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TECHNICAL REPORT

Recent Advances in Artificial Intelligence and their Impact on Defence

Glennn Moy, Slava Shekh, Martin Oxenham
and Simon Ellis-Steinborner

Joint and Operations Analysis Division
Defence Science and Technology Group

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Joint and Operations Analysis Division
Defence Science and Technology Group

DST Headquarters
Department of Defence F2-2-03
PO Box 7931
Canberra BC ACT 2610

www.dst.defence.gov.au
Telephone: 1300 333 362

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EXECUTIVE SUMMARY

There have recently been a variety of high-profile demonstrations of artificial intelligence (AI) — with significant progress being made in fields as diverse as self-driving cars, game-playing machines and virtual assistants. In this report we discuss some of the recent breakthroughs in AI research, and explore some of the opportunities these provide within the Australian Defence Force (ADF) context. This paper is intended to contribute to both the dialogue around the use of AI in the ADF, as well as to provide a useful resource for ADF members to enhance their education and understanding about the technologies of artificial intelligence, with a particular focus on deep learning.

We begin with a high-level summary of the history of AI research, to provide some context to the current wave of AI development. We discuss the drivers for the current growth in AI interest and, in particular, introduce the field of deep learning and the reason for its exponential growth and dramatic successes over the last decade. The success of deep learning has been driven by three main catalysts: data, computation and algorithms. The availability of increasingly large data sets, coupled with readily available and massive computational resources, has enabled the development of a variety of algorithms to solve real world problems, which only a decade ago seemed intractable.

We present five significant problem-domains that have seen rapid advances during the last decade, and discuss the drivers for these developments and prospects for future successes. These application areas were not practical for machines prior to the recent growth in deep learning. These are:

1. image understanding
2. intelligent decision making
3. artificial creativity
4. natural language processing
5. physical automation.

This list is not exhaustive, and does not reflect the breadth of the AI field, but each of these areas has shown significant and rapid change over the last decade and are likely to see further successes moving forward.

We also discuss the potential applications for these techniques in the military domain. We argue that, to avoid losing its capability edge in the future, the ADF needs to invest in a number of areas that will be critical for future AI systems. In order to embrace the potential of AI, there will need to be a significant cultural shift in the way that military data are generated, captured, stored and processed. In addition, Defence needs to invest heavily in high performance computing. However, given the inability for Defence to replicate the data

or computational resources of the commercial AI industry as it currently exists, the ADF also needs to invest in research into algorithmic improvements that maximise data and computational efficiency. In addition, with its legacy systems and complex environment, the ADF needs to carefully consider elements of system integration to fully employ AI technologies into the future. Finally, to ensure the ethical use of AI and contribute to the worldwide debate, the ADF needs to carefully consider social and ethical issues around the employment of AI in military operations.

CONTENTS

GLOSSARY

Artificial intelligence (AI)	This refers to the broad class of techniques in which seemingly intelligent behaviour is demonstrated by machines.
Artificial neural network (ANN)	Machine learning systems that are inspired by biological neural networks. ANNs are built upon a collection of connected units (called artificial neurons) with connections between them and an associated weight for each connection. Each neuron takes the inputs that come into it and combines them using the weights and other parameters to generate an output, which in turn feeds other neurons. Through the process of learning the weights, an ANN can learn to transfer complex input data into an appropriate output for a wide range of problems.
Connectionism	A theory wherein mental phenomena can be generated through the use of interconnected networks of relatively simple computational units. Connectionism is the precursor to today's artificial neural nets.
Convolutional neural network (CNN)	A type of deep neural network that is most commonly applied to analysing images. CNNs have a specially designed architecture that makes them comparatively easy to train, even for relatively deep networks. The success of CNNs for image classification tasks, in 2012, was one of the main drivers for the rapid increase in interest in deep learning, more generally.
Deep learning	A form of machine learning that is based on artificial neural nets (ANNs) which involve multiple layers in a neural net, each progressively extracting more abstract (higher-level) features from the initial raw input. Deep learning is the AI technique which has been most responsible for the rise in AI applications over the last decade. Deep neural networks are components within a number of other successful AI techniques over the last decade.
Expert system	An early form of symbolic AI that became popular in the 1980s. Expert systems base their decisions on a set of rules, much like a nested set of "if-then" statements, which serve to connect human-defined symbols together in a meaningful way. The rules are typically defined by human experts in the field in which the expert system performs.
Machine learning (ML)	A collection of techniques in which a machine learns to perform a specific task without explicit instructions provided by a human – instead relying on patterns, inference and statistical models applied to data. Three main types of machine learning include supervised

	learning, unsupervised learning and reinforcement learning.
Recurrent neural network (RNN)	A type of deep neural network where loops or cycles are possible – that is, the output from one node can be connected via a loop of other nodes back into its input. RNNs are particularly useful for processing sequences of input, with the looping behaviour able to function as a form of internal memory of what input has been parsed previously.
Reinforcement learning (RL)	A form of machine learning where software agents learn to take appropriate actions in an environment in order to maximise some form of long-term reward.
Search-based AI	Search-based techniques are a set of AI techniques in which an agent searches for a solution to a problem. Search problems typically consist of a "state space", which is the set of all possible states you could be in, a start state, which is the initial state from which the search begins and a goal test, which provides a function to check if the current state is a goal state. Search-based techniques provide a solution in the form of a plan or sequence of actions that transform the start state to the goal state.
Sub-symbolic AI	AI techniques which apply operations to underlying data without first representing or transforming it into a human-understandable form. An example of sub-symbolic AI is an artificial neural net (ANN). Sub-symbolic AI is in contrast to symbolic AI, which reasons on human-readable representations of the problem.
Supervised learning	A form of machine learning where an algorithm learns a function which maps inputs to outputs based on labelled training data.
Symbolic AI	Term used for a number of related AI methods that attempt to reason about problems using high-level human understandable representations (symbols). These techniques include early expert systems and logic-based approaches. Most symbolic methods do not involve machine learning, but instead attempt to represent knowledge and its relationships using human-defined (pre-programmed) concepts, and then calculate over this to solve problems.
Unsupervised learning	A form of machine learning where an algorithm learns previously unknown patterns in data set without human-defined (or otherwise known) labels.

1. INTRODUCTION

Over the last decade there has been a major resurgence of interest in the field of artificial intelligence (AI). In the public domain there have been many recent high-profile demonstrations of AI — with significant progress being made in fields as diverse as self-driving cars [1], game-playing machines [2,3,4] and virtual assistants [5]. Alongside these impressive and often high-profile successes, academic interest in AI has significantly surged over the last ten years. Since 2010, the number of academic papers on AI has increased 8-fold [6], with some subfields such as machine learning (ML) having even greater increases. This academic interest has led to a number of major new AI approaches, as well as incremental improvements in earlier techniques.

However, despite these advances, many AI application areas are still fairly immature and, in some cases, have failed to fully meet expectations and early hype. As early as 1965, Herbert Simon predicted that “machines will be capable, within twenty years, of doing any work that a man can do” [7]. Now some 60 years later, AI remains unable to assist in the majority of human tasks. More recently, even in narrow, applied AI fields, many AI predictions have proven overly optimistic, and the challenges more significant than initially appreciated. This has been the case even where there has been some technological success, and significant resources have been applied. For instance, in 2015, based on significant developments in self-driving car technology, *The Guardian* reported that “from 2020 you will be a permanent backseat driver” [8]. However, while advances have been made in autonomous vehicles, most now agree that the challenges of full autonomy are still significant and it is likely that fully autonomous vehicles are some time away [9]. However, despite the lack of breakthroughs in some areas, in other areas of AI research, significant advances have been made that occurred well ahead of predictions. In 2016, for instance, Google's AlphaGo agent successfully beat the world's best Go player [10], despite predictions only a year or two earlier that this achievement was well over a decade away [11].

In this report, we discuss some of the recent breakthroughs in AI research, and explore some of the opportunities these provide within an Australian Defence Force (ADF) context. Rather than examine the entire field of AI, we focus on five significant areas that have seen rapid advances during the last decade, and discuss the drivers for these developments and prospects for future successes. In this report, we attempt to provide a balanced perspective, reflecting on both the potential strengths of AI as well as its weaknesses and current limitations. We present an outline of some of the technological breakthroughs that have led to the current growth in AI research for the non-specialist reader and we also discuss some of the requirements for applying these technologies in the context of the ADF. This report is intended to inform Australian military and Defence civilian staff of some of the opportunities presented by this rapidly developing field, and to educate non-specialists on some of the limitations of current techniques.

We begin with a high-level summary of the history of artificial intelligence research. A number of authors have previously provided summaries of the history of AI [12, 13, 14, 15, 16]. We encourage the reader to consult these if interested in a more comprehensive overview of the history of AI. Here we provide a condensed synthesis of the history, drawing on a range of these, with particular focus on the historical path to deep learning and the military context. We then discuss the drivers for the current growth in AI interest and, in particular, provide an explanation of the field of deep learning and the reason for its exponential growth over the last decade. We then discuss some emerging application areas that were chosen as they represent technologies that have advanced significantly over the last decade and, as such, provide new opportunities for applications in the military context. Finally, we discuss some enabling capabilities that need to be addressed by the ADF if they are to successfully embrace these emerging technologies.

2. A BRIEF HISTORY OF ARTIFICIAL INTELLIGENCE

2.1. Antiquity-1956 — Origins of AI

The dream of creating machines with a human-like intelligence has existed in one form or other for much of human history [17]. From the Greek myths of artificial beings through to nineteenth century stories such as *Frankenstein*, human literature is full of references to mechanical men or artificial sentient beings. However, the modern field of artificial intelligence has a relatively short history, beginning in the 1940s and 1950s. During the 1940s, advances in a number of fields led to scientists first seriously considering the possibility of building an artificial brain. In addition to significant developments in formal systems and game theory, this period saw a number of early advances in search algorithms for playing games, like chess. This period also saw the initial development of "connectionism" concepts. Connectionism was a theory wherein mental phenomena could be generated through the use of interconnected networks of relatively simple computational units — precursors of today's neural networks. Early thinking on AI culminated in the 1956 Dartmouth College Summer AI Conference — which is commonly considered to be the birthplace of the AI field. At this event, the term "artificial intelligence" was coined by John McCarthy [18].

2.2. 1956-1974 — Growth in AI: Symbolic and Connectionist

The 1956 Dartmouth Conference began a period of significant discovery in AI. During this period, research was undertaken across a wide range of different techniques and approaches — mostly focusing on what is collectively known as symbolic AI. Symbolic AI is a term for a number of related AI methods that attempt to reason about problems using high-level human understandable representations (symbols). These techniques include early expert systems and logic-based approaches. Most symbolic methods do not involve ML, but instead attempt to represent knowledge and its relationships using human-defined (pre-programmed) concepts, and then calculate over this to solve problems.

Some early examples explored spaces of logic or mathematical symbols, with the AI algorithm searching through a range of possible decision points in problem solving or logical inference, looking for actions that lead it towards the specified goal. For example, in 1956, a computer program called "Logic Theorist" used such methods to prove mathematical theorems [19]. Similarly, "The General Problem Solver" computer program, developed in 1959, could solve a wide range of problems, specified in its custom language [20, 21]. Game search techniques were also further developed during this period, with new developments in search algorithms for playing games, such as chess [22].

The 1950s and 1960s also saw the rise of other kinds of symbolic reasoning and knowledge representation, such as the development of early semantic networks that represent the relationships between different concepts. This period also introduced early expert systems [23] — AI systems based on rules that connect symbols in relationships like a nested set of "if-then" statements.

While symbolic methods were becoming increasingly popular during this period, there was a corresponding stagnation in artificial neural network and connectionism research. The stagnation in interest in this field was precipitated by a paper in 1969 which outlined two key issues with early neural networks [24]. Firstly, they noted that the basic neural network building blocks of the day were not able to represent some very simple, but important logic units ("exclusive-or"). They also noted that significant computing power, by the standards of 1960s, would be required to support any reasonable-sized neural network.

2.3. 1974-1980 — The First "AI Winter"

The early successes of symbolic AI techniques, had led to sometimes extreme optimism in the AI community about the prospects of thinking machines. For instance, in 1970, Marvin Minsky made multiple predictions , claiming "with certitude" that "In from three to eight years we will have a machine with the general intelligence of an average human being" [25]. However, despite some early successes in narrow problem fields, in many cases AI researchers had underestimated the complexity of the general problems. Search methods combined with appropriate symbolic representations demonstrated early promise, but their practical value was often limited. As the number of choices available grew, the algorithms were unable to efficiently find solutions. Assumptions that success in formal theorem proving or game playing could quickly translate into seemingly easier human activities, like facial recognition, proved to be untrue. With 1970's computational capacity being extremely limited, early AI demonstrations often proved to work only on simple examples, and failed to scale to meaningful human problems.

Reports, such as the 1973 Lighthill Report in England, presented significant scepticism regarding the promise of AI research, leading to a dramatic reduction in the funding for AI research in that country [26]. The combination of early optimism and limited real-world progress led to many funding bodies elsewhere also dramatically reducing or cutting almost all funding for AI research that wasn't directed at specific client problems. This period of stagnation in AI research has become known as the first "AI winter".

2.4. 1980-1987 — The Rise of Expert Systems

After this period of stagnation in AI research, the 1980s ultimately saw the rise once again of symbolic, knowledge-based approaches to reasoning. This occurred predominantly through the growth of expert systems [23], applied to specific industry use cases. Expert systems are the best known of a class of AI techniques known as knowledge-based systems. Knowledge-based systems are so-named due to the presence of an explicit representation of the knowledge of the system (knowledge base), along with an associated reasoning system (inference engine) that allows it to generate new knowledge. In the case of expert systems, “if-then” rules, derived from the knowledge of experts in a field, are typically used to represent knowledge and employ it to perform automated reasoning, although a notable exception to this are those based on Bayesian networks, which use probabilities instead. While early expert systems such as MYCIN (for the diagnosis of blood-clotting diseases) were developed in the 1960s and 1970s, the 1980s saw AI research begin to focus on more narrow domains - avoiding the difficulties with encoding implicit knowledge, such as common sense. Expert systems had a relatively simple conceptual underpinning, making them easy to build and modify as knowledge was made more explicit. One key early success was the XCON system [27]. Completed in 1980, XCON was used at the hardware company DEC and proved extremely successful in assisting customers to order computer systems with the correct components based on requirements. While XCON's knowledge was limited to an extremely narrow field, it led to enormous savings for DEC estimated at between $25M and $40M a year. Following this success, expert systems proliferated, with large numbers of companies applying expert systems to their businesses.

While applications of AI in this period were firmly focused on expert systems, this period also led to new research developments in the “connectionism” (artificial neural network) ideas of the 1960s. A new form of neural network (now known as a Hopfield net) was described, providing insights into theories of memory. Novel ways to train neural networks through “backpropagation” were discovered. However, despite the research success, these ideas were still not commercially successful, with computational power insufficient for all but the most toy models.

2.5. 1987-1993 — Second AI Winter

While the early 1980s was another period of optimism around promises of AI, by the end of this period some of the early expert systems that had been deployed commercially were beginning to seem fragile. A period of relative stagnation, following the early enthusiasm, occurred partly due to over-promising on the part of expert systems advocates, and partly fuelled by the rise in personal computing. Prior to 1987, most expert systems were provided by specialised companies on purpose-built hardware. As desktop computers gained power through the 1980s, the business model for custom-built AI machines was undermined and many businesses failed. In addition, as early expert systems exemplars aged, the cost of maintaining them increased. Business rules became out-of-date, and the systems needed to be updated - an expensive and time-consuming process. Expert systems lacked the ability to learn and, with greater use, increasingly failed to provide good results on atypical edge-cases. While research efforts continued throughout this period, perceptions from business leaders and governments on the role of expert systems were significantly dampened - an understandable corrective to the enthusiasm of the early 1980s.

2.6. 1993-2012 — Rapid Growth in Computation

With increasing computational power in the 1990s and 2000s, the field of AI began to evolve from the rigid, rule-based systems of the 1980s and embrace a range of new techniques. The additional computing power also re-invigorated interest in a number of older techniques that were not computationally feasible at the time of discovery. During this period there was a steady resurgence in statistical and connectionist (neural network) methods for approaching AI, as well as renewed interest in practical application of search-based techniques. During this period, major advances were made in a number of areas of AI, including new demonstrations of machine learning, multi-agent planning, scheduling, case-based reasoning, data mining, games, natural language processing, vision and translation.

In the area of search-based AI, Deep Blue became the first machine to play chess at a world-champion level in 1997 [28], beating the reigning world chess champion, Garry Kasparov in a six-game match. This result was not primarily due to advances in the underlying AI search techniques, but to the incredible increase in computational speed, combined with careful engineering of the algorithms. Related successes in machines playing checkers, Othello and other board games occurred around the same time.

The 1990s also saw developments and application of intelligent agents as a new paradigm in the AI community — with the emphasis being on the development of an agent that can perceive an environment and then take actions to achieve a specified goal. Within the US military, intelligent agents were applied with success to optimise and schedule logistics, with the Dynamic Analysis and Replanning Tool (DART) an intelligent-agent-based support system that provided decision support for logistics planning. The system was introduced in 1991, with use in planning logistics during Operation Desert Storm [29].

At the same time, significant advances in autonomous vehicles were made, with demonstrations of self-driving cars in France, Germany, USA and elsewhere. In one of the most famous demonstrations, in 1994 semi-autonomous vehicles drove around 1000 km on a Paris three-lane highway in standard heavy traffic with only limited human interventions [30].

As shown in these examples, this period saw the increased use of AI techniques to solve specific problems, with increased computational resources making earlier techniques practical on more real-world problems in specific domains. The increases in computing power also sparked the evolution of new AI techniques within the research community. Unlike the AI of earlier decades, much of this progress during this period was in methods that are known as “sub-symbolic”. Sub-symbolic AI systems apply operations to underlying data without first representing or transforming it into a human-understandable form, while symbolic AI systems (like expert systems) reason on human-readable representations of the problem. A neural network is one example of a sub-symbolic approach.

As part of that development, approaches that focused on machine learning became more prominent, with new forms of machine learning developed and refined. These included advances in reinforcement learning, such as "temporal difference learning" and "Q-learning". Advances were also made in supervised learning algorithms for non-linear classification, with a number of powerful new techniques invented, such as the "kernel trick", "max-pooling layer" and advances in backpropagation for artificial neural nets. Other concepts, such as soft computing - incorporating fuzzy logic and fuzzy sets - were also further developed.

However, while there was steady progress in scientific research during this period, the applicability of these new techniques were still mostly limited to a small number of relatively narrow domains - and in many cases simple toy problems without real-world applicability. For instance, in the area of machine learning and neural networks, while most of the theory behind neural nets had been discovered prior to 2000, it remained infeasible to train anything but very shallow, small networks well into the first decade of the 21st century. Similarly, search techniques, were also strongly limited in problem-scope by the available computational power, even though a number of sophisticated methods for reducing the required computational power had been invented. In practice, therefore, while there was substantial research progress, the growth in the areas that were amenable to AI solutions remained fairly slow.

2.7. 2012-2020 — The Rise of Deep Learning

Around the year 2012, a number of trends in the field of AI combined to produce a relatively sudden increase in AI successes. Since 2012 there have been impressive and extremely rapid advances in the capability of AI to achieve a range of new tasks in practical areas across a wide range of fields. These include seemingly diverse fields from game playing, image recognition, natural language processing through to artificial creativity. While these achievements might appear, at first glance, to span a large range of different fields, in all of the cases mentioned, successes have all been built upon the rise of a form of machine learning known as deep learning [31]. While deep learning builds on much of the theory and steady progress of the AI field prior to this decade, a number of factors combined to make deep learning a practical approach around 2012. In turn, this led to a significant change in the rate of AI progress and practical success over the last decade, spawning further algorithmic advances in related fields. Deep learning has, thus, created new benchmarks of capability across a range of fields and has been the main driver for the wide growth in AI successes over the last decade.

In the next section we discuss in more detail the nature of deep learning and of the changes that made its application possible. We describe five important application areas where the deep learning revolution has made new AI applications practical, and consider what the advances in each of these broad application areas mean for the ADF.

3. THE RISE OF DEEP LEARNING

Over the last decade there have been tremendous advances in the capability of many AI techniques, fuelled by the rise of deep learning [32]. Deep learning is a form of machine learning, based on neural networks, where the neural net consist of multiple (typically more than three) layers. Each layer progressively extracts increasingly high-level features from earlier, simpler feature-layers in the network. For instance, a neural network that is identifying a human face uses raw pixel data as the input to the network. The first layer might then extract edges or lines, using the standard neural network mechanism of combining inputs using a combination of weights and non-linear functions. A subsequent layer might extract combinations of those lines that form various shapes and the final layer could extract the appropriate combination of shapes that suggest a human face (or note their absence, depending on the picture).

With this basic concept, much of the progress in AI in the last decade has been driven by the ability to train deeper and deeper networks, thereby identifying more and more complex or abstract features - not just in the domain of image recognition, but across a wide variety of problems. The sudden increase in applications and success for deep learning over the last decade has been driven by three main catalysts: data, computational speed, and algorithms.

3.1. Data

One of the biggest drivers of the growth in deep learning is the availability of data. Whereas symbolic AI techniques (such as expert systems) reason over human-defined knowledge or symbols, deep learning is sub-symbolic. It takes raw data (sometimes with human-defined labels) and attempts to extract statistical patterns, with increasingly complex concepts emerging at each layer. Deep networks often contain many millions of connections, and thousands of individual nodes, and to adjust these to correctly identify relevant patterns requires massive amounts of data. For instance, in order to train an image recognition system, a deep learning approach typically requires in the order of tens of millions of images to train. An example of this was the demonstration by Google X in 2012 of a computerised deep learning system that worked as a “cat detector”. It used roughly 10 million digital images found in YouTube videos to learn to identify cats in images [33]. Without data sources at this scale being available, deep learning wasn't practical for most problems prior to the early 2010s.

It is difficult to properly comprehend the rate at which the increase in data generation has occurred. In 2013, estimates were made that 90% of the world’s data had been generated in the two years from 2011 until then [34]. Another way to get a sense of the change is to consider the growth in Internet traffic, which generates and transfers much of the world's data. It has been noted that in the early 1990s, Internet traffic across the entire world amassed to little more than 100GB per day, whereas by 2017 this had increased to over 45,000 GB every second [35]. This trend has continued since that time. The amount of high-quality data available in a range of fields has grown exponentially. These data are essential to the successful application of deep learning.

3.2. Computational Speed

In order to train neural networks for most practical problems, a large amount of computational resources are required. As mentioned above, deep neural networks typically involve multiple layers of neurons, each with multiple nodes interacting with one another. In a practical system, many thousands of neurons must interact with each other, with the computations ideally occurring in parallel for maximum efficiency. By 2010, decades of computational speed advances finally made training practical neural nets possible.

From the 1970s until the present, computation speeds have increased dramatically, with approximately exponential growth in the number of operations per second possible on a single thread from 1970 through to the mid-2000s [36]. However, even with the computational power available in the late 2000s, it could still take weeks for a traditional central processing unit (CPU) to train a neural network. Another step-change in computational speed was required.

The year 2009 saw the introduction of new hardware tools - graphics processing units (GPUs) - for deep learning [37]. Unlike CPUs, which can perform a large range of operations, but typically in sequence, one at a time, GPUs are able to perform a more limited set of simple mathematical calculations, but in parallel. A GPU’s parallel processing architecture allows it to perform many calculations at the same time. GPUs were first created by NVIDIA in 1999 [37] for specialist graphics rendering. They were developed to handle the parallel calculations required to render video, which requires images being updated hundreds of times (or more) each second.

However, in 2009, Andrew Ng and colleagues demonstrated the use of GPUs for large-scale deep learning [38]. As a practical example of the power of GPUs, in 2013, Andrew Ng and his team re-implemented the Google X “cat detector” system using GPUs instead of CPUs [39]. From a computational perspective, the original demonstration in 2012 used 10 million images and was achieved using 16,000 CPUs (1000 computers with 16 CPUs) at an estimated cost of $1 million USD [33]. In the 2013 demonstration, Ng was able to show similar performance using just 16 computers, each with 4 GPUs, reducing the cost in just 1 year to around $20,000 USD [39]. This demonstration showed that vast amounts of computing power could be available for deep learning at a fraction of the cost of using CPUs. This rise in new GPU hardware, combined with the ever-increasing performance of general computational speed was a second key driver in the rise of successful deep learning.

More recently, further developments in computational speed and flexibility have been made possible by further hardware advances. Most notably, in 2015 Google began using tensor processing units (TPUs) for its deep learning [40]. TPUs are application-specific integrated circuits (ASICs) developed by Google for neural network machine learning. While not made available outside of Google until 2018, this hardware has contributed to some of the most impressive deep learning results that Google has achieved in the last few years.

3.3. New Algorithms and the Perfect Storm

As outlined above, a range of algorithm advances had already progressed deep learning forward, despite the relative lack of computational speed and data in the 1990s. These include the invention of a number of technical improvements with names like "max-pooling layers" and "backpropagation for neural networks", developed in the 1990s. Other foundational discoveries were made during the mid-2000s, including by Geoffrey Hinton and his team, who introduced a new algorithm for fine-tuning each layer of a neural network separately and further championed the use of deep (many-layered) neural networks, rather than the relatively shallow networks of earlier work.

All of these improvements were brought together in 2012, when Hinton and his team used a special kind of deep network, called a "convolutional neural network", combined with several improvements and the use of GPUs, to win the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC- 2012) [41]. They were able to identify images and classify them into one of 1000 categories, with an error rate of only 15.3%. The second place entry, by comparison, had a 26.2% error rate.

The success of deep neural networks (particularly CNNs) for image classification led to a rapid explosion in research in the field of deep learning. Ever-increasing availability of data, combined with advances in hardware for high-speed computing spurred on development of new techniques that embraced these new resources. This has proven to be a significant feedback loop with countless new advances made over the last 6-7 years that build on the basic ideas of deep learning.

In the next section, we describe some of these recent advances in deep learning and the successful applications areas that these advances have made possible. We discuss, in particular, application areas that may have applications, or pose threats, for the military decision-maker.

4. NEW APPLICATION AREAS

While there are numerous potential application areas for growth in AI, a smaller number of areas stand out as showing potential for practical real-world application. Most of these have only become practical due to the rise of deep learning, and the scientific innovation that this has, in turn, fuelled. Here we provide a summary of five application-areas that have advanced rapidly due to the growth in deep learning. They are: (1) image understanding; (2) intelligent decision making; (3) artificial creativity; (4) natural language processing and (5) physical automation. In each of these areas, machines had previously demonstrated only very limited ability, mostly outside the range of practical applications. However, with the rise of deep learning, capability in each of these areas has progressed very rapidly, and, in each case, technologies now demonstrate promising potential to solve or assist with real-world problems.

4.1. Image Understanding

4.1.1. Current State

Successes in image recognition provided the initial catalyst for the recent interest in deep learning [41]. For over 60 years, scientists had grappled with the task of having machines extract meaning from visual data. In the early 2000s, most approaches focussed on humans trying to identify or generate image features that could be manually coded into a system and these human-specified features were used to identify and classify images in various categories. Using these manual feature techniques, researchers were able to get approximately a 26% error-rate in image classification, labelling objects from one of 1000 different categories in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [42]. Deep learning has dramatically reduced that error rate. For example, in the most recent reported ILSVRC competition (2017), the error rate of the best method was “below 3%”, compared to a human error-rate of around 5%.

Deep learning is able to improve classification without using human-defined features. Instead the neural network simply takes a large dataset of images that already had objects classified in them and, using this large dataset, learns through supervised learning its own computer-defined features to identify images. This approach requires large datasets that have already been labelled with the objects in them, as well as significant computational power. However, once data becomes available, using deep learning avoids the need for human-deciphering of what features separate one species of dog from another (the 1000 categories in ILSVRC contain 90 different species of dog, for instance), or what features separate a dog from a cat. Instead of the human hand-crafting these features, the algorithm simply learns which properties are most useful for identifying differences between different categories.

Since the early successes of 2012, deep learning has only improved at object recognition and classification. By 2015, advanced CNNs were getting lower error rates than humans at object recognition tasks involving the 1000 ILSVRC categories [43]. Deep learning object recognition systems are now as good or better than humans at recognising objects in images and categorising them into a relatively small (~1000) number of categories. One of the most significant recent advances in this area was made in 2017 with the development of "Capsule Networks" by Geoffrey Hinton. These have almost halved the error rate possible in some recognition tasks [44]. While humans can still be better than machines at recognising larger numbers of categories, or the context of images, machines only continue to improve in this area.

In the specialist field of object recognition (which includes face recognition), significant advances have recently been made. In 2014, Facebook launched its DeepFace program which can correctly identify whether two photos represent the same person over 97% of the time - approximately the same success rate as humans [45]. Similarly, in 2015, Google launched FaceNet - an algorithm that achieved 100% accuracy in a reference test on the "Labelled Faces in the Wild" data set [46].

Building on such successes, there have been related developments in image captioning and visual question answering. Image captioning is the task of taking an image and generating a human-meaningful description of the image. Visual question answering involves taking an image and then answering natural language questions about the picture. However, at the time of writing this report, unlike the performance of AI systems on object recognition and face recognition tasks, the performance of state-of-the-art image captioning and visual question answering systems remain well below human performance levels.

4.1.2. Military Applications

The significant success in areas of image recognition opens a range of possible military applications. One of these is in the area of threat monitoring, surveillance and search-and-rescue. Military search tasks (such as maritime surveillance) often involve long periods of time searching monotonous backgrounds (e.g. open ocean or desert) looking for a small number of features of interest (e.g. lost vessel, suspected illegal entry vessel, enemy units, and other anomalies such as changes or alterations in the operating environment). For such tasks, it is likely that the current generation of algorithms could outperform humans, once appropriately trained. Unmanned vehicles (UxVs) with properly trained on-board AI could patrol border areas, identify potential threats, and coordinate with human response teams. In the USA, the Maven Project is using machine learning to quickly and efficiently scan UAV imagery to identify potential targets, including vehicles, buildings and people [47].

Object recognition techniques also raise the prospect of enhanced target recognition techniques. At its best, these technologies could be used to significantly reduce human error, friendly-fire or collateral damage. However, there are significant ethical considerations around the use of deep learning technologies within the context of weapons. The ADF should develop clear policies in this area, and take the opportunity to influence the ethical use of this technology in the wider military community. At the time of writing, we note that this process is already underway, as part of the Australian Defence Enterprise Artificial Intelligence Strategy [48].

Developments in biometrics have increased the capability for individual targeted surveillance. Features such as facial recognition, voice recognition, and gait analysis capabilities enable higher confidence of individual identification, and therefore an ability to be remotely tracked. Again, there are significant ethical and human-rights issues that need to be considered with such use of ML technologies. However, the ADF also needs to be aware that other actors (state and non-state) may soon be using such techniques, and awareness of their capabilities is required to appropriately defend against their use on Australian citizens. Such capability, in the hands of an adversary, might lead to new military capabilities - ranging from Orwellian surveillance within a nation-state, through to its use in weapons or information-capture, focused on particular individuals. Currently, the US DARPA "Target Recognition and Adaption in Contested Environments" (TRACE) program uses ML to locate and identify targets [49], however the level of such activity in many other foreign militaries is unknown to the authors.

Using deep-learning for image recognition has become a routine task, given a number of software packages that simplify the creation of convolutional neural nets (CNNs) and other deep learning classifiers. This makes the application of this technology increasingly practical for a wide-range of more routine military tasks, potentially saving time and money for the ADF and increasing efficiency. Smaller, niche application areas could be wide-ranging, such as the opportunity to digitise and classify imagery material where not previously possible. For example, scanned images with complex military symbology could now be interpreted using systems that recognise military symbols in a manner analogous to handwriting recognition, supporting C2 and planning applications. In the area of information management, these technologies could support better search and retrieval for material that contains pictures or images without appropriate meta-information to tag the content of those images. The possibility to implement image-recognition techniques across a wide range of business processes could increase efficiency and reduce costs for the ADF, especially as much of the current ADF imagery is not well indexed with appropriate meta-data.

The use of AI to analyse imagery raises new opportunities and challenges in the ways we process and analyse imagery. In particular, AI techniques can be located on surveillance platforms or remotely (for example at an associated HQ). In the former case, AI techniques may be able to analyse high-resolution imagery without the usual issues around bandwidth, as only processed information needs to be sent back to HQs. In the latter case, more processing power may be available, but potentially at the cost of reduced quality imagery, due to bandwidth restrictions. Another dimension of this issue relates to the increasing availability of cloud-based ML solutions and platform-as-a-service products. High quality imagery analysis products are now available at competitive prices from a number of industry players (for example, Microsoft Azure). These can provide cost-effective analysis of imagery, but raise new risks for Defence in storing data on platforms that they don't own.

4.2. Intelligent Decision Making

4.2.1. Current State

Another application area that has seen surprising successes and significant growth over the last decade is the area of intelligent decision making. Many of the most notable successes in this field outside of Defence have occurred through research in game-playing machines. Over the last decade, techniques that can develop high-level strategies in increasingly complex games have been developed. In part, this built on the successes of deep learning for image recognition, combining the increasing ability for machines to "understand images" with planning techniques.

In 2013, deep Q-learning [50] (a form of reinforcement learning) rose to prominence when Google DeepMind used it to play Atari games. This demonstrated the ability of a single deep learning agent to learn to play multiple different games using the same approach. This led to a significant effort in applying deep learning to a variety of games. Further success was demonstrated in 2016, when the Google Deep Mind team used a deep learning technique called "AlphaGo" to become the first computer system to beat a world-champion Go player [51]. Later AlphaZero improved on this, playing at a super-human level in Go, chess and shogi using the same deep learning architecture. [52]

More recently a range of other techniques have demonstrated human-level or super-human performance at increasingly complex games. These include complex strategy games, like DOTA and StarCraft which have much greater real-world like complexity, compared to classic board games. To achieve this success, massive computational resources were used and new techniques were invented that combined advances from a variety of areas in AI. For example, the AI system, AlphaStar, successfully beat a professional StarCraft II player using a combination of techniques including self-play techniques, transformer networks, pointer networks, actor-critic approaches, self-imitation learning and population-based training [53].

There have also been recent advances in mixed-strategy games, involving chance, bluffing, multiple players and partial observability (in which players don't have access to all information about the game). An example is poker, where players can't see opponents' hands, random dealing of cards impacts on play and psychological factors also play a role. In poker, Facebook AI with Carnegie Mellon University achieved another world first in complex strategy game playing, with "Pluribus" - the first AI system that was able to beat professional humans at 6-player Texas hold 'em poker [54]. This agent used self-play techniques with "counterfactual regret minimisation" to achieve this, despite poker being a game that has imperfect information, and multiple players.

The current capability in this field is evolving rapidly - in many cases outpacing expectations. At the time of writing, machines can beat all humans at many standard board strategy games, including chess, Go, shogi, checkers, gomoku and others. In some specific, constrained environments, machines are now significantly better than even the best human players. In more nuanced and less formal games, humans still have the edge. However, the rate of progress is significant. The most notable aspect of the game-playing approach to decision making is that really large computational resources are required for machines to learn appropriate behaviours. As hardware continues to improve, more and more complex games are proving to be amenable to AI analysis. Games that only a few years ago were considered beyond the capabilities of machines are now being mastered by algorithms.

While game-playing provides the most high-profile examples of "intelligent decision making" capabilities of AI, there are many other fields of AI where advances, combined with increasing data and computation have begun to make analysis and data synthesis possible in a way that was inconceivable a decade ago. These include developments in recommender systems, and general data analytic techniques for enhanced situation awareness and sense making. For example, recommender systems have been developed by entertainment companies, social media companies and retailers, with increased capacity to analyse large data sources. These techniques provide increasingly effective targeted advertising, as well as advances in personalisation, such as automatic movie and song recommendations.

4.2.2. Military Applications

There are a large number of application areas where AI techniques could support military decision making. Application areas where a large amount of data is available are likely to be the most amenable to AI support initially, due to the reliance of many deep learning techniques on large datasets and the analysis of statistical patterns in that data. For example, areas such as logistics and transportation where there is a lot of relevant data (supply-chain information, stock levels and order information) could achieve efficiency dividends from the application of AI. These are application areas where optimal decision-making typically depends on interdependence of a large number of data sources, making it difficult for humans to process, but ideal for suitably tuned AI techniques. Intelligent decision making AI capabilities (including traditional techniques, such as optimization and operations research) may be able to lower transport costs, identify inefficiencies and reduce operational efforts.

Current efforts to support military decision-making naturally focus on specific use-cases, where tools provide low-level assistance to relatively narrowly defined decision-making domains. The emphasis in these systems tends to be on increasing effectiveness and efficiency of low-level decisions. However, there is also an increasing role for AI techniques in high-level command and control, strategic planning and decision-making.

Military decision making at these higher levels becomes increasingly complex [55], spanning tactical, operational and strategic concerns, and involving complex situation understanding and planning to meet high-level goals [56]. Providing high-level strategy decisions is currently beyond the state-of-the-art of AI, but there is ongoing work to broaden the applicability of AI techniques to support the humans making these complex decisions. We believe the ADF would benefit from following these developments closely, and investing as appropriate. It is likely that adversaries who embrace such technology will have a dramatically reduced decision making cycle as the capabilities in this area improve.

While these algorithms are currently not sufficiently reliable to work in an unsupervised manner, the field of human-machine teaming is another important and active area of research of relevance to the ADF, with applications to high level command and control and decision-making. Human-autonomy teaming (or human-machine teaming) research aims to utilise the power of machines in data synthesis and analysis, with the general decision-making ability and broader contextual awareness of humans.

Modern AI techniques also have the potential to support military decision-makers in more routine information management needs - with AI able to support the gathering of appropriate data, and searching for potentially relevant information. One of the most promising roles for AI within the context of ADF decision-making is in the general field of situation awareness and sense making. Situational awareness is a key requirement for operators, decision makers, and analysts. Routine AI techniques are likely to improve the ability of human operators to search, analyse and display relevant information. However, these technologies may also come with drawbacks in human situation awareness. In the normal course of their roles, humans achieve situation awareness, in part, by immersion, exploration and manipulation of the information space in order to establish the appropriate mental model and produce the evidence or products needed to support their actions, decisions or analysis. When AI is introduced to handle the big data problems of volume, velocity, and variety, this pathway to situational awareness is largely lost. Fundamentally new mechanisms may be needed for the interactions with the AI system to ensure that the user has the appropriate mental model and context to understand the analysis being provided [57].

Other military applications, relevant to command and control, and decision support include the use of AI for plan-monitoring, task management and recommendation and course of action analysis. Some of these capabilities have already been demonstrated in a military context, through the Allied Impact (AIM) program, which demonstrated human-autonomy teaming for the task of managing a large number of diverse autonomous vehicles [58].

Another important developing AI technology related to intelligent decision making is the rapid improvement in strategy game-playing capabilities of AI agents, mentioned above. An obvious application for this AI, within the military context, is in AI-enabled wargaming [59]. Where existing militarily-useful structured simulations or models exist, AI game-playing techniques have the potential to rapidly analyse the scenarios and learn strategies that eclipse or complement human abilities [52, 53, 54]. The most recent successes with poker suggest that machines can even out-bluff and work with uncertainty, as long as the parameters for the game, options available for the agent, and payouts are clearly defined [54].

In addition to wargaming, these techniques have the ability to analyse options in any scenario that can be defined in a computer model or simulation. These techniques have significant promise in military C2 decision support tools, wargaming tools and within the broader context of situation awareness. Game-playing techniques are also likely to play a role in future cybersecurity analysis and defence. Alongside more traditional anomaly detection and pattern-detection capabilities, advanced ML approaches may be able to undertake more complex detection tasks, or better identify likely threat vectors.

4.3. Artificial Creativity

4.3.1. Current State

For many years, one of the perceived dividing lines between human intelligence and machines was the seemingly unique ability that humans have to be creative, whereas traditional machines followed pre-programmed rules that could not surprise or exhibit genuine creativity. However, this perspective has been challenged over the last 5-10 years. The key breakthrough that led to the growth in "artificial creativity" was the invention of a new deep learning technique in 2014 by Ian Goodfellow called "generative adversarial networks" (GAN) [60]. A GAN is an ML technique that involves two neural networks playing against each other. One (the generative network) is attempting to generate objects that "look like" the training set. The other (the discriminative network) attempts to identify which objects are generated and which are really from the training set. As they evolve, the discriminator gets better at "spotting fakes" and the generator gets better at generating real-looking samples.

Generative adversarial networks (GANs) have enabled computers to automatically generate realistic-looking "fake" data. In the initial paper, GANs were demonstrated to generate semi-realistic looking images, including examples representing handwriting (digits) and human faces. However in recent years the quality of images being generated has continued to increase. In 2018, a portrait of Edmond Belamy was created by a GAN and sold for over

$432K at a Christie's auction [61]. More recently, GANs have continued to improve, leading to successful generation of celebrity faces that don't exist in the real world. GANs have also been used for photo and video creation and manipulation, with results that are currently impossible for a casual human observer to distinguish from the genuine article. While it is still possible to identify differences between artificially generated images and real photos, these differences are not noticeable on casual observation. Images generated by GANs can be photo-realistic, and can be used to provide a number of complex forms of video and photo manipulation. These include the ability to age photographs to show plausible representations of how people might look as they age, to construct images of a person based on their voice pattern, to reconstruct three dimensional models from flat imagery and generate plausible video. This has led to the term "Deep Fakes" which describes the fake images, video and other content generated by these techniques [62].

More recently, additional new techniques have further advanced the field of artificial creativity into other areas, such as text generation. In 2019, the first "Generative Pretrained Transformer 2" (GPT-2) network was developed by OpenAI [63]. GPT-2 is an AI system that artificially generates novel text. The generated text can match the subject and tone of an input passage of text. It is based on a "Transformer Network", which was itself only first introduced in 2017, and undertakes sequence to sequence transformation - changing one sequence into another using an encoder and decoder and an "attention" network to replace the recurrent neural network that had previously been used in this sort of task. GPT-2 networks are now able to generate plausible stories from a very short piece of input text. While the prose generated can have a tendency to repeat passages, and in some cases, is relatively easily detectable as non-human, the text generated is often sufficiently close to human-generated that it would be difficult to detect without some investment of time or resources. In fact, initially OpenAI did not release its full GPT-2 models over concerns of potential misuse, such as flooding social media with "reasonable-sounding context-appropriate prose which would drown out all other speech and be impossible to filter" [64]. Alongside these developments a separate (but related) technology, Generative Pretrained Transformer, was trained on large datasets of written language, learning the flow and structure of the language sufficiently to be able to generate new stories [65].

4.3.2. Military Applications

One of the most militarily-relevant aspects of the current growth in machine creativity relates to the increasing importance for the ADF to be able to detect such fakes. While the use of artificial creativity to *generate* fake narratives or confuse adversaries is ethically problematic, it would be unwise for the ADF to assume that other nations may not utilise these techniques to sow confusion, discord or to generate support for policies in line with others' strategic interest, rather than our own. As such, it is important that the Australian military be armed with awareness of the growing capabilities of these AI techniques, including exploring research into automated detection and management of potentially fake content.

Another role for artificial creativity would be in narrative generation. Narratives can be used in a range of situations, such as algorithm explainability and enhancing situation awareness. For instance, as machines become more and more capable, they are likely to act increasingly autonomously. However, human decision-makers need to maintain sufficient situation awareness to make appropriate decisions, despite not monitoring the situation directly at all times. As the roles of human and machine evolve, it will become increasingly important for artificial agents to explain the current situation, in a succinct and human-meaningful way. The use of artificial creativity to generate sensible narratives that summarize a complex military situation for an operator could enhance situation awareness in situations where that operator is not already immersed in the low-level tactical situation.

In addition, within the training environment, artificial creativity may also have an important role to play in the cost-effective generation of content, and in support of training and simulation goals. Such techniques may be able to provide more realistic imagery, video and text within the context of a fictitious scenario, as well as increase the realism of military training exercises, at reduced cost.

4.4. Natural Language Processing

4.4.1. Current State

Natural language processing is another aspect of artificial intelligence that has undergone a rapid evolution and transition over the last decade. The field of natural language processing is somewhat broader than the previous areas we've discussed, spanning a wide variety of topics from machine translation and chatbots, through to information extraction, retrieval, text summarisation, parsing of text into parts of speech, topic modelling, sentiment analysis, natural language understanding and generation, and even question answering. As such, the number of different technologies and advances that have paved the way for the current growth in capability is quite varied.

The current interest in deep learning for natural language processing began around 2011 with the introduction of a unified neural network architecture and learning algorithm for natural language processing by Collobert et al. [66]. Following this work, and the successes of deep learning in image processing in 2012, research in applying deep learning to NLP surged greatly.

In 2014, Ilya Sutskever et al. [67] introduced “sequence to sequence learning” with neural networks, using two “long short term memory” (LSTM) networks – a form of recurrent neural network that is able to handle sequences of information. Around the same time, a range of developments in recurrent neural networks, and attention-based networks led to steady improvements in the ability of deep learning to handle language sequences. These advances helped to pave the way for increasingly large language models, such as BERT, XLNet, ERNIE 2.0, RoBERTa and GPT-2 [68, 69, 70, 71, 63], which contain millions of parameters and are trained on massive datasets using huge computational resources.

In the field of language translation, while neural machine translation techniques are rapidly approaching human levels, to date there remains a significant gap between the capability of the best machine translators and humans. While some articles [72] suggest that machines are quite close to human translation capabilities, the reality is a bit more nuanced. Translation engines are now able to produce text that is mostly fluent and human-like, but the majority of systems are less reliable than humans. Typically translation is sufficiently accurate for other humans to get a general understanding of the words, but is still not reliable enough for high-accuracy applications, like diplomacy, or applications where structure and tone are critical, such as in literature.

4.4.2. Military Applications

There are many areas where advancements in natural language processing may prove useful in military applications. Different aspects of information retrieval could be automated through the use of AI and deep learning. Question answering systems (such as IBM's Watson and Google's Talk to Books [73, 74]) and chatbots could assist military planners with requests for information (RFIs) and other forms of information retrieval, especially as the volume of information in existence continues to rise exponentially. In a similar vein, automated text summarisation and machine translation systems are becoming increasingly necessary for processing the massive volume and diversity of information that is available. In addition, an increasing portion of the data that are needed for military applications can now be sourced publicly. Moving forward, a range of information retrieval and processing tools will be needed for effectively dealing with these data and harnessing them for military applications. Information management is a key capability within Defence C2, and the ability of modern AI techniques to parse free text opens new possibilities in storage and retrieval of free-text information. Deep learning may also now support data capture and processing from speech and informal communication channels, in addition to more traditional transactional data that are available. This additional data capture could also aid in planning and decision-making processes.

Another area with potential military applications is sentiment analysis. Huge data sources such as the Global Database of Events, Language, and Tone (GDELT) [75] provide a glimpse of human behaviour at the societal level over time. In the case of GDELT, the data are paired with powerful analysis tools that are available through Google's cloud-based BigQuery service, providing the means for an average Internet user to perform large scale data analysis without personal access to supercomputing facilities.

4.5. Physical Automation

4.5.1. Current State

The injection of artificial intelligence into physical systems is an area of AI where the difficulty of the task was significantly underestimated. An observation made several decades after the emergence of the field, known as Moravec's paradox, states that “it is comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility” [76]. Although significant progress has been made in areas of physical automation, these areas continue to pose considerable challenges for AI. Some of the most well-known areas where recent research efforts continue to improve the state-of-the-art are in the fields of self-driving cars, robotics and autonomous systems.

Self-driving cars have a long history, with small experiments starting as early as the 1920s and development continuing in various forms until the present day. Today's self-driving cars are powered by computer vision and deep learning algorithms, combined with powerful hardware and massive amounts of data gathered by driving the vehicles in a range of environments over thousands or millions of kilometres [77]. Companies like Tesla, Waymo, General Motors, Nissan and BMW are all investing significant resources into self-driving technology, and while there have been many demonstrations of partial autonomy, level 5 systems (representing full autonomy) remain beyond current capabilities. Self-driving cars have encountered numerous technical, economic, legal, ethical and social challenges along the way, and until these are resolved, fully autonomous self-driving vehicles are likely to remain “around the corner”.

Aside from self-driving cars, other types of autonomous systems are also beginning to utilise AI and deep learning more readily. Examples include robotic manipulator arms that perceive and act based on learnt models of real-world objects, and a variety of mobile robots and unmanned autonomous systems (UAS) that are capable of moving through land, sea and air environments to varying degrees, including adapting to environmental changes in some circumstances. At the same time, more advanced robotic systems such as Atlas (Boston Dynamics), which can be seen on YouTube performing backflips with apparent ease, are generally operated using control theory methods such as inverse dynamics and inverse kinematics [78], rather than machine learning, simply due to the complexity of solving the problem with AI. As these robotic control methods do not use AI techniques in the most traditional sense, they are outside the scope of this report. Nevertheless, it is worth noting that these technologies are very impressive and evolving rapidly, which means they will likely be of considerable interest to the ADF in tasks that involve “the three Ds” - dirty, dull and dangerous [79].

4.5.2. Military Applications

Unmanned physical systems already play a critical role in current military affairs and this can be expected to continue into the future. For instance, as of 2014, the US military operates thousands of unmanned aerial vehicles (UAVs), including Ravens, Pumas, Shadows, Predators, and Reapers. The ADF also has UAV units in both the Army and RAAF, with plans to introduce additional UAVs like the MQ-4C Triton into active service over the coming years. While early UAV technology did not involve significant AI – instead relying on human-in-the-loop controllers – there is currently ongoing research into enhanced autonomy and robotics, using ML and AI techniques in conjunction with control theory methods. As these combined techniques become more capable, it is important for the ADF to invest in a range of technologies to increase the effectiveness, flexibility of these systems and reduce their cost. Currently, for instance, the Australian Government is investing in a Defence-led Cooperative Research Centre on Trusted Autonomous Systems [80] as well as exploring concepts for autonomous systems in the Land [81], Maritime and Air [82] domains. These programs help to explore the relationship between autonomy, robotics and AI as a future ADF capability enhancer. As part of this, however, the ADF needs to be conscious of the ethical and legal aspects that come with operating these systems, particularly within the domain of autonomous weapons.

A less bespoke, but equally important potential military application in the field of physical automation is in the use of self-driving vehicles for logistics and autonomous resupply. Soldiers on the battlefield are constantly facing high risk situations and off-loading the task of resupply to an autonomous vehicle can help to reduce this risk and avoid unnecessary casualties. Even beyond the frontline, enhancing military supply chains through autonomy will lead to improved efficiency and allow humans to focus on other tasks. However, given the existing challenges with self-driving cars in the commercial sector, self-driving military vehicles are likely to be an application for the longer term, especially when considering the hostile and unpredictable environments that the military often operate in.

5. FUTURE OF AI AND DEEP LEARNING

5.1. Future in Society – The next AI Winter and the hype of AI?

There is currently a surge of interest in artificial intelligence and machine learning, with corresponding increases in funding and business interest. However, in the history of AI, this is not the first time the field has received significant public and corporate funding, with corresponding general interest. In the past this has been followed by significant under-delivery, and ultimately a loss of confidence leading to an "AI winter". In the current climate, it is worthwhile to consider whether this is likely, again, or if not, what factors are different this time. Ultimately, for the ADF, an accurate assessment of the potential of AI is essential for making sensible investment decisions into future capability.

Our assessment, perhaps unsurprisingly, is that neither extreme optimism nor extreme pessimism accurately captures the current state of AI development. It is certainly true that, as for previous periods of AI excitement, there is currently significant hype around the field of AI. As in previous periods of AI exuberance, this hype is leading to unrealistic expectations, and likely disappointment for investors and scientists alike. For instance, recent predictions by high-profile AI proponents, such as Elon Musk, that fully-autonomous self-driving cars will be widely available in 2020 are probably overly optimistic [83]. Other predictions that extrapolate the current successes of AI into fields that are fundamentally different from current applications are also likely to be overblown, and experience significant setbacks, with real-world applications likely to be some time away.

However, while we acknowledge that there is considerable hype around AI at the moment – and, in some cases, AI claims are being significantly over-stated and misrepresented, we feel that there is a fundamental difference between the current period of AI enthusiasm and earlier historical precedents. In particular, there are now a range of real-world practical applications that have already been identified and proven for the AI technology – deep learning, in particular. In the past, AI research had only demonstrated toy-applications, or required very specific, high-maintenance hardware to embrace. As such, statements of the potential of the AI techniques were almost entirely speculative. With current developments, AI technologies have become far more mainstream, deployed at a larger scale and in a number of application areas have proven themselves to be both already practical and cost-effective for use in industry. While some of the more optimistic claims around artificial general intelligence (AGI), or unproven application areas will, almost certainly, not succeed, the presence of many successful application areas makes a significant AI winter of the kind experienced previously less likely. We believe the application areas outlined in this paper are all, to varying degree, sufficiently proven to require serious investment consideration, within the context of the ADF.

That being said, however, there are some very significant limitations on the current deep learning AI techniques, with their reliance on statistical methods, and limited explainability. While the current AI techniques are extremely successful in a number of areas, it seems likely that there are many (if not most) complex human-problems that the current generation of techniques will not be able to solve, no matter how much data or computational resources are made available. It is likely that significant advances in AI algorithms will be required to solve these more complex, nuanced, human-level problems. In particular, we anticipate that the current trend towards statistical deep-learning methods will need a future correction, combining symbolic (or model-based) methods with existing statistical machine learning methods in some novel (and, to date, unknown) manner [84, 85]. However, as there is already considerable effort in the research community towards developing such new techniques, there is plenty of scope for further breakthroughs in the years to come.

5.2. Future in the ADF

The use of AI within Defence is subject to a number of additional constraints that are not present in other application areas. Defence security requirements have historically constrained information technology (IT) systems, leading to relatively slow and non-agile development processes. Historically, innovation and exploration of new software is a slow and difficult process on Defence IT systems [86]. In addition, AI technology comes with additional uncertainty that makes accreditation and certification difficult. As a result, the ADF has had only a relatively minor adoption of AI technologies - mostly in back-end areas, such as information management and process automation [87]. However, while there are significant challenges with AI adoption, we foresee that the ADF risks being outpaced by military developments in other countries and, ultimately, losing its decision-making edge if an appropriate level of investment in this area is not forthcoming.

To avoid losing its capability edge in the future, the ADF needs to invest in a number of areas that will be critical for future AI systems. Some of the most important ingredients in the successful use of AI technologies, for the ADF to develop moving forward, include: (1) data; (2) computation; (3) algorithms; (4) system integration and (5) ethics & trust.

5.2.1. Data

Perhaps the most important ingredient for effective AI implementation in the ADF is relevant data at scale. Although there are significant open-source data sets available online, there are far fewer military-specific datasets that can be used for analysis. Without military relevant data, the power of AI and machine learning is greatly diminished and these techniques are less likely to provide useful insights for military decision making. Historically, a lot of military data are not captured, with information that is captured often not being structured or in the right format for automated processing or applying machine learning. There will need to be a significant cultural shift in the way that military data are generated, captured, stored and processed to harness the potential of AI technologies.

In addition, it is worth noting that many of the successes in deep learning come through the use of extremely large data-sets ("big data"). There are very few datasets in Defence that satisfy this criterion. Without access to sufficient data many of the techniques in deep learning will fail to realise their potential.

Finally, it is worth noting that one of the most successful deep learning techniques, supervised learning, requires labelled data – that is a corpus of data where the correct answer or label is already known and provided to the algorithm to learn from. An example might be identifying specific objects in a corpus of military image data. In the military context, even if data (e.g. appropriate images) exists and is in sufficient quantity, often it will not be appropriately labelled (e.g. identifying military features of interest). While labelled data may exist in many non-military domains, or can be generated cost effectively using processes like the Amazon Mechanical Turk, this is unlikely to be possible in militarily-specific domains, or with imagery that may be sensitive or classified. In such cases, the process of labelling existing data may prove to be time consuming and cost prohibitive.

5.2.2. Computation

Once relevant data sets exist, the next key ingredient to achieving AI capability is computation. As is the case for data, the scale of computation required for many deep learning successes is many orders of magnitude higher than what is typically available to most Defence users at the moment. For instance, the computational resources used by Google DeepMind to learn state-of-the-art chess play in only four hours would actually take multiple years on a machine with a single GPU [87].

In a similar vein, OpenAI Five succeeded in training a deep reinforcement learning system to compete at professional level in DOTA 2. Their system plays 180 years' worth of games against itself every day by running a massively scaled version of proximal policy optimization (PPO) on a cluster of 256 GPUs and 128,000 CPU cores [88]. The kind of computational resources available to DeepMind and OpenAI are generally not available to Defence users. Researchers often have access to machines with only a handful of CPUs and GPUs, making many commercial achievements difficult to reproduce [87]. These resources are, in turn, much less than the computational resources applied to even more complex problem domains, such as learning to play StarCraft II at a professional level [53].

Moving forward, the ADF also needs to invest heavily in high performance computing. However, even with significant investment, it is unlikely the ADF will be able to replicate the resources of major players, like Google.

5.2.3. Algorithms

Given the inability for Defence to replicate the data or computational resources of the commercial AI industry as it currently exists, the ADF needs to also invest in developing algorithms with better efficiency. In particular, while the current trend in AI techniques which rely on deep learning have been extremely effective, they achieve this success through the use of massive computation and big data. However, there is evidence that algorithms that combine traditional symbolic AI, alongside more modern statistical deep learning approaches may be more effective [89, 90]. Such approaches could combine some degree of knowledge about specific problem domains, with the power of deep learning to arrive at comparable performance using significantly reduced data and computation. Such algorithms would place the ADF in a much better position to harness the potential of modern AI without the massive computing and data resources that have been required for current state-of-the-art achievements.

In other cases, existing approaches may be appropriate for military problem-domains, but specific algorithms may need to be adapted to the military context, computational resources and data. For instance, algorithms may need to be modified or potentially extended to handle the specific nuances that exist in Defence problems. For example, the asymmetric nature of wargames provides different challenges to the standard games that AI techniques have solved successfully thus far. DST is well-positioned to assist the ADF and provide advice on how COTS techniques can be effectively adapted to the military domain.

5.2.4. System Integration

As a large, modern bureaucracy, the ADF relies on many existing legacy systems to undertake its day to day business. The issue of integrating modern technology, such as AI algorithms, into these legacy systems is a difficult one. We believe that, alongside investments in AI technology, the ADF needs to consider the underlying systems and software architectures of both legacy and new software. While not always easy to achieve with legacy systems, for new systems (and upgrades) the ADF needs to begin the process of transition to more flexible, agile software architectures, which are both evolvable, adaptable and secure – and provide better support to the integration of more advanced components, such as AI systems.

In addition, the ADF also needs to monitor and review its investment in AI Operations (AI Ops) automation technology [91]. AI Ops is a term used for a field of software development where AI technologies are used to prevent, identify and resolve outages in critical Information Technology (IT) operations. These techniques can provide the ADF with enhanced service availability and performance monitoring as well as analysis when things go wrong. AI Ops techniques use big data with machine learning to enhance the response to issues in software the ADF relies on. A related issue is the need for enhanced cyber-security and automated threat monitoring. Both of these fields are broad and also involve non-AI techniques outside the scope of this paper. Nevertheless, we note that AI techniques play an important role in responding to, and mitigating some of the issues of system-integration and monitoring.

5.2.5. Ethics and trust

Finally, the ADF needs to intentionally and carefully consider the ethical factors that arise in the use of AI technologies as part of its capabilities. While developing an ethical framework for the use of AI in the ADF is outside the scope of this report, we believe there are a number of factors that the rise of deep learning have raised from the perspective of trust and ethics.

In particular, many underlying deep learning algorithms are statistical, with the neural networks unable to explain decision making to humans except in a statistical way. As such, the ability to verify the performance of deep learning techniques in new or unusual environments is difficult and requires expert consideration. Moreover, underlying biases in the training data for statistical techniques are likely to surface as inaccuracies, or introduce bias into the algorithms that learn from that data. The impact of these issues needs to be carefully revisited, within the military context. Risks that might be acceptable in a civilian commercial context (such as poor recommendations in an entertainment suggestion) may be unacceptable within the military context of recommending a course of action to military decision makers.

Finally, there are broad ethical questions that should be considered from a whole-of-society perspective, such as questions around autonomous weapons, or automated surveillance. While there is considerable work already exploring the ethics of AI in society [92], there is less research available focusing on the interaction between AI and military force. The ADF, and Australia more generally, has an opportunity to consider these questions carefully and provide leadership to ensure frameworks are in place to ensure both the ADF and other world militaries embrace this technology in an ethical and responsible way.

6. CONCLUSION

The rapid growth of artificial intelligence technologies over the last decade, along with the large number of claims around the technologies involved, has left many people within the ADF and the wider community unclear about the application and importance of various artificial intelligence technologies. Along with the rapid growth in techniques, there have been many sensational claims regarding the current capabilities and future potential of AI. However, without detailed technical knowledge it is difficult to assess these claims, or even keep track of the rapid growth in techniques or opportunities that AI provides.

In this report, we have provided a non-technical overview of the current state of AI development, as of early 2020. In particular, we note that the rise in interest in AI over the last decade has come about most significantly due to the increasing practicality of a subset of AI techniques known as deep learning. Following the initial successes of deep learning to classify images, in 2012, there has been a rapid expansion in techniques that build on the basic building blocks of deep learning. We have discussed how the success of deep learning relied on three key advances that converged around the beginning of the last decade. These were significant advances in data, computational speed and algorithms.

The availability of increasingly larger datasets, coupled with readily available and massive computational resources, have allowed a variety of deep learning algorithms to solve real-world problems, which only a decade ago seemed intractable. This ability to solve practical, real-world problems marks this period of AI growth as different from previous eras of AI hype. However, not all domains are equally well-suited for the current range of AI techniques. While the value of AI looks promising in a number of problem-domains, this is not the case universally, with some problem-domains still being over-sold and likely to fail to meet expectations. Against that backdrop, we have identified five significant areas that have seen some of the most rapid advances during the last decade, with likelihood of further rapid development and have discussed the drivers for these developments and prospects for future successes. These areas are: (1) image understanding; (2) intelligent decision making; (3) artificial creativity; (4) natural language processing and (5) physical automation. While not exhaustive, this list does provide a set of key domains where AI techniques have proved their value in commercial or non-military applications. We have provided an overview of the current state-of-the-art for AI in each of these areas and have used that to provide suggestions of possible realistic military application areas that are worth further exploration and potential investment by the ADF.

We have also discussed some of the challenges likely to be faced by the ADF in adopting AI technologies. These challenges centre on data, computation, algorithms, system-integration and ethics. While each of these challenges has parallels in the civilian space, we have argued that there are particular issues likely to face the ADF that require cultural change as well as formal policy development. Regarding data, we note that a lot of the military data are either not captured or are captured in a way that is not suitably structured for automated processing. We note that a cultural change around data needs to occur within the ADF to leverage deep learning and related AI techniques. Similarly, we note challenges around computing power, with the ADF traditionally not investing in the kinds of high-performance computing required for deep learning. We recommend that the ADF also needs to invest more heavily in high performance computing, but have noted that even with significant investment, it is unlikely the ADF will be able to replicate the resources of major players, like Google. As such, the ADF also needs to invest in research on more data-efficient algorithms and approaches if it is to embrace AI in a practical manner. Unless more data-efficient algorithms are developed, it is unlikely the ADF will be able to harness deep-learning for many practical problems.

At a system-wide level, we have highlighted that research is also required into the practical issues around integration of AI into existing legacy systems, within the ADF. This includes implementing policies for new systems to support agile, modular development that is better situated to support AI. In addition, policies around the ethical use of these technologies are also needed, in order to aid in enhanced trust as well as better position Australia to provide leadership on the military applications of AI. We believe that developing a better non-technical understanding across the ADF of the underlying AI technologies, and their strengths and limitations, will be important for making the most of emerging opportunities in AI. We hope that this paper contributes to both the dialogue around the use of AI in the ADF, as well as providing a useful resource for ADF members to enhance their education and understanding around both deep learning and artificial intelligence more generally.

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