational platforms like aircraft, there are several considerations that must be made before trying to apply the technology in a real-time setting. The following chapter will discuss some of those tactical considerations for the adoption of ML to enhance the conduct of ASW.

CHAPTER 5: TACTICAL CONSIDERATIONS

Chapter 2 outlined the distinction between AI and ML, with the former considered able to replicate a human operator's ability to carry out a breadth of high-level cognitive tasks and make complex decisions and the latter being more of a task-specific application (for example, playing chess, but not other games). While arguably achievable one day with a completely autonomous platform, aiming for a system as broadly capable as implied by Artificial Intelligence, including directing Tactics, managing a crew, applying all rules and regulations and innumerable other tasks carried out by humans on ASW platforms, would certainly be unachievable in a single leap from current manned platforms to the next generation. Conversely, as outlined in the previous chapter, teaching a computer to conduct some of the repeatable, bounded tasks currently performed by humans is certainly within the scope of current computing power and machine learning technology levels. In considering whether ML or, ultimately AI, could be adopted on ASW platforms, there is more than simply carrying out analysis on active and passive SONAR returns. This chapter will explore topics related to the development of tactics, overcoming bias in data, human factors which influence tactical decision making, trust of algorithms' outputs and the design of communication systems, all of which would need to be thoroughly examined before attempting to integrate an ML sensor operation system with human crews in a tactical environment.

Human operators use their experience and judgment to determine what information to pass to tactical coordinators and when, such as position, course or speed updates or refinements to classification based on the sound sources being emitted. Another important duty, which may be performed infrequently, involves recognizing relevant information which should be passed to co-operating platforms, such as an acoustic vulnerability that could be exploited, or information

on vulnerabilities of friendly ships, such as indications that a propeller has become ‘fouled’ by debris or that the ship is generating excess noise due to damage or machinery running state. A ML system would have to be approaching the definition of ‘intelligent’ to be able to determine the types of anomalies that should be captured and reported to other platforms, whether via voice or some form of acoustic datalink, but it is not unfathomable that it could be trained to do so.

In games, we saw that “thinking machines are capable of original thought,” sometimes coming up with novel strategies to solve problems or complete their tasks.¹⁴⁷ In some approaches, this consists of the system being trained to select moves and at the end of the game evaluating the contribution of each intermediate move to winning or losing the game.¹⁴⁸ With the predicted transition away from ‘blue water’ ASW and toward littoral regions, the “global trend towards smaller, but more lethal fleets” and the significant advancement of capabilities like ASW helicopter dipping SONARs, tactics for cooperative ASW have not been updated in doctrine to reflect these new capabilities.¹⁴⁹ While not directly related to the tasks of sensor operators, having ML systems learn how to “play the game” of ASW could allow for optimization of co-ordinated ASW between platforms and the development of novel experimental tactics that humans may never consider.

According to Perkins, the quieting of submarines has resulted in targets that “may be so quiet that the background ocean noise is louder than the source the ASW force is attempting to detect.”¹⁵⁰ This could drive changes in tactical development, with ML systems tuned to identify these “holes” in sounds in the ocean, where they may be able to exploit the quietness of a

¹⁴⁷Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . , 51

¹⁴⁸Ethem Alpaydin, *Machine Learning, the New AI*. . . , 138

¹⁴⁹William Perkins, “Alliance Airborne Anti-Submarine Warfare”. . . , 61; Gareth Evans, “Cat and Mouse: The Art of Submarine Detection,” *Naval-Technology.com*, 13 June 2011 <https://www.naval-technology.com/features/feature121453/>

¹⁵⁰William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 115

submarine by how it causes a drop in ambient noise along a certain bearing. This discrepancy could be missed by a human operator whose system may not be optimized to search for this characteristic, or who is not actively scrutinizing his sensors for this phenomenon. While a human operator cannot physically monitor several hydrophones at once, and must instead cycle between them, an ML system could examine all sensors simultaneously to look for clues to the presence of a target and could be trained to advise on optimum positioning of sensors based on the oceanographic profile to carry out a task like finding quieter-than-the-ocean targets. These tactics could either consist of identifying scenarios and applying pre-determined tactics, as was done with early computerized versions of chess, or could be in the form of a simulations carried out on station to assesses alternate options in real time to determine which tactics to employ before beginning a live search.

An area where new tactics are under development, and which will no doubt be heavily influenced by ML is Low Frequency Multi-Static Active (MSA) search, which is carried out through a network of transmitters and receivers which interact to achieve significantly longer detection ranges, as compared to older traditional passive or high frequency active sonobuoys. Since “receiver buoys are not collated with the source buoys,” the submarine “cannot know which direction to turn to avoid the pattern.”¹⁵¹ MSA also gives platforms the ability to cover larger areas, enhancing acoustic search as well as tracking and attack capability. While ML/AI could manage the timing and correlating of information across multiple receivers, as well as optimize the positioning of sensors based on oceanography and sound return characteristics of the submarine (aspect), much of the Canadian research into tactical development of MSA seems

¹⁵¹William Perkins, “Alliance Airborne Anti-Submarine Warfare” . . . , 41

to involve experimentation using mathematical models heavily influenced by inputs from human experts' experience and intuition.¹⁵²

As has been well established in other fields of study, there have been numerous instances of bias being unintentionally input into AI systems by programmers. Whether seen in voice recognition software being more likely to accurately recognise male speech, and ultimately threatening safety if adopted in a car with a female driver, or algorithms landing innocent people in jail, or influencing their sentences, bias in training AI systems is a serious concern.¹⁵³ As seen in the use of deep learning in games, sometimes allowing the system to learn without supervision “may actually be better since there will not be any teacher bias.”¹⁵⁴ Likewise, the development of tactics can benefit the more the ML system is free to generate its own solutions.

The impacts of fatigue and other physiological factors was discussed in the Problem Framing chapter. Another aspect of this factor is that the design of platforms like aircraft, ships and submarines are restricted by the need for a “degree of comfort, to lessen the crew’s fatigue, and thus enhance their efficiency” in the conduct of their duties.¹⁵⁵ The addition of “adequate rest arrangements for off-watch crew-members,” “efficient soundproofing,” and any number of other amenities such as more comfortable ship accommodations, means that platforms need to be larger and heavier and may thus be restricted in their maneuverability.¹⁵⁶ ASW platforms also sometimes determine their operating parameters, such as altitude for an aircraft or how many

¹⁵²Cristina D.S. Tollefsen, “Multistatic Planning Requirements,” *Defence Research and Development Canada*. May 2016, 8

¹⁵³Caroline Criado-Perez, “The Deadly Truth About a World Built For Men – From Stab Vests to Car Crashes,” *The Guardian.com* 23 February 2019, <https://www.theguardian.com/lifeandstyle/2019/feb/23/truth-world-built-for-men-car-crashes>; Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . , 58; Karen Hao, AI is Sending People to Jail – and Getting it Wrong, *MIT Technology Review*, 21 January 2019 <https://www.technologyreview.com/2019/01/21/137783/algorithms-criminal-justice-ai/>

¹⁵⁴Ethem Alpaydin, *Machine Learning, the New AI*. . . , 136

¹⁵⁵NATO M3A SOR. . . , 19

¹⁵⁶Ibid

stations are manned on a ship in a certain sea state, based on impacts on crew ability to carry out their tasks, which generates a kind of human bias in developing tactics. Without restrictions due to either crew comfort, design of the platform, or number of people onboard, ML systems would likely generate tactics unfathomable to human operators. While AI systems do not have to consider impacts of stress and other physiological factors when problem solving, human factors must still be taken into account and the balance between their needs and tactics generated by an ML system could result in more creativity and wider operating envelopes.

Another limitation to the use of ML generation of ASW tactics is the hesitation to trust ‘black boxes’ that calculate outputs but give no indication of how they came to their conclusions.¹⁵⁷ In discussing medicine, but equally applicable to the subject of this DRP, Topol describes a “legitimate worry about adoption of new technologies before they have been adequately vetted and validated, or proven to be cost-effective and ideally cost saving.”¹⁵⁸ High-profile incidents of problems with AI related to safety, including self-driving cars running red lights, surely have not alleviated these worries.¹⁵⁹

Layton argues that next-generation aircraft “need electronic order of battle data that includes the characteristics and electronic signatures of systems likely to be encountered while on operations...to allow aircraft systems to be able to identify friendly, neutral, and adversary systems when airborne.”¹⁶⁰ This could be achieved by storing large amounts of data on board with advanced search tools or database look-up functions. For operators who are now used to carrying smart devices in their pockets, which can carry out complex tasks using AI (such as speech recognition), however, it does not seem unreasonable to have a system that can “access

¹⁵⁷Tollefsen, Cristina D. S., “Multistatic Planning Requirements” . . . , 10

¹⁵⁸Eric Topol, *The Creative Destruction of Medicine*. . . , xi

¹⁵⁹Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . , 58

¹⁶⁰Peter Layton, *Fifth Generation Air Warfare*. . . , 8

the cloud from anywhere to exchange data or request computation that is too large or complex to do locally.”¹⁶¹ Using the speech recognition example, a smart phone does not do the process on the device; instead it “captures the acoustic data, extracts the basic features, and sends them to the cloud,” and the “actual recognition is done in the cloud and the result is sent back to the phone.”¹⁶²

Having data transmitted over a network for a ground-based AI to conduct the analysis and sending it back may be necessary given the small size of some platforms and the physical space that would be required for computers to carry out advanced ASW calculations. Also beneficial would be redundancy and ability to share data among platforms in real-time, which may be required for tasks like multi-static active processing and tactical co-ordination in shared operating areas. On the other hand, theatre ASW is often carried out in remote operating areas and real-time processing would require significant bandwidth and would be subject to potential jamming or interception of data transmissions.¹⁶³ Given the need for the systems to work in contested environment where data flow may not be reliable, a self-contained solution to the real-time processing may be required. This could be complemented by real-time updates to and from a central database being broadcast as the networks allow, for example to provide updates on previously unseen operating regimes for a sub, particularly useful tracking sources, or sounds indicating serviceability issues which could be exploitable during the mission. Whether housed onboard and powered by significantly more processing power being housed in much smaller

¹⁶¹Ethem Alpaydin, *Machine Learning, the New AI. . .*, 153

¹⁶²Ibid

¹⁶³Joseph Trevithick, “Russian Submarines Getting Countermeasures that Jam Sonobuoys Dropped by Enemy Aircraft,” *The Warzone*, 13 March 2020, <https://www.thedrive.com/the-war-zone/32584/russian-submarines-getting-electronic-warfare-buoys-that-jam-sonobuoys-dropped-by-enemy-aircraft>

spaces, or facilitated by use of a ‘combat cloud,’ platforms will be able to collect and leverage massive amounts of data, which will ultimately impact their tactical employment.

This chapter explored factors related to carrying out ASW in a real-world environment aboard an ASW platform, but was single-sided in the sense that it only considered the perspective of the hunter. Since the hunted submarines play a key role in whether an ASW prosecution will be successful or not, the next chapter be devoted to examining initiatives on the part of Canada’s adversaries.

CHAPTER 6: ADVERSARY INITIATIVES

Submarine inventories among many nations are growing, including our historical ASW adversaries and many nations against whom we could potentially be in conflict. The submarines being produced or acquired by those countries are not only growing in number, but in quality as “almost all nations in possession of submarines have put forth significant resources to make submarines and torpedoes operate more quietly.”¹⁶⁴ At the same time that submarines are becoming less detectable via traditional passive acoustic methods, nations such as Russia and China are increasing the regularity and range of their submarine patrols.¹⁶⁵ This chapter highlights some of their initiatives to advance their submarine capabilities.

Russia

As mentioned in the introduction to this paper, following the conclusion of the Cold War, out of area deployment of Russian submarines was virtually non-existent. Over the last decade, however, that trend has reversed, with a modernized Russian Navy and a “leadership willing to use it to achieve national strategic objectives” and demonstrate a strong and agile military.¹⁶⁶

Starting with the 2009 deployment of two Akula class submarines to the eastern seaboard of the U.S., many of these submarine deployments, which would have in the past occurred without the knowledge of the public, are now headline news.¹⁶⁷ This increased activity level has continued until at least October of 2019, when Russia conducted an exercise with eight nuclear

¹⁶⁴Canada, “Underwater Warfare Suite Upgrade Protects Sailors From Quieter Submarines and Torpedoes.”

¹⁶⁵Christopher Woody, “Russian submarine activity in the North Atlantic has reportedly 'increased tenfold,' and the UK is struggling to keep up,” *Business Insider*, 24 May 2018 <https://www.businessinsider.com/russian-submarine-activity-increasing-around-uk-and-in-north-atlantic-2018-5>

¹⁶⁶William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 4, 23

¹⁶⁷Mark Mazzetti and Thom Shanker, “Russian Subs Patrolling Off East Coast of U.S.,” *New York Times*, 4 August 2009, <https://www.nytimes.com/2009/08/05/world/05patrol.html>

and two diesel submarines sailing concurrently, gaining significant media attention in the West.¹⁶⁸

As described by Perkins, with these ‘detected’ deployments Russia has reminded NATO that it has the capability to deploy its submarines at will, while at the same time testing NATO’s response, vital information it can use in future “undetected” missions.¹⁶⁹ While the Russian Navy’s re-focusing on submarine capabilities has not been without challenges, such as the delays in deploying its AIP capability on the St. Petersburg class, their continuing development of quieter and more capable submarines will challenge Canada’s allies in being able to detect and track them.¹⁷⁰

Some examples of these technology advancements for new platforms, which are replacing the Cold War-era submarines at the end of their service lives, include advances to quieting technology, for example the propulsion system on the Yuri Dolgoruky SSBN, the Yasen-class being built with a relatively small displacement and low magnetic signature steel and the Lada-class designed with an AIP fuel cell to allow it to stay submerged much longer than a conventional diesel submarine.¹⁷¹

While these new submarine classes are expected to be extremely capable, they are not the only underwater threat that Canada’s allies need to be concerned with detecting and tracking. In 2015, Russian news ‘leaked’ the concept of a massive submarine-launched nuclear drone

¹⁶⁸Alec Luhn, “Russian Submarines Power into North Atlantic in Biggest Manoeuvre Since Cold War,” *The Telegraph*, 29 October 2019, <https://www.telegraph.co.uk/news/2019/10/30/russian-submarines-power-north-atlantic-biggest-manoeuve-since/>

¹⁶⁹William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 89

¹⁷⁰Ibid, 70; Christopher Woody, “Top US commander in Europe says Russia's subs are getting busier, as Trump cuts sub-hunting planes from the Pentagon budget,” *Business Insider*, 26 February 2020, <https://www.businessinsider.com/russia-subs-getting-busier-and-harder-to-track-in-atlantic-2020-2>

¹⁷¹William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 28, 30. As denoted elsewhere in the Perkins document, SSBN denotes a Nuclear-powered ballistic missile carrying submarine and the Yasen-class is the replacement for the Akula class which has been in service for several decades.

torpedo, which has been referred to as both “Status-6,” and “Poseidon.”¹⁷² This drone would be launched from a purpose-built submarine, the Sarov, and claims about its purpose included the ability to either create a targeted tsunami or generate “extensive radioactive contamination” in coastal areas. While mostly dismissed as Russian disinformation, the fact is that Russia is spending significant amounts of money and research on underwater capabilities and the West is taking notice and will need to figure out ways to counter modern, quiet submarines and other emerging technologies.

China

While “the design of the indigenous Chinese submarines lags both Russian and Western high-end submarines,” its newest submarines are seen as catching up to western and Russian subs in terms of stealth.¹⁷³ The Type-093 ‘Shang’ Class incorporates “advanced quieting technology with a hydro-dynamically efficient hull form” and the Type-094 ‘Jin’ Class ballistic missile submarines are recognized to be much quieter than previous generations of Chinese-built classes.¹⁷⁴

In some areas China may even be surpassing other nations, although some of their claims are viewed with skepticism. One example is the potential re-engineering of propeller designs to incorporate Rim-Driven Pumpjet technology, which could be stealthier than other current designs, on its new Type 095 nuclear sub.¹⁷⁵ Regardless of the validity of some of these claims,

¹⁷²David Hambling, The Truth Behind Russia’s Apocalypse Torpedo, *Popular Mechanics*, 18 January 2019, <https://www.popularmechanics.com/military/weapons/a25953089/russia-apocalypse-torpedo-poseidon/>; Global Security.org, “Status-6 / Canyon-Ocean Multipurpose System,” accessed 2 March 2020, <https://www.globalsecurity.org/wmd/world/russia/status-6.htm>

¹⁷³William Perkins, Alliance Airborne Anti-Submarine Warfare. . . , 33

¹⁷⁴Ibid. . . , 34; H.I. Sutton, “China’s Submarines May Be Catching up With U.S. Navy,” *Forbes*, 24 November 2019, <https://www.forbes.com/sites/hisutton/2019/11/24/latest-chinese-submarines-catching-up-with-us-navy/#229a7a2c298c>

¹⁷⁵Globe Composite Solutions, LLC, “Is China Taking the Lead in Submarine Propulsion?” *globecomposite.com*, accessed 2 March 2020, <https://www.globecomposite.com/blog/china-submarine-propulsion-technology>

China is improving its submarine capabilities and has been shown to be experimenting with modern hull designs that differ from any seen before.¹⁷⁶

China is a worldwide leader in AI research and the Chinese government has “declared its ambition for China to become the world’s leading AI innovator by 2030.”¹⁷⁷ Some of the research cited in this paper originated from Chinese institutions (Yue,¹⁷⁸ Yang,¹⁷⁹ Yang¹⁸⁰) so it seems a safe assumption that while it is pouring effort and research into advancing its submarine capabilities, it would also be on the leading edge of ASW research, including reported development of “unmanned submarines which rely upon AI technology.”¹⁸¹ While anticipated to augment rather than replace submariners, the technology developed for these UUV are expected to provide support to submarine crews.

Whether intended to patrol an area collecting oceanographic data, or more sinisterly, being loaded with weapons and lying in wait silently until ordered to carry out an attack, these virtually silent UUVs would be extremely hard to locate and very difficult to defeat, especially if also run by AI algorithms proven to be able to outmaneuver and out-strategize human opponents, like those proven in games like chess or Go.

¹⁷⁶H.I. Sutton, The Chinese Navy’s New Mystery Submarine, *Forbes*, 9 October 2019, <https://www.forbes.com/sites/hisutton/2019/10/09/china-navy-new-mystery-submarine/#31212dbb55ac>

¹⁷⁷Will Knight, “China’s AI Awakening,” *Technology Review.com*, 10 October 2017 <https://www.technologyreview.com/2017/10/10/148284/chinas-ai-awakening/>; Jeff Loucks, Susanne Hupfer, David Jarvis, Timothy Murphy, Future in the Balance? How Countries are Pursuing an AI Advantage, *Deloitte Insights*, 1 May 2019, <https://www2.deloitte.com/us/en/insights/focus/cognitive-technologies/ai-investment-by-country.html#endnote-14>

¹⁷⁸Hao Yue, Lilun Zhang, Dezhi Wang, Yongxian Wang and Zengquan Lu, “The Classification of Underwater Acoustic Targets Based on Deep Learning Methods,” *Advances in Intelligent Systems Research*, volume 134, Atlantis Press

¹⁷⁹Honghui Yang, Junhao Li, Sheng Shen and Guanghui Xu, “A Deep Convolutional Neural Network Inspired by Auditory Perception for Underwater Acoustic Target Recognition,” *Sensors: Sensors 2019*, 19, 1104

¹⁸⁰Rui Yang, Lin Feng, Huibing Wang, Jianing Yao and Sen Luo, Parallel Recurrent Convolutional Neural Networks-Based Music Genre Classification Method for Mobile Devices, *IEEE Access*, Volume 8 2020, 20 January 2020

¹⁸¹Pat Rabbitte, “AI Will Help Submarine Crews Better Understand What Adversaries Are Doing Underwater,” *The Sociable*, 5 July 2019, <https://sociable.co/technology/ai-will-help-submarine-crews-better-understand-what-adversaries-are-doing-underwater/>

Russia and China, as well as several western nations, have developed Air Independent Propulsion (AIP) systems, a group of technologies that significantly reduce how often submarines must carry out surfaced battery re-charging sequences, including but not limited to, Proton Exchange Membrane Fuel Cells, Stirling Cycle Engines, Rankine Cycle Power Plants and Closed Cycle Engines.¹⁸² Submarines fitted with AIP do not need to expose a snorkelling mast to recharge their batteries as often, if ever, reducing detection by means such as Radar or the “hydrocarbon sensor designed to pick up fuel vapor” reportedly carried by the P-8.¹⁸³ As submarines benefit from research carried out by the automotive industry into improving battery technology, the “need for a diesel-electric submarine ever to surface” could ultimately be eliminated, further changing tactics and detection methods of ASW platforms.¹⁸⁴ The German-built Type 212 AIP models, powered by hydrogen fuel cells, “are almost completely silent and radiate virtually no heat,” which, along with “high-tech energy management, acoustically optimised equipment and non-magnetic construction,” adds up to what some equate to near-impossible detection of these submarines.¹⁸⁵

Adversary and friendly nations alike use special coatings, or Anechoic tiling, to “both reduce noise and mitigate active SONAR detection.”¹⁸⁶ Researchers are exploring advanced versions of these coatings, such as the use of nanotechnology to create a type of cloaking device

¹⁸²Psallidas, Konstantinos, Clifford A. Whitcomb, and John C. Hootman. “Design of Conventional Submarines with Advanced Air Independent Propulsion Systems and Determination of Corresponding Theater-Level Impacts.” Cambridge, MA: *Massachusetts Institute of Technology*, 2010.

¹⁸³Chris Woody, “Submarines are increasingly lurking in seas around the world, and the US Navy's high-tech Poseidon is there to hunt them,” *Business Insider*, 14 May 2018, <https://www.businessinsider.com/us-navy-p8a-poseidon-sub-hunting-aircraft-features-sales-2018-5>

¹⁸⁴William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 90

¹⁸⁵Gareth Evans, “Cat and Mouse: The Art of Submarine Detection,” *Naval-Technology.com*, 13 June 2011 <https://www.naval-technology.com/features/feature121453/>

¹⁸⁶William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 39

that would essentially make submarines invisible to SONARs.¹⁸⁷ While still conceptual, the idea would be to coat a submarine with a material that bends sound waves around the hull to avoid sensors. Other futuristic options include the potential generation of ultra-low frequency sound through the use of carbon nano-tubes which could, in effect, provide a noise-cancelling coating, reducing emitted noise and possibly rendering enemy active SONAR pings ineffective.¹⁸⁸

The advantage in ASW has traditionally alternated between the hunter and the hunted. With today's limited resources and manpower shortages on the side of the hunters and significant advances by adversaries in submarine quieting technologies, it would seem the advantage is shifting back to submarines in being able to avoid detection, with even recent prosecutions unable to maintain visibility on targets "for 100% of the time."¹⁸⁹ As outlined throughout this paper, adoption of Machine Learning and AI by Canada and her allies are viable ways to counter this shifting of the balance.

¹⁸⁷Gareth Evans, "Cat and Mouse: The Art of Submarine Detection," *Naval-Technology.com*, 13 June 2011 <https://www.naval-technology.com/features/feature121453/>

¹⁸⁸Ibid

¹⁸⁹Christopher Woody, "Top US commander in Europe says Russia's subs are getting busier, as Trump cuts sub-hunting planes from the Pentagon budget," *Business Insider*, 26 February 2020, <https://www.businessinsider.com/russia-subs-getting-busier-and-harder-to-track-in-atlantic-2020-2>

CHAPTER 7: ALLIED INITIATIVES

Canada's closest allies are investing heavily in AI and ML to augment, if not fight, their future wars. This chapter will look at examples of initiatives from the United States, Australia and NATO, as they relate to ASW and AI/ML.

United States

The director of the U.S. Joint Artificial Intelligence Center, Lt. Gen. Jack Shanahan described battles of the future as “algorithms vs. algorithms.”¹⁹⁰ The existence of a Joint AI Center speaks to their level of commitment to adopting the technologies. Each of the services is also looking at how to harness the capabilities of AI and ML. In the maritime environment, “both the Navy and the Marine Corps are working on ways to better integrate artificial intelligence into their weapons systems and business practices,” seeking to use technology to assist “human operators with making decisions faster.”¹⁹¹

As early as 2017, the U.S Navy solicited proposals for “new computing and sensor technologies for active and passive SONAR systems involved in surveillance, situational awareness, and anti-submarine warfare (ASW).”¹⁹² These included Submarine and Surface Combat System Sensor and Signal Processing Technologies, including “applying sophisticated computing technologies such as artificial intelligence, deep learning, machine learning, and predictive analytics to help detect man-made signals.”¹⁹³

¹⁹⁰David Vergun, “Without Effective AI, Military Risks Losing Next War, General Says,” *Defense.gov* Accessed 6 February 2020 <https://www.defense.gov/Explore/Features/story/Article/2009288/without-effective-ai-military-risks-losing-next-war-says-ai-director/source/GovDelivery/>

¹⁹¹Yasmin Tadjeh, “Navy, Marine Corps Boost Investment in AI Platforms,” *National Defense*, 25 June 2019, <https://www.nationaldefensemagazine.org/articles/2019/6/25/navy-marine-corps-boost-investment-in-ai-platforms>

¹⁹²John Keller, Navy Interested in New Computing and Sensor Technologies for Shipboard and Submarine SONAR. *Military & Aerospace Electronics*, July 10, 2017, <https://www.militaryaerospace.com/computers/article/16726249/navy-interested-in-new-computing-and-sensor-technologies-for-shipboard-and-submarine-SONAR>

¹⁹³Ibid

One of the primary ASW platforms for the U.S. Navy (USN), and for an expanding network of ASW allies including Australia, the UK and Norway, is the P-8 Poseidon aircraft. Touted as “the best sub-hunting aircraft on the market,” the P-8 has been in service with the USN since 2012, when it began replacing the P-3.¹⁹⁴ A scan of open-source articles describes a slew of highly advanced technologies aboard the aircraft, but there is no mention of AI on the P-8. In fact, newer deliveries have extra crew stations for expanded number of human operators.¹⁹⁵ In late 2019, the U.S. announced that it would be stopping its purchases of P-8s at 117 airframes, falling short of the 138 the Navy determined it needed to counter Russian and Chinese naval forces.¹⁹⁶ Perhaps future adoption of ML for ASW, as outlined in this paper, could bridge the gap between the requirements and number of aircraft acquired.

The USN is the leader in submarine technology, and is consistently advancing its submarine classes to maintain its edge in submarine warfare, including plans to build several more Virginia-class submarines and to replace its Ohio-class ballistic-missile carrying submarines “with 12 Columbia-class submarines, the first of which is expected in fiscal year 2021.”¹⁹⁷ In the face of increasing adversary submarine numbers and capabilities, some have speculated that the U.S. will have to adjust tactics away from its current “one-on-one” model and

¹⁹⁴Christopher Woody, “Top US commander in Europe says Russia's subs are getting busier, as Trump cuts sub-hunting planes from the Pentagon budget,” *Business Insider*, 26 February 2020, <https://www.businessinsider.com/russia-subs-getting-busier-and-harder-to-track-in-atlantic-2020-2>

¹⁹⁵John Keller, “Boeing to Integrate Extra Crew Workstations in Upgrade to P-8A Poseidon Maritime Surveillance Aircraft,” *Military and Aerospace Electronics*, 5 August 2019, <https://www.militaryaerospace.com/computers/article/14037684/p8a-poseidon-crew-workstations-upgrade>

¹⁹⁶Loren Thompson, “U.S. Navy Plans to Stop Buying P-8 Poseidon Sub Hunters Despite Growing Undersea Threat,” *Forbes*, 2 December 2019, <https://www.forbes.com/sites/lorenthompson/2019/12/02/us-navy-plans-to-stop-buying-p-8-poseidon-sub-hunters-despite-growing-undersea-threat/#3c2c6bfl59fe>

¹⁹⁷Zachary Cohen, US Launches ‘Most Advanced’ Stealth Sub Amid Undersea Rivalry, *CNN.com*, 26 October 2017, <https://www.cnn.com/2017/10/26/politics/navy-uss-south-dakota-submarine-china-russia/index.html>

explore different ways of fighting, including the possible addition of unmanned platforms to cover an area against multiple adversaries.¹⁹⁸

With traditional sensors, like passive SONARs, encountering limitations against quieter submarines, initiatives to gather higher quality information and better utilize oceanographic data to optimize predictions of acoustic propagation are being recognized as an area of opportunity and the USN is seeking leading-edge computing and sensor technologies for both active and passive SONAR systems for its surface ships and submarines, which will combine and analyze multiple data sets and are likely to leverage AI and ML to process the data.¹⁹⁹

One highly-publicized project, the Anti-Submarine Warfare (ASW) Continuous Trail Unmanned Vessel (ACTUV) was a prototype employing “non-conventional sensor technologies,” including AI to run the system autonomously “to robustly track quiet diesel electric submarines.”²⁰⁰ It was designed “under the premise that a human is never intended to step aboard,” and employed “non-conventional sensor technologies” to manage its “interactions with an intelligent adversary” and track submarines “over their entire operating envelope” and over a long duration, between 60 and 90 days, by some accounts.²⁰¹ After successful sea trials, responsibility for further development of the technology was handed over to the Office of Naval

¹⁹⁸Ibid

¹⁹⁹Pat Rabbitte, AI Will Help Submarine Crews Better Understand What Adversaries Are Doing Underwater, *The Sociable*, 5 July 2019, <https://sociable.co/technology/ai-will-help-submarine-crews-better-understand-what-adversaries-are-doing-underwater/>; Yasmin Tadjdeh, “Navy, Marine Corps Boost Investment in AI Platforms,” *National Defense*, 25 June 2019, accessed 30 January 2020 <https://www.nationaldefensemagazine.org/articles/2019/6/25/navy-marine-corps-boost-investment-in-ai-platforms>

²⁰⁰DARPA, “ACTUV “Sea Hunter” Prototype Transitions to Office of Naval Research for Further Development,” *DARPA.mil*, 30 January 2018, <https://www.darpa.mil/news-events/2018-01-30a> -

²⁰¹Dr. Alexander M.G. Walan, “Anti-Submarine Warfare (ASW) Continuous Trail Unmanned Vessel (ACTUV),” *DARPA.mil*, <https://www.darpa.mil/program/anti-submarine-warfare-continuous-trail-unmanned-vessel>; William Perkins, Alliance Airborne Anti-Submarine Warfare. . . , 68

Research, whose research initiatives are heavily focussed on ML and AI for active and passive SONAR signal processing.²⁰²

ONR has acknowledged that the USN “is currently employing AI for automated data processing on its unmanned systems,” and is using the technology for mine countermeasure missions, by having UUVs equipped with AI collect data, examine it and then “recognize mines and discard clutter.”²⁰³ There are some who even believe that the U.S. should transition completely to unmanned systems in ASW and that this change would offer significant cost savings compared to manned platforms. With line-of-sight or satellite communications, they argue, unmanned platforms could use links with operators on shore, manned platforms or even each other to achieve their tasks of deploying sensors and detecting or deterring submarines, even without operators on board.²⁰⁴

Many systems are still manned and the U.S. is also leading the way on optimizing methods of how to train operators. One initiative to augment the traditional training of SONAR Operators is to apply the attributes of video games, such as being “fast-paced, exciting and engaging” as well as available for regular use unlike traditional simulators, to try to maintain operator proficiency and strengthen teams’ coordination in ASW.²⁰⁵ The solicitation for a “Multiplayer Serious Game for Anti-Submarine Warfare SONAR Operator Training” specifically outlines leveraging “performance collection, big data analysis, and Machine Learning” to “provide for high-velocity learning” and specifies that the game “should allow play

²⁰²Office of Naval Research, “Undersea Signal Processing,” <https://www.onr.navy.mil/en/Science-Technology/Departments/Code-32/all-programs/undersea-signal-processing>

²⁰³Yasmin Tadjdeh, Navy, Marine Corps Boost Investment in AI Platforms, *National Defense*, 25 June 2019, accessed 30 January 2020 <https://www.nationaldefensemagazine.org/articles/2019/6/25/navy-marine-corps-boost-investment-in-ai-platforms>

²⁰⁴John Keller, Opinion: U.S. Navy Should Rely on Unmanned Systems and Sensors to Find, Track, and Attack Enemy Submarines, *Military and Aerospace Electronics*, 23 April 2020, <https://www.militaryaerospace.com/unmanned/article/14174623/unmanned-antisubmarine-warfare-asw-sensors>

²⁰⁵<https://www.sbir.gov/node/1606287>

with or against real and artificial intelligence.”²⁰⁶ The project further specifies that in future phases, the training tool could be integrated into the AN/SQQ-89(V) undersea warfare system, whose purpose is to provide “surface warships with a seamlessly integrated USW[Undersea Warfare]/ASW detection, localization, classification and targeting capability.”²⁰⁷ Considered the state of the art, this system and the new Multi-Functional Towed Array (MFTA), are considered capable enough to require the generation of new tactics in order to fully employ them.²⁰⁸ Given the emphasis of the multi-player ASW training tool to be able to “support big data analytics and include AI and ML,” and the previously discussed initiatives by the USN to incorporate AI into its fleets, it would not be too great a stretch to assume that the data collected through training SONAR Operators will also be used to train the USN’s AI algorithms to carry out ASW, or at least develop and validate new tactics, in a method similar to how Chess, Go and other game systems were initially trained by studying databases of human matches.

Australia

Another close ally of Canada, Australia is investing heavily in technology to counter next-generation challenges. Not only has it purchased the P-8, which gives its ASW aircraft a reported four-fold increase in acoustic processing capacity over its P-3 aircraft, but through its Plan Jericho, is exploring potential capabilities to protect against “technologically sophisticated and rapidly morphing threats.”²⁰⁹ This strategy is based on four lines of effort: Autonomous Processing; Advanced Sensors; Combat Cloud; and Human-Machine Augmentation, partnering

²⁰⁶Ibid

²⁰⁷Department of the United States Navy. “AN/SQQ-89(V) Undersea Warfare / Anti-Submarine Warfare Combat System,” accessed 2 May 2020. https://www.navy.mil/navydata/fact_display.asp?cid=2100&tid=318&ct=2

²⁰⁸William Perkins, Alliance Airborne Anti-Submarine Warfare. . . , 69

²⁰⁹Royal Australian Air Force, “P-8A Poseidon”, accessed 28 April 2020, <https://www.airforce.gov.au/technology/aircraft/intelligence-surveillance-and-reconnaissance/p-8a-poseidon>; Royal Australian Air Force, <https://www.airforce.gov.au/our-mission/plan-jericho>

people and machines.²¹⁰ In but one example of how this overarching plan to leverage technology for the Australian Defence Force has already proven effective in spurring application of AI, an initiative to use ML to assist search and rescue aircraft with identifying targets was implemented, with the algorithms written and data collected from an airborne C-130 within the span of just a few weeks.²¹¹

Under Plan Jericho, Australia is looking to integrate intelligence, surveillance and reconnaissance data and command and control systems between its new Hobart Class Air Warfare Destroyer, which also conducts ASW, its Wedgetail Airborne Early Warning and control aircraft, its P-8s and its MQ-4 Triton UAVs, which could provide cueing to the network based on radar periscope detection or ELINT.²¹² This integration will certainly require AI and ML systems due to the sheer volume of data involved and will presumably have a significant impact on how those platforms are employed.

NATO

While many nations are purchasing the U.S.'s P-8 aircraft to replace aging ASW aircraft fleets, several NATO countries, including Canada, have signed an agreement to jointly purchase a NATO Maritime Multi-Mission Aircraft (M3A).²¹³ The M3A Statement of Requirements (SOR), which has been referred to elsewhere in this document, identifies that “the NATO ASW

²¹⁰Royal Australian Air Force, “Edge Focus Areas.” Accessed 5 April 2020, <https://www.airforce.gov.au/our-mission/plan-jericho/edge-focus-area>

²¹¹Royal Australian Air Force, “AI-Search to Transform Search & Rescue,” accessed 5 April 2020, <https://www.airforce.gov.au/news-and-events/news/ai-search-transform-search-rescue>

²¹²Lockheed Martin, “Plan Jericho: Giving Australia the Edge.” *Lockheedmartin.com*, accessed 5 April 2020 <https://www.lockheedmartin.com/en-us/news/features/2017/plan-jericho-giving-australia-the-edge.html>; William Perkins, Alliance Airborne Anti-Submarine Warfare. . . , 66

²¹³Aaron Mehta, “Poland, Canada join NATO members in potential maritime surveillance aircraft buy.” *Defense News*, February 15 2018, <https://www.defensenews.com/smr/munich-security-forum/2018/02/15/poland-canada-join-nato-members-in-potential-maritime-surveillance-aircraft-buy/>

community is experiencing challenges resulting from a reduced M3A inventory,” which could be extrapolated to imply we need to be more efficient with the resources we do have.

While still envisioned to be a crewed platform, the M3A will contain “sensor and mission system improvements,” which will allow reductions to the size of the operating crew to the extent that smaller aircraft could be utilized.²¹⁴ The SOR recommends that to be able to respond to “evolving technologies or emerging threats, the M3A must have capacity to grow its capability, sensors and means over time.”²¹⁵ In order to shrink crew sizes while growing sensor capacity and fusing together all of this information, advanced processing will be required. The SOR mentions flexibility to incorporate ‘quantum technologies’ and ‘others,’ which would certainly have to include ML or AI capabilities, as outlined in this paper.²¹⁶

A concept envisioned for the M3A, and also discussed regarding the P-8, is the possibility of interacting with UAS, or even launching and controlling them directly, to expand the operating area, potentially to act as a communications relay or even delegated magnetic anomaly detection.²¹⁷ Likewise, the UAS could be fitted to lay extra sonobuoys for the M3A’s use, supporting the higher usage rates described by Perkins and discussed earlier in this paper. In any of these concepts, however, the time on-station for onboard personnel is extended, which would, without ML or AI augmentation, likely offset the potential crew reductions promised by more efficient sensors and increased processing capability.

With the transition from analog tape to digital systems, co-operating ASW nations recognized that they lost the ability to share acoustic information between their platforms. With

²¹⁴NATO M3A SOR. . . , 8, A-4

²¹⁵Ibid

²¹⁶NATO M3A SOR. . . , 13

²¹⁷John Keller, Boeing to Integrate Extra Crew Workstations in Upgrade to P-8A Poseidon Maritime Surveillance Aircraft, Military and Aerospace Electronics, 5 August 2019, <https://www.militaryaerospace.com/computers/article/14037684/p8a-poseidon-crew-workstations-upgrade>; NATO M3A SOR. . . , A-3

nations signing on to common platforms such as the P-8 or the NATO M3A, there seems to be an acknowledgement for the need to return to common data formats and a better ability to share information. If the future of ASW is a “Network-Centric-Based ASW Force coordination,” then an ability to continuously share information among all units and between their sensors, or better interoperability, will be necessary.²¹⁸

Interoperability

NATO has generated hundreds of Standardization Agreements (STANAG) for systems in order to ensure a common standard and, to some extent, interoperability. Future sonobuoys, for example, are planned to each have their own IP address in order to minimize RF interference and will be designed based on an agreed format for shared use by partners.²¹⁹ This will certainly extend to other sensors, and, as previously discussed, entire aircraft and naval platforms.

When nations incorporate ML and AI in to their ASW assets, they will also need to ensure that sharing of information is considered in the development of mission data files and algorithms. In the example of a ‘black box’ ML system that carries out calculations and advises the crew onboard that it has found a submarine, an aircraft tracking that submarine would need a method to pass the pertinent information to a relieving aircraft, including the frequencies and parameters it is using to carry out the tracking. A parallel to this has been identified with the adoption by several countries of the F-35. On that platform, mission data files need to “be updated before each sortie to ensure optimum combat effectiveness and aircraft survivability,” with each nation preparing its own files, due to their inherent sensitive intelligence data.²²⁰

²¹⁸William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 16

²¹⁹NATO M3A SOR. . . , A-3

²²⁰Peter Layton, *Fifth Generation Air Warfare*. . . , 8

In discussing the variation of acoustic processors on the variety of ASW airborne and naval platforms, Perkins points out that “target classification capability by each detection sensor also remains within national channels.”²²¹ For this to change, common systems, and data, for mission planning, including oceanographic prediction, would need to be established.

Additionally, in discussing fifth-generation fighters, Layton points out that in a conflict, platforms will try to change their emission signatures “to gain some tactical advantage.”²²² This could be extrapolated to the case of ASW, where submarines would certainly attempt to change their operating parameters to avoid being detected and classified. Layton argues that in this case, until the adversary’s signature is determined, the algorithms will be searching for the wrong parameters and that “incorrect information entered into the network” by users or algorithms will be disseminated to all other users on the network, potentially creating an “inaccurate common picture.”²²³ Furthermore, as nations update their data files and algorithms, the odds that shared detection and tracking algorithms will begin to deviate between nations as software blocks are updated increases, potentially negatively impacting interoperability.²²⁴

NATO’s M3A SOR tackles this challenge somewhat by establishing the importance of establishing appropriate STANAGs to enable interoperability to “support exchange and collaborative use of surveillance data and information,” but it remains to be seen exactly what information will be shared and what will be guarded at the national level.²²⁵ Ultimately, nations have their own restrictions on what acoustic intelligence (ACINT) can be shared with which nations, but in order to adopt shared ML databases and systems that can truly fuse data and

²²¹William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 75, 76

²²²Peter Layton, *Fifth Generation Air Warfare*. . . , 15

²²³*Ibid*

²²⁴*Ibid*

²²⁵NATO M3A SOR. . . , 12

collaborate across platforms, the sharing of common software, data and algorithms will be extremely important.

CHAPTER 8: CANADIAN INITIATIVES

Canada is a leader in AI, having released the first national AI strategy in 2017 and consistently appearing high in rankings of top countries for AI research.²²⁶ Previous chapters have highlighted the extent to which Canada's Data Strategy, Defence Policy and MND mandate letter seek to integrate ML and AI technologies into military platforms. While much of the focus in these documents is on managing the large flow of data from future platforms, and within the bureaucracy of the organization itself, a summary of the status and future plans for ASW-specific platforms and their potential to utilize ML follows.

Aircraft

Having just reached Interim Operational Capability in 2018 and projected to be fully operationally capable in 2025, the CH-148 Cyclone is Canada's newest ASW platform. The standard crew for the Cyclone is two pilots, one ACSO TACCO, and a single Sensor Operator responsible for a number of leading-edge sensors, including passive acoustics and the HELRAS active SONAR, claimed to be the "highest-performance helicopter dipping SONAR in the world."²²⁷ If the advertised performance of other modern equivalents is accurate, this could entail an increase in "detection ranges from three to seven times that of legacy systems."²²⁸ The SONAR is also claimed to be interoperable "with shipboard SONARs and sonobuoys in bistatic or multistatic employment."²²⁹ The adoption of ML algorithms to optimally process passive and

²²⁶Oxford Insights, "Government Artificial Intelligence Readiness Index 2019," *Oxfordinsights.com*, accessed 5 May 2020, <https://www.oxfordinsights.com/ai-readiness2019>; Alexandra Mousavizadeh, Alexi Mostrous and Alex Clark, "The Global AI Index: The Arms Race," *Henkel Ventures*, Accessed 5 May 2020, <https://members.tortoisemedia.com/2019/12/03/global-ai-index/content.html>

²²⁷L3 Technologies. "HELTRAS DS-100 – Helicopter Long-Range Active Sonar," accessed 1 April 2020. https://www2.l3t.com/oceansystems/helras_ds-100.htm

²²⁸Jeff Benson, "A new era in Anti-Submarine warfare," *USNI News*, 27 August 2014 <https://news.usni.org/2014/08/27/opinion-new-era-anti-submarine-warfare>

²²⁹L3 Technologies. "HELTRAS DS-100 – Helicopter Long-Range Active Sonar."

active SONARs, in particular multi-static operations, would augment the capability of the single sensor operator and would arguably optimize fusion of data with and from other platforms.

The CP-140 Aurora, in service since 1980, has undergone numerous upgrades to modernize its sensor suite and has received modifications to extend its service life until 2030.²³⁰ Canada's project to replace the Aurora is in the very early stages and no Statement of Requirements exists yet, but SSE specifically mentions recapitalization of the CP-140 fleet.²³¹ Given that Canada has signed on to the NATO M3A forum, it can be assumed that any replacement for the Aurora will have similar requirements to those outlined for M3A elsewhere in this paper.²³² As previously discussed, these requirements do not specifically refer to AI or ML systems on board, but do extensively mention advances in sensors and computer processing capability. For human operators, the challenge of dealing with the volume of information being generated by the current version of the CP-140 will only increase with the adoption of the latest block of upgrades, and will certainly be a consideration with any replacement platform. While tactics are continually being developed to account for "the volume of information now being generated by the sensor systems" of the upgraded CP-140, human operators could become a limiting factor on what current or future Canadian ASW aircraft can achieve, given the untapped potential of the systems on board.²³³

In envisioning the breadth of acoustic AES Op tasks an ML system would need to achieve, the current configuration of the CP-140 does not have large amounts of empty space for

²³⁰Canada, Department of National Defence. "CP-140 Aurora Fleet Modernization and Life Extension," accessed 23 April 2020, <https://www.canada.ca/en/department-national-defence/services/procurement/cp-140-aurora.html>

²³¹Canada. Strong, Secure, Engaged. . . , 103

²³²David Donald, "NATO Joint Tanker/Transport and MPA Programs Advance," *AIN Online*, 21 February 2018. <https://www.ainonline.com/aviation-news/defense/2018-02-21/nato-joint-tanker/transport-and-mpa-programs-advance>

²³³Chris Thatcher, Submarine Hunter, RCAF Today 2018. . . , 49
<https://army.ca/forums/index.php?action=dlattach;topic=66394.0;attach=57166>

the addition of computing equipment. If, however, the two entire crew stations for Acoustic Sensor Operators were to be removed entirely, including desk space, monitors, chairs and the protective equipment for the operators, along with not having two or more operators on board each mission, hundreds of kilograms and several square meters could be freed up, which would likely be necessary given the size and space requirements for the computing power that would be required. On a next-generation platform, these considerations could be made while the platform is being designed, either for a new build or to be easily retrofitted once a system is ready, so that power, weight, balance and centre of gravity challenges could be avoided.

Halifax Class Frigate

The Halifax-class frigates have been in service with the RCN since 1992 and have gone through a modernization project which included upgrades to systems, addition of new capabilities and extended the service life out until the delivery of the next generation of ships.²³⁴ They are “multi-purpose platforms” designed and built in the latter stages of the Cold War, with an emphasis on ASW, to “operate in the Northern Atlantic and find Soviet nuclear submarines.”²³⁵ The ships’ ASW systems are being upgraded through the Underwater Warfare Suite Upgrade (UWSU), which includes a new Towed Array SONAR, Hull Mounted SONARs and the Torpedo SONAR Intercept & Classification system, which can detect SONAR from enemy torpedoes, and “offer unique capabilities and world leading performance.”²³⁶

The improved sensors and SONARs “will be able to detect quieter targets at increased ranges providing the greatest possible detection capability to protect ships from underwater threats,” which “increases the window operators and command teams have for decision

²³⁴Canada. Royal Canadian Navy. “Canadian Patrol Frigates.” Accessed 1 May 2020. <http://www.navy-marine.forces.gc.ca/en/fleet-units/frigates-home.page>

²³⁵Canada, “Underwater Warfare Suite Upgrade Protects Sailors From Quieter Submarines and Torpedoes.”

²³⁶Ibid

making.”²³⁷ This system, while highly advanced, still relies on human sensor operators to interpret the incoming information. As discussed throughout this paper, integration of ML systems with capable sensors could allow optimum performance in ASW scenarios.

Canadian Surface Combatant

The Canadian Surface Combatant (CSC) will be the replacement for the Halifax Class, with deliveries planned beginning in the mid 2020s and continuing until the late 2040s.²³⁸ The Type 26 design will feature an “acoustically quiet hull,” and “an advanced SONAR system with a towed array system for tracking submarines.”²³⁹ Beyond these details, not much is known about its planned sensor systems, except that the RCN has explicitly stated that it is “not pursuing any AI that is connected to employing weapon systems.”²⁴⁰ This paper has argued throughout that ML should be used to provide decision-makers with high quality information to inform tactical decisions. With the capability of sensors that will exist by the time the final ships are delivered and the rapid advances in Artificial Intelligence and Machine Learning, it seems certain that the CSC will incorporate ML for sensor operation at some point in its lifespan, but to what degree, and when, is yet to be determined. As a central ASW platform, interoperability with allies and future aircraft will be essential and foresight and significant planning will need to occur to ensure these capabilities can be successfully integrated.

Victoria Class Submarines

²³⁷Ibid

²³⁸Canada. Government of Canada. “Canadian Surface Combatant.” Accessed 1 May 2020. <https://www.canada.ca/en/department-national-defence/services/procurement/canadian-surface-combatant.html>

²³⁹David Dunlop, “Future-Proofing the Type 26 Frigate,” *Canadian Naval Review* Volume 15, Number 1, Spring 2019

²⁴⁰James McLeod, “Canada’s Navy is Developing an AI Voice Assistant for Warships, but Don’t Worry: It Won’t Control the Weapons,” *Financial Post*, 1 May 2019, <https://business.financialpost.com/technology/canadas-navy-is-developing-an-ai-voice-assistant-for-warships-but-dont-worry-it-wont-control-the-weapons>

SSE identifies the Victoria-Class submarines (VCS) as a key element of maritime domain awareness, through their sub-surface surveillance role, and highlights the importance of their role in sovereignty operations and continental defence.²⁴¹ The four submarines, which were brought into service by Canada beginning in 2000, were scheduled to reach their end of service lives beginning in 2022, but will now undergo an incremental modernization programme, “which will ensure their continued effectiveness out to the mid-2030s.”²⁴² The VCS acoustic sensors include an active/passive bow SONAR, a towed array system and a flank array, which is slated for upgrade in the Victoria Class Modernization Program, in order to achieve “better detection and performance.”²⁴³ It is unlikely that ML is being considered for addition to the upgraded systems, given the position of the RCN against incorporating AI, but as with the next generation of surface ships, it may be essential to further improve the operating capacity of the SONAR systems and manage the amount of information generated on board.

Shore-Based

SONAR Ops and AES Ops are also employed in acoustic analysis roles at the Naval Ocean Processing Facility (NOPF) at Whidbey Island, in the U.S., at the Acoustic Data Analysis Centre (ADAC) department of the Trinity Naval Intelligence unit in Halifax? and at Acoustic Sensor Analysis (ASA) sections on maritime helicopter and long range patrol home Wings.

At NOPF Whidbey Island, the 30 CAF personnel assist in providing “timely and accurate acoustic cueing to operating and supporting forces, and conduct continuous maritime surveillance,” by analyzing information from either the five Surveillance Towed Array Sensor

²⁴¹Canada, Strong Secure, Engaged, Canada’s Defense Policy, 65

²⁴²Lee Berthiaume, “Canadian Navy Decides to Start Upgrades to Extend Life of Aging Submarine Fleet,” National Post, 22 January 2019. <https://nationalpost.com/news/politics/canadian-navy-pressing-ahead-on-life-extensions-for-submarines>; Canada, Strong Secure, Engaged, Canada’s Defense Policy, 65

²⁴³Canada. Public Works and Government Services Canada. “RFI-Provision of a Flank Array System – Victoria-class Modernization (VCM) (W8472-195763/A),” Accessed 20 April 2020. <https://buyandsell.gc.ca/procurement-data/tender-notice/PW-VCM-002-27335>

System (SURTASS) ships, which operate a towed hydrophone array over 8,000 feet long, or working on the operations watch floor, which monitors a network of fixed arrays.²⁴⁴

At ADAC and ASA, they analyze recorded acoustic information from operational platforms to derive acoustic intelligence and assess submarine and other contact encountered by operators, which is then fed back into intelligence and training products and debriefs to crews to prepare them for follow-on missions.

In any of these positions, incorporation of ML to analyze the extensive acoustic data coming in to the facilities would significantly expand the capability of these organizations to increase their outputs in terms of tactical advice and intelligence products to higher command and the on-platform operators.

²⁴⁴United States Navy, “Naval Ocean Processing Facility Whidbey Island WA,” accessed 1 May 2020, <https://www.public.navy.mil/subfor/cus/Pages/NOPFWI.aspx>; William Perkins, Alliance Airborne Anti-Submarine Warfare. . ., 66

CHAPTER 9: TRANSFERRABLE INITIATIVES

There is little indication that the primary methods of conducting ASW will deviate from methods exploiting sound in water, specifically passive and active acoustics, employed in co-ordination with other sensors. There are, however, several initiatives being explored that hold potential to, at the least, complement current technologies, if not replace them outright.

The concept of Pervasive Sound Technology, which would see a network of ships, buoys, submarines and other platforms linked through advanced networks as a single system, rather than the current collection of stand-alone systems, is seen a probable next bound in ASW.²⁴⁵ While still using sound as a primary source of detection and tracking, such a network would entail the correlation of significantly more data than is currently processed by human operators, including not only sound sources and location information, but the advanced analysis of oceanography and sound source levels across multiple sensors in real time, a task perfectly suited for AI methods.

In addition to Multi-Static Active processing, which has previously been discussed and which also entails the close co-ordination of information across platforms, research is being carried out into entirely different types of SONAR pulses. Twin Inverted Pulse SONAR (TWIPS), for example, is based on the natural SONAR used by dolphins. Research has shown “that a dual stream of underwater pulses can penetrate bubbles more effectively than conventional SONAR and provide a significantly better detection rate – at least under laboratory conditions.”²⁴⁶

Another research project based on natural processes to interpret human activity was the initiative in 2018 and 2019 to fit albatrosses with sensors and GPS loggers to monitor fishing and

²⁴⁵William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 70

²⁴⁶Gareth Evans, “Cat and Mouse: The Art of Submarine Detection,” *Naval-Technology.com*, 13 June 2011 <https://www.naval-technology.com/features/feature121453/>

other maritime activity.²⁴⁷ It was discovered that one third of vessels in international waters had no AIS signal, creating a discrepancy between the reported number of ships, with identifying information, and actual ships present. Military surveillance aircraft, such as the CP-140, dedicate time to correlating tactical plots and other sensors with AIS data to deduce which vessels are operating where, and by extension, which returns could be submarines or other vessels of interest. Harnessing natural processes like sea life movement by adding a sensing capability has the potential to clarify the status of the operating environment, although it would come with an increased information management workload, which could be offset by using ML systems to correlate and fuse the data.

Akin to leveraging flocks of birds as sensor platforms, the concept of using a formation of drones for ASW has been proposed, which would use allow to re-positioning of out-of-range sensors to re-gain acoustic contact.²⁴⁸ While these could be commanded by humans on a platform, this would increase the workload on operators, whereas leveraging AI and ML tools to allow them to determine the best position for sensors, correlate the incoming acoustic data and self-synchronize optimum positioning would arguably optimize employment of this concept.

The use of space-based assets has also been incorporated into ASW and an ever-increasing number of potential sensors is being explored to search for and track submarines. From tracking of surface maritime traffic via RADARSAT satellites, which “will allow us [Canada] to track maritime traffic over much larger swathes of ocean and provide for more timely identification of vessels that may require further scrutiny” to attempting to “detect the

²⁴⁷Emily Chung, “Albatrosses used as flying spies to detect illegal fishing boats,” *CBC News*, 28 Jan 2020, <https://www.cbc.ca/news/technology/albatrosses-illegal-fishing-1.5443154>

²⁴⁸William Perkins, *Alliance Airborne Anti-Submarine Warfare*. . . , 67

minute changes in ocean surface level due to the deep passing of a submarine,” there are several ways that space-based sensors can contribute to ISR and ASW.²⁴⁹

As opposed to looking for clues that a submarine may be present, future technologies like hyperspectral imaging promise to simply be able to “look through” the ocean to find a targets of interest.²⁵⁰ While these systems are currently in early stages of research, and are limited in their ability to cover broad swaths of ocean until they are viable to be fitted on aircraft or satellites, this type of technology is certainly promising.

One more future technology that holds the promise of rapidly accelerating the development of AI and that “will find a use anywhere where there’s a large, uncertain complicated system” such as ASW in the ocean environment, is quantum computing.²⁵¹ While having a quantum computer onboard an aircraft or ship is unlikely, it is not unreasonable that they could eventually be used to carry out very precise environmental modelling, generate tactics that human operators could never imagine or create efficient ML/AI algorithms to be used locally on other platforms.

While a case could be made for any of the above becoming game-changers in ASW and replacing acoustics as a primary ASW method in the future, they each would add to the existing massive amounts of data coming into ASW platforms, would entail additional training requirements for operators and would drive changes to future ASW tactics, three characteristics that would make them as suitable for ML systems as for being added to the current task load carried out by human operators.

²⁴⁹Canada, Strong Secure, Engaged, Canada’s Defense Policy, 2017; William Perkins, Alliance Airborne Anti-Submarine Warfare. . . , 42

²⁵⁰William Perkins, Alliance Airborne Anti-Submarine Warfare. . . , 81; David Stein, Jon Schoonmaker and Eric Coolbaugh, “Hyperspectral Imaging for Intelligence, Surveillance, and Reconnaissance. Data Acquisition and Exploitation. SSC San Diego, August 2001.

²⁵¹Amit Katwala, “Quantum Computers Will Change the World (If They Work),” *Wired.com*, 5 March 2020, <https://www.wired.co.uk/article/quantum-computing-explained>

CHAPTER 10: ANALYSIS AND RECOMMENDATIONS

As outlined throughout this paper, significant research on AI, and specifically its application to ASW, is underway. Canada is a leader in AI research and has laid down government and military-specific policies outlining that in the future, AI will be a factor in military affairs. ASW has historically been carried out via multiple sensors, but with highly trained acoustic sensors operated by humans as a key component, which has been considered as potentially “inaccurate due to the need for continuous monitoring of the operating SONAR console.”²⁵² Future platforms will inevitably entail much more in-depth sensor tasks than currently carried out on current Canadian ASW platforms. While current phases of acquisition for aircraft, ship and submarine upgrades and replacements do not define specifically how these additional tasks will be processed or carried out, they would certainly be more easily carried out by the addition of advanced automation and ML techniques than by further overloading already busy human sensor operators or by adding personnel to current crew structures. The continuing expansion of computer processing power at ever-decreasing costs has been a driving factor in ML and AI development and will continue through the development and adoption of this technology for the CAF, whether applied to acoustic analysis for ASW or processing of other sensor data.

One model of many on the stages required to implement AI/ML, the “AI hierarchy of needs” will be applied through this chapter to analyze actions that would be required to adopt ML to replace the tasks of acoustic sensor operators.²⁵³

²⁵²Iksu Seo, Seongweon Kim, Youngwoo Ryu, Jungyong Park and Dong Seog Han, “Underwater Moving Target Classification Using Multilayer Processing.”

²⁵³Monica Rogati, “The AI Hierarchy of Needs,” *Hackernoon.com*, 12 June 2017, <https://hackernoon.com/the-ai-hierarchy-of-needs-18f111fcc007>

Collect

This phase, the collection of active and passive data, is already happening continually. In discussing fifth generation air warfare, Layton says “in the initial big data phase, a high volume, velocity, and variety of data from multiple diverse sources across time and space are collected.”²⁵⁴ With every mission, ASW platforms have sensors in the water and record ambient noises, biological noises and merchant shipping traffic, as well as warships and submarines during exercises and operations. Acoustic analysis is logged and annotated and recordings are forwarded into an established system of increasingly detailed analysis.

Move/Store

This level is based on how data flows through the system.²⁵⁵ Following collection, data is transferred off the platform to a post-mission facility for further analysis. This transfer currently happens primarily through physical transfer of storage devices, like hard drives, with some networked transmission of files. Real-time transmission from a platform into an information ‘cloud’ would also qualify in this stage. As the data is transferred into storage, it needs to be annotated, and structured in a way that can be used by the tools which will ultimately analyze the data. In order for ML to help us make sense of the complexities in the data and find relationships that cannot be processed manually, the data will need to be further prepared.

Explore/Transform

This stage involves data scientists carrying out cleaning, anomaly detection and preparation for further use. Libraries of acoustic contacts include annotations of research and trend analysis on submarine signatures and systems, as analyzed by humans. These databases would need to be verified for accuracy before incorporating them into training data for ML. All

²⁵⁴Peter Layton, “Fifth Generation Air Warfare” . . . , 9

²⁵⁵Monica Rogati, “The AI Hierarchy of Needs.” *Hackernoon.com*.

of the research reviewed in the preparation of this paper used “cleaned” or optimized data to train ML systems to carry out analysis and classification of biological sounds or man-made platforms. None described techniques that were ready for real-time raw data, which would be necessary for use on an ASW platform.

The use of an acoustic database populated by trained personnel brings up the concept of an ‘expert system’ which is a system programmed with manually specified rules and algorithms. Typically, “an expert system is composed of a knowledge ... represented as a set of if-then rules, and the inference engine uses logical inference rules for deduction. The rules are programmed after consultation with domain experts, and they are fixed.”²⁵⁶ Alpaydin gives two reasons that expert systems were difficult to implement. The first, that the “knowledge base needed to be created manually through a very laborious process” which is somewhat overcome by the fact that the acoustic databases already exist, and just need to be cleaned. His second reason “was the unsuitability of logic to represent the real world.”²⁵⁷ Contrary to many problems ML tries to deal with, there are concrete relationships between, for example, the type of system on a submarine and the sound it generates. While expert systems have resulted in limited success as compared to systems that learn directly from data, there is an existing body of knowledge in acoustics which captures the experience of experts on how submarines and other platforms generate sounds, and the relationships between those sounds, perhaps justifying beginning with an expert system.

Another aspect of data analysis is generating hypotheses and verifying whether the data supports the hypothesis. Manual analysis of the data in this way, however is limited, as Alpaydin points out in that “we can test only the hypotheses we can imagine.”²⁵⁸ Rather than

²⁵⁶Ethem Alpaydin, *Machine Learning, the New AI* . . . , 50

²⁵⁷Ibid, 51

²⁵⁸Ethem Alpaydin, *Machine Learning, the New AI* . . . , 155

having fixed rules, however, a hybrid system that starts with an initial ‘how to analyze passive acoustic recordings’ and ultimately allows the system to identify and analyze the deeper hidden relationships in the data is recommended. These hidden relationships could include undiscovered relationships between pieces of information regarding oceanography and sound propagation or could potentially fill gaps in knowledge where the CAF does not have information on specific submarines or have not collected on them in certain operating profiles.

Aggregate/Label

Once the existing data is collected and cleaned, the next step is to label the information for use by the ML system. Currently, acoustic data is prepared for use in training and storage by highly trained operators and analysts. The labelling stage would take this data and label it for use by the ML system, which would need to be based on having an idea of how the algorithms will work. Along with the classification information, which was the primary type of information discussed in much of the research reviewed for this paper, acoustic data examples also need to be annotated with an assessment of what is happening tactically, in order to differentiate the impact of specific speed regimes, depths and maneuvers on the acoustic signature.

Again, much of this knowledge is already in existence and would simply need to be labelled. Alpaydin points out that with supervised learning, “structure is imposed by the supervisor who defines the different classes and labels the instances in the training data by these classes.” A caution with this hand labeling is to ensure it is free from bias and to acknowledge that there is a chance of errors in the labeling, also known as “teacher noise.”²⁵⁹

Since the acoustic library would contain raw audio files, as well as files consisting of annotations of operator analysis, either raw audio or processed files could be input into the

²⁵⁹Ibid, 117

system. Research has been carried out using both approaches, with some preferring to use preprocessed audio, such as LOFAR grams, in order to ensure that key features are retained and that “useless information” like noise does not interfere with feature extraction in deep learning.²⁶⁰

Since the ultimate goal will be incorporating ML into real-time platforms, another benefit of using processed files is that the system could be ‘taught’ how to concurrently process information with multiple settings to derive the best information, for example, the strongest signal). The NATO M3A SOR supports this idea in describing an ability for sensors to “collect all data that presents at the aperture and...process it in multiple modes in real time.”²⁶¹

Likewise, instead of choosing a single algorithm, multiple learning algorithms can be combined which “may lead to better performance,” according to Alpaydin.²⁶² Combining models is probably more reflective of how humans carry out acoustic analysis, with different approaches depending on the nature of the information presented making it an ‘art’ as opposed to an entirely systematic approach. Most of the surveyed research supports that combined methods show better results than stand-alone applications, with a 4 to 11 percent better performance noted by Yang et al and similar positive results by Yue et al in their research.²⁶³

In his analysis, Perkins states that “NATO should explore development of the capability to record active SONAR for post-mission analysis and the fidelity for active SONAR to classify

²⁶⁰Guanghao Jin, Fan Liu, Hao Wu & Quinzeng Song (2020) “Deep Learning based Framework for expansion, recognition and classification of underwater acoustic signal,” *Journal of Experimental & Theoretical Artificial Intelligence*, 32:2, 205-218, DOI: 10.1080/0952813X.2019.1647560

²⁶¹NATO M3A SOR. . . , A-9

²⁶²Ethem Alpaydin, *Machine Learning, the New AI. . .*, 71

²⁶³Honghui Yang, Guanghui Xu, Shuzhen Yi, Yiquing Lia, “A New Cooperative Deep Learning Method for Underwater Acoustic Target Recognition,” *Oceans 2019 Conference June 2019 Conference Paper*; Hao Yue, Lilun Zhang, Dezhi Wang, Yongxian Wang and Zengquan Lu, “The Classification of Underwater Acoustic Targets Based on Deep Learning Methods,” *Advances in Intelligent Systems Research*, volume 134, Atlantis Press, January 2017

submarines by type in real time while on station.”²⁶⁴ Seo et al, in their work on target classification, noted that “even if there is no target in the sea, data acquisition with active SONAR in the underwater environment is needed to accumulate clutter distributions.”²⁶⁵

This is but one of example of the benefit of retaining and metatagging or labeling all data, which Layton points out “ensures that what seems like valueless data now can be later located, retrieved and manipulated to create high value information when new requirements emerge or improved analysis methods are developed.”²⁶⁶ Baselines of oceanographic information, whether clutter for active systems, or ambient noise distributions for passive processing, may be generated from data currently held, but not seen as holding value. This would apply not only to developing ML for active acoustic processing, but in retaining data for further ML developments, such as advanced modelling of oceanographic profiles or fusion of data with other sensors. Annotating data of unknown future utility would be time consuming and potentially induce errors if done by humans, but could easily be achieved with excess computer processing power when it is not in use for other applications.

Learn/Optimize

The successful implementation of ML relies on “a lot of example data and sufficient computing power to run the learning methods on that much data” and in some cases “generating the algorithms themselves from the data.”²⁶⁷ This portion of the implementation process is the area to which much of the research cited in this paper was carried out. Whether developed internally, by contractors or in collaboration, the CAF would need to set up for passive acoustics

²⁶⁴William Perkins, “Alliance Airborne Anti-Submarine Warfare” . . . , 106

²⁶⁵Iksu Seo, Seongweon Kim, Youngwoo Ryu, Jungyong Park and Dong Seog Han, “Underwater Moving Target Classification Using Multilayer Processing.”

²⁶⁶Peter Layton, “Fifth Generation Air Warfare” . . . , 10

²⁶⁷Ethem Alpaydin, *Machine Learning, the New AI* . . . , xii

based on the classified military holdings. Whereas the research papers based their experiments on limited databases of open source recordings, such as World War 2 recordings of defunct platforms, implementation for use on real world platforms would have, at some point, to use current platforms. The process could, however, start with recordings of merchant shipping, which typically consists of few maneuvers, stable running states and tactical data, such as position, course and speed, which can be correlated by data collected from AIS and other sensors such as RADAR. This library would also enable a supervised expert system by allowing human analysts' assessments of characteristics of frequency line sources to be incorporated in order for the computer to be able to differentiate between sources, for example the signature of a diesel engine source, versus the appearance of propeller noise can be quite different and have different characteristics. Much like with a human operator, known basic information, like blade fitments and engine configuration, can be used as a starting point for learning to classify. Using unclassified sources and recordings of surface ships, it should be possible to teach the ML to differentiate between vessels using widely available databases like the Lloyd's Shipping Registry, which contains information on ship dimensions, propulsion train and engine types.²⁶⁸

The ML system could thus be taught to identify and interpret the known and 'hidden' relationships between frequencies. Our own warships, for example, can provide details through logs as to their running configuration and which specific equipment is turned on at any given time, which can be cross-referenced with acoustic recordings. In some cases, the ML could use this information to learn to map or fingerprint sounds to specific systems and subsequently to specific vessels. The system should be set up to allow the contacts being analyzed to become

²⁶⁸Lloyd's Register, "Marine & Shipping." Accessed 1 May 2020. <https://www.lr.org/en/marine-shipping/>.

more complex, eventually allowing the ML to recognize hidden relationships which could be imperceptible to or missed by even the most highly trained human analyst.

Incrementally, the supervisor could begin adding very straightforward examples of warships transiting and minor deviations to ‘teach’ the system to identify tactical maneuvers and speed changes. Concurrently, the system should ‘learn’ how to identify the ‘closest point of approach’ on a sensor and derive tactical data, such as speed and range, through well-known acoustic formulas.

Ultimately, the goal would be to transfer what was learned about acoustic sources on a basic platform to warships and eventually submarines, which may have some systems which are the same structurally and mechanically as on marine shipping vessels. Next, it could be taught to identify anomalies (highly dynamic targets like fishing vessels or small pleasure craft), and carry out what tactical analysis it can, which by that point should include deviations in propulsion, engine and certain other sources by their characteristics and frequency spectrum. Very straightforward submarine contacts (not maneuvering or changing operating modes) could be introduced next, along with calculation of tactical information, like depth. Finally, more dynamic submarine targets, could be added to the database(s), identified by the system as outliers from background noise. Throughout this process, the system should be building and refining its analysis capability as well as its ocean propagation models, in order to be able to transition to real-time data analysis.

As pointed out by Alpaydin, “in many applications, the underlying characteristics of the problem may change in time; in such a case, previously collected data becomes obsolete and the need arises to continuously and efficiently update the trained model with new data.”²⁶⁹ This

²⁶⁹Ethem Alpaydin, *Machine Learning, the New AI* . . . , 26

would be the case with a recording of a ship or a submarine operating in a tactical profile that was previously not held in the database, or a recording of a platform after emerging from a re-fit work period. The new information would have to be incorporated into the overall knowledge base of the system, without re-starting every time new information was added.

Alpaydin mentions that a system must know “what it knows and what it does not know” and should be able to indicate the level of certainty in its prediction.²⁷⁰ This would be critical in passing information to a decision maker in a tactical environment, but would be useful in training a ML system so the level of accuracy can be assessed. With more data can come more uncertainty, but “if the trained model knows where it has high uncertainty, it can actively ask the supervisor to label examples in there.”²⁷¹ Once the acoustic ML system has been trained and validated using the unclassified sources, it could be implemented at a shore-based facility to filter incoming recordings and identify contacts present. In filtering incoming acoustic recordings, the system could carry out active learning, where it would highlight areas of interest for human analysts to review, while at the same time identifying its own areas of uncertainty, which once resolved would contribute to its proficiency.

Many of the studies reviewed in Chapter 4 took very small sample databases and “sliced and diced” them to attain thousands of samples against which to train and assess their approaches. None discussed taking individual acoustic features and “teaching” them to the computer and cross-referencing them with known sources. Instead, most followed machine learning methods with very small sample sizes and resulting accuracies that would be too low to apply to an ASW environment, with results such as 90% chance of “submarine,” versus classifying a known hostile platform. With larger data samples from modern platforms, the

²⁷⁰Ibid, 79

²⁷¹Ethem Alpaydin, *Machine Learning, the New AI* . . . , 80

researchers may have had higher accuracies, but if the intent is to replicate all of the tasks of ASOs, systems must be able to identify and classify all acoustic sources, in all operating modes, and extract relevant tactical data, which is why this paper is arguing for a supervised method. That said, if researchers are able to achieve better results using unsupervised methods and gain a higher accuracy than other methods that involve supervised learning, an unsupervised path should be pursued. The strength of unsupervised methods was discussed earlier in this paper and in some fields AI researchers have even been able to create “AI that’s capable of generating its own AIs,” an example of which is Google’s system, which was able to automate the design of its own machine-learning models using unsupervised reinforcement learning.²⁷²

In Thomas et al’s study on identifying marine mammal sources, they note that the “algorithms are heavily dependent on the filtering, normalization, and smoothing operations that are performed on each spectrogram.”²⁷³ As ML systems better learn to analyze information, they could also be trained to optimize their own performance in signal processing. Jin et al identified that samples generated by their own network were “more clearly displayed and have more prominent characteristic lines than the original training samples,” implying that this approach could be useful.²⁷⁴

If such a system could be created to incrementally refine and optimize its own performance, while streamlining its own use of processing power and hardware, it would pave the way for implementation on future platforms, such as aircraft, where weight, power and space requirements are all considerations.

Machine Learning Rollout

²⁷²Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . , 49

²⁷³Mark Thomas et al, “Marine Mammal Species Classification using Convolutional Neural Networks” . . . , 4

²⁷⁴Guanghao Jin, Fan Liu, Hao Wu & Quinzeng Song (2020) Deep Learning based Framework for expansion, recognition and classification of underwater acoustic signal, *Journal of Experimental & Theoretical Artificial Intelligence*, 32:2, 205-218, DOI: 10.1080/0952813X.2019.1647560

As Thomas et al mention, acoustic data collection is “often carried out using moored recorders equipped with hydrophones,” which generates significant data once collected.²⁷⁵ Filtering and analysis of this type of data would be a logical first test of a trained ML system, for both accuracy and processing capability. While much of this data, including that referred to by Thomas et al, and that in a recent Environmental Studies Research Fund project, is geared toward sea life, and it typically holds a wide variety of marine sound sources and oceanographic information.²⁷⁶ Filtering and analyzing this type of non-operational information would confirm the system’s capability to process large quantities of unannotated data, add examples to a acoustic databases and build oceanographic information repositories. Once proven, the system could be employed to filter and process the acoustic recordings generated by ships, submarines and aircraft.

A second phase could consist of real-time monitoring of data from ocean sensors, such as the Ocean Networks Canada’s VENUS project, cross-referenced with AIS data and libraries of ocean-going sources.²⁷⁷ This phase would allow for real-time operation of the system and could highlight deficiencies in tactical interpretation that need to be addressed. When ready, the system could be implemented, in parallel with human operators, at real-time ocean processing facilities, such as NOPF Whidbey Island. Again, after a trial period and establishment of its capabilities, a system could be trialled on surface vessels, which produce their own noises that the system would have to filter through, and which move through the ocean, a further challenge not encountered on stationary sensors.

²⁷⁵Mark Thomas et al, Marine Mammal Species Classification using Convolutional Neural Networks. . . , 2

²⁷⁶JASCO Applied Sciences, “Acoustic Monitoring of Canada’s East Coast,” accessed 3 May 2020, <https://www.jasco.com/esrf>

²⁷⁷Ocean Networks Canada, “Overview of Observatories,” accessed 3 May 2020, <https://www.oceannetworks.ca/observatories>

Finally, an optimized and proven system could be rolled out on warships and aircraft as data collection platforms, and operated in parallel with manned systems. Ultimately, as tactical capabilities and real-time analysis is proven, human operators could be phased out or have their roles adapted as required for other sensors or tasks that cannot be replicated by ML on the platform.

Throughout this model of implementation, data on active acoustic processing, particularly multi-static operations with multiple platforms, can be collected and implemented into the oceanographic models, as well as the operating systems. Along all of these stages, there will be a need to incorporate new data into subsequent upgrades and prepare the system for the next step of implementation.

It may go without saying, but any future platform acquired by the CAF must be capable of rapid upgrades to technology without having to go through extensive contracting or upgrade processes that render the ‘new’ technology obsolete before it is implemented. The use of an open architecture is already planned for the Canadian UWSU and the USN’s P-8 and submarine upgrades.²⁷⁸ It is widely acknowledged that common off-the shelf equipment, with an open architecture, allows “onboard computing power to grow at nearly the same rate as commercial industry” and allows experimentation and rapid upgrades, as seen with the Australian C-130’s initiative to adopt ML algorithms for search and rescue.²⁷⁹ Ensuring rapid and regular upgrades

²⁷⁸John Keller, “Boeing to upgrade sonar signal processing on Navy P-8A anti-submarine warfare (ASW) aircraft,” *Military & Aerospace Electronics*, 20 February 2017, <https://www.militaryaerospace.com/computers/article/16726431/boeing-to-upgrade-SONAR-signal-processing-on-navy-p8a-antisubmarine-warfare-asw-aircraft>; Canada, “Underwater Warfare Suite Upgrade Protects Sailors From Quieter Submarines and Torpedoes.”

²⁷⁹John Keller, “SONAR Signal Processing Job using Commercial off-the-shelf (COTS) equipment goes to Lockheed Martin,” *Military & Aerospace Electronics*, 9 March 2015 <https://www.militaryaerospace.com/computers/article/16713710/SONAR-signal-processing-job-using-commercial-offtheshelf-cots-equipment-goes-to-lockheed-martin>

can be made is desirable and COTS equipment with an open architecture should be the standard for future platforms, particularly if adoption of ML is planned.

There may be many arguments for why the adoption of ML onboard military platforms for ASW will be difficult, not least of which are the number of people who would need to be involved in the effort, the partnerships required between government organizations and contractors and the scope of the project over several years and through multiple phases. Securing the expertise to execute the project, from within the military's already short-staffed cadre of acoustic analysts and from among data analysts and ML experts who are in high demand across nearly every industry, would also be challenging, but not impossible.

Finally, cost, as with any project of this magnitude, would need to be carefully considered. Thomas et al outlined the equipment used in their experiment. A cursory search into the cost of components used for their research totalled \$33,000.²⁸⁰ While the world is witnessing ever-increasing computing power and “unfathomable data storage capacity,” the requirements for a project of the magnitude of replicating all tasks of acoustic sensor operators on platforms in real time, and all the stages leading up to it, would need to be accurately costed in order to weigh the benefits against the resources required.²⁸¹

Once this cost-benefit analysis is completed, however, it is the position of this paper that the benefits of adopting ML aboard military ASW platforms will far outweigh the costs and disadvantages and should be explored further, and the first steps undertaken without delay.

²⁸⁰Thomas et al, “Marine Mammal Species Classification using Convolutional Neural Networks. . . , 10. Thomas et al state that “The CNNs were implemented in Python using the PyTorch open source deep learning platform. Training was distributed over four NVIDIA P100 Pascal GPUs each equipped with 16GB of memory.” A cursory search showed similar components priced at \$7500 each. “The sampling routine and subsequent data processing was performed in parallel on two 12-core Intel E5-2650 CPUs.” Again, a quick search was conducted and priced these at \$1200 each.

²⁸¹Eric Topol, *The Creative Destruction of Medicine*. . . , 4

CHAPTER 11: CONCLUSION

Football's great dichotomy lies in the juxtaposition of its hidebound conservative social culture against professional sports' most incessant tactical innovation. In other words, revolutionary ideas are derided until they become integrated.

- Chris Wesseling, *The Ohio River Offense*²⁸²

While this is a quote about football, ASW and naval operations have likewise featured a contrast between cutting-edge technology and an affinity for maintaining the status quo. At one point in the development of AI, Deep Neural Networks were dismissed by the AI community “as the non-sensical ramblings of a scientist working on the fringe,” but have since been established as the backbone of most of the advances of AI in the last few years.²⁸³

As previously described, the title of this paper alludes to “transformation that accompanies radical innovation.”²⁸⁴ This paper aimed to outline how advances in ML could radically change the field of ASW through application to the sensor operator tasks currently carried out by human sensor operators in ASW, as well as to demonstrate how Canada’s manning challenges, position as a technology leader and current stages in the acquisition process of new ASW platforms represent an ideal time to consider making what amounts to an essential technological leap for Canada’s next generation of ASW platforms in order to maintain our position as a capable ASW partner.

Across the chapters of this paper, it has been argued that ML processes that have been used to transform countless industries and products have also been successfully applied to classify ships, submarines and marine life and hold the potential to carry out many of the individual tasks currently carried out by acoustic sensor operators on Canadian ASW platforms.

²⁸²Chris Wesseling, “The Ohio River Offense,” *NFL.com*, accessed 28 January 2020
<http://www.nfl.com/ohioriveroffense>

²⁸³Amy Webb, *The Big Nine How the Tech Titans & Their Thinking Machines Could Warp Humanity*. . . , 42

²⁸⁴Eric Topol, *The Creative Destruction of Medicine*. . . , v

This was done through first outlining basic principles of ASW, AI and ML concepts, as well recent CAF and government documentation related to the military adoption of AI. Chapter 3, which gave an overview of the tasks of sensor operators, their platforms, job progression and challenges inherent in the conduct of their jobs framed the discussion of AI and ML capabilities to follow. Chapter 4 examined recent research into the application of ML to ASW tasks and outlined how current applications in seemingly unrelated fields can potentially be applied to the multitude of tasks across the phases of ASW. The transition from the research laboratory to the tactical environment generates several tactical implications for ASW platforms, which were explored in Chapter 5. These include addressing bias in data, the hesitancy of operators to trust the inner workings of ‘black box’ systems, interoperability with allies and the advantages and pitfalls of a version of networked warfare to exchange data between platforms. The exploration of current and future initiatives of our adversaries, allies and the status of Canadian ASW platform life-cycles was presented and demonstrated that for other nations, the adoption of ML in sensor operations, including ASW, is not a revolutionary idea, nor is the idea of integrating it radical, in fact, it is already underway. Chapter 9 looked to the future to demonstrate how transformative to ASW emerging technologies could be and that a common thread through the future is the incorporation of ML into those technologies.

While this paper did not propose a single “magic algorithm” that will carry out all of the tasks sensor operators conduct in ASW, it did outline a series of implementation steps that could transform all areas of the ASW mission, from pre-mission information gathering and mission planning, through to the detection and tracking of a submarine in real time, to post-mission data extraction and intelligence production. The CAF should make a concerted effort to identify other areas currently being performed by humans which could either be replaced or be more

effectively carried out by leveraging these technologies, such as Processing, Exploitation and Dissemination of intelligence products that could be automated or carried out by ML-trained computers. Since algorithms and advances in one field can often be used in seemingly unrelated areas, the CAF should also identify any areas where ML is already in use to augment other sensors and tasks and look to how they could be applied to ASW sensors.

This paper's ultimate conclusion is that there is massive potential for implementation of ML to augment human sensor operators' multitude of tasks and, with a concerted effort, an ML system could be assembled which reproduces all of the individual non-physical tasks carried out by these highly trained experts. Implementing the recommendations of this paper would be only one of the countless ways the CAF could gain advantages through leverage of AI/ML. These technologies offer the potential to significantly augment the performance of our tactical units against adversaries and execute more tasks concurrently over a larger battlespace while at the same time reducing costs in terms of manning and potentially in terms of number of platforms required. In an ideal case of full implementation, there is also an opportunity to directly replace the current roles of hundreds of positions, which could then be reallocated to other tasks in emerging domains in which the CAF is seeking to expand the number of positions, such as cyber and space operators.

The Government of Canada and the CAF/DND have implemented numerous "first steps" in terms of data strategies and other initiatives, as outlined in this paper. With the planned acquisition of new ASW naval vessels and aircraft within the coming decade, the time is now to begin the process of implementing ML innovations into these ASW platforms, in order to remain a relevant and capable ASW partner among our allies and to ensure we are able to continue to defend our national maritime interests.

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