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Revolution in Military Affairs: A Study on the Application of AI Technology in the Defense Innovation of Korea

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The Research Institute for National Security Affairs (RINSA), South Korea's leading research institute at Korea National Defense University, dedicates itself to strengthening national security through a promotion of international collaboration and efficient defense practices.

The global security landscape in 2025 is expected to be highly complex, shaped by the re-election of Donald Trump as President of the United States and its subsequent effects on the ongoing conflict in Ukraine. South Korea faces the imperative of both bolstering its own defenses and fostering strategic partnerships with its allies.

The rapid change in technological landscape is shaping the future of battlefield strategies. The core objective of South Korea's Defense Innovation 4.0 is to integrate emerging technologies from the Fourth Industrial Revolution into military operations, as a means to secure information superiority in intelligent battlefields. By improving the speed of information collection, analysis, and response, South Korea aims to enhance its defense capabilities and respond effectively to asymmetric threats, particularly from North Korea.

Amid these challenges, our international research project focuses on the concept of the Revolution in Military Affairs (RMA), which comprises recent innovations in the integration of AI, big data and autonomous systems. Using a classification system by the Ministry of National Defense to guide the adoption of these innovations, the report emphasizes the strategic importance of information superiority and AI-driven defense technologies in ensuring South Korea's readiness for future battlefield challenges and aligning military strategy with long-term security objectives.

PREFACE

RINSA believes an open discussion and data-driven analysis are vital in shaping effective defense strategies. In a world fraught with uncertainty, RINSA stands committed to promoting international cooperation and strengthening national defense capabilities. We believe our research serves not only South Korea, but also contributes to a more peaceful and prosperous future for Indo-Pacific region as a whole.

December 31, 2024

Director-General of Research Institute for National Security Affairs
Professor Park, Young June

South Korea's National Defense Innovation and Information Superiority Strategy in the Future Intelligent Battlefield

This report examines the evolving global security environment in the post-Cold War era and South Korea's response through Defense Innovation 4.0. The primary objective of Defense Innovation 4.0 is to integrate cutting-edge technologies from the Fourth Industrial Revolution—such as AI, big data, and autonomous systems—into military operations, enabling the South Korean military to secure information superiority in intelligent battlefields and actively respond to North Korea's asymmetric threats with enhanced defense capabilities.

The key topics covered in this report are as follows:

1. **Strategies for Securing Information Superiority:** This report discusses strategies to significantly improve the speed of information collection, analysis, and response by integrating AI, big data, and autonomous systems. By securing high-quality data, South Korea aims to achieve information superiority over adversaries, which is essential for rapid decision-making and effective responses to diverse threats in intelligent battlefields.

2. **The Revolution in Military Affairs and AI Synergies:** Focusing on the concept of the Revolution in Military Affairs (RMA) and synergies with AI, the report examines the impact of AI technologies on military innovation. The analysis questions whether the proliferation of AI represents a disruptive shift in warfare or merely extends modernization efforts within traditional military frameworks, exploring the strategic applicability of these advanced technologies in modern combat.

3. **Systematic Application of Defense AI Technologies:** Leveraging the South Korean Ministry of National Defense's AI technology classification system, this report proposes a logical and consistent framework to support the systematic adoption of AI-based technologies. This classification system is designed to enhance defense education, training, and technology development, laying the groundwork for sustainable, efficient AI-driven capabilities across South Korea's defense ecosystem.

In conclusion, this report underscores the importance of achieving information superiority through AI integration and maximizing the application of advanced defense technologies to strengthen South Korea's defense capabilities. Through Defense Innovation 4.0, South Korea's military can ensure ongoing readiness in complex future battlefield environments, and advance both military strategy and defense systems in alignment with long-term security goals.

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Ⅰ. INTRODUCTION

The post-Cold War era saw the rise of the Liberal International Order (LIO) or Rule-based International Order (RBIO), which has been supported by three core pillars: democracy, free trade, and Pax Americana. However, this framework has faced significant challenges. Democracy has devolved into what is often termed an "audience democracy," where citizens' participation is largely reduced to voting during elections, with little influence in daily governance. Free trade has failed to distribute prosperity evenly, instead fostering internal inequality and economic sacrifices. The 2008 financial crisis, which some have likened to the Great Depression of the 1920s, further exposed systemic vulnerabilities, raising questions about the sustainability of the global capitalist system. This marked the end of the post-World War II era of rapid economic growth and prosperity, characterized instead by prolonged global economic stagnation, rising unemployment, and growing disparities between the wealthy and the poor. Furthermore, the deepening strategic rivalry between the United States and China has rendered the notion of Pax Americana increasingly obsolete.

In this context, global conflicts such as the Russian invasion of Ukraine in 2022 and the Israel-Hamas war, triggered by Hamas's surprise attack in 2023, have resulted in significant human casualties and prolonged instability. North Korea's growing strategic involvement in these conflicts underscores the relevance of these global security shifts for South Korea's national defense. In particular, North Korea's declaration to fully abolish the 2018 inter-Korean military agreement, along with its provocative military actions, such as the unauthorized release of balloons containing hazardous materials into South Korean territory, highlight the escalating tensions on the Korean Peninsula.

Amid these challenges, South Korea's Ministry of National Defense has introduced "Defense Innovation 4.0," an initiative aimed at leveraging advances from the Fourth Industrial Revolution to build a more resilient and technologically advanced military. The objective is to create a robust combat-ready force capable of overwhelming North Korea's asymmetric threats, including its nuclear and missile capabilities, while positioning South Korea for success in future battlefield environments. Central to this vision is the development of AI-driven military capabilities, the enhancement of joint military operations, and the timely acquisition of advanced defense technologies. Defense Innovation 4.0 focuses on five key priorities, including enhancing nuclear deterrence, advancing military strategy, securing AI-based technologies, restructuring military education and training, and overhauling defense research and development.

Despite these ambitious goals, there is a pressing need for a deeper and more holistic evaluation of AI's role in defense innovation. While AI is widely regarded as a potential game changer in military operations, practical limitations could hinder its implementation. In particular, it is crucial to examine the implications of Network-Centric Warfare (NCW) and the Revolution in Military Affairs (RMA) in light of rapid technological advancements. Therefore, the purpose of this study is to critically assess the current state of AI-driven defense innovation in the Republic of Korea's military and offer strategic recommendations to ensure its successful implementation. The structure of this study is as follows.

Chapter 2, South Korea's Intelligence Superiority Strategy for the Future Intelligent Battlefield, addresses South Korea's strategies for securing intelligence superiority in future intelligent battlefields. Specifically, it discusses methods to dramatically enhance the speed of information collection, analysis, and response by integrating AI, big data, and autonomous systems, and to achieve intelligence superiority over adversaries by securing vast amounts of high-quality data.

Chapter 3, The Revolution in Military Affairs: Diffusion Models and AI Synergies, explores the concept of the Revolution in Military Affairs and the synergies with AI. It analyzes the impact of advanced technologies like AI on military innovation and diffusion models, questioning whether the spread of AI technologies is indeed bringing about disruptive changes in warfare or merely continuing the modernization of the military.

Chapter 4, Harnessing AI in the Military: Navigating the AI Surge, examines the ways to leverage AI in defense and adapt to the rapid advancements in AI technology. It provides an overview of the South Korean Ministry of National Defense's Defense AI Technology Classification System, explaining how AI-based technologies can be systematically applied. The chapter explores the system's logical, exclusive, scalable, and consistent aspects, supporting structured adoption of defense AI innovation.

Ⅱ. South Korea's Intelligence Superiority Strategy for the Future Intelligent Battlefield

1. Introduction: The Need for Preparing for the Era of Intelligent Warfare

"What will the future battlefield look like, and how should we prepare?" This question has been an age-old inquiry of humanity, and it will continue to be a crucial question for future generations. The answer has evolved over the long history of wars and conflicts, constantly changing with the times. The purpose of this paper is to explore what kind of response we must provide today, as we live in the present on the Korean Peninsula.

In the near future, the core of future warfare will be achieving intelligence superiority on an intelligent battlefield. Intelligence superiority means having faster and more accurate comprehension of the battlefield than the enemy, enabling us to make superior decisions based on that understanding, thereby achieving dominance not through physical strength, but through superior intelligence. Such superiority is not just about possessing advanced technology; it requires deep consideration of how to effectively apply that technology based on an understanding of the battlefield. Recent advancements in artificial intelligence (AI) and autonomous systems are at the center of this intelligent battlefield, demanding the integration of technological understanding with domain knowledge of warfare and the military.

The use of AI in conflicts such as the Russia-Ukraine war (e.g., Clearview facial recognition, GIS-Arta) or the Israel-Hamas conflict (e.g., Gospel, Lavender assassination target generator) provides a glimpse into the future intelligent battlefield that we will face. AI-based autonomous drone systems offered tactical superiority by rapidly collecting and analyzing information to predict enemy movements and respond swiftly. In this way, AI has enhanced the ability to control and coordinate all elements of the battlefield in real time, becoming a key factor in winning wars.

How prepared are we for this era of the intelligent battlefield? Through the national defense AI strategy, we are already keeping pace with this trend. The Ministry of

National Defense has completed the first phase of a project in 2023 to build an intelligent platform for data integration and analysis (based on general military data) and is pursuing the second phase starting in 2024 (focused on classified data distributed through the battlefield network). These efforts aim to improve not only the efficiency of military operations during peacetime but also the capability to collect and analyze real-time information on the battlefield during wartime. Additionally, the continuous introduction of AI-based autonomous systems is part of our strategy to achieve intelligence superiority.

In conclusion, the future battlefield will gradually transform from an information-based battlefield to an intelligent one, and victory on the battlefield will go to the nation that secures intelligence superiority over its adversaries. This paper aims to explore the concept of the future intelligent battlefield, intelligence superiority, and to discuss the current status of our preparations and the capabilities we need to strengthen to prepare for such future wars.

2. Concepts of the Intelligent Battlefield and Intelligence Superiority

In ancient times, the variables determining victory or defeat in war were relatively few. For example, by comparing about three factors—such as the enemy's troop size, swords, and shields—one could roughly predict the strategy and outcome of the battle. But what about the current battlefield? Today, there are six distinct domains of warfare: land, sea, air, space, cyberspace, and the electromagnetic spectrum. Some scholars even argue that the cognitive domain should now be included. On such battlefields, various sensors and platforms operate in real-time, interconnected to collect, analyze, and make decisions based on information.

If we were to consider all the variables needed for responding to the enemy based on such analysis, it would exceed the human capacity to process. Thus, countries around the world are increasingly utilizing AI, big data, autonomous systems, and high-performance computing to reduce the growing uncertainty of the battlefield (often referred to as the "fog of war"). Moreover, countries are rethinking strategic paradigms suited to these new forms of warfare. This reflection extends beyond the nature of warfare to the details of decision-making structures at the operational and strategic levels. Therefore, at this moment of paradigm shift in the battlefield, contemplating the concepts of the intelligent battlefield and intelligence superiority is essential for preparing for the future wars we are bound to face.

A. The Intelligent Battlefield

Through analyzing the characteristics of the intelligent battlefield, this section will discuss the concept of "intelligence superiority," which will ensure victory in such environments. The intelligent battlefield should not be seen as a fragmented evolution from the current information-based battlefield but rather as a further developed version of it. For example, by integrating AI and autonomous systems into existing information collection and analysis systems, faster and more precise decision-making becomes possible. While utilizing the existing infrastructure of the information-based battlefield, AI helps to dominate the speed of decision-making by accelerating the tasks of collecting, processing, analyzing, and formulating responses. AI processes and makes decisions from vast amounts of data, while autonomous systems act swiftly based on this data and decisions, overwhelming the enemy in terms of action speed.

B. The Concept of Intelligence Superiority

In an intelligent battlefield, the concept of intelligence superiority is crucial. Intelligence superiority refers to the ability to analyze information more quickly and accurately than the enemy and, based on that analysis, propose and implement effective countermeasures. To achieve intelligence superiority, three core elements—ABC (Algorithm, Big Data, Computing Power)—are essential.

First, **algorithmic superiority** is vital. The advancement of AI algorithms allows rapid and adaptive responses to combat situations. Superior algorithms can analyze large-scale data, predict enemy patterns, and offer countermeasures faster than the enemy. In ever-changing combat environments, robust and flexible AI algorithms are indispensable.

Second, **computing power** is crucial. Even with fast information collection and superior algorithms, swift decision-making cannot be achieved without the hardware to support such calculations. The availability of GPUs like NVIDIA's or NPUs optimized for AI is essential. Autonomous weapon systems, drones, and robotic weapons also require on-device AI to operate independently on the battlefield, collecting necessary information and carrying out missions. This enhances decision-making speed and precision, allowing us to maintain a superior position over the enemy.

Third, the **quality and quantity of data** are critical. Essentially, AI learns by training on data, and the quality of its answers to new questions depends more on the amount and quality of data it has learned than on the algorithm itself. Therefore, achieving intelligence superiority requires securing vast amounts of high-quality data. Real-time data generated on the battlefield is a crucial variable, and AI must effectively learn and analyze it to provide precise insights that influence combat outcomes.

Among these three elements, the **most influential factor** in determining intelligence superiority in the future will undoubtedly be data. Algorithmic and computing power differences between nations are rapidly narrowing, for example, as open-source platforms like GitHub enable rapid sharing of algorithmic advances. Similarly, computing power is being equalized as companies ranging from major players like Apple and Google to smaller firms develop and produce their own NPUs. However, military data is secured within each country for security reasons, meaning that the quality and quantity of data each nation can gather for AI training will create the critical gap in intelligence superiority.

In conclusion, the intelligent battlefield will become the primary form of future warfare, and intelligence superiority will be the key condition for victory in such a battlefield. The integration of AI, big data, and autonomous systems will dramatically enhance the speed of information collection, analysis, and response on the battlefield, and securing intelligence superiority over the enemy will be essential to gaining an upper hand. Especially in the area of data, securing vast amounts of high-quality information will be the key to achieving intelligence superiority.

In the next part of this study, we will explore the concept of the Revolution in Military Affairs (RMA) that our military must undergo to achieve intelligence superiority, the conditions that can be transformed through the RMA, and the classification of the technologies required to apply AI for military purposes.

Ⅲ. The Revolution in Military Affairs : Diffusion Models and AI Synergies

1. Emerging Technologies and Military Innovation: A Conceptual Overview

In the 2020s, military innovation is once again subject to debates on the impact of emerging novel technologies, concepts, and broader patterns of geostrategic competition between great powers on the future direction and character of warfare. The convergence of advanced technologies such as artificial intelligence (AI) systems, robotics, additive manufacturing (or 3D printing), quantum computing, directed energy, and other 'disruptive' technologies, defined under the commercial umbrella of the 4th Industrial Revolution (4th IR), promise new and potentially significant opportunities for defense applications and, in turn, for increasing one's military edge over potential rivals. With the accelerating shift toward "automation warfare", in which emerging technologies such as AI systems are seen as 'disruptive' technologies in both civil and military spheres, the underlying complexity in the sources, paths, and patterns of innovation is widening. In this context, this article aims to provide conceptual and theoretical contours of military innovation studies. The article therefore proceeds by reflecting on the evolving military innovation debates and its continuity and change over the past two decades, followed by contending debates of theories of military innovation and its diffusion in the current setting in the context of strategic competitions for emerging technologies.

2. The Evolution of Military Innovation in the 21st Century

In the 2020s, military innovation is once again subject to debates in strategic studies on the impact of emerging novel technologies, concepts, and broader patterns of geostrategic competition between great powers on the future direction and character of warfare. The convergence of advanced novel technologies such as artificial intelligence (AI) systems, robotics, additive manufacturing (or 3D printing), quantum computing, directed energy, and other 'disruptive' technologies, defined under the commercial umbrella of the 4th Industrial Revolution (4th IR), promise new and potentially significant opportunities for defense applications and, in turn, for increasing one's military edge over potential rivals. For example, advanced sensor technologies such as hyperspectral imagery, computational photography, and compact sensor design aim to improve target detection, recognition, and tracking capabilities and overcome traditional line-of-sight interference.[1] Advanced materials such as composites, ceramics, and nano materials with adaptive properties will make military equipment lighter but more resistant to the environment.[2] Emerging photonics technologies, including high-power lasers and optoelectronic devices, may provide new levels of secure communications based on quantum computing and quantum cryptography.[3] The application of novel machine-learning algorithms to diverse problems promise to provide unprecedented capabilities in terms of speed of information processing, automation for weapons platforms and surveillance systems, and ultimately, decision-making.[4] In short, the use of emerging technologies - robotics, artificial intelligence and learning machines, modular platforms with advanced sensor technologies, novel materials and protective systems, cyber defenses and related technologies that blur the lines between the physical, cyber, and biological domains, is widely seen as having profound implications for how militaries adopt new technologies; how on an operational level, militaries adapt to and apply new technologies, and our understanding of the future battlespace.

1) See for example: David Stein, Jon Schoonmaker, and Eric Coolbauh, 'Hyperspectral Imaging for Intelligence, Surveillance and Reconnaissance, *Space and Naval Warfare Systems Center (SSC) San Diego Biennial Review* (2001); Sara Freitas, Hugo Silva, José Almeida & Eduardo Silva, 'Hyperspectral Imaging for Real-Time Unmanned Aerial Vehicle Maritime Target Detection,' *Journal of Intelligent and Robotic Systems* 90 (2018), 551-570;

2) Mark Burnett (et. al.), 'Advanced Materials and Manufacturing - Implications for Defence to 2040,' *Defence Science and Technology Group Report*, Australia Department of Defence (2018), https://www.dst.defence.gov.au/sites/default/files/publications/documents/DST-Group-GD-1022.pdf

3) International Institute for Strategic Studies, 'Quantum Computing and Defence,' *The Military Balance* (2019),18-20.

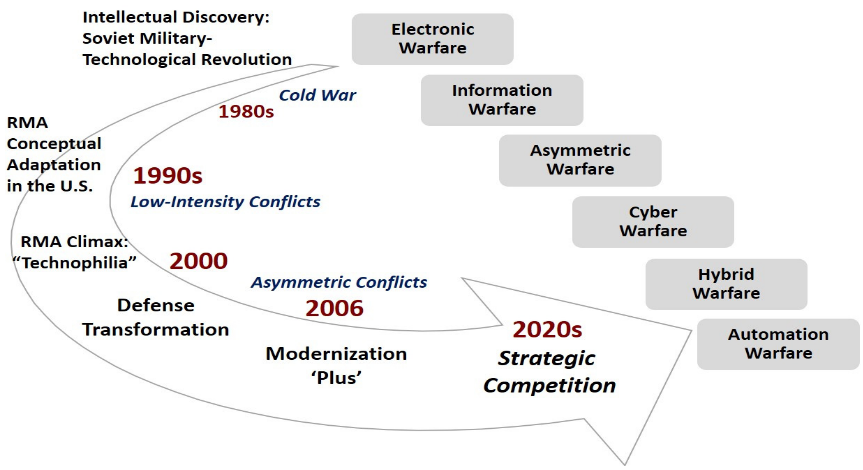
4) Michael Horowitz, 'The Promise and Peril of Military Applications of Artificial Intelligence,' *Bulleting of the Atomic Scientists*, 23 April 2018; Mary L. Cummings, 'Artificial Intelligence and the Future of Warfare,' *Chatham House Research Paper* (2017).

Much of the current debate arguably portrays the “next-frontier” defense technologies as synonymous with a “discontinuous” or “disruptive” military innovation in the character and conduct of warfare – akin to a new wave of a Revolution of Military Affairs (RMA), albeit in a context of accelerating strategic competition between great powers. Since its early inceptions as a *Military-Technical Revolution* theory by Soviet strategic thinkers in the early 1980s, the underlying narratives of future warfare have been predominantly contextualized through the lens of emerging technologies as a main driver in an ongoing shift from the “industrial-age” toward “information-age warfare”, and now increasingly toward “automation-age warfare.”[5] The baseline arguments in these evolving narratives have arguably not changed – i.e. the application of new technologies – such as AI systems - into a significant number of military systems coupled with innovative operational concepts and organizational adaptation will fundamentally alter the character and conduct of warfare by producing a dramatic increase in the combat potential and overall military effectiveness.[6] Attaining qualitatively new levels of military effectiveness through emerging technologies that transcends marginal improvements will essentially mitigate risks of the widening spectrum of security challenges of the 21st century, stipulated by the convergence of conventional, low-intensity, asymmetrical, and non-linear types of conflicts. States and military organizations adopting novel concepts, advanced technologies, and innovative force structures will possess a considerable strategic advantage, if not superiority, over those that do not.[7] In retrospective, however, the RMA of the 1990s has arguably followed a distinctly less than revolutionary or transformational path, consisting of incremental, often near-continuous, improvements in existing capabilities.[8] While major, large-scale, and simultaneous military innovation in defense technologies,

5) Michael Raska, ‘Five Waves of RMA Theory,’ *Pointer - Journal of Singapore Armed Forces*, 36/3 (2011), 1-12.
6) Andrew Krepinevich, ‘Cavalry to Computer: The Pattern of Military Revolutions,’ *National Interest* 37 (1994), 30-43.
7) Thomas Mahnken and James FitzSimonds, T*he Limits of Transformation: Officer Attitudes toward the Revolution in Military Affairs* (Newport: Naval War College Press, 2003).
8) Andrew Ross, ‘On Military Innovation: Toward an Analytical Framework,’ *IGCC Policy Brief* 1 (2010), 14-17.

organizations, and doctrines have been a rare phenomenon, military organizations over the past two decades have progressed through a sustained spectrum of military innovation ranging from a small-scale to large-scale innovation that have shaped the future conduct of warfare. Emily Goldman, for example, captured the spectrum in terms of "adaptive strategic adjustments" or minor innovations to existing goals, strategies, and/or structures, compared to "innovative strategic adjustments" that define major military innovations.[9]

Since the 2010s, however, the "disruptive" narrative of emerging technologies has been experiencing a revival in a broader popular narrative of the impending 4th Industrial Revolution, embedded not only in broader global socio-economic and political transformations brought by accelerating global hyper-connectivity, but also in the intensifying strategic competition for emerging technologies in both civil and military domains. Notwithstanding the multifaceted character of the competition, at the core of debate has been whether China and Russia will have the requisite capabilities to project power in the Indo-Pacific and beyond on par with the United States, and how the United States and its key allies, with other major powers, will respond to such challenge



〈Figure 3-1〉 Six "Waves" of the RMA

9) Emily Goldman, 'Mission Possible: Organizational Learning in Peacetime,' In: Peter Trubowitz, Emily Goldman, and Edward Rhodes (eds), *The Politics of Strategic Adjustment: Ideas, Institutions, and Interests* (New York: Columbia University Press, 1999).

Strategic competitions between great powers are not new; they have been deeply rooted in history – from the Athenian and Spartan grand strategies during the Peloponnesian War in the third century BCE, to the bipolar divide between the Soviet Union and the United States in the Cold War during the second half of the twentieth century. The character of the emerging strategic competition, however, differs from analogies of previous strategic competitions, most recently in the period of the Cold War, when the United States focused solely on maximizing the containment of the Soviet Union across all dimensions – political, economic, ideological, and military, while the Soviet Union countered with comprehensive efforts to shift the overall "correlation of forces" to favor Moscow.[10] In the 21st century, the United States faces an array of current and long-term security challenges across different geographical areas, while the Sino-U.S. relationship is much more complex in terms of integrating varying drivers of cooperation, competition, and conflict simultaneously. In other words, the current patterns of the strategic competition are more complex, unpredictable, and diverse, reflecting multiple competitions under different or overlapping sets of rules.[11] Long-term economic interdependencies co-exist with core strategic challenges, while ideological and institutional contests focus on the making and interpretation of rules and norms. Consequently, the ways and means of engaging in strategic competitions have varied - from pursuing security and prosperity through cooperative and institutional terms strictly in the economic arena, to sharp political-military-technological competition for power and status. The latter essentially embraces the logic of long-term competitive strategies aimed to attain or sustain a comparative advantage - relative to peer adversaries - across geopolitical, technological, military, economic, and other areas in order to significantly constrain competitor's strategic options and choices.[12]

10) Thomas Mahnken, 'Thinking about Competitive Strategies,' In Mahnken, Thomas (ed.), *Competitive Strategies for the 21st Century: Theory, History, and Practice* (Stanford, CA: Stanford University Press, 2012), 6.

11) Chung Min Lee, *Fault Lines in a Rising Asia*, 119-175.

12) Thomas Mahnken, 'A Framework for Examining Long-Term Strategic Competition Between Major Powers,' *SITC Research Brief* (January 2017).

At the same time, however, in a contest over future supremacy, technological innovation has been portrayed as a central element of strategic competitions – a potent source of international influence and national power - generating economic competitiveness, political legitimacy, military power, and in case of authoritarian states, also "social stability." The current competition for emerging technologies has extended to multiple dimensions as commercial spending on R&D has outpaced military spending, and today's "militarily relevant advanced technologies" are becoming harder and harder to identify and classify. Consequently, modern militaries no longer drive military-technological innovation, but instead increasingly rely on dual-use technologies to sustain or even extent the margins of their strategic and operational advantage. Technological advances, especially in the area of military systems, are a continuous, dynamic process; breakthroughs are always occurring, and their impact on military effectiveness and comparative advantage could be both significant and hard to predict at their nascent stages. Novel technologies and resulting capabilities also diffuse in varying ways across geopolitical lines. In short, the diffusion of new and potentially powerful militarily relevant technologies – as well as the ability of militaries to exploit their potential – varies widely,[13] conditioned by a range of organizational, conceptual, and operational challenges as well as varying historical path dependencies and strategic cultures.[14] How militaries interact with particular commercial science and technology ecosystems to reap synergies for force development and modernization has become a key determinant in the ongoing competition.

Yet, technological innovation its military variations can be equally tied to the enduring principles of strategy - the ways and means of waging war for political ends: from the development of new or different instruments (technology), practices (doctrines and operational concepts), to formation of new organizational force structures.[15] This includes, for example, strategies for the development of advanced,

13) Michael Raska, 'Strategic Competition for Emerging Technologies,' PRISM – *Journal of Complex Operations* 8/3 (2020), 64-81.

14) See for example, Dima Adamsky, *Culture of Military Innovation - The Impact of Cultural Factors on the Revolution in Military Affairs in Russia, the US, and Israel* (Stanford: Stanford University Press, 2010).

15) Tai Ming Cheung, Thomas Mahnken, Andrew Ross, 'Frameworks for Analyzing Chinese Defense and Military Innovation,' *SITC Policy Brief* 27 (2011).

reliable, cost-effective *defense industrial* base capable of producing innovative defense technologies based on innovations in the civilian/commercial arena; strategies enhancing *defense institutional agility* to identify new paths for integrating innovation into armed forces and their supporting systems to pursue novel technologies, while sustaining sufficient military capabilities to achieve national security objectives; and *operational adaptability of military forces* to engage in a range of military operations, and the potential to integrate and exploit innovative concepts, organizational structures, and novel technologies in combat. In other words, military innovation can be viewed in the capacity for *strategic, organizational and operational competitiveness and adaptability* – not only in detecting new sources of military innovation such as emerging technologies, but more importantly, implementing military change in response to shifts in geostrategic environment, novel military technologies, the realities of cost, performance, and organizational behaviour, and national security priorities.[16]

Ultimately, military innovation has always been relative – viewed through the lens of the *competitive strategies* reflected in the efforts to develop effective counter-innovation measures, which make innovation contextual, relative, and often limited in duration. In this context, the purpose of this article is to provide conceptual and theoretical contours of military innovation coupled with select analytical frameworks for a comparative assessment of innovation trajectories, which are reflected in subsequent case studies in this special issue. Structured into three parts, the article begins by reflections on the evolving RMA debate and its continuity and change over the past two decades, followed by contending debates of theories of military innovation and its diffusion in the current emerging technology setting, and concluding with three analytical frameworks for a comparative assessment of military-technological trajectories.

16) Paul Davis, 'Defense Planning in an Era of Uncertainty: East Asian Issues,' In: Natalie Crawford and Chung-in Moon (eds), *Emerging Threats, Force Structures, and the Role of Air Power in Korea* (Santa Monica: RAND, 2000), 25-47.

3. Reflections on the RMA Debate: Continuity and Change

Prior to presenting a conceptual overview of military innovation, it is important to reflect on the underlying strategic context. For over two decades, the conceptual impact of disruptive innovation on warfighting has been articulated in the theory, process, and debate of the "revolution in military affairs" (RMA). Above all, in the minds of its proponents and advocates, the RMA has been viewed a process of *discontinuous, disruptive*, and *revolutionary* change, as opposed to i*ncremental, sustaining, and evolutionary* change.[17] Andrew Krepinevich, for example, argued that an RMA occurs when "the application of new technologies into a significant number of military systems combines with innovative operational concepts and organizational adaptation in a way that fundamentally alters the character and conduct of a conflict. It does so by producing a dramatic increase…in the combat potential and military effectiveness of armed forces."[18] The emphasis on "discontinuous" or "disruptive" character of the RMA has shaped range of debates in international security studies, military history, defense economics, and public policy. RMA advocates argued that attaining qualitatively new levels of military effectiveness that transcends marginal improvements would essentially mitigate the widening spectrum of security challenges of the 21st century, stipulated by the convergence of conventional, low-intensity, asymmetrical, and non-linear types of conflict. In particular, at the operational level, a combination of systems and advanced technologies, including wide area of electronic sensors for long-range, all-weather, target detection and acquisition, would essentially enable near real-time situational awareness of the battlefield, and in doing so, mitigate the adverse effects traditionally synonymous with the fog of war – or the pervasive nature of uncertainty, ambiguity, fear and friction of battle.[19] At the same time, the networking of individual weapons systems, platforms, and "sensors and shooters" of the various

17) Peter Dombrowski, Eugene Gholz, and Adrew Ross, 'Selling Military Transformation: The Defense Industry and Innovation,' Orbis, Summer (2002), 527.

18) Krepinevich, 'From Cavalry to Computer: The Pattern of Military Revolutions,' 30.

19) David Alberts, John Garstka, and Frederick Stein, *Network Centric Warfare: Developing and Leveraging Information Superiority* (Washington D.C.: DOD Command and Control Research Program, 1999).

military services through innovative operational concepts would significantly enhance their interoperability, bringing about unprecedented levels of organizational synchronization, agility, and speed in the use of force. Together with a range of precision-guided munitions (PGMs) and their inter-service application, RMA-oriented military organizations would be able to conduct rapid, standoff, and precision strikes beyond the reach of enemy's defenses. In theory, this would significantly mitigate the scope and magnitude of collateral damage, shorten the duration of conflicts, and also minimize combat casualty rates traditionally associated with high-intensity conventional wars. In short, military organizations adopting RMA-oriented concepts, advanced defense technologies, and relevant force structures would possess a considerable strategic advantage over those that do not.[20)]

With its ambitious and wide-reaching aims and scope, however, the intellectual thrust on what defines and drives the RMA, its strategic templates and operational terms have changed over the past two decades. Indeed, the trajectory of the RMA - as a theory, process, and debate – evolved through six progressive stages or "waves": (1) the initial intellectual discovery by the Soviet military thinkers in the early 1980s, (2) the conceptual adaptation, modification, and integration in Western strategic thought during the early 1990s, (3) the climax of the RMA debate during the mid-to-late 1990s, (4) a shift to the broader "defense transformation" and it partial empirical investigation in the early 2000s, (5) second and third thoughts questioning the RMA thesis from 2005 onwards, and (6) return of RMA narrative in the form of the Fourth Industrial Revolution and "automation warfare" in the 2020s.[21)] At the turn of the century, the disruptive notion of the varying RMA-oriented

20) Eliot Cohen, 'A Revolution in Warfare,' *Foreign Affairs* 75/2 (1996), 37-54.; MacGregor Knox and Williamson Murray (eds), *The Dynamics of Military Revolution 1300-2050* (Cambridge: Cambridge University Press, 2001); Richard Hundley, *Past Revolutions, Future Transformations: What can the History of RMA Tell Us About Transforming the U.S. Military?* (Santa Monica: RAND, 1999); Michael Mazarr, *The Revolution in Military Affairs: A Framework for Defense Planning* (Carlisle: Strategic Studies Institute, 1994); Thomas Mahnken and James FitzSimonds, *The Limits of Transformation: Officer Attitudes Toward the Revolution in Military Affairs* (Newport: Naval War College, 2003).

21) Colin Gray, Strategy and History: Essays on Theory and Practice (London: Routledge, 2006), 113; Raska, 'The Five Waves of RMA Theory, Process, and Debate," 4-11.

conceptions and visions of future warfare has largely outpaced actual implementation, particularly in the U.S. strategic thought, defense management, and operational conduct. As Stephen Biddle noted, the RMA thesis has evolved "from exposition to consideration for implementation as a policy" so quickly that it "outpaced the ability of scholarship to examine its underlying premises and evidence."[22] Critics pointed that the RMA and its broader policy of defense transformation created high expectations that far exceeded available capabilities, resources, and realities.[23] Critics also pointed to its unfulfilled promises and ambiguities as an open-ended process, suggesting the concept has turned into an empty slogan, cliché or a buzz-phrase. The rationale for "new way of thinking and a new way of fighting" justifying virtually every defense initiative or proposal, whether RMA related or not, signaled disorientation rather than a clear strategy.[24] Skeptics further warned about single-dimensional or "locked-in" solutions to complex strategic challenges, overreliance on technological means that may be offset by adaptive enemies, and unacceptable risks in ignoring current or near-term defense requirements. Others warned that RMA-oriented defense transformation is a misguided or even a dangerous concept as it is driven by the military's weapons systems preferences and capability sets rather than policy imperatives.[25] In large part, the RMA in the U.S. strategic thought has been undermined by the challenges and operational demands in the conflicts in Afghanistan and Iraq, which turned into protracted "hybrid conflicts" with elements of counter-insurgency and counter-terrorism.[26] In this context, the U.S. and its allies became confronted by a wide spectrum of political, socio-economic challenges of a non-linear conflict that it was not prepared for, nor had it anticipated."[27] Both conflicts also raised

22) Stephen Biddle, *The RMA and the Evidence: Assessing Theories of Future Warfare* (Alexandria, VA: Institute for Defense Analyses, 1996).

23) Richard Bitzinger, *Transforming the US Military: Implications for the Asia-Pacific* (Barton: Australian Strategic Policy Institute, 2006).

24) Lawrence Freedman, *The Transformation of Strategic Affairs* (London: International Institute of Strategic Studies, 2006).

25) Kevin Raynolds, *Defense Transformation: To What? For What?* (Carlisle: Strategic Studies Institute, 2006).

26) Thomas Adams, *The Army After Next: The First Postindustrial Army* (Westport, CN: Praeger Security International, 2008).

questions about the effectiveness of RMA-technologies such as UAV drones in winning the "hearts and minds" of the people.[28]

In retrospective, the ebbs and flows of the RMA debate have also shifted from the (1) definition, metrics, magnitude and impact of the revolution or change in itself; (2) the pace, direction, and cost of technology in warfare, (3) the resulting implications for defense management; (4) projected and actual effectiveness of the RMA concepts in the use of force; to (5) the sources, character, and pace of RMA diffusion and adaptation. In the process, however, the idea of major military change as disruptive innovation seemed to permeate into each stage of the RMA debate.[29] Indeed, one of the most intellectually stimulating phases of the debate occurred in the mid-1990s, when select group of historians began to discuss the RMA in the broader context of strategic history. In particular, the RMA of the 1990s has been associated, often interchangeably, with a broader strategic concept of Military Revolutions (MRs). The idea behind MRs dates back to Michael Roberts' inaugural lecture in 1955 titled "The Military Revolution 1560–1660" at Queens University in Belfast. Roberts examined European military history at the end of the 16th century, when Dutch military leaders faced new weapons and tactics in their war with the Spaniards. In the analysis, he characterized the period as a single MR consisting of four distinct elements: revolution in tactics, revolution in strategy, increased intensity in the scale of warfare, and the impact of war on society.[30] For the next 50 years, military historians debated the issue whether there was a 'military revolution', and if so, when it occurred, and what form it took.[31] Notwithstanding the non-conclusive nature of this debate, the term MR began to signify a larger

27) Keith Shimko, T*he Iraq Wars and America's Military Revolution* (Cambridge: Cambridge University Press, 2010), 203.

28) Terry Terriff, Frans Osinga, and Theo Farrell (eds), *A Transformation Gap? American Innovations and European Military Change* (Palo Alto: Stanford University Press, 2010).

29) Doug Bland, 'The RMA: Managing an Idea,' In: Ron Matthews and John Treddenick (eds), *Managing the Revolution in Military Affairs* (New York: Palgrave, 2001), 10-36.

30) Geoffrey Parker, 'Military Revolution 1560-1660 - A Myth?' T*he Journal of Modern History*, 48/2 (1976), 196-214.

31) Laurent Henninger, 'Military Revolutions and Military History,' In: Matthew Hughes and William Philpott (eds), *Modern Military History* (New York: Palgrave, 2006), 8-22.

socio-political and military paradigm shift in how society, the state, and military organizations prepare and conduct war. According to Williamson Murray and MacGregor Knox, "military revolutions recast society and the state as well as military organizations. They alter the capacity of states to create and project military power⋯They [are] uncontrollable, unpredictable and unforeseeable."[32] In other words, MRs reflect a grand-strategic dimension of military change, whose effects extended beyond the battlefield and military organizations. In contrast, within or alongside the cataclysmic MRs are lesser RMAs characterized by Murray and Knox as "periods of innovation in which armed forces develop novel concepts involving changes in doctrine, tactics, procedures, and technology⋯ RMAs [also] take place almost exclusively at the operational level of war. They rarely affect the strategic level, except in so far as operational success can determine the large strategic equation. RMAs always occur within the context of politics and strategy--and that context is everything."[33] In many ways, the discussion on MRs and RMAs have been shaped by Alvin and Heidi Toffler's *War and Anti War* (1993), which viewed military innovation as a function of broader socio-economic changes, as explained in their theory of *The Third Wave* (1980).[34] Their central premise was the notion that MRs are dependent on overall or cumulative paradigm shifts in the society, economy, politics, and technology: "A military revolution, in the fullest sense, occurs only when a new civilization arises to challenge the old, when an entire society transforms itself, forcing its armed services to change at every level simultaneously–from technology and culture to organization, strategy, tactics, training, doctrine, and logistics. When this happens, the relationship of the military to the economy and society is transformed and the military balance of power on earth is shattered."[35] In this context, the emergence of advanced technologies in the 2010's, such as artificial intelligence, biometrics, robotics, nanotechnology, and biotechnology, can

32) Knox and Williamson Murray (eds), *The Dynamics of Military Revolution 1300-2050* (Cambridge: Cambridge University Press, 2001), 7.

33) *Ibid.* 12.

34) Alvin Toffler, *The Third Wave* (New York: Morrow, 1984), 125-131.

35) Alvin and Heidi Toffler, *War and Anti-War: Survival at the Dawn of the 21st Century* (Boston: Little Brown, 1993), 32.

be seen also as a Military Revolution - in the search for innovative ways organizations, processes, infrastructure, and systems function; while the military applications of these novel technologies corresponds to a new "automation wave" RMA.

4. Legacy Theories of Military Innovation – Still Relevant?

One of the questions in the ongoing debate is whether 'classical' theories of military innovation, conceptualized over the past four decades, are still relevant in the context of the 4th Industrial Revolution and its impact on why and how militaries innovate, when, how, and why do militaries succeed or fail in adopting and adapting to novel technologies, strategies, and concepts? The debate on the sources, paths and patterns of military change, learning, and innovation has been one of the quintessential threads in strategic studies since 1984, when Barry Posen examined how and why military organizations innovate in a comparative study of interwar military doctrines of Great Britain, France, and Germany.[36] Posen's work triggered a primary debate in military innovation studies on the causes, catalysts, conditions, and trajectories of innovation. In particular, when, how, and why do military organizations change? What are the key variables, internal or external, that determine the paths and patterns of military innovation? Why do select military organizations succeed or fail in pursuing military innovation, under what conditions? How do major military innovations emerge, diffuse, and shape or change the international security environment relative to evolutionary, sustaining innovations? The nearly four-decade long debate generated a number of approaches and models with varying explanations of key drivers, patterns, processes and outcomes of military innovation. Nearly all, however, start from the basic assumption that propensity of change in military organizations - institutionalizing new approaches to warfare – is neither probable nor simple. At the same time, nearly all theories

36) Barry Posen, *The Sources of Military Doctrine: France, Britain, and Germany Between the World Wars* (Ithaca: Cornell University Press, 1984).

of military innovation have been projected as 'hierarchical' – initiated and operated in a top down trajectory through senior leaders – whether civilian decision-makers or military senior service decision-makers.[37] Notwithstanding the increasing quantity of studies projecting "bottom-up" innovation as well as the importance of cultural and horizontal approaches over the past decade, much of the new scholarship has been inherently also grounded in the "compatibility with traditional theories."[38] The prevailing conservatism in the military innovation field can be attributed to its policy-orientation, driven by an overlapping scholar-practitioner community, which has built inherent structural bias within the field toward applied research and discouraged overly theoretical scholarship.[39]

Classical debates in military innovation studies typically identify at least three types of barriers to innovation: (1) organizational rigidity, (2) bureaucratic politics, and (3) organizational culture.[40] For example, according to organizational theory, military organizations function as large, complex, and functionally specialized bureaucracies, placing a premium on predictability, stability, and certainty.[41] Coupled with institutionalized standard operating procedures, core missions, goals, strategies, and structural norms, these factors reinforce military stagnation. Similarly, bureaucratic politics theory blames uniformed leaders, seeking to promote the importance of their organizations, maximize resource allocation, and preserve their distinct organizational roles, missions, and capabilities.[42] In other words, military organizations tend to protect their self-interests in an environment of scarce resources, which strengthens their risk aversion and resistance to change, including new technologies.[43] Therefore, innovations that pose no threat to the organization's

37) Adam Grissom, 'The Future of Military Innovation Studies,' *Journal of Strategic Studies*, 29/5 (2006), 920.

38) Stuart Griffin, 'Military Innovation Studies: Multidisciplinary or Lacking Discipline?' *Journal of Strategic Studies*, 40/1-2 (2016), 196-224.

39) *Ibid.*, 205.

40) Janine Davidson, *Lifting the Fog of Peace: How Americans Learned to Fight Modern War*, 11.

41) Barry Posen, *The Sources of Military Doctrine: France, Britain, and Germany Between the World Wars*, 46.

42) Morton Halperin, *Bureaucratic Politics and Foreign Policy* (Washington D.C.: Brookings Institution, 1974).

mission, resources, autonomy, or essence are readily adopted, while those innovations perceived as a major threat may be strongly resisted.[44] In contrast, culturalist theorists view barriers to innovation embedded in particular strategic as well as organizational cultures. Williamson Murray defines strategic culture as an "ethos and professional attributes, both in terms of experience and intellectual study, which contribute to a common core understanding of the nature of war within military organizations."[45] While strategic culture shapes ideas about the use of force within a state through their historical experiences and lessons learned, organizational culture comprises of identities, norms, and values that have been internalized by military organizations in their military regulations, training, routines, and practice. Strategic culture thus conditions the preconceived notions on the character and conduct of war, and serves both as an enabler or constraint in the effectiveness of organizational learning, adaptation, and innovation.[46] Ultimately, pursuing and managing military innovation, including emerging technologies, does not arise in a vacuum – the range of cultural, bureaucratic, and organizational barriers to military innovation are amplified by diverse contextual variables that include intrinsic geostrategic, political, economic, and operational variables shaping a state's ability to generate military power.[47] Indeed, there are conditioning factors such as geographic proximity or distance to the areas of conflict, fragmented national security consensus, weak state structure, internal security focus, alliance obligations, weak economic growth, low defense spending, limited technological base, limited defense resources, dependence on external material support, segregated defense sectors, export controls, and others.[48]

43) Jeffrey Isaacson, Christopher Layne, and John Arquilla, *Predicting Military Innovation* (Santa Monica: RAND, 1999).

44) Emily Goldman and Thomas Mahnken (eds), *The Information Revolution in Military Affairs in Asia* (New York: Palgrave Macmillan, 2004), 1-21.

45) Williamson Murray, 'Does Military Culture Matter?' *Orbis* 45/1 (1999), 27-57.

46) Michael Eisenstadt and Kenneth Pollack, 'Armies of Snow and Armies of Sand: The Impact of Soviet Military Doctrine on Arab Militaries,' *Middle East Journal*, 55/4 (2001),549-578;

47) Isaacson, Layne, and Arquilla, *Predicting Military Innovation*, 9.

48) Goldman and Mahnken, (eds) *The Information Revolution in Military Affairs in Asia*.

Mapping the barriers to military innovation through different theoretical lenses subsequently yields different arguments on the appropriate mechanisms to overcome them. The classical debate has focused on four major contending schools of thought: (1) civil-military conflict, (2) intraservice conflict, (3) interservice conflict, and (4) organizational culture.[49] The first three frameworks view major military innovation or disruptive innovation as a result of conflicts in decisive relationships - between civilian and military leaders, within services, or between services, while incremental innovation results from suppressing such conflicts. The first model, Barry Posen's *civil-military competition* framework integrates seemingly contrasting propositions of structural realist theory (balance of power) and organizational theory, arguing that external threats and civilian intervention are primary determinants of military innovation.[50] Posen views military organizations resisting change by design – as rational, functional, specialized bureaucracies, militaries have institutionalized vested interests to preserve their autonomy, size, and wealth, while reducing operational uncertainties. As a result, military innovation can proceed either through a direct combat experience with a new technology, major failure on the battlefield, and most importantly, external civilian intervention forcing change in the military decision-making processes. In this context, civilian intervention is conditioned by the perennial insecurity and threat perceptions shaped by the anarchic structure of the international system. Civilian leaders interpret continuity and change in the security environment, and react by modifying internal organizational, bureaucratic, and military commitments. When threat perceptions are low, civilian intervention and military innovation are incremental; when security threats are high, civilian leaders have a greater incentive to intervene, and essentially impose major changes on the military. According to Posen, the pathways for such intervention can be either direct or indirect, channeled through a link between civilian leaders and select "maverick" officers, who provide the civilian leadership with necessary military expertise and stimulate innovation within military organizations.[51] In this context,

49) Grissom, 'The Future of Military Innovation Studies,' 905-934.
50) Posen, *The Sources of Military Doctrine: France, Britain, and Germany Between the World Wars.*
51) *Ibid.*

one could argue that external threat of strategic competition for power and influence by means of emerging technologies coupled with civilian intervention to accelerate resource allocation into the research and development of these technologies puts pressure on military organizations to innovate.

In contrast, proponents of *intraservice competition* model such as Stephen Peter Rosen, argue that military innovation can be facilitated internally – between branches of the same service; without external civilian interference that often fails.[52] According to Rosen, peacetime military innovation emanates from an ideological struggle for power between established and reform-oriented branches within a single service over competing visions of future warfare. Innovation diffuses through internal structural changes, which are gradual and evolutionary, altering the distribution of organizational power among competing organizational factions or subgroups and their preferences. Rosen argues that when intraservice competition between branches is high, innovation accelerates as a result of each branch trying to dominate the other. The essential mechanism for innovative military change is the determination and success of visionary senior officers or "product champions" advocating a new vision of future warfare, and searching for allies and resources in reform-minded junior officers tasked to develop and experiment with innovative operational concepts, tactics, and techniques. In order to spearhead innovation, the senior officer "mavericks" open "promotional pathways" such as the establishment of new arms or branches of service for select junior officers, protecting them from political threats and internal struggles within the service, gradually enabling them to foster innovation, and ultimately empowering them to dominate the service. The process may take up to a decade, depending on the rate of junior officers' promotions.[53]

The third school of thought is that of *interservice competition*, which has evolved from studies by Vincent Davis, Bradd Hayes, Owen Cote and others.[54] Its proponents

52) Stephen Peter Rosen, *Winning the Next War: Innovation and the Modern Military* (Ithaca: Cornell University Press, 1991).

53) *Ibid.*

54) Vincent Davis, *The Politics of Innovation: Patterns in Navy Cases* (Monograph Series in World

acknowledge that if civilian intervention or intraservice competition may selectively accelerate military innovation by offering solutions for particular strategic or operational problems, so can interservice relations also moderate innovative effects through competitive and cooperative patterns. However, the dynamics of interservice conflict - between the military services within a state for new roles, missions, and resources - has a greater effect on innovation, and can act alone and independently even in the presence of strong civilian and intraservice opposition.[55] This is because military organizations are driven by professional ethos to provide security for the state under conditions of great uncertainty, which stimulates debate and amplifies both competition and cooperation between the services for scarce defense resources. Such interservice conflicts – i.e. over the development of a new doctrine for the use or integration of a new technology, will be more intense and openly politicized than intraservice conflicts, resulting in greater spill-over effects into political decision making arenas.[56]

The fourth school of thought rejects military innovation as a result of conflicting relationships; it explains sources of military innovation through differences in *strategic and organizational cultures* – i.e. distinctive, consistent, and persistent views on how states and their military organizations think about warfare. According to Dima Adamsky, "different cultures think differently about military innovation and produce various types of doctrinal outcomes from the same technological discontinuity."[57] In this view, military innovation, including the diffusion of emerging technologies, is conditioned by different national "cognitive styles" – i.e. strategic preferences, perceptions, ideas and knowledge, techniques and professional attributes and patterns of habitual behavior acquired over time within

Affairs: University of Denver, 1967); Bradd Hayes and Douglas Smith (eds), *The Politics of Naval Innovation* (Newport: US Naval War College, 1994); Owen Cote, *The Politics of Innovative Military Doctrine: The US Navy and Fleet Ballistic Missiles* (PhD Dissertation: MIT, 1996).

55) Cote, *The Politics of Innovative Military Doctrine: The US Navy and Fleet Ballistic Missiles*, 86.

56) *Ibid.*, 91-94.

57) Adamsky, *The Culture of Military Innovation: The Impact of Cultural Factors on the Revolution in Military Affairs in Russia, the US, and Israel*, 1.

member of national strategic community. Theo Farrell defines military culture as "comprising those identities, norms and values that have been internalized by a military organization and frame the way the organization views the world, and its role and functions in it."[58] He argues that both cultural norms and professional traditions set the context for military innovation, fundamentally shaping organizational choices, preferences, and reactions to technological and strategic opportunities.[59] This process occurs through three key mechanisms: (1) senior leaders may plan and direct military organizations toward innovation through changes in strategic thought; (2) external shocks can trigger a process of cultural change; and (3) cross-national cultural norms can shape the paths and patterns of military emulation.[60] Similarly, Elizabeth Kier argues that organizational culture shapes the direction and character of strategic thought of military leaders, and in doing so, state's choices in military doctrine and innovation.[61] At the same time, organizational culture can "play a critical role in determining how effectively organizations can learn from their own experiences."[62] In short, strategic and organizational cultures can serve as both enabler and constraint of military-technological innovation such as the diffusion of AI systems in military affairs.

58) Theo Farrell, 'The Dynamics of British Military Transformation,' I*nternational Affairs*, 84/4 (2008),783.

59) Theo Farrell and Terry Terriff (eds), *The Sources of Military Change: Culture, Politics, Technology*; Theo Farrell, 'Culture and Military Power,' *Review of International Studies*, 24 (1998),407-416.

60) *Ibid.*

61) Elizabeth Kier, *Imagining War: French and British Military Doctrine Between the Wars* (Princeton: Princeton University Press, 1997).

62) John Nagl, *Counterinsurgency Lessons from Malaya and Vietnam* (Westport: Praeger, 2002), 11.

5. Concluding Thoughts: Toward AI RMA?

From the above theoretical and conceptual overview, it is clear that the military innovation debate has been evolving, reflecting contending views, different strategic and operational concepts, organizational cultures, and defense policy imperatives. In the context of emerging advanced technologies, however, some of the most persistent questions continue to reflect the path of traditional debate: is there a new wave of a transformative revolution in military affairs driven by technologies such as AI systems, and if so, what does it mean for military and strategy – what is new or revolutionary? Does the diffusion of these technologies signify a real "disruptive" shift in warfare or a mere continuation of technological progress and modernization of armed forces? If the next-RMA indeed stipulates a paradigm shift in the ways and means of using force, what are the defense resource allocation priorities, force structure requirements and procurement needs in the context of short and long-term defense planning? In other words, how to balance existing military readiness cycle requirements with future capabilities. And ultimately, how effective are these technologies in mitigating the complexity of the "fog and friction" of warfare reflected in the global security challenges of the 21st century, characterized by the increasing volatility and uncertainty through the convergence of traditional security threats and non-linear/asymmetric threats?

With the prevailing focus on the strategic competition between great powers – China, Russia, and U.S. debates, there is also an increasing interest in analyzing the impact of emerging technologies in divergent strategic settings, particularly its character, relevance, and implications on the military modernization trajectories of small states and middle powers. Indeed, a number of advanced small states and middle powers, especially in the Asia-Pacific and Europe, have been pursuing the research and development of advanced dual-use technologies such as AI and robotics as a means not only to strengthen their defense capabilities, but also shape the global direction and character of ethics and norms on how to use them. Accordingly, the emerging military innovation debate cannot be confined solely to the great power perspectives and military domains alone. While in the short-term, the magnitude and impact of the high-tech innovation in the military modernization paths of advanced small states may not encompass a “full spectrum” discontinuity in the means and modes of war *per se*, in the long-term its integration propels a comprehensive rethinking of defense policies, military doctrines, defense technology management processes, organizational force structures, and force employment. This in turn amplifies the policy relevance and implication of the military-technological diffusion and adaptation by select small states. Accordingly, if national security planners are to make appropriate strategic decisions, they need to understand the varying trajectories from comparative perspectives.

Ⅳ. Harnessing AI in the Military : Navigating the AI Surge

1. Defense AI Technology Classification System Overview

The Ministry of National Defense of the Republic of Korea has established a classification system for Defense AI technology to facilitate its systematic application. The following describes the conceptual framework for the classification system of Defense AI technology.

The purpose of using the defense AI technology classification system was to prioritize the aspect of national defense utilization, considering AI-related tasks and projects, AI-related requirements planning, and technology planning at the future 'Defense AI Center'. The classification system was prepared by dividing it into 'methodology' and 'hardware' aspects, with each aspect independently classified into large, medium, and small categories. Additionally, the classification of defense AI technology considered logic, exclusivity, scale, consistency, and other relevant aspects.

In terms of logic, considering that nothing has been standardized as a result of the review of the existing AI technology classification system, it was written with the organization and purpose of using the AI technology classification system in mind. The following two aspects were considered: 1) the concept was established to maintain logic as much as possible in the same concept and context as the 'Defense AI Promotion Strategy' being promoted by the Ministry of National Defense, and 2) it was written focusing on the technical perspective when considering the organization and purpose of using this technology classification system.

In terms of exclusivity, although AI technologies have characteristics that complement each other and develop together, the classification has been structured to minimize the overlap of technologies between the 'large-medium-small' classifications and within each classification to reduce confusion in their use.

In terms of scale, considering the differences in the development and utilization of AI technologies, the classification was structured to make the scale of each technology similar for ease of use. The following two aspects were considered:

1) for technologies that have developed relatively more so far, the scale may be relatively large, so some technologies were further detailed below the 'small classification'

2) the medium classification was designed with a scale that can be referenced at the level of specific tasks and projects, while the small classification was structured considering the scale of university research lab topics.

In terms of consistency, the classification between 'large-medium-small' was created considering exclusivity and scale based on the same logic. Additionally, considering the rapid pace of AI technology development, the classification includes not only currently utilized technologies but also those for which theories and concepts are beginning to be established in academia and which may emerge in the future.

2. Classification System for Large and Medium Categories of Technology

The large category system was classified based on two criteria to focus on 'technology' rather than AI-related actions or data forms. It was designed to maintain the same principles and context as the 'Defense AI Development Model', which aims to be divided into the stages of 'perception', 'judgment', and 'decision'. Specifically, the areas of AI technology application were defined as 'core problem areas' and were detailed into four stages.

1) The area where machines replace human perceptual abilities to 'perceive/understand'

2) The area where machines are trained from data and can 'learn/infer' to predict and explain new data

3) The area where machines 'plan / control' autonomously

4) The area where machines and humans communicate and control actions, involving 'interaction/intelligent behavior'

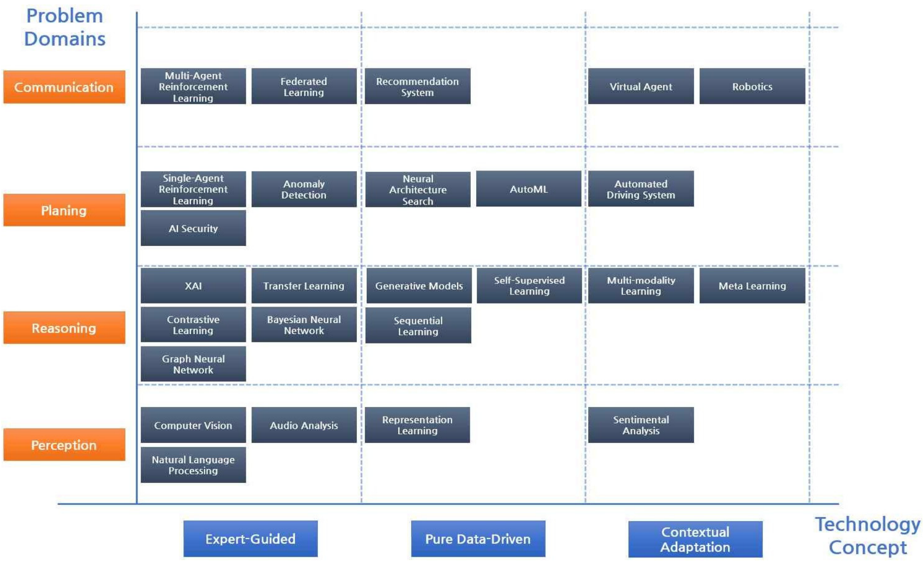
Additionally, the characteristics of AI technology were classified into three categories as a 'conceptual technology classification'.

1) Technology that requires relatively high human intervention, termed 'expert intervention'

2) Technology that operates based on data, termed 'pure data-based'

3) Technology where machines understand context and implement multidimensional intelligence, termed 'composite intelligence-based'

The medium classification system comprises a total of 12 combinations of the three 'conceptual technology classifications' and the four 'core problem areas' from the large classification. Each combination includes specific technologies. To align with the national agenda 'Fostering a Strong AI-based Military' and the principle of 'Prioritizing AI-based Core Advanced Forces', it broadly encompasses future technologies required for 'remote control', 'semi-autonomous', and 'autonomous transition'.



〈Figure 4-1〉 Large and Medium Category Classification System for Defense AI Technology in Terms of Methodology

In the classification system, action-oriented classifications such as ‘preprocessing’ and ‘data collection’ were excluded to focus on the technologies themselves. The technologies classified under the ‘medium classification’ generally exhibit a trend of development from the lower left to the upper right. Although some technologies have not yet matured enough for practical use, they are included considering the purpose of this study, which is to broadly encompass technologies that will emerge soon. The range of currently developed technologies may vary depending on their maturity and degree of utilization.

〈Table 4-1〉 Intermediate and Subclassification Techniques

Large Categories		Medium Categories	Small Categories
Core Problem Areas	Conceptual Technology Classification		
Perception/ Undersanding	Expert Intervention	Computer Vision	Object Detection, Object Tracking, 3D Image Reconstruction, Image Segmentation, Super-Resolution Imaging Technology, Image Denoising, Pose Estimation and Action Recognition
		Sound Analysis	Speech Recognition, Audio Separation Technology, Generative Audio Models
		Natural Language Processing	Natural Language Understanding, Natural Language Generation
	Pure Data-Based	Representation Learning	Supervised Representation Learning, Unsupervised Representation Learning
	Composite Intelligence -Based	Emotion Understanding	Lexicon-Based Sentiment Analysis, Machine Learning-Based Sentiment Analysis
Learning/ Inference	Expert Intervention	Explainable AI	LIME, LRP, SHAP, Model-Specific Methods
		Transfer Learning	Inductive Transfer Learning, Transformational Transfer Learning, Self-Taught Transfer Learning, Unsupervised Transfer Learning
		Contrastive Learning	Supervised Contrastive Learning, Self-Supervised Contrastive Learning
		Bayesian Neural Network Models	Bayesian Convolutional Neural Network, Bayesian Recurrent Neural Network
		Graph Neural Network Models	Directed Graph-Based Model, Heterogeneous Graph-Based Model, Dynamic Graph-Based Model

Large Categories		Medium Categories	Small Categories
Core Problem Areas	Conceptual Technology Classification		
	Pure Data-Based	Generative AI Models	Variational Autoencoder Model, Generative Adversarial Network Model, Generative Diffusion Model
		Self-Supervised Learning	Data Attribute-Based Pretext Learning, Data Temporal Sequence and Spatial Position-Based Pretext Learning
		Sequential Learning	Online Learning, Incremental Learning
	Composite Intelligence-Based	Multimodal Learning	Multimodal Transformer Model, Multimodal Generative Model
		Meta Learning	Distance-Based Learning Model, Optimization Learning Model, Model-Based Learning Model
Planning/Control	Expert Intervention	Single-Agent Reinforcement Learning	Value-Based Reinforcement Learning, Policy-Based Reinforcement Learning, Actor-Critic Based Reinforcement Learning
		Anomaly Detection	Supervised Anomaly Detection, Semi-Supervised Anomaly Detection, Unsupervised Anomaly Detection
		AI Security	Adversarial Attack-Based Model, Adversarial Defense-Based Model
	Pure Data-Based	Neural Architecture Search	Bayesian Optimization-Based Search, Evolutionary Algorithm-Based Search, Reinforcement Learning-Based Search, One-Shot Architecture Search
		Automated Machine Learning	Automated Hyperparameter Tuning, Automated Feature Engineering
	Composite Intelligence-Based	Autonomous Driving Systems	RADAR, LiDAR, and Specialized Sensor Data Processing, SLAM, Sensor Fusion Technology
Interaction/Intelligent Behavior	Expert Intervention	Multi-Agent Reinforcement Learning	Multi-Agent Based Simulation Technology, Multi-Agent Collaboration-Based Reinforcement Learning, Multi-Agent Competition-Based Reinforcement Learning
		Federated Learning	Horizontal Federated Learning, Vertical Federated Learning, Transfer Federated Learning
	Pure Data-Based	Recommender Systems	Collaborative Filtering, Content-Based Recommender System
	Composite Intelligence-Based	Virtual Agents	Simple Reflex Agent, Model-Based Reflex Agent, Goal-Based Agent, Utility-Based Agent, Learning Agent
		Robotics	Multi-Sensor Communication and Perception, Virtual/Physical Integration Technology, Intelligent Autonomous Control

3. Intermediate and Subclassification Techniques

The following summarizes the contents of some key technologies among the classified technologies.

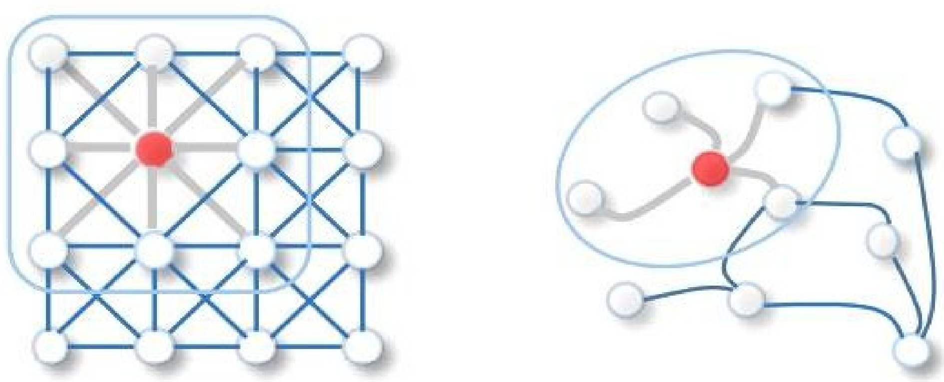
1) Graph neural network model

A) Concept

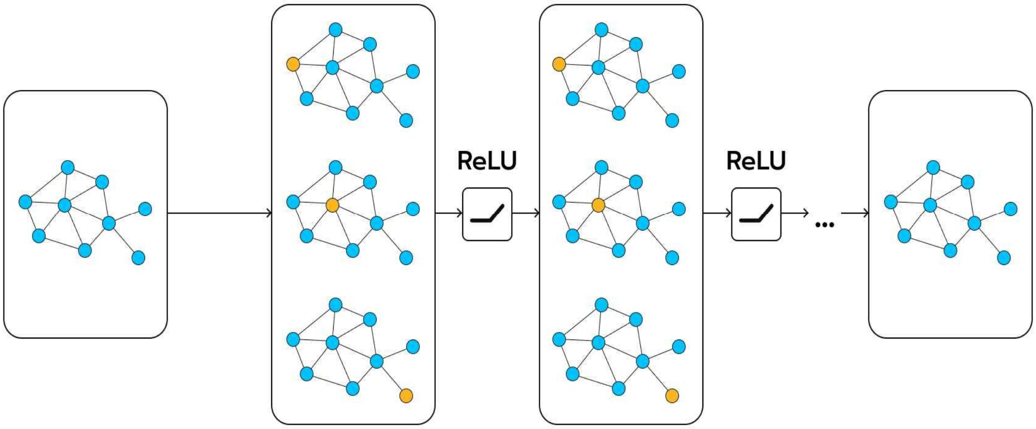
As the diversity of data and the complexity of relationships increase, graph-structured data consisting of nodes and edges is gaining attention. Compared to traditional data structures, it is more flexible and can be generalized to various types of data structures. This makes it applicable in various fields such as social networks, behavior recognition and classification, chemical molecular structures, and new drug development.

Since the introduction of deep neural networks on graph structures in 2009, research has become more active with the development of Graph Convolutional Networks (GCN) in 2017.

Unlike traditional two-dimensional data (Euclidean space), Graph Neural Networks model information based on connections between nodes. They utilize matrix information constructed from these connections to build deep neural networks.



〈Figure 4-2〉 Traditional data of two-dimensional structure (left), concepts of graph structure (right)



〈Figure 4-3〉 Deep Neural Network Concepts for Graph Structural Data

B) Military Use Cases and Plans

While significant advancements have been made in object detection and identification in images, classifying human behaviors in images (or videos) using graph structures remains relatively complex and esoteric.

Existing methods for action recognition in various situations, such as when only part of the body is visible in the image or when multiple people's actions are mixed, are theoretically feasible. However, the computational load is too large to achieve sufficient performance.

In 2017, Carnegie Mellon University proposed 'Open Pose', a method that estimates core joints of all individuals in an image and connects them probabilistically to form a so-called 'skeleton'. Previously, a 'top-down' approach was used, where the process of detecting a person was followed by identifying their actions. In contrast, 'Open Pose' introduced a 'bottom-up' method, where this process is reversed.

〈Figure 4-4〉 The case of ‘open pose’

Beyond merely identifying designated objects, more sophisticated boundary systems can be implemented by classifying human behavior. For example, systems can detect and alert for abnormal behaviors such as ‘intrusion’, ‘loitering’, and ‘wall-scaling’, or classify, track, and monitor individuals based on their behavior.[63]

The effectiveness of military training can be enhanced by classifying and determining whether combat behaviors during basic training, such as shooting and maneuvering, are performed correctly.

C) Private Use Cases

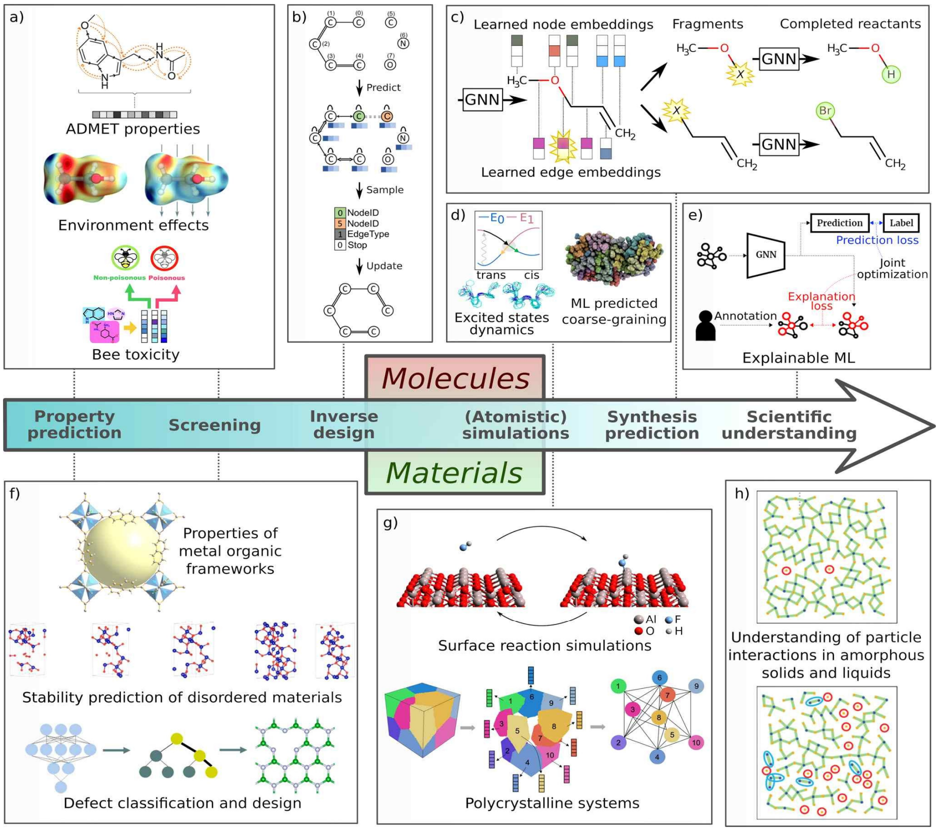
Graph Neural Networks (GNN) are highly active in chemical fields such as new drug development and research on new physical properties, owing to the intuitive representation of chemical molecular structures as graphs. Examples of GNN applications include :

- Predicting the toxicity of substances to bees
- Proposing GNN models based on reinforcement learning for reverse molecular design

63) Choi Kyu-jung, Oh Soo-young and Son Chae-bong. (2020). A study on the application of Open Pose and Deep Learning technologies to build an intelligent surveillance and reconnaissance system. Advanced International Studies, 3(3), 113-132.

· Conducting 'retrosynthesis' research without a template

· Predicting methane adsorption volumes in metal-organic frameworks through explainable
GNNs



〈Figure 4-5〉 A Study on Graph Neural Networks in Chemistry

D) Sub-classification results

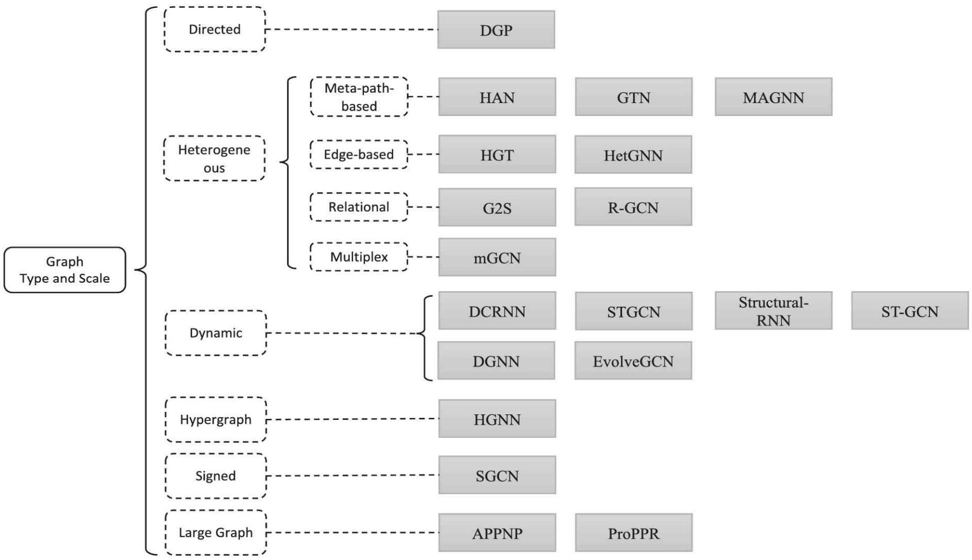
Considering that graph neural networks are fundamentally different from existing two-dimensional data structures, a wide variety of sub-classifications are possible. The methods are typically classified based on the type and size of graphs, which essentially represent the form of data, as follows.

If the edges have directions, graphs can be classified into several types:

- Heterogeneous Graphs: These graphs have various types of nodes and edges
- Dynamic Graphs: Nodes and edges in these graphs change over time
- Other types include Hypergraphs, Signed Graphs, and Large Graphs

Heterogeneous graphs, which consolidate several homogeneous graphs, can be sub-classified based on different methods:

- Meta-path-based Method: Determines the connection schema between two nodes for each specific path
- Edge-based Method: Defines the type and meta relationship between two nodes from the edge connecting them
- Relational Method: The edges contain more information compared to the meta and edge methods
- Multiplex Method: Various types of edges exist between nodes

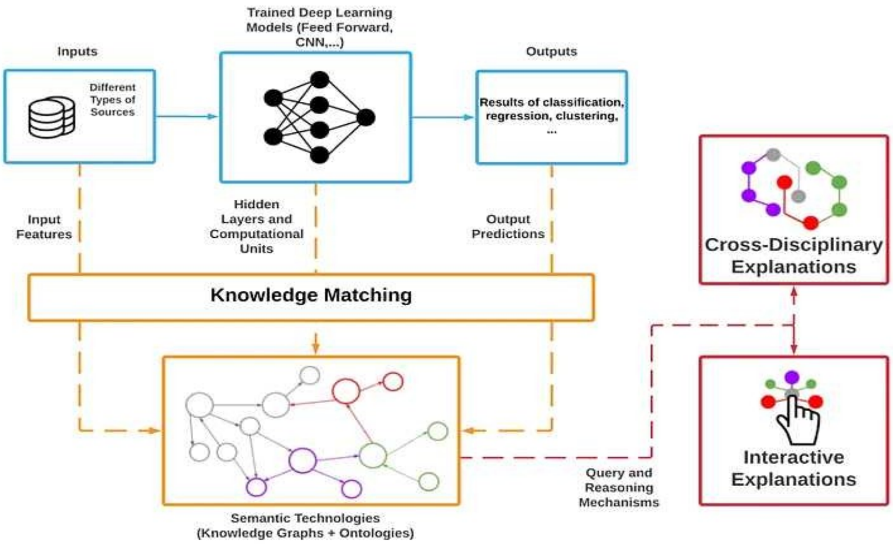


〈Figure 4-6〉 Classification of graph neural network methods by graph structure and size

2) XAI, Explainable Artificial Intelligence

A) Concept

Explainable AI refers to a series of processes and methodologies that enable human users to understand and trust the results and outputs produced by various machine learning algorithms. It first emerged in the 1970s when expert systems failed to explain their results to experts. Since then, its importance has been increasingly recognized, leading to the establishment of the term 'XAI' in 2004.



〈Figure 4-7〉 Representation of the XAI system

As a step in the evolution of AI, it is predicted that AI will be given the ability to explain its processes, allowing humans to understand the application of AI much more easily. This is generally expected to bring rationality to the interaction between computers and humans.

The General Data Protection Regulation (GDPR) promoted by the European Union is accelerating the introduction of 'Explainable AI' by enforcing the right to demand explanations. Cloud platform companies such as Amazon Web Services (AWS) and Google are also pursuing various forms of development in this area.

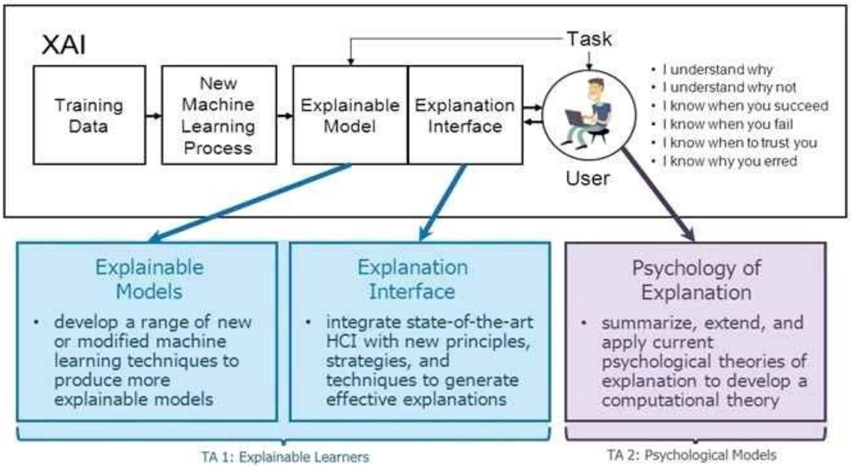
In Korea, as part of the government's 'AI National Strategic Project', support is being provided to industry, academia, and research fields to develop AI that can logically explain the basis for its reasoning and judgments.

B) Military Use Cases and Plans

The U.S. Department of Defense's Defense Advanced Research Projects Agency (DARPA) announced an XAI investment program in 2016 to ensure that practitioners can understand AI decision-making and trust the results for effective work in the fields of classified

information and strategic analysis, as well as the operation of unmanned autonomous systems. Since 2017, DARPA has been the most proactive in supporting XAI-related projects with substantial funding.

DARPA aims to develop explainable models that maintain high performance, ensuring that human users can understand, appropriately trust, and efficiently manage AI. To achieve this, DARPA has divided AI explainability into several aspects: predictive accuracy, inspection and traceability of actions performed by AI, among others.



〈Figure 4-8〉 The XAI conceptual diagram of 'DARPA'

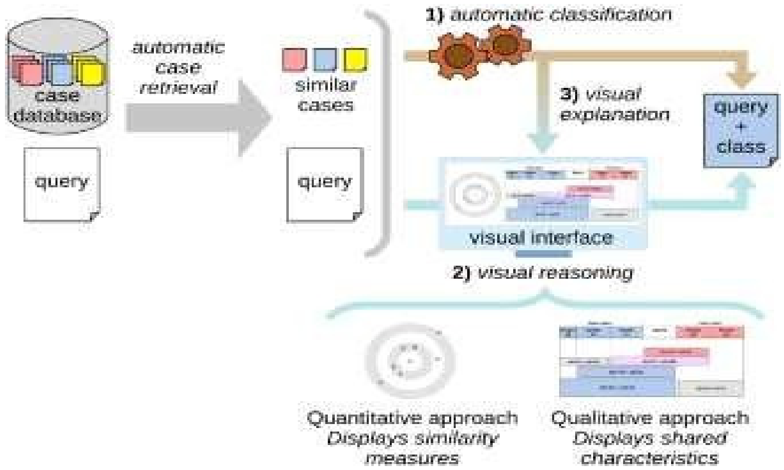
The XAI technique is a generic term for a kind of concept and method, and may be used in various military ways. For example, it may be applied to object identification for image information using a Convolutional Neural Network (CNN).

C) Private Use Cases

Although deep neural network-based models generally have high accuracy, it is pointed out as a representative problem of AI that it is difficult to find the basis for prediction and judgment in the form of a kind of 'black-box'.

In the private sector, explanations are needed from models in many fields such as medical care, finance, and various other domains.

In medical care, when AI models analyze medical records, brain images, and biometric data to diagnose various cancers and dementia, the reasons for the diagnosis can be identified. Lamy et al. (2019) automatically extracted similar cases for breast cancer screening and applied the concept of XAI both quantitatively and qualitatively.



〈Figure 4-9〉 The concept of applying XAI to breast cancer screening, as proposed by Lamy et al. (2019)

Japan's 'Skydisc' developed 'MotionBoard for SkyAI', an XAI model that identifies and explains the timing and causes of defects in automobile parts manufacturing. This model monitors real-time processes, predicts future failures and defects, and maximizes efficiency.

〈Figure 4-10〉 A demonstration screen of XAI monitoring of 'Skydisc' company

D) Sub-classification results[64)]

LIME(Local Interpretable Model-agnostic Explanations) is a concept that provides reasons for the results derived from the significant local features around a specific instance being explained. For example, if an image is predicted to contain a 'soldier', LIME would provide 'gun', 'boots', and 'uniform' as the reasons. The advantage of LIME is that it can be widely applied to artificial neural networks, ensemble methods, and traditional machine learning algorithms. Additionally, it can handle both structured data and unstructured data, such as images and text.

64) Choi, Jeong, Lee, Ahn & Lee. (2023). Explainable Artificial Intelligence on the Battlefield (Military-XAI, MXAI): Research for Military Application Scenarios. Korean Defense Industry Association, 30(1), 1-13.

LRP(Layer-wise Relevance Propagation) is a concept that backtracks the results of an artificial neural network model, calculates the contribution of each input in terms of sensitivity, and then identifies the parts that affect the model's performance. For example, if the image is predicted to contain a 'soldier', the degree to which each pixel contributed to this prediction is expressed in numbers or colors. Generally, this method involves decomposing the weight by calculating the Relevance score in the input direction, starting from the output value.

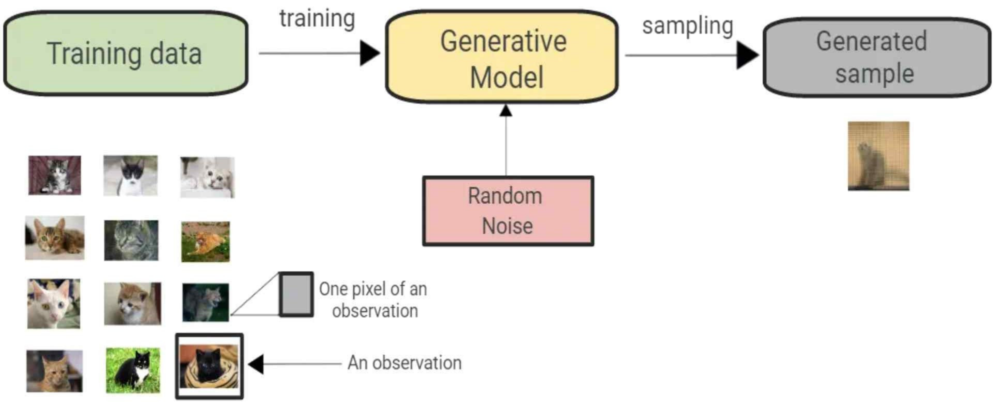
SHAP(Shapley Additive Explanations) is a method of explaining an AI model by calculating how much each data point affects the output based on the 'Shapley value'. The Shapley value, a concept introduced in game theory, calculates the contribution of each player in a game. In terms of data analysis, combinations of several features are formed to determine the contribution of a single data point, and the value is derived through the average changes according to the presence or absence of the feature. For example, when purchasing a car, if the price is $20,000 for the following specifications: 1) 2000cc engine, 2) four-wheel drive, 3) a specific brand, and 4) model year 2022, the concept involves determining how much each of these factors (1 to 4) influenced the price. For unstructured data such as images, the AI model calculates and presents the 'Shapley value' of the image features that influenced each inference result for candidate objects detected in order of probability.

Model-specific methods refer to explanation techniques that are suitable for specific types of AI models. For example, in the case of convolutional neural networks, representative methods include the 'activation method', 'weight visualization method', 'attribution method', and 'deconvolution method'.

3) Generative AI Model

A) Concept

Generative AI models generate synthetic data that follow the distribution of given data. These models use artificial neural networks to transform random numbers generated from commonly known probability distributions into synthetic data that resembles the original data.



〈Figure 4-11〉 Conceptual diagram of generative AI model

Representative generative AI models include Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and Generative Diffusion Models.

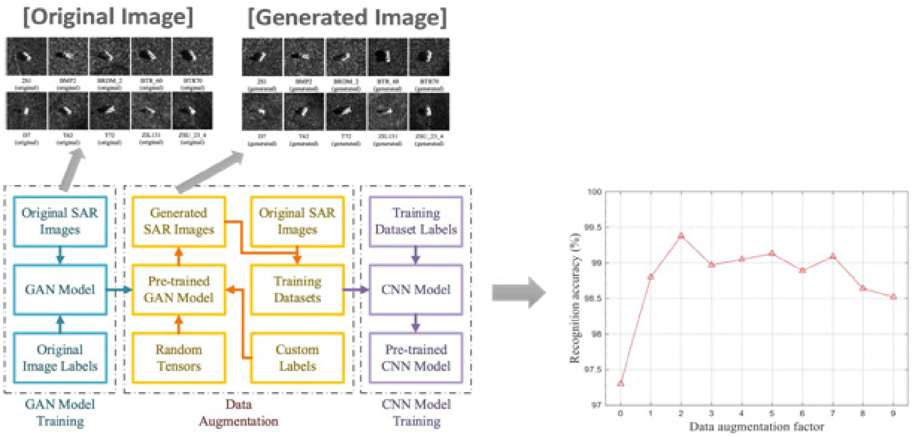
Initially, research was focused on VAE-based models. However, with the development of GANs, the GAN model has become widely used for applications such as image and voice generation. Additionally, active research is ongoing for generative diffusion models.

〈Figure 4-12〉 Applications of Generative Adversarial Networks

B) Military Use Cases and Plans

Generative AI models can be widely used in various domains such as image, voice, and text generation. In this study, to avoid redundancy with other technology classifications, use cases are presented focusing on data augmentation and high-resolution image generation.

Generative AI models are continuously improving their performance in generating image data. For example, it has been reported that data augmentation using GANs can improve performance in Synthetic Aperture Radar (SAR) satellite images.[65]

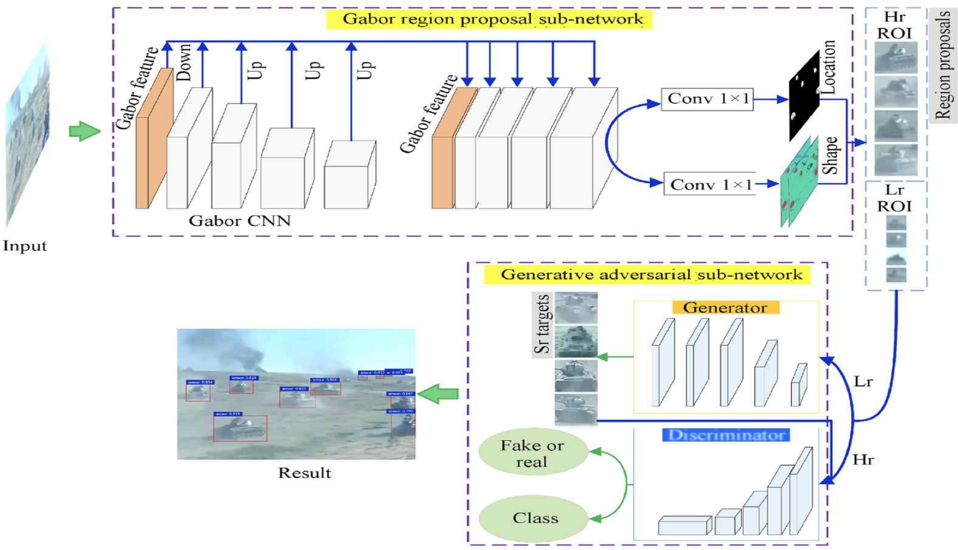


〈Figure 4-13〉 A Case Study on the Improvement of Object Detection Performance through GAN Model-Based SAR Data Augmentation

GAN models can be employed to enhance the resolution of low-resolution original images. This method involves training a generator to produce high-resolution images such that a discriminator cannot distinguish between the low-resolution original image and the high-resolution image.[66]

65) Kong, J. & ZHang, F. (2021). SAR target recognition with generative adversarial network-based data augmentation, In 13th International Conference on Advanced Infocom Technology (ICAIT), (pp. 215-218).

66) Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., Aitken, A., Tejani, A., Totz, J., Wang, Z. & Shi, W. (2017). Photo-realistic single image super-resolution using a generative adversarial network. In IEEE Conference on Computer Vision and Pattern Recognition, 105-114.



〈Figure 4-14〉 High resolution image generation case based on GAN model

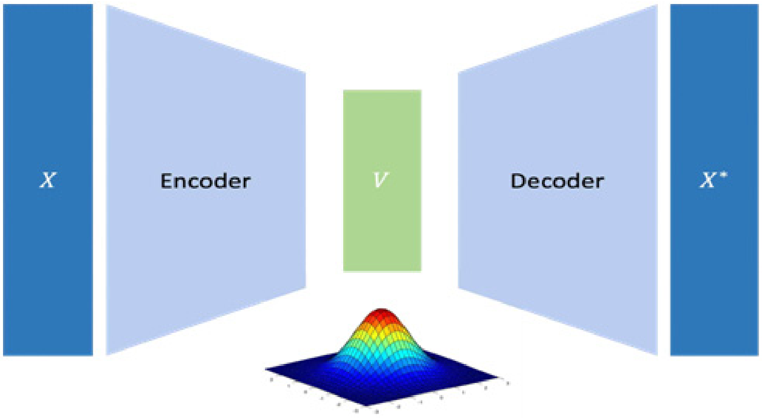
C) Private Use Cases

Naver's subsidiary Snow launched the "AI Profile Service," which utilizes technology to generate image photos of various concepts based on 10 to 20 user-uploaded photos.

D) Sub-classification results

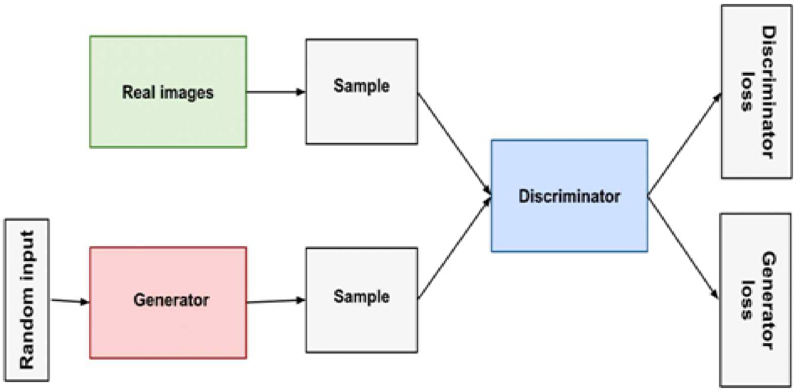
A Variational Autoencoder (VAE) approximates the distribution of latent representations using a variational posterior distribution based on the prior distribution of the latent expression in the autoencoder model of representation learning. It generates random numbers through the distribution of latent representations like the original data using the Decoder.[67]

67) Kingma, D. P., & Welling, M. (2014). Auto-Encoding Variational Bayes. stat, 1050, 1.



〈Figure 4-15〉 Conceptual Structure of the VAE Model

The Generative Adversarial Network (GAN) consists of a generator and a discriminator. The generator aims to produce data like the original data by receiving random numbers from a predefined probability distribution. The discriminator is trained to classify between the original data and the synthesized data generated by the generator.[68]

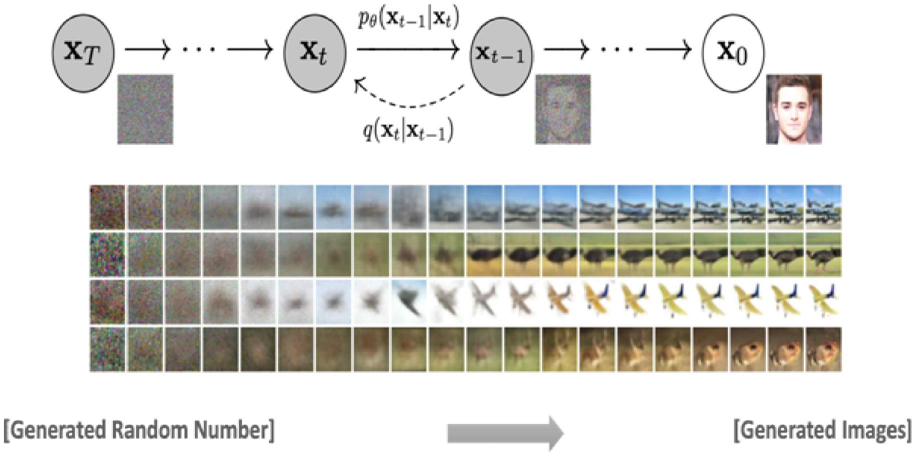


〈Figure 4-16〉 Conceptual Structure of GAN Model

The Generative Diffusion Model, a recently studied generative model, assumes the original data is in an error-free initial state and considers the diffusion model over

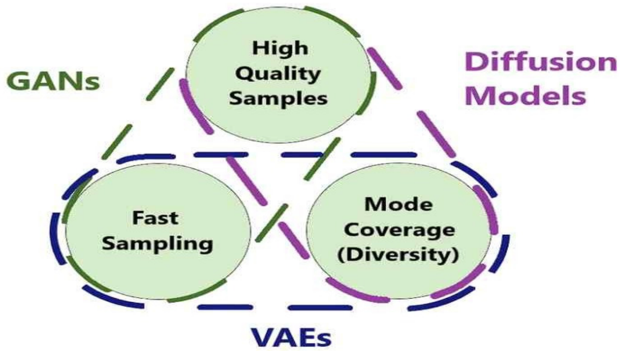
68) Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville A. & Bengio Y. (2014). Generative adversarial nets. Advances in neural information processing systems, 2672-2680.

time. It assumes the probability process follows a known probability distribution at the final point when errors accumulate over time. By offsetting the accumulated error, the model generates synthetic data through a reverse conversion process to the initial state.[69].



〈Figure 4-17〉 Examples of the conceptual structure of the generative diffusion model and the process of data generation

When comparing the characteristics of representative generative AI models, each has its own advantages and disadvantages in terms of fast sampling, high-quality samples, and model coverage (diversity).



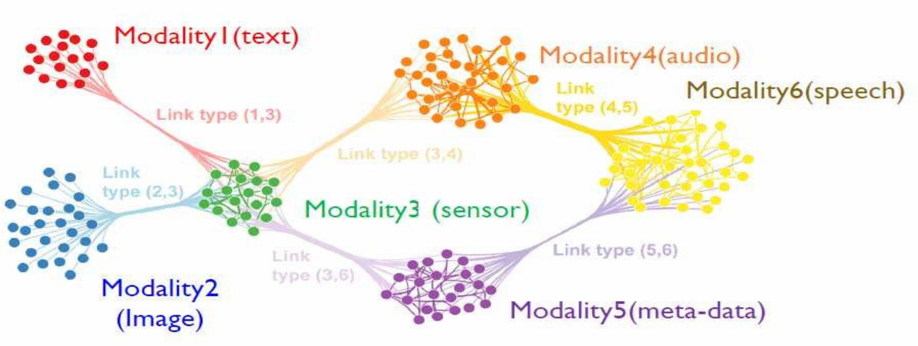
〈Figure 4-18〉 Comparison of sub-classification technology features

69) J. Ho, A. Jain, and P. Abbeel. (2020). Denoising diffusion probabilistic models, In Proceedings of the 34th International Conference on Neural Information Processing Systems (pp. 6840-6851).

4) Multi-modal Learning

A) Concept

'Multi-modal' stands for a Multi-modal interface, which involves exchanging information using voice, keyboard, and pen for communication between people and machines. Multi-modal data refers to expressing information from various sources.



〈Figure 4-19〉 Concept of Multi-modal

Multi-modal learning is a method of training a model using data from various modalities (vision, text, speech, touch, smell) collected from the five human sensory organs.

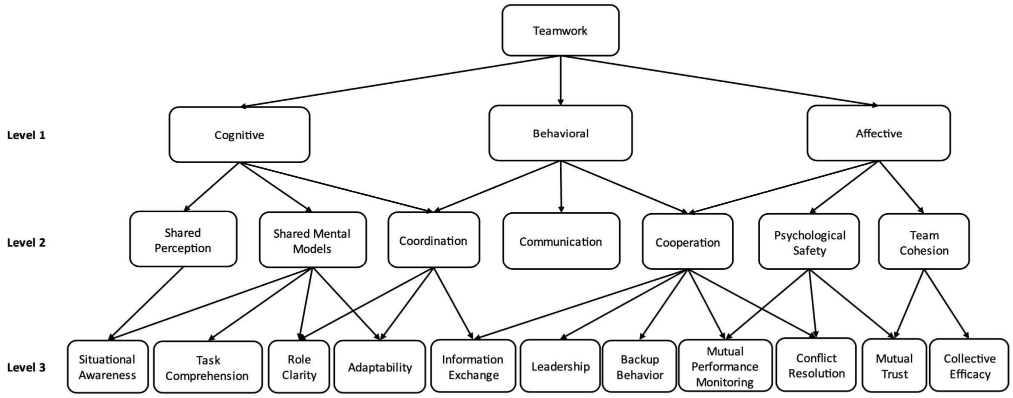
The purpose of Multi-modal learning is to learn a model using various types of data and to obtain more accurate results using richer information based on this, which has recently attracted attention in various fields.

Multi-modal learning utilizes a variety of resources, which can alleviate the data shortage problem that can occur in existing AI models.

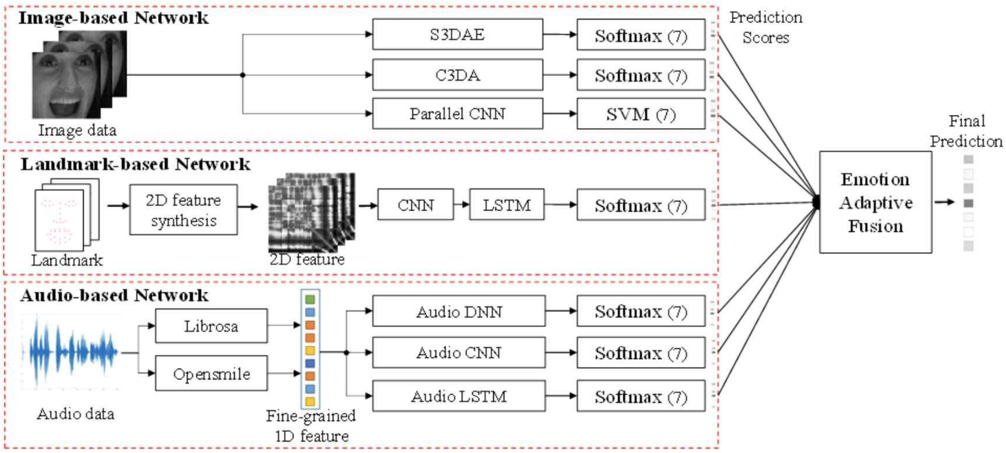
Furthermore, the complementary nature of the data further improves the performance of the AI model, allowing it to solve problems more accurately and effectively.

B) Military Use Cases and Plans

'Human activity recognition' is a technology that automatically detects and analyzes human actions or activities using computer vision, artificial intelligence, sensor technology, etc. Multi-modal learning can be applied in the field of human activity recognition, which can be utilized in training systems for soldiers. Teamwork is crucial when soldiers carry out operations, and it is composed of hierarchical forms of affective, cognitive, and behavioral interactions. Since CNN and LSTM are deep learning models that perform well in processing video and audio data, combining them enables more sophisticated training by accurately analyzing soldiers' data obtained from various sensors during training.70)



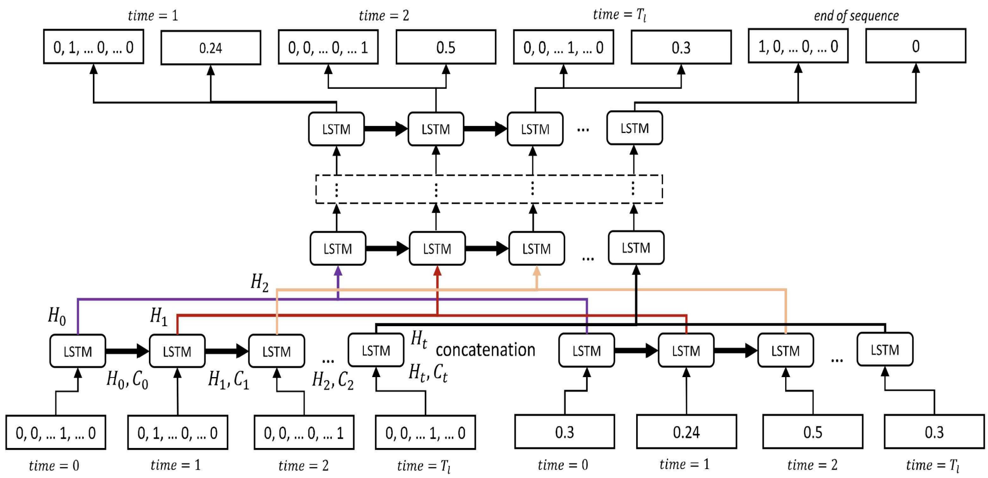
〈Figure 4-20〉 The framework of interaction, cognition, and behavior that make up teamwork



〈Figure 4-21〉 Example of Multi-modal learning model combining deep learning model

70) Kim, Song (2018). Multi-modal Emotion Recognition using Semi-supervised Learning and Multiple Neural Networks in the Wild. JBE, 23(3), 351-360.

Multi-modal learning can be applied to military surveillance systems. The data obtained from military surveillance systems consists of real-time video and audio. Since deep learning models based on Long LSTM(Short-Term Memory) can effectively analyze real-time data, constructing a Multi-modal architecture that analyzes both video and audio simultaneously will enable more accurate detection of abnormal behaviors and objects by leveraging the information obtained from both data types.71)



〈Figure 4-22〉 Multi-modal LSTM architecture

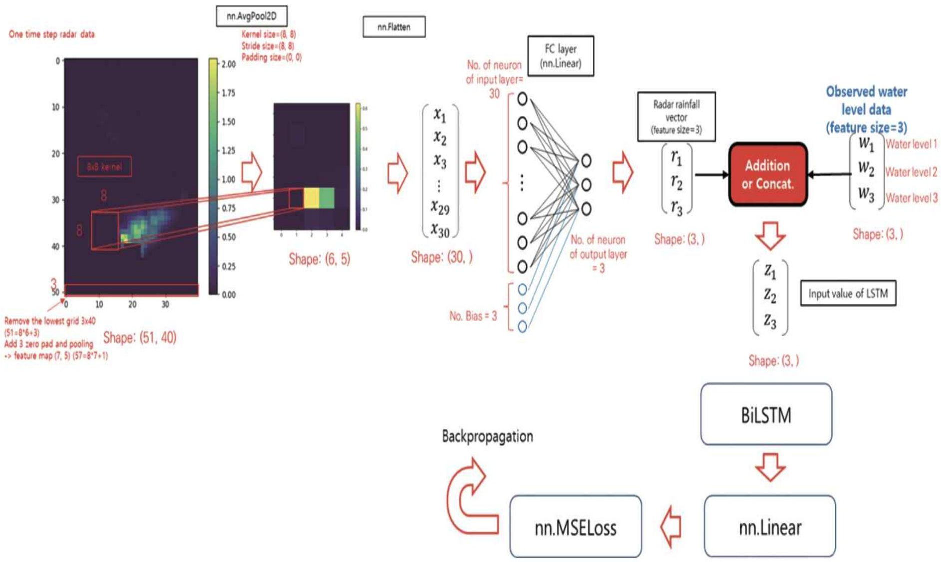
C) Private Use Cases

Considering that Multi-modal learning, combined with deep learning, is being utilized in various fields, this study presents cases where Multi-modal learning based on deep learning models is applied.

With the advancement of cutting-edge observation technology, various forms of data are being constructed, making it possible to utilize deep learning model-based Multi-modal learning models in water resource management. Traditionally,

71) Nedelkoski, S., Cardoso, J., and Kao, O. (2019). Anomaly detection from system tracing data using Multi-modal deep learning. 2019 IEEE 12th International Conference and Cloud Computing (CLOUD).

time-series data of rainfall, water levels, and flow rates have been used in water resource management. However, recent advancements in observation technologies such as sensors, RADAR, and satellites have enabled the collection of various types of data. Therefore, utilizing deep learning model-based Multi-modal learning models allows for more sophisticated water resource management.72)



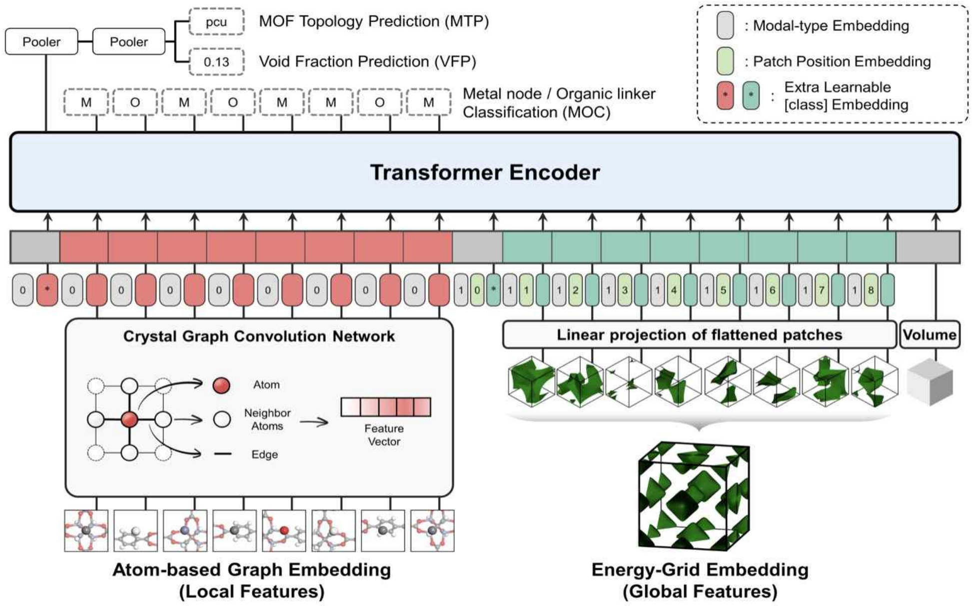
〈Figure 4-23〉 Example of the structure of a Multi-modal learning model based on a deep learning model for water resource management]

D) Sub-classification results

A Multi-modal transformer applies the transformer architecture to Multi-modal data, modeling interactions between various modalities. In the Multi-modal transformer, input data from various modalities are inputted into separate encoders, where the characteristics of each modality are extracted and then combined to effectively represent Multi-modal information. While transformers have shown strong performance mainly in natural language processing, Multi-modal transformers are

72) Yoon (2023). Multi-modal Deep Learning Technology and Utilization of Water Resources. Korean Society of Water Resources, 56, 2023.6.

useful for considering interactions between different modalities. Multi-modal transformers are utilized in various fields, including image captioning, video QA, and Multi-modal machine translation.[73)]

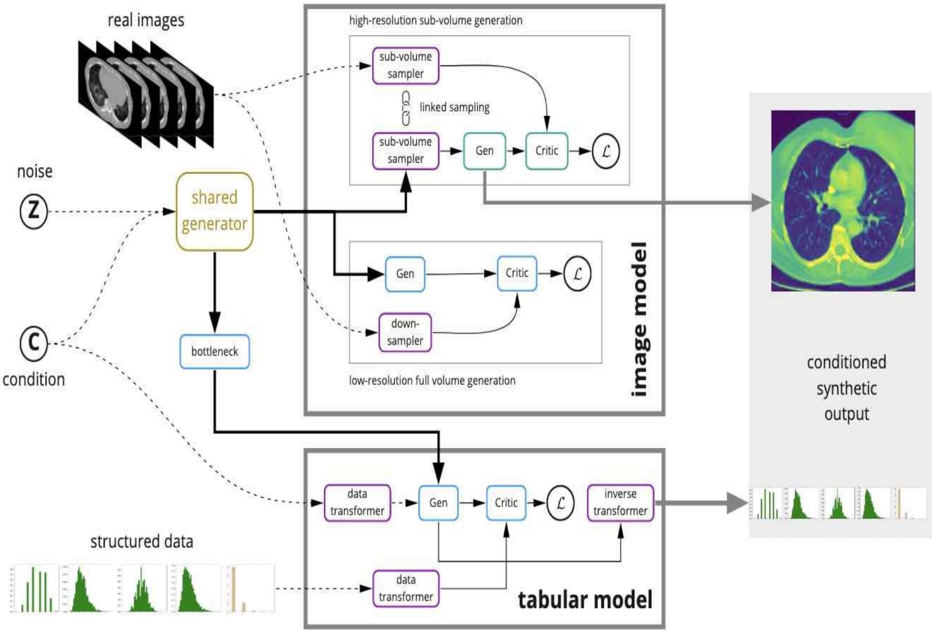


〈Figure 4-24〉 Example of Multi-modal transformer architecture

A Multi-modal generative model is a deep learning model that takes data from various modalities as input and generates new data for those modalities. Compared to traditional generative models, Multi-modal generative models use data from various modalities, increasing data diversity and making them useful for data augmentation and enhancement. Multi-modal generative models are utilized in various fields, including image caption generation, text-to-image generation, speech synthesis, and image generation.[74)]

73) Kang, Y., Park, H., Smit, B., and Kim, J. (2023). A Multi-modal pre-trainning transformer for universal transfer learning in metal-organic frameworks. Nature Machine Intelligence, 5, 309-381.

74) Ziegler, J. D., Subramaniam, S., Azzarito, M., Doyle, O., Krusche, P., & Coroller, T. (2022). Multi-modal conditional gan: Data synthesis in the medical domain. In NeurIPS 2022 Workshop on Synthetic Data for Empowering ML Research.

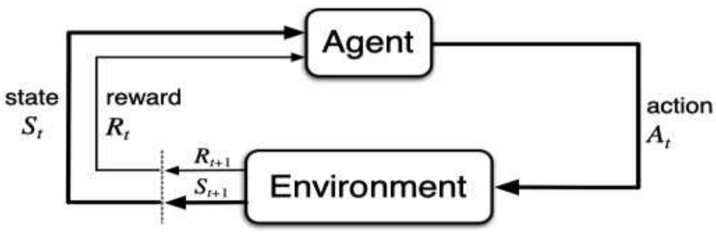


〈Figure 4-25〉 Example of Multi-modal Conditional-GAN architecture

5) Single Agent Reinforcement Learning

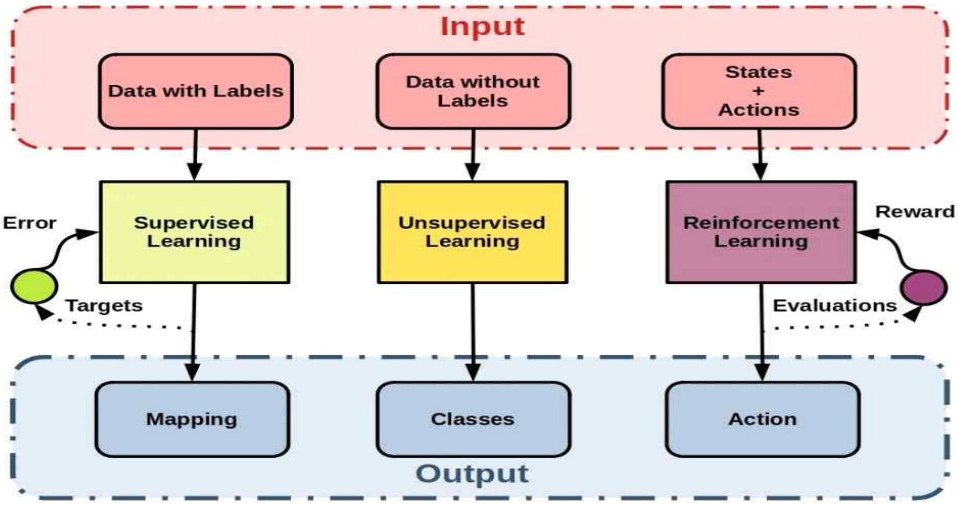
A) Concept

Single agent reinforcement learning involves an agent that determines actions based on the state, environment, action, and reward, which are the components of reinforcement learning. The state, environment, behavior, and reward continuously circulate and interact. Reinforcement learning selects one action at each time point, with these choices being sequential and iterative. The optimal action is the one that maximizes the reward in each state and environment.



〈Figure 4-26〉 Components and Overview of Reinforcement Learning

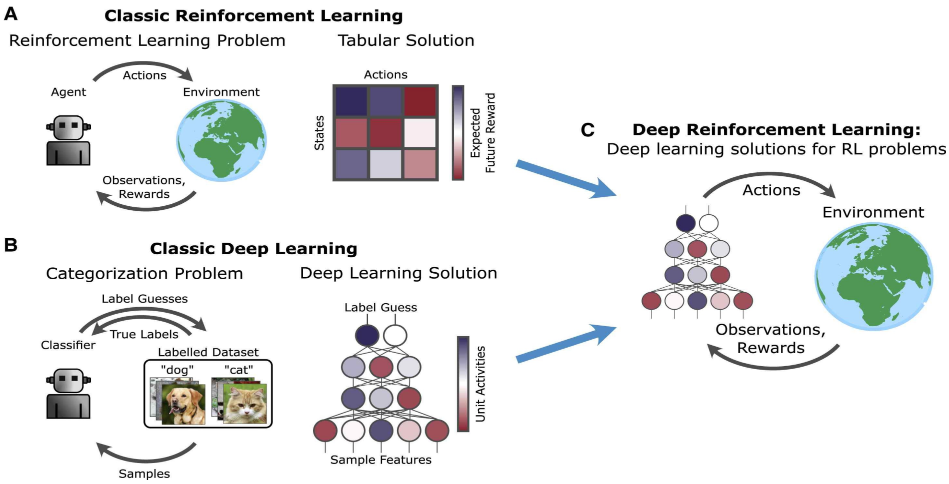
Reinforcement learning aims to develop a model that makes the best decision under a given state. Recently, it has evolved from traditional probability model-based reinforcement learning to artificial neural network-based reinforcement learning. Historically, reinforcement learning involved designing the entire interaction between environment, state, and behavior as a probabilistic model and estimating the model's parameters. However, current research focuses on using artificial neural network models that observe the state within a given system and learn the optimal decision-making policy.75)



〈Figure 4-27〉 A form of reinforcement learning based on artificial neural networks

Reinforcement learning starts from an initial state without given data and gathers information (state, action, and reward) at each time point. Unlike supervised and unsupervised learning, which rely on given data, reinforcement learning continuously balances the exploration of new information and the exploitation of acquired information.

75) Botvinick, M., Wang, J. X., Dabney, W., Miller, K. J. & Kurth-Nelson, Z. (2020). Deep reinforcement learning and its neuroscientific implications, Neuron, 107(4), 603-616.



〈Figure 4-28〉 Comparison of Reinforcement Learning, Supervised Learning, and Unsupervised Learning

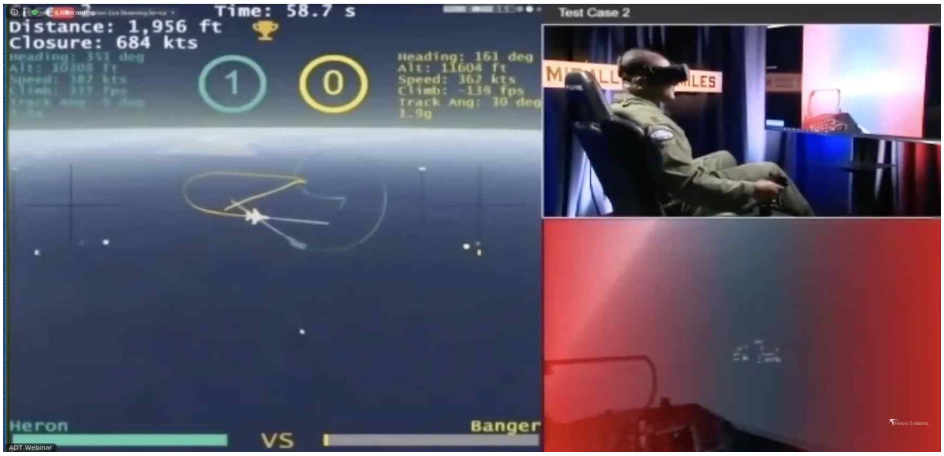
B) Military Use Cases and Plans

Reinforcement learning can be utilized to learn optimal operational plans or instructions within a simulated combat environment and can also be applied to mandatory evacuation plans. A study based on the Markov decision process demonstrated that optimal asset placement and operation for mandatory evacuation during wartime casualties significantly improved in terms of utility and asset management balance compared to the policy of deploying the nearest assets to casualties through simulation.[76)]

In DARPA's AlphaDogfight Trial, the AI agent of the Heron system, trained with reinforcement learning, won the aerial warfare simulation against F-16 aircraft. Additionally, researchers from Lockheed Martin and the U.S. Air Force presented a reinforcement learning model for AI agents that ranked second in DARPA's AlphaDogfight Trial in a published paper.[77)]

76) Keneally, S. K., Robbins, M. J. & Lunday, B. J. (2016). A Markov decision process model for the optimal dispatch of military medical evacuation assets, Heath Care Management Science, 19, 111-129.

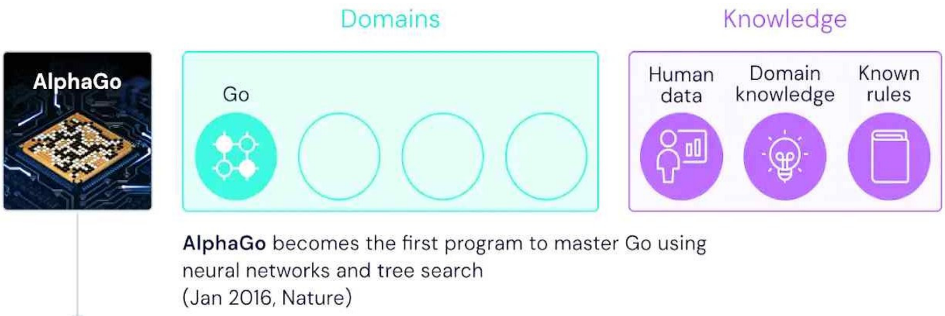
77) Pope, A. P., Ide, J. S., Mićović, D., Diaz, H., Rosenbluth, D., Ritholtz, L., ... & Javorsek, D. (2021, June). Hierarchical reinforcement learning for air-to-air combat. In 2021 international conference on unmanned aircraft systems (ICUAS) (pp. 275-284). IEEE.



〈Figure 4-29〉 Example of a simulated battle between an AI agent and an F-16 pilot

C) Private Use Cases

A typical example of reinforcement learning is Google's AlphaGo, which demonstrated its capabilities in games such as Go and chess.



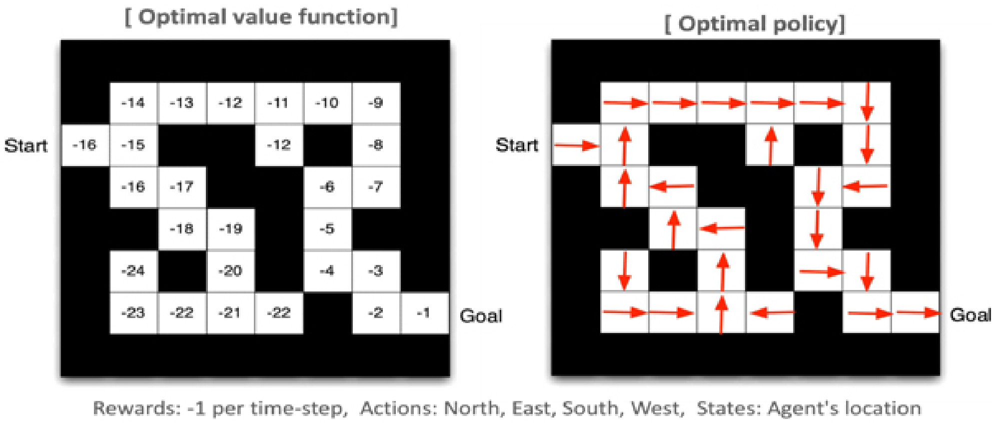
〈Figure 4-30〉 AlphaGo by Google DeepMind

D) Sub-classification results[78)]

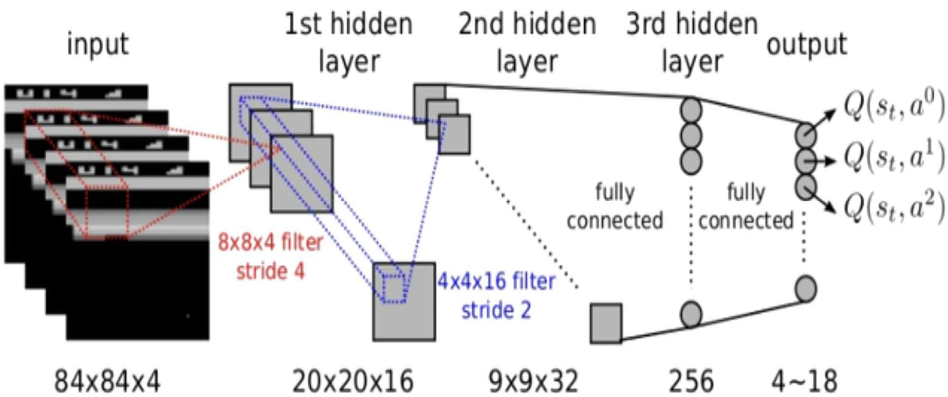
In value-based reinforcement learning, the value function is defined as the expected reward for a given state and policy. The optimal policy is the one that maximizes

78) Arulkumaran, K., Deisenroth, M. P., Brundage, M. & Bharath, A. A. (2017). A brief survey of deep reinforcement learning, IEEE Signal Processing Magazine, 34, 26-38.

the value function for all states within the possible state space. The state-action value function, commonly denoted as the Q-function, represents the expected reward for the initial state and action. Deep learning-based value reinforcement learning estimates the Q-function using an artificial neural network model, with the Deep Q-learning Network (DQN) being a representative model, particularly exemplified in reinforcement learning for Atari games.[79]



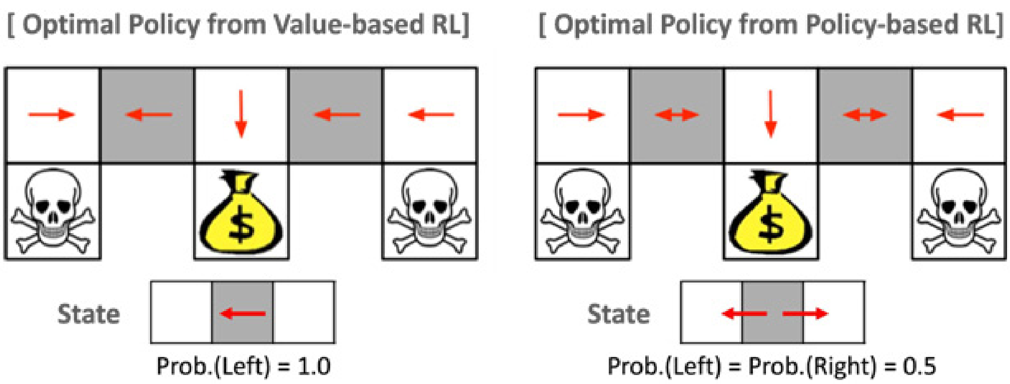
〈Figure 4-31〉 Example of Reinforcement Learning for Maze Exit Example



〈Figure 4-32〉 Learning Case for DQN's Atari Game

79) Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., and Riedmiller, M. (2013). Playing atari with deep reinforcement learning. arXiv:1312.5602.

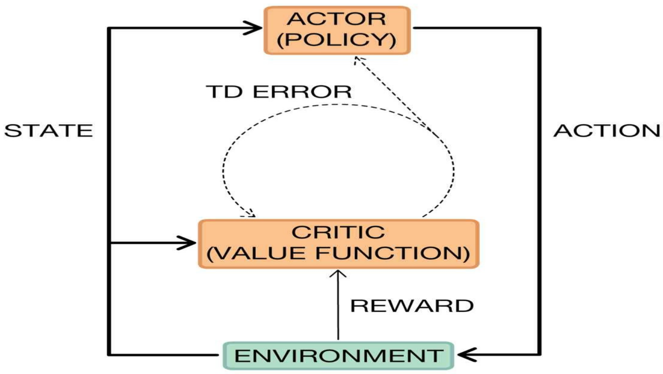
Policy-based reinforcement learning treats the value function as a function of a policy and learns parameters based on this policy model. While value-based reinforcement learning is efficient for small action spaces, policy-based reinforcement learning excels in high-level or continuous action spaces. Compared to value-based methods, policy-based reinforcement learning often converges to a local optimum rather than a global optimum, and the learned policies exhibit relatively high volatility. Whereas value function-based reinforcement learning tends to choose deterministic policies, policy-based reinforcement learning can select probabilistic policies.



〈Figure 4-33〉 Comparison of value-based reinforcement learning and policy-based reinforcement learning

Actor-Critic reinforcement learning combines value function estimation with policy evaluation to reduce variance in policy gradient learning. Depending on the function used in policy evaluation, methods include Q Actor-Critic, Advantage Actor-Critic, and TD Actor-Critic.[80]

80) Arulkumaran, K., Deisenroth, M. P., Brundage, M. & Bharath, A. A. (2017). A brief survey of deep reinforcement learning, IEEE Signal Processing Magazine, 34, 26-38.



〈Figure 4-34〉 Actor-Critic-Based Reinforcement Learning Conceptual Structure

6) Autonomous System

A) Concept

The autonomous system is installed in a vehicle to enable it to drive autonomously. The principles of autonomous driving can be broadly divided into localization, perception, decision-making, and control.

Using GPS technology to determine the vehicle's location and sensors such as LIDAR, RADAR, and cameras to understand the surrounding environment, the system then employs AI technology to decide the control methods and execute the driving tasks.

The autonomous system uses various technologies, including RADAR, LIDAR, GPS, odometers, and computer vision, to detect its surroundings.

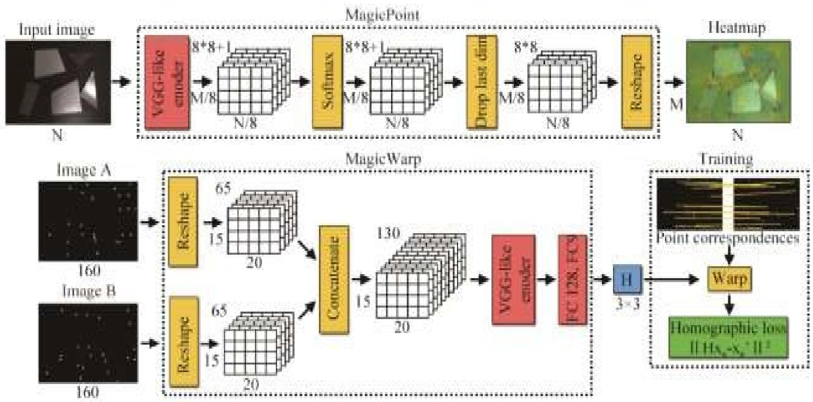
LIDAR(Light Detection and Ranging) is a device that emits laser pulses and measures the distance to surrounding objects by receiving the reflected light from these objects. This allows it to accurately map the surrounding environment.

RADAR is a wireless surveillance device that emits microwaves (ultrahigh frequency waves with wavelengths ranging from 10 cm to 100 cm) at an object and receives the electromagnetic waves reflected from that object to determine the distance, direction, and altitude of the object.

Ultrasonic sensors refer to sensors that utilize the properties of ultrasound. They play roles in various fields, including speed measurement, distance measurement, and concentration/viscosity measurement. There are different types of sensors depending on their purpose.

B) Military Use Cases and Plans

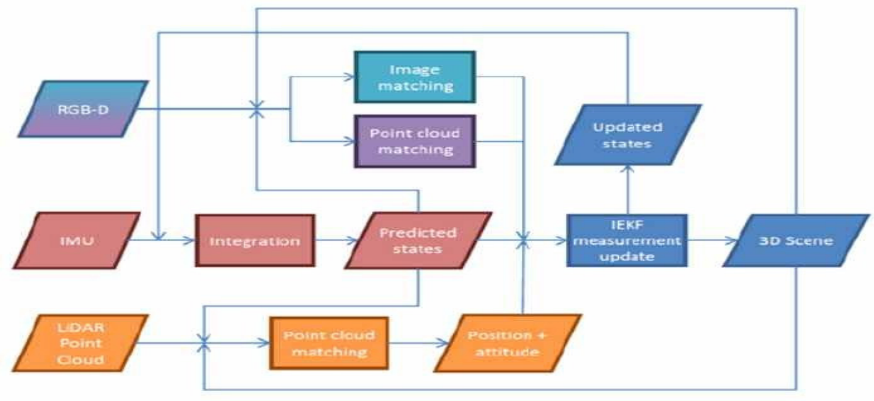
This study presents a military autonomous system utilizing sensor fusion technology and Simultaneous Localization and Mapping (SLAM). Sensor fusion technology refers to the technique of combining inputs from multiple sources, such as cameras, RADAR, and LIDAR, into a single cohesive input. In research[81], a model is proposed that applies a CNN-based neural network to traditional SLAM, enabling more accurate localization. By applying sensor fusion technology to drones, robots, unmanned aerial vehicles, and mobile equipment equipped with LIDAR, RADAR, and optical-based sensors, data features can be extracted, and deep learning-based SLAM technology can be applied. This can be utilized in the development of autonomous systems capable of accurately perceiving and understanding the surrounding environment and situations.[82]



〈Figure 4-35〉 CNN and SLAM technology convergence structure

81) Zhang, H. (2022). Deep learning applications in simultaneous localization and mapping. In Journal of Physics: Conference Series (Vol. 2181, No. 1, p. 012012). IOP Publishing.

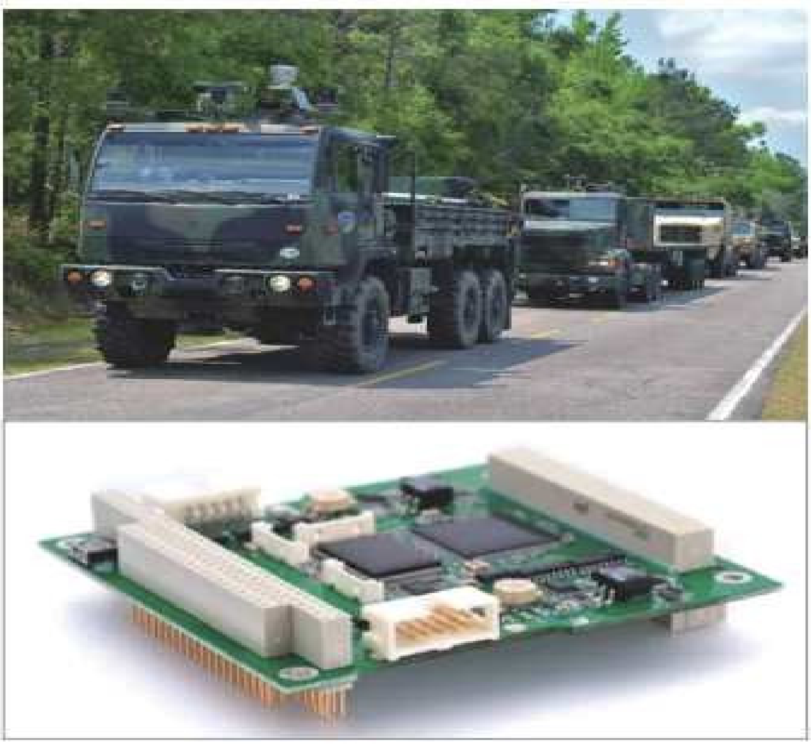
82) Chow, J. C., Lichti, D. D., Hol, J. D., Bellusci, G., & Luinge, H. (2014). IMU and multiple RGB-D camera fusion for assisting indoor stop-and-go 3D terrestrial laser scanning. Robotics, 3(3), 247-280.



〈Figure 4-36〉 SLAM technology using LiDAR and various input data

The CAN (Controller Area Network) board is a device that implements basic sensor fusion, developed through the collaboration of the U.S. Army's TARDEC (Tank Automotive Research, Development, and Engineering Center), the ARDEC (Armament Research, Development, and Engineering Center), and the UK's DSTL (Defence Science and Technology Laboratory). Military autonomous vehicles operated through the CAN board[83] include the CAN bus. The CAN board is a board that implements a message-based protocol that simplifies communication between various sensors inside the vehicle. Without a central computer, each sensor or piece of equipment can send and receive information in series through the CAN board, quickly exchanging the information necessary for driving. The advantage of not having the central computer is that it reduces the time required for information exchange between sensors, which is particularly suitable for military vehicles in wartime that require more immediate responses. The CAN bus equipped with the CAN board communicates information from four sensors to identify the surrounding environment and the location of the vehicle. The CAN board aggregates data from LIDAR for front three-dimensional road maps, stereo cameras that collect information such as obstacle locations and road signs, infrared cameras for night obstacle detection, and GPS sensors, and makes driving judgments appropriate to the surrounding situation.

83) Kim. (2023). Sensor convergence technology for autonomous driving of military vehicles. Defense and technology, (533),150-159.

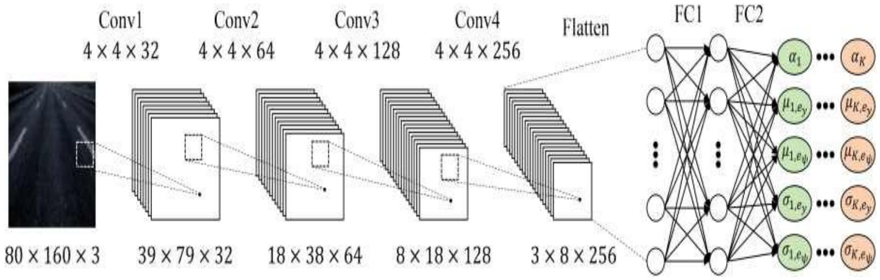


〈Figure 4-37〉 CAN bus of the U.S. military and sensor fusion board

C) Private Use Cases

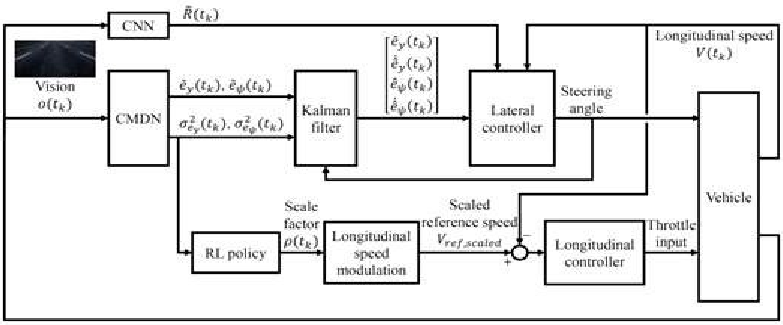
A deep learning model can be trained to predict lane deviation, obstacle detection, and collision risk from camera vision, and this can be used for driving situation awareness. In research[84], a vision-based lane-keeping system that considers uncertainty was developed. CMDN (Convolutional Mixture Density Network) is a new deep learning model that combines a CNN model for extracting spatial features from images and an MDN (Mixture Density Network) model for estimating the uncertainty of driving state variables. The Mixture Density Network is a type of neural network structure where the output variable is modeled as a mixture of multiple probability distributions.

84) Kim, M., Seo, J., Lee, M., & Choi, J. (2021). Vision-based uncertainty-aware lane keeping strategy using deep reinforcement learning. Journal of Dynamic Systems, Measurement and Control, Transactions of the ASME, 143

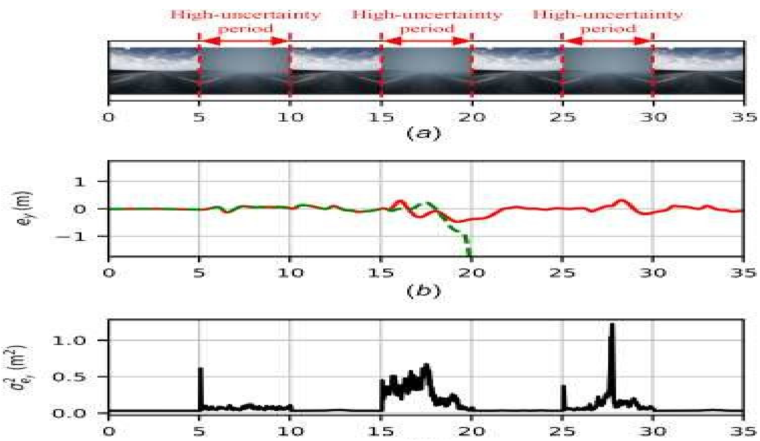


〈Figure 4-38〉 Convolutional Mixture Density Network (CMDN) model

A higher-level gain-scheduled control system hierarchically controls the lower-level lateral control inputs and longitudinal speed, taking uncertainties into account. This system adjusts the speed according to conditions such as snow, rain, or fog, where image accuracy may be compromised, thereby reducing the risk of accidents.



〈Figure 4-39〉 Vision-based uncertainty-considered lane keeping system



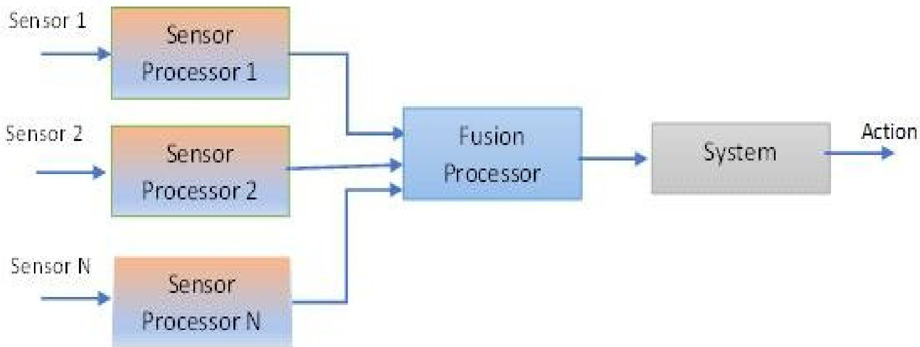
〈Figure 4-40〉 Misty conditions and location error data

D) Sub-classification results

RADAR, LIDAR, and specialized sensor data processing technologies are used in autonomous systems for detecting objects in blind spots, short-range object detection, long-range object detection, and 3D map reconstruction. Technologies such as 3D CNN, PointNet, and PointNet++ models are commonly utilized to implement object detection and environmental perception capabilities.

Simultaneous Localization and Mapping (SLAM) is a technology that allows agents such as robots or autonomous vehicles to simultaneously estimate their position and map the surrounding environment in an unknown area. Prominent technologies include visual SLAM, which uses cameras to understand the environment, LiDAR SLAM, which processes 3D point cloud data more effectively to detect and map objects, and Deep SLAM technology.

Sensor fusion technology integrates data collected from various sensors, such as LIDAR, RADAR, and cameras, to obtain more accurate and comprehensive information, thereby enabling more reliable decision-making. Various models are used to combine data collected from various sensors. These include Recurrent Neural Networks (RNNs), CNNs, Transformer Networks, PointNet and PointNet++ for generating 3D point clouds, Kalman Filters, and Variational Autoencoders. PointNet is a type of artificial neural network that, unlike general CNNs, uses point clouds as input and produces labels for the input points as output.



〈Figure 4-41〉 Sensor fusion input data processing process

7) Federated learning

A) Concept

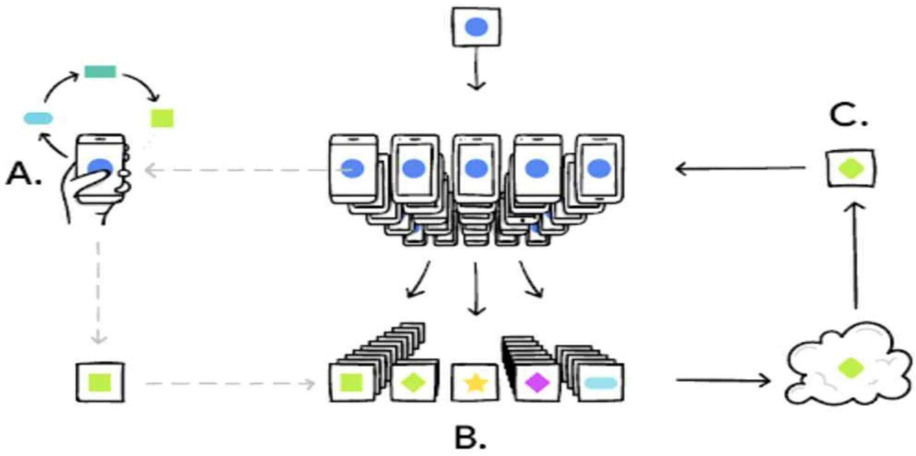
Federated learning is a distributed machine learning method that trains AI models by aggregating distributed data generated and stored in various locations to a central server. It emerged as a solution to overcome the limitations of centralized data processing methods used in traditional distributed machine learning.

Since Google proposed federated learning as a next-generation AI learning method in 2016, it has primarily been studied in the context of supervised learning. However, its scope is expanding through integration with other AI learning methods such as unsupervised learning and transfer learning.

Federated learning analyzes data from local storage where data is created and stored without directly sharing the data itself. This approach improves the data throughput of the central server, ensures data anonymity, and protects personal information while allowing its use.

The federated learning process consists of three main steps:

- Local Training: Each local AI model is trained using local data
- Global Model Update: The weights derived from local training are sent to the central server, where they are combined in various ways (e.g., FedAvg, FedSGD) to update the global model
- Local Model Update: The updated weights of the global model are transmitted back to the local servers to update the local models



〈Figure 4-42〉 Example of Combined Learning on Smartphones

B) Military Use Cases and Plans

Federated learning can efficiently manage the complex computations required to operate numerous unmanned combat systems simultaneously. It can also be utilized to develop AI learning architectures for different units with heterogeneous characteristics.

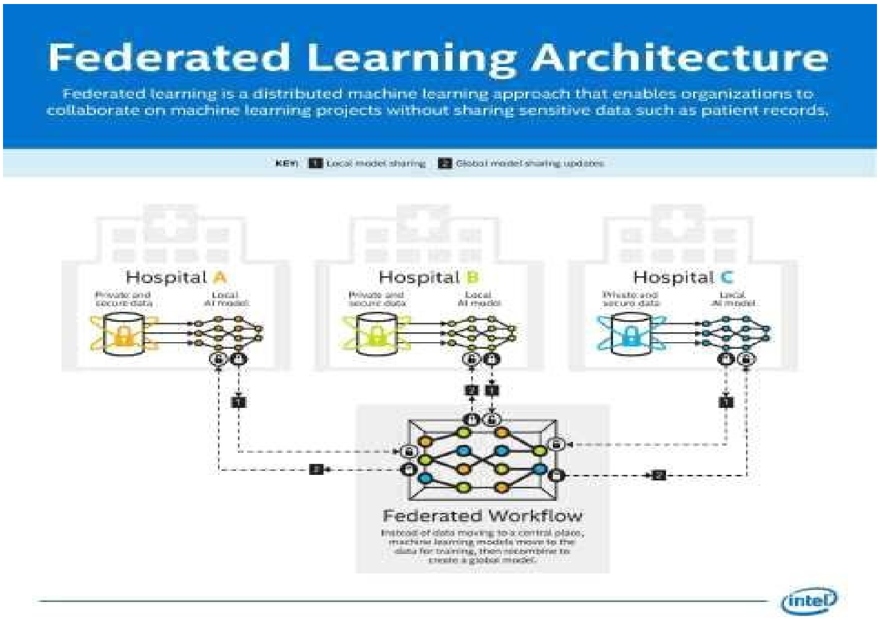
Utilizing existing tactical data links, it is possible to construct an AI learning architecture based on the joint learning concept. This involves integrating the weapon system models of each platform with a central headquarters server.

Applying federated learning algorithms to scientific boundary systems can enhance effectiveness by reducing communication load and ensuring military security. Starting with an initial CNN model transmitted from the center, each unit can conduct boundary operations, update their models, and send weight update information to the central server. The central server then updates the entire CNN model, reflecting the similarity rates of the unit environments based on terrain, thus enabling federated learning.

C) Private Use Cases

Federated learning is most actively utilized in the medical field, where it ensures personal privacy while using data that are otherwise difficult to obtain.

Scheller et al. (2018) from Intel Lab and the University of Pennsylvania Perelman School of Medicine presented results showing that federated learning for brain tumor identification can achieve accuracy approaching more than 99% of existing AI model learning methods, even without compromising privacy.[85)]



〈Figure 4-43〉 Structures of a combined learning system for brain tumors proposed by Intel Labs and the University of Pennsylvania

In 2019, NVIDIA and King's College London proposed a neural network-based federated learning algorithm for brain tumor identification at the Medical Imaging Technology Society, demonstrating its effectiveness.[86)]

85) Sheller, M. J., Reina, G. A., Edwards, B., Martin, J., & Bakas, S. (2019). Multi-institutional deep learning modeling without sharing patient data: A feasibility study on brain tumor segmentation. In Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: 4th International Workshop, BrainLes 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 16, 2018, Revised Selected Papers, Part I 4 (pp. 92-104). Springer International Publishing.

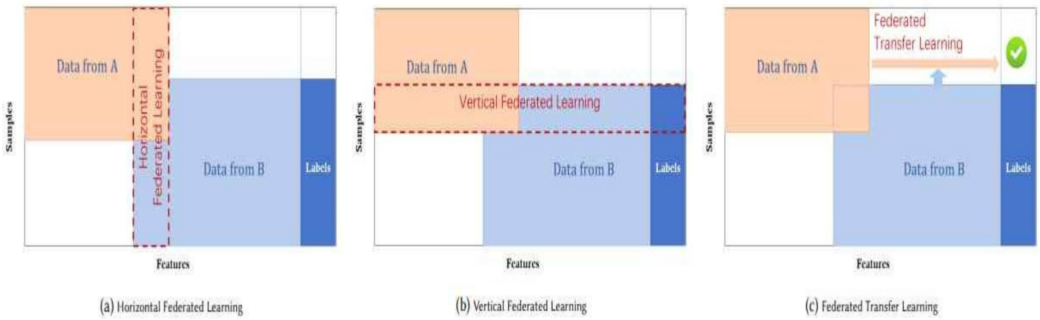
86) Li, W., Milletari, F., Xu, D., Rieke, N., Hancox, J., Zhu, W., Baust, M., Cheng, Y., Ourselin, S., Cardoso, M. J., & Feng, A. (2019). Privacy-preserving federated brain tumour segmentation. International Workshop on Machine Learning in Medical Imaging, MLMI 2019: Machine Learning in Medical Imaging, 133-141.

D) Sub-classification results

Horizontal federated learning is a method applied to data from different groups that share the same features. Individuals train locally and then share updated parameters to collectively update the global model, like the method used by Google for Android model updates. This approach is advantageous for areas such as the medical and financial sectors, where AI utilization is hindered by privacy concerns.

Vertical federated learning applies to different data features within the same group, integrating these features to produce a common model without directly exchanging data to ensure data security. Because data sharing is impossible, an uninterested third party typically intervenes to update and distribute the global model. This method can be utilized to expand new business opportunities.

Federated transfer learning applies to different features from different groups and is characterized by having the least common data compared to other federated learning methods. It borrows the large framework of the vertical federated learning architecture but provides different results by focusing on minimizing prediction errors while exchanging common features. This method extends the scope of existing federated learning, enabling the development of more flexible and powerful models to address new problems.



〈Figure 4-43〉 Classification of federated learning

V. Conclusion

This report examines South Korea's approach to securing intelligence superiority on the future intelligent battlefield and enhancing AI-driven defense capabilities through Defense Innovation 4.0. South Korea aims to achieve intelligence superiority over adversaries by adopting strategies that integrate AI, big data, and autonomous systems to dramatically enhance the speed of information collection, analysis, and response, leveraging high-quality data to gain a strategic advantage. Intelligence superiority is essential for victory in future intelligent battlefields, and continuous technological development will be critical to achieving and maintaining this edge. Furthermore, this report analyzes the impact of advanced technologies like AI on military innovation, examining how the diffusion of AI technology transforms military modernization and the nature of warfare. These advancements play a crucial role in reshaping traditional military frameworks and exploring the ways AI-driven technologies can provide strategic advantages in actual operations.

Additionally, the report proposes a technology classification system designed to be effectively applied in defense education, training, and technology development, providing a logical foundation for the systematic adoption of AI technologies. In the context of Defense Innovation 4.0, this classification system will be instrumental in laying the groundwork for South Korea's military to strengthen AI-based defense capabilities and utilize advanced technologies effectively. AI technology extends beyond mere data collection, with the potential to maximize operational efficiency through the automation of data analysis and strategic decision-making processes. The Ministry of National Defense can leverage these technologies to optimize weapon systems, enhance combat readiness, and enable proactive responses to asymmetric threats posed by adversaries.

Securing AI-based intelligence superiority on the future battlefield will require sustained research and development in line with technological advancements, as well as strategic approaches to effectively integrate these capabilities into military operations. South Korea's military must continue to adapt to these changes, improving information collection and analysis capabilities through advanced technologies like AI to predict and respond to potential threats. By integrating AI across all areas of defense, South Korea can actively address the complexities of future warfare and advance its military strategies and defense systems for long-term success.

This study provides recommendations for defense policymakers to support the integration of AI technologies within military innovation. Given the rapid development of AI, defense policies are evolving to encompass a range of applications, from advanced weapon systems to the enhancement of routine defense operations. This report suggests a structured approach using a defense-specific AI technology classification system, as outlined in this study, to guide policy development in line with broader AI advancements. This classification system can assist in identifying key technology areas needing focus in both project and technology planning, such as joint learning, which may lack investment despite its strategic importance.

These recommendations align with initiatives by the Yoon Suk Yeol administration, such as the establishment of the Defense AI Center under the Defense Innovation 4.0 project. Announced in March 2023, this center aims to support military AI planning and foster collaboration across industry, academia, and research sectors to adapt private-sector AI innovations for defense applications. Developing a strategic roadmap for emerging AI technologies will be essential to advance these goals effectively.

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