Harnessing Deep Learning for Enhanced Military Simulations: A Comprehensive Approach

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ABSTRACT

This paper delves into the transformative potential of deep learning in advancing military simulations. With the rapid evolution of Artificial Intelligence (AI), there's a pressing need to integrate these advancements into military modeling and simulation practices to achieve more realistic, efficient, and predictive outcomes. Will explore a combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to process and predict complex military scenarios. The paper will look at training models on a dataset comprising various military exercises, strategies, and outcomes. The model's predictions will then be validated against real-world outcomes to measure accuracy and reliability. The research encompasses the integration of AI in military simulations, focusing on the application of deep learning algorithms. The scope extends from data collection and preprocessing to model training, validation, and deployment in real-world military simulation environments. In conclusion, the integration of deep learning in military simulations offers a promising avenue for more accurate and dynamic predictive modeling. This research paper not only showcases the potential of AI in this domain but also provides a robust methodology for its implementation.

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Luis E. Velazquez retired from the Marine Corps in 2008. In October of 2013 Luis transitioned into the federal government workforce as the Deputy Modeling & Simulations (M&S) Lead under the Systems Engineering, Interoperability, Architecture and Technology (SIAT) division for Marine Corps Systems Command (MARCORSYSCOM). In 2010 he became the Chief Technology Officer (CTO) for the Marine Corps Systems Command under the office of the Systems Engineering and Acquisition Logistics (SEAL) office. .

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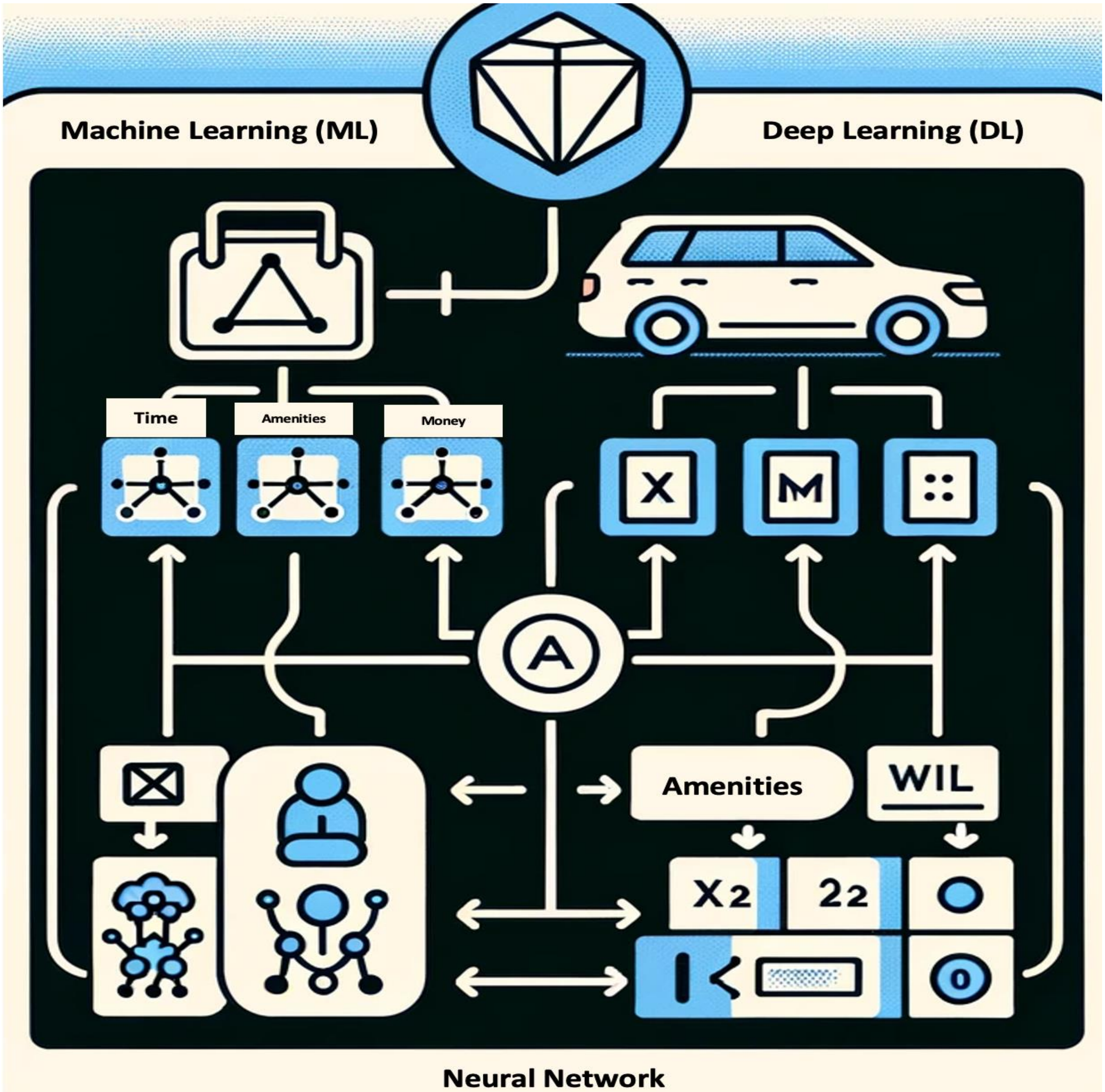
Exploring the Transformative Potential of Deep Learning in Military Simulations

The steady advancement of Artificial Intelligence (AI) and its potential applications to military modeling and simulation practices have prompted the need to explore the integration of deep learning technology. This paper examines the combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to process complex military scenarios and predict their outcomes, aiming to achieve more realistic, efficient, and predictive results. The research will recommend training models on a dataset that includes various military exercises, strategies, and outcomes, followed by validation against real-world results to measure its reliability and accuracy.

First, let me establish what is the difference between Machine Learning (ML) and Deep Learning (DL). Deep learning is a subset of machine learning. The hierarchy goes like this, the top we have AI. A subfield of AI is ML. Beneath that, then we have neural networks (NN) and they make up the backbone of DL algorithms. Machine learning algorithms leverage structured labeled data to make predictions. To build one a model to determine whether we should order complete a simple task let's look at a simple scenario where we use ML to determine if we should order an UBER ride. There are three main factors that influence this decision (***time, amenities, and save money);*** therefore, I will map those out as inputs. The first of those inputs is subjectively called X1. And X1 will inquire will it save **<u>time</u>** by ordering an UBER? We can say yes with a one (1) or no with a zero (0). In this example an UBER will benefit me due to not having any other means of transportation so Yes, therefore X equates to 1 (X=1). Now my next input is X2. That input checks if the UBER ride has amenities like WIFI. Specifically, will the amenity allow me to work while I am in the UBER? That's a 0, I'm ordering an UBER that does have those benefits (X2=0). Finally, with X3, will it save me money? Let's say I have a coupon for a free Uber, so that's a 1, (X3=1). Now look at the binary responses, zeros and ones. Using them for simplicity. But neurons in a network can represent values everything (negative infinity to positive infinity). With the inputs defined, we can assign weights to determine importance. Larger weights make a single inputs contribution to the output more significant compared to other inputs. I therefore establish my threshold value is 5. Now assign weights, W1, give this a full 5 (W1=5) because time is the most significant value for considering ordering an UBER. For W2 - are there amenities that allow me to work while in the UBER ride that value is 3 (W2=3). The weight for W3 is 2 because Ubers are cost effective solutions compared to taxis (W3=2) (Goodfellow et. al 2016).

Now we put these weights into our model and using an activation function, in machine learning, particularly in neural networks, an activation function is a mathematical function applied to a node (or "neuron") that determines the output of that node given an input or set of inputs. The role of the activation function is to introduce non-linearity into the output of a neuron. The choice of activation function depends on the architecture of the neural network and the specific task at hand. This is important because most real-world data is non-linear, meaning we cannot separate classes or predict real-world outcomes without non-linearities. Activation functions make back-propagation possible since the gradients are supplied along with the error to update the weights and biases. we can calculate the output, which in this case is the decision to order an Uber or not. So, to calculate that, we're going to calculate the why and we're going to use these weights and these inputs. So here we've got 1x5. We've got 0x3. And we've got 1x2. And we need to consider



our threshold as well, which was 5. So that gives us if we just add these up 1x5, that's 5 - plus 0x3, that's zero plus 1x2, that's 2 - minus 5. Well, that gives us a total of +2. And because the output is a positive number, this correlates to ordering an Uber.

$$(\text{Input } 1 * \text{Weight } 1) + (\text{Input } 2 * \text{Weight } 2) + (\text{Input } 3 * \text{Weight } 3) - \text{Threshold } (5)$$
$$(X1*W1) + (X2*W2) + (X3*W3) - \text{Threshold } (5)$$
$$(1*5) + (0*3) + (1*2) - 5$$
$$5+0+2-5 = \mathbf{2 \text{ (positive value)}}$$

That is a rough layman's description of machine learning. But what differentiates machine learning from deep learning? Well, the answer to that is more than 3. As in, a neural network is considered a deep neural network if it consists of more than three layers, and that includes the input and the output layer. So, we've got our input and output, we have multiple layers in the middle. And this would be considered a deep learning network. Classical machine learning is more dependent on human intervention to learn. Human experts determine a hierarchy of features to understand the differences between data inputs. Viewing a series of images of different types of Uber vehicles like Toyota, Honda and Mercedes Benz, we could label these pictures in a dataset for processing by the Neural network. A human expert would determine the characteristics which distinguish each vehicle as the specific vehicle types. So, for example, it might be the brand of each vehicle make type might be a distinguishing feature across each picture. Now, this is known as supervised learning because the process incorporates human intervention or human supervision. Deep machine learning doesn't necessarily require a label dataset. It can ingest unstructured data in its raw form like text and images, and it can automatically determine the set of features which distinguish Toyota, Honda and Benz from one another. By observing patterns in the data, a deep learning model can cluster inputs appropriately. These algorithms discover hidden patterns of data groupings without the need for human intervention and then known as unsupervised learning. Most deep neural networks are feed forward (Goodfellow et. al 2016). That means that they go in one direction from the input to the output. However, you can also train your model through something called back-propagation. That is, it moves in the opposite direction from output to input. Back-propagation allows us to calculate and attribute the error associated with each neuron and allows us to adjust and fit the algorithm appropriately. So, when we talk about machine learning and deep learning, we're essentially talking about the same field of study. Neural networks, they are the foundation of both types of learning, and both are considered subfields of AI. The main distinction between the two are that number of layers in a neural network, more than three and whether human intervention is required to label data. Toyota, Honda, Benz.

So how does this help us with military simulations? Integration of deep learning in military simulations is promising, providing a highly accurate and dynamic predictive modeling approach for cost-effective and efficient military operations potential of AI in this domain and a robust methodology for its implementation. There are multiple simulations and simulators that make up the current inventory across the Marine Corps. These simulations, simulators, are classified under the Live, Virtual, and Constructive (LVC). I will focus on a subset that I had first-hand experience during its employment by the Marine Corps Large-Scale Exercise (LSE) event in 2014.

The LSE 2014 LVC simulations included:

- AH-1W 'Cobra' Aviation Procedural Trainer (APT)
- AH-1Z 'Cobra' APT operating on the Aviation Distributed Virtual Training Environment (ADVTE)
- MV-22 'Osprey' APT operating on the ADVTE.
- UH-1Y 'Huey' APT operating on the ADVTE.
- AV-8B 'Harrier' APT operating on the ADVTE.
- Advanced Simulation Combat Operations Trainer (ASCOT)
- Combined Arms Command and Control Trainer Upgrade System (CACCTUS)
- MAGTF Tactical Warfare Simulation (MTWS)
- Deployed Virtual Training Environment (DVTE) Virtual Battlespace 2 (VBS2)
- Supporting Arms Virtual Trainer (SAVT)
- Combat Convoy Simulator (CCS)
- Tactical COP Server (TCS)
- Command and Control Personal Computer (C2PC)
- Voice-Over-Internet-Protocol (VOIP) communications

In 2014 while working with then Master Sergeant Robert Sousa, During the LSE 2014 Live Virtual and Constructive (LVC) Coordinator for the Ist Marine Expeditionary Force (I MEF), I observed how he effectively integrated simulator devices and had them worked seamlessly to support training mission scenarios. Note that certain ground simulator devices, like the SAVT and CCS, were on an unclassified network so their use was not as robust as the aviation simulators and the joint terminal attack controller (JTAC)] simulations. The systems were integrated but took over a year to prepare the federation of models and over 70 people subject matter experts, eventually there were all integrated. Here is a listing of the simulators along with their description that could have benefited from AI the most:

Virtual Battle Space (VBS): The VBS is a flexible simulation training solution for scenario training, mission rehearsal, and more. It is used for Tactical Decision Kits to help Marines make better decisions in various combat scenarios.

Combat Convoy Simulator (CCS): Used to train personnel in tactics and procedures for convoy operations, including how to react to threats such as improvised explosive devices (IEDs).

AV-8 Harrier, MV-22 Osprey, AH-1 Cobra, and UH-1 Huey Simulators: These aircraft simulators are designed to provide pilots and crew members with realistic training experiences. They allow for the practice of flight operations, mission planning, and emergency procedures in a controlled environment.

Supporting Arms Virtual Trainer (SAVT): The SAVT has been replaced by the Joint Virtual Fires Trainer (JVFT), which is a deployable system supporting training for aviation and surface-to-surface fires, offering a doctrinally compliant, realistic, and tactically relevant training for Close Air Support (CAS) and other types of terminal attack controls.

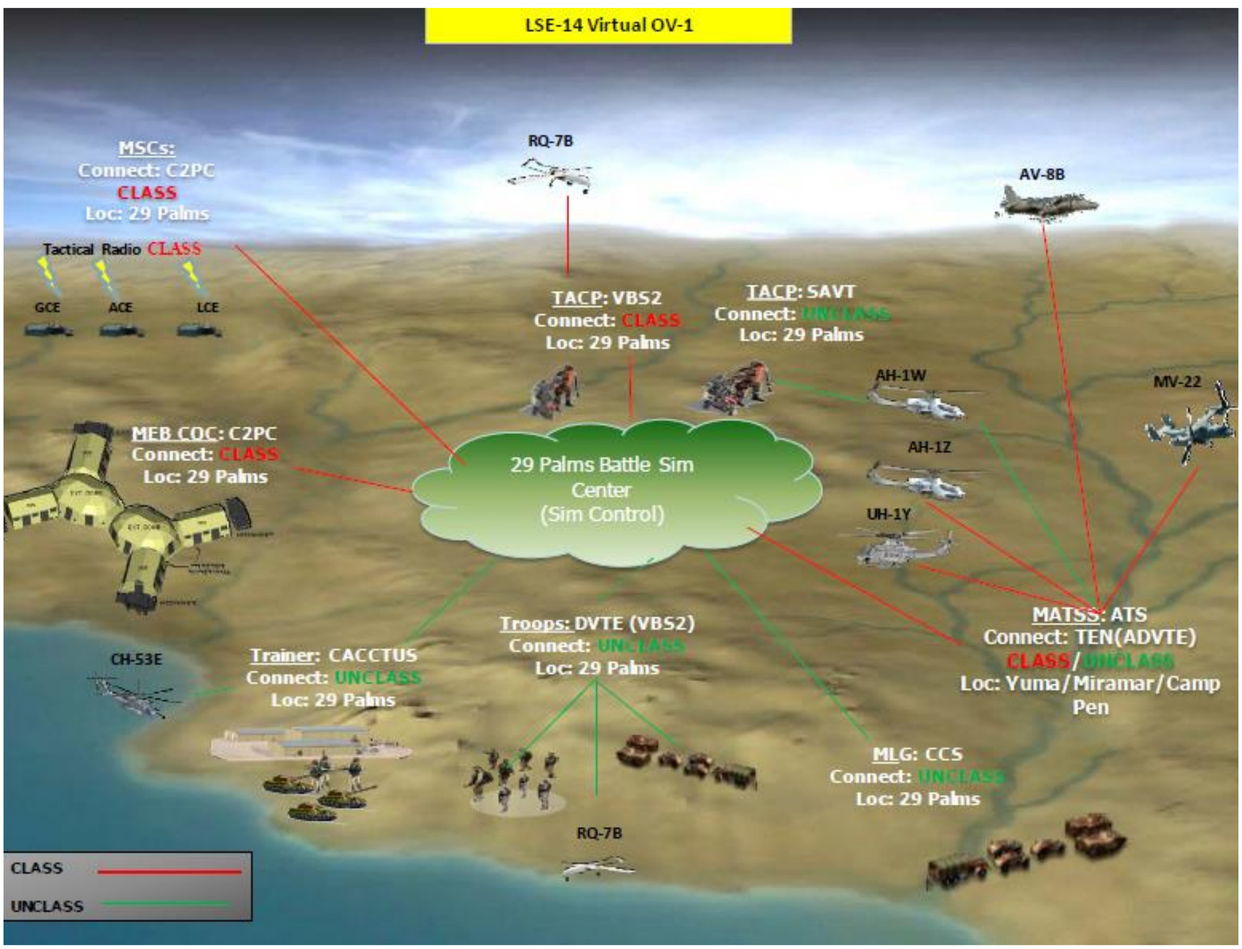


Figure 1: LSE-14 Operational View One (OV-1) (2014)

These simulation systems are part of the Marine Corps' broader initiative to modernize their training environment, known as Project Tripoli (Training and Education et. al 2030), which aims to create an on-demand, all-domain LVC training environment aligned with the future operating concepts outlined in Force Design 2030. The integration of these tools is expected to provide Marines with a comprehensive training experience that enhances decision-making capabilities and operational readiness for real-world missions. It is a challenge to fully synchronize virtual and constructive elements of LSE-14 into live fire and maneuver. The Tactical Training and Exercise Control Group (TTECG), part of the Marine Corps Air Ground Combat Center (MCAGCC), plays a pivotal role in the training and readiness of Marine units. This group is responsible for designing, enabling, and overseeing Service Level Training Exercises (SLTE) for the Marine Air Ground Task Force (MAGTF). Their focus is on sustaining and evolving live-fire and maneuver combined arms tactics, techniques, and procedures (TTPs). They also integrate emergent friendly and threat capabilities to improve rapid decision-making and simulate combat conditions that enhance the training experience.

Current TTECG regulations preclude mixing live (non-simulated) and constructive supporting arms fires by units in the field. For LVC actions to be seamless, it requires a considerable amount of coordinated planning and 'up front' work, both vertically and laterally, involving and impacting targeting, the Air Traffic Order (ATO), Battle Damage Assessment (BDA), exercise control, Joint Terminal Attack Controller (JTAC)s, pilots, intelligence, safety, Higher Head Quarters (HHQ) and adjacent commands. Adding the live, virtual and constructive environment to an exercise must add value and be of benefit to the primary and secondary training audience. The TTECG is also known informally as "Coyotes," and they work as mentors and evaluators during pre-deployment Integrated Training Exercises (ITX). They provide units with various scenario-based trainings and add elements of resistance to these scenarios to test and improve the Marines' responses to unexpected challenges. The Coyotes' role includes ensuring safety, bringing scenarios to life, and providing assessments of the forces in training (TTECG et. al 2030).

The simulation support staff at Twentynine Palms provides training across the spectrum of military operations, from individual to regiment level, and for all warfighting disciplines. This encompasses full-scale war to the establishment of local governance, integrating simulation into each unit's training pipeline to maximize the benefits of live training venues available within MAGTFTC.

While AI can provide valuable insights and predictions, the human element in military operations remains crucial. AI should be seen as a tool to support and enhance the decision-making processes of trained military personnel, rather than replace them. Therefore, the development and deployment of deep learning algorithms in military simulations should be done in collaboration with military professionals to ensure that AI is used to complement and enhance their skills and expertise.

The transformative potential of deep learning extends beyond military simulations, with applications in various fields such as healthcare, finance, and transportation. However, responsible and ethical considerations must be at the forefront of its development and deployment to minimize its potential harms. By prioritizing these considerations, we can ensure that the benefits of deep learning are maximized while avoiding harm and discrimination. The integration of AI in military simulations is just one example of how deep learning can support and enhance human expertise and decision-making, and it is crucial that we continue to explore its potential in a responsible and collaborative manner. It is also important to remember that AI should be seen as a tool to support and enhance the decision-making processes of trained military personnel, rather than replace them. Therefore, the development and deployment of deep learning algorithms in military simulations should be done in collaboration with military professionals to ensure that AI is used to complement and enhance their skills, human expertise and decision-making.

Deep learning technology described above, in military simulations holds immense promise in terms of providing a more accurate, efficient, and dynamic predictive modeling approach for cost-effective military operations. DL can revolutionize the way military operations are conducted by providing a more accurate and predictive modeling approach. This can lead to the development of more cost-effective and efficient military strategies. However, it is important to prioritize ethical considerations when developing and deploying deep learning algorithms in military simulations. Unbiased and representative data must be used to train models, and the predictions made by the models should not perpetuate discrimination or harmful stereotypes.

Deep Learning's Impact on Decision-Making in Military Simulations

The advent of deep learning has ushered in a new era of decision-making capabilities within military simulations. By simulating countless scenarios and outcomes with a level of complexity and variability that traditional algorithms cannot match, deep learning models facilitate a more nuanced understanding of potential real-world events. Such sophistication in simulations enables military strategists to examine the repercussions of their decisions in a safe, controlled environment, thus preparing them for the exigencies of actual combat situations. These advanced models can factor in a multitude of variables, from geopolitical considerations to resource allocation and troop morale, painting a comprehensive picture of the battlefield that informs strategic decisions at the highest levels.

Adaptive Learning for Unpredictable Scenarios

Another breakthrough facilitated by deep learning in military simulations is the capacity for adaptive learning. Unlike static models, deep learning algorithms can adjust to the trainees' actions, evolving the scenario in real-time. This adaptability ensures that military personnel are not merely learning to respond to a fixed set of circumstances but are prepared for the unpredictability inherent in real-world military operations. Such dynamic simulations are invaluable in developing agile and flexible military tactics, as they foster a mindset that is both proactive and reactive, crucial for modern military engagements.

Enhanced Realism for Improved Training Outcomes

Deep learning also significantly enhances the realism of military simulations. By integrating CNNs and RNNs, simulations can now incorporate realistic visual and auditory inputs, making the training experience more immersive. The sensory-rich environments created by these networks facilitate better retention of strategic concepts and skills, translating to improved performance in actual military operations. Furthermore, the realism afforded by deep learning can extend to the emotional and psychological aspects of warfare, allowing military personnel to be better prepared for the stressors of combat (Hochreiter et. al 1997).

Practical Implications and Operational Readiness

The integration of deep learning into military simulations is not merely a theoretical advancement; it has concrete implications for operational readiness. By incorporating AI that can learn from and adapt to a wide range of scenarios, military forces can better prepare for the unpredictable nature of modern warfare. This preparation goes beyond tactical readiness, extending to logistical support, threat assessment, and resource management. The ability of deep learning models to process and synthesize vast amounts of data can lead to more informed decisions regarding troop deployment, equipment maintenance, and even diplomatic responses to evolving international incidents.

The Ethical Landscape of AI in Military Simulations

As we advance in our ability to simulate complex scenarios with deep learning, the ethical landscape becomes increasingly multifaceted. The use of AI in military simulations must be governed by stringent ethical guidelines to prevent the normalization of conflict and ensure that such technologies are not misused. The development of these AI systems must be transparent, accountable, and subject to rigorous ethical review. This includes the consideration of potential biases in data sets that can lead to skewed outcomes, as well as the implications of using simulated environments to train for real-world engagements.

Deep Learning and the Human-Machine Partnership

The future of military operations will likely be characterized by a partnership between humans and intelligent systems. Deep learning technologies offer a complement to human decision-making, bringing a data-driven perspective that can highlight patterns and consequences not immediately apparent to even the most experienced strategists. However, the final decision-making authority must remain with human operators who can consider moral and ethical dimensions beyond the scope of AI. The goal is to foster a symbiotic relationship where AI enhances human capabilities without encroaching on the autonomy and moral responsibilities of military personnel.

Challenges and Future Directions

Revolution in military training and operations, it is imperative to recognize the challenges that lie ahead. The rapid pace of AI development necessitates continuous learning and adaptation, not only from the AI itself but also from the military personnel who use it. Future research must focus on creating robust AI systems that can function seamlessly with existing military technologies while remaining flexible enough to adapt to future innovations. Moreover, the integration of AI into military strategies must be conducted with caution to prevent over-reliance on technology. The nuances of human judgment, borne out of experience and intuition, remain indispensable. As such, the goal of incorporating deep learning into military simulations should not be to create an autonomous decision-making system but rather to augment human capabilities with AI's analytical power (Militaries et. al 2022).

The Way Forward: Innovation with Responsibility

Focusing on the Marine Corps lessons learned from training conducted at 29 Palms is is clear to see how the TTECG staff and simulations could benefit from AI technologies like CNNs and RNNs to enhance military training incorporating advanced data analysis and pattern recognition into their simulations. AI can streamline the decision-making process in wargames, offering rapid feedback and adaptability to military strategies. It allows for the processing of large datasets to improve simulation realism and training outcomes. However, AI adoption in military training is still in the early stages, with challenges such as the need for standardized data and the integration of AI into current training systems. CNNs and RNNs can enhance training simulation programs of record and exercises that leverage them such as the Large-Scale Exercises (LSE) in several ways (Hochreiter et. al 1997):

Improved Scenario Generation: CNNs can analyze vast amounts of visual data and recognize patterns that humans might not easily detect. By processing images and videos from previous exercises, CNNs can help to create more diverse and realistic training scenarios. For example, they can assist in the generation of synthetic environments that are more reflective of real-world terrains and potential combat zones.

Behavior Prediction: RNNs are adept at processing sequences of data, which makes them ideal for predicting temporal or sequential events. In a training context, RNNs could analyze historical data to predict enemy behavior or outcomes based on given military strategies. This would enable more dynamic and responsive training scenarios, where the simulated enemy adapts to the actions of the trainees in real-time (Hochreiter et. al 1997).

After-Action Review Enhancement: By employing CNNs and RNNs, the TTECG can develop systems that automatically analyze training sessions to provide detailed after-action reviews. These AI-driven systems can identify key moments in training exercises, assess the effectiveness of tactics, and suggest areas for improvement.

<u>Customized Training Programs:</u> RNNs can be used to analyze the progress of individual units or soldiers over time, tailoring training programs to address specific weaknesses or to build upon demonstrated strengths. This personalized approach can help ensure that all personnel are reaching their highest potential.

<u>Logistics and Resource Allocation:</u> CNNs can be used to optimize the logistics of setting up and conducting training exercises. They can help predict the resources needed for different training scenarios, enhancing efficiency and reducing waste.

<u>Safety Monitoring:</u> CNNs can be implemented to monitor video feeds in real-time to ensure safety protocols are followed during training exercises. They can be trained to detect unsafe behavior or conditions and alert human supervisors to potential hazards.

By integrating CNNs and RNNs into their training systems, the Marine Corps can significantly advance the capabilities of simulation tools, providing Marines with an enhanced training experience that better prepares them for the complexities of modern combat. The adaptability and predictive power of these neural networks mean that every exercise at locations such as 29 Palms could be more closely aligned with the unpredictability of real-world operations, leading to a more effective and responsive military force.

Looking forward, the priority must be to cultivate an environment where innovation in deep learning is matched with responsibility. As the technology evolves, continuous dialogue among technologists, ethicists, military strategists, and policymakers will be vital in guiding the responsible development and deployment of AI in military contexts. This includes establishing international norms and agreements on the use of AI in military simulations and operations, ensuring global stability and the prevention of an AI arms race. Overall, the transformative potential of deep learning technology is immense. The integration of deep learning technology in military simulations holds immense promise in terms of providing a more accurate, efficient, and dynamic predictive modeling approach for cost-effective military operations. Equally important that we prioritize ethical considerations throughout the development and deployment process to minimize potential harm and discrimination. AI should be seen as a tool to support and enhance the decision-making processes of trained military personnel, rather than replace them. Collaboration between AI experts and military professionals is essential to ensure that AI is used to complement and enhance human expertise and decision-making. By exploring the transformative potential of deep learning in a responsible and collaborative manner, we can strive towards a better future for all.

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