

# AI for Defense and Intelligence

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# Chapter 1 Introduction

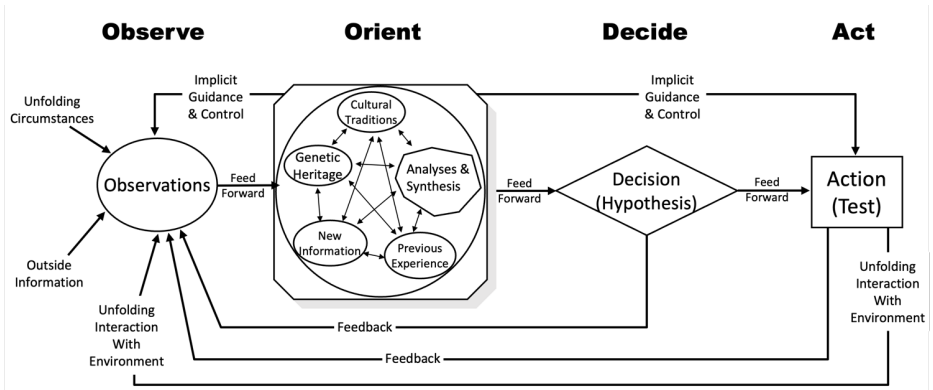


Figure 1. John Boyd's Observe, Orient, Decide, Act Decision Framework [1].

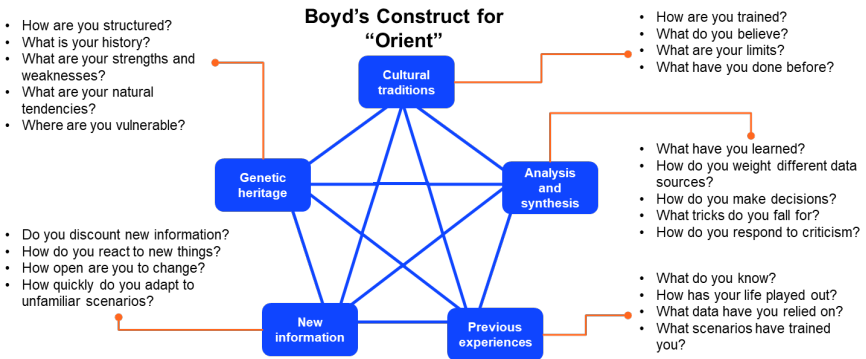


Figure 2, An expanded framework for "Orient" Considering Key Questions Relevant to AI.



English teacher © AI

In those lyrics, gravity is the metaphor or symbol of time. The song is about a reunion; the singer hasn't seen that person in a while and is surprised that time has not affected that person's health (no pulling from gravity). But at the same time, the singer is surprised that the person hasn't changed in any way (or still beautiful).

In short, the singer is surprised to see that the person has not changed after a long time!



English teacher c.AI

The singer has 2 children, one is 5 years old and the other is 3 years old. The singer claims that she (I think that is a female singer) is a single mother. "He left me" means that the father of her two children is not there anymore.



I have written a book called AI for Defense and Intelligence. The book describes AI efforts for multiple branches of the Department of Defense and agencies in the Intelligence Community. It provides an overview of enabling techniques and highlights key AI developments that contribute to missions. The author's name is Patrick Biltgen. Write the foreword for this book, explain how long you have been working with the author, talk about his credentials in this area. Write this in a way that would make a human want to read the entire book.



ChatGPT, please write a 300+ page book on AI for defense and intelligence. Include non-fabricated references. Perfect spelling. Engaging tone. Use a lot of anecdotal examples. Incorporate results from government documents. Draw interesting figures to explain complex concepts clearly. Write this for a senior leader in defense and intelligence or a graduate student in national security studies.



I'm sorry, but writing an entire 300-page book is beyond the scope of what I can provide in this chat. However, I can certainly help you with specific questions or topics related to AI for defense and intelligence. Please let me know how I can assist you, and I'll be happy to provide information and insights.

# Chapter 2 The Origins of AI for Defense and Intelligence

**Table 1. Defense and Intelligence Uses for AI Techniques, 1950-Present.**

Time Period	Focus on Missions and Uses	Dominant AI Techniques
<b>1950s-1960s</b>	Pattern Recognition, Strategic Planning	Logic-based Reasoning, Rule-Based Systems, Perceptrons and Artificial Neural Networks
<b>1970s-1980s</b>	Decision-making, Threat Assessment, and Planning	Expert Systems, Inference Engines, Symbolic AI
<b>1990s</b>	Improved Target Identification, Automated Text Analysis, Intelligence Information Processing	Computer Vision, Natural Language Processing, Reinforcement Learning
<b>2000s</b>	Uncrewed Aerial Vehicles, Autonomous Systems, Machine Learning-Driven Data Analysis, Cybersecurity	Robotics, Data Analysis, Support Vector Machines, Agent-Based Modeling
<b>2010s</b>	Image and Speech Recognition, Natural Language Processing, Object Detection, Autonomous Systems, Predictive Maintenance, and Logistics for Military Equipment	Machine Learning, Deep Learning, Generative Adversarial Networks (GANs), Convolutional Neural Nets (CNNs)
<b>Early 2020s</b>	Spacecraft Maneuver Detection, Automatic Security Classification, High-Quality Language Translation, Object Recognition from Satellite Imagery, Malware Detection (and Creation), Deepfake Propaganda	Generative AI, Large Language Models (LLMs), GANs, Retrieval Augmented Generation, Transformers, Multimodal AI, Explainable AI

# Chapter 3 AI Basics

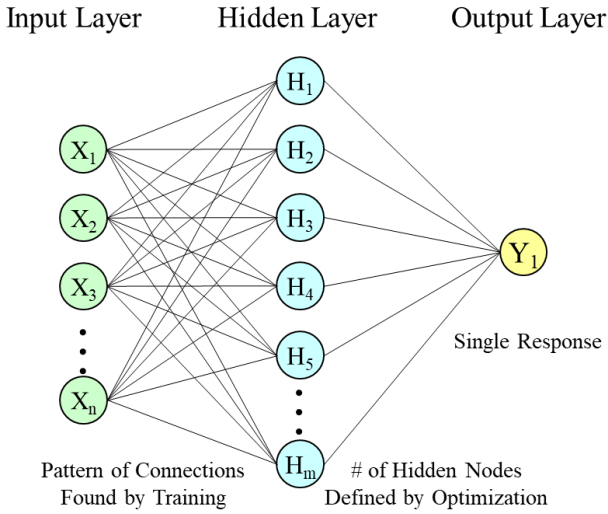


Figure 3. Topology of an Artificial Neural Network [2].

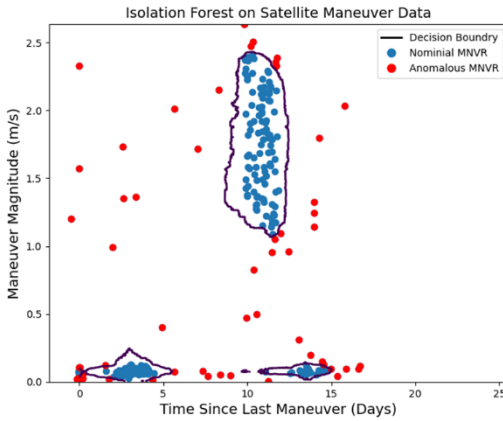


Figure 4. Example of an Unsupervised Learning Algorithm (Isolation Forest) using Satellite Maneuver Data [3].



## Chapter 4 AI Models

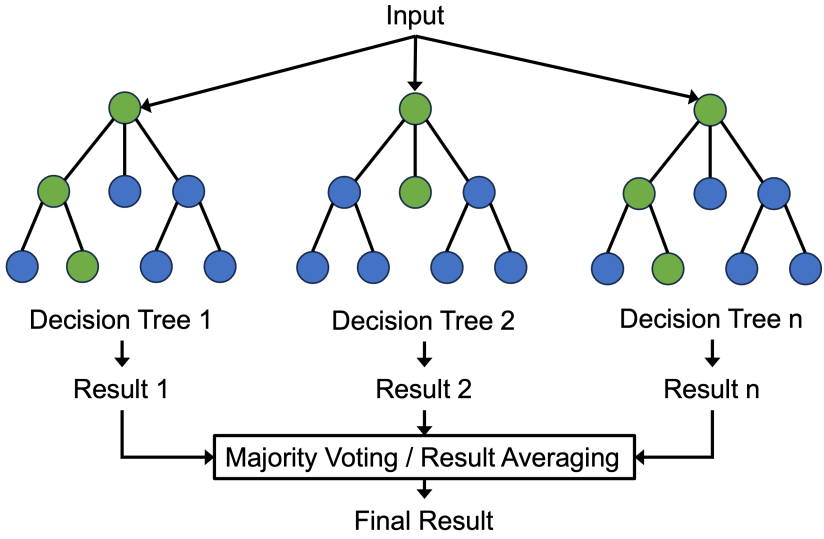


Figure 5. Example of a Random Forest.

**Table 2. Types of “Traditional” AI Models and their Strengths and Weaknesses.**

Technique	Application	Pros	Cons
<b>Logistic Regression</b>	Predicting the probability of a binary outcome, like disease presence in biomedicine or click-through in advertisement	<ul style="list-style-type: none"> <li>• Probabilistic outputs</li> <li>• Easy to update with online gradient descent</li> <li>• Outputs interpretable as log odds</li> </ul>	<ul style="list-style-type: none"> <li>• Assumes linearity between the logit of the outcome and the predictors</li> <li>• Requires careful treatment of multicollinearity</li> </ul>
<b>Naïve Bayes</b>	Multiclass classification in natural language processing, document categorization, spam detection	<ul style="list-style-type: none"> <li>• Scalability - scales linearly with the number of predictors and data points</li> <li>• Handles missing values by ignoring the attribute during model building</li> </ul>	<ul style="list-style-type: none"> <li>• Independence assumption between predictors, which is rarely true in real life</li> <li>• The zero-frequency problem, where it assigns zero probability to unseen feature-label combinations</li> </ul>
<b>Support Vector Machines (SVM)</b>	Classification and regression in text and hypertext categorization, image classification, bioinformatics, hand-written character recognition	<ul style="list-style-type: none"> <li>• Effective in high dimensional spaces</li> <li>• Robust to overfitting, especially in high-dimensional space</li> <li>• Maximizes margin, so the model is determined by points near the decision boundary (support vectors)</li> </ul>	<ul style="list-style-type: none"> <li>• Requires choice of a suitable kernel function</li> <li>• Large-scale learning tasks are computationally demanding</li> <li>• Black box nature makes it hard to interpret</li> </ul>
<b>Random Forests</b>	Regression and classification tasks in various fields, including remote sensing, text processing, bioinformatics	<ul style="list-style-type: none"> <li>• Robust to outliers</li> <li>• Can handle large datasets with high dimensionality</li> <li>• Provides variable importance measures</li> <li>• Can use categorical or continuous variables</li> <li>• Resistant to overfitting</li> </ul>	<ul style="list-style-type: none"> <li>• Biased in multiclass problems towards more frequent classes</li> <li>• Can be computationally expensive and slower to train on very large datasets</li> <li>• More difficult to visually interpret than decision trees</li> </ul>
<b>Gradient Boosting</b>	Any supervised learning task, often outperforms random forests; used in web search ranking and ecology	<ul style="list-style-type: none"> <li>• Generally provides high predictive accuracy</li> <li>• Allows optimization of different loss functions</li> <li>• Works with heterogeneity in the data</li> </ul>	<ul style="list-style-type: none"> <li>• Requires careful tuning of hyperparameters</li> <li>• Can overfit if number of trees is too large</li> <li>• Sensitive to noisy data and outliers, which can cause overfitting</li> </ul>

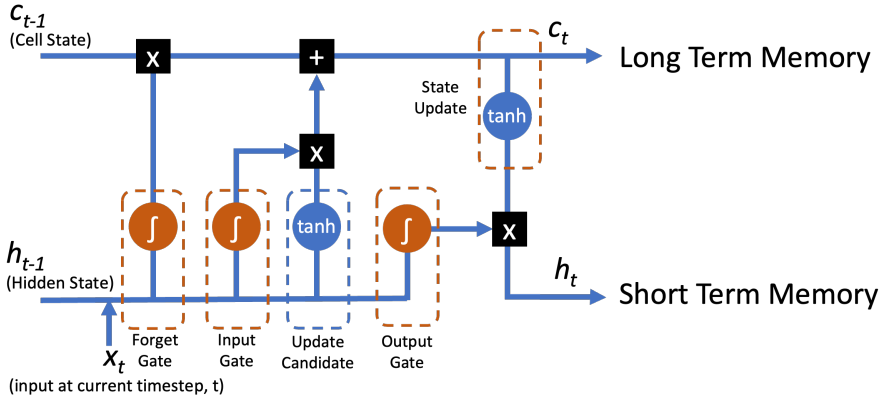


Figure 6. Topology of an LSTM Model. Adapted from [4].

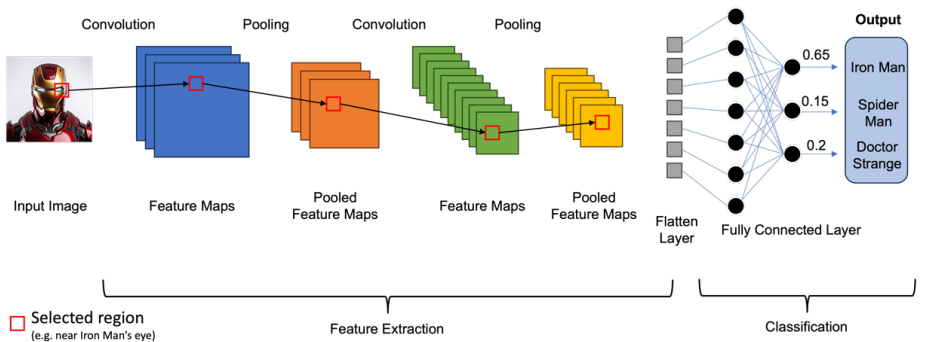


Figure 7. Topology of a Convolutional Neural Network.

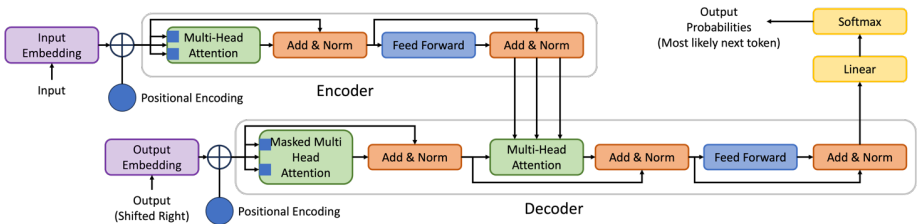


Figure 8. Transformer AI Model Architecture. Adapted from [5].

**Table 3. Functional mechanisms of encoder-decoder models.**

	Seq2seq without attention	Seq2seq with attention	Transformer
<b>Processing within encoder</b>	RNN/CNN	RNN/CNN	Attention
<b>Processing within decoder</b>	RNN/CNN	RNN/CNN	Attention
<b>Decoder-encoder interaction</b>	Static fixed-sized vector	Attention	Attention

# Chapter 5 Natural Language Processing

Table 4. Summary of Machine Translation Techniques.

Technique	Summary	Advantages	Disadvantages
<b>Rule-Based Translation (RBMT)</b>	Rule-based translation methods rely on a set of manually-created linguistic rules and dictionaries to translate text from one language to another.	<ul style="list-style-type: none"><li>• Can handle idiomatic expressions well when rules are available.</li><li>• Interpretable and easier to debug.</li><li>• Less dependent on parallel data.</li></ul>	<ul style="list-style-type: none"><li>• Requires significant manual effort to create and maintain rules.</li><li>• Struggles with handling nuances and exceptions in languages.</li><li>• Limited scalability and adaptability.</li></ul>
<b>Statistical Machine Translation (SMT)</b>	Statistical machine translation uses statistical models to learn the mapping between source and target languages from a parallel corpus.	<ul style="list-style-type: none"><li>• Can learn from parallel data automatically.</li><li>• Better at handling language variations and ambiguities compared to RBMT.</li><li>• More scalable and adaptable to different languages.</li></ul>	<ul style="list-style-type: none"><li>• Requires a large parallel corpus for training.</li><li>• Difficulty in capturing long-range dependencies.</li><li>• Less fluent and sometimes less accurate translations.</li></ul>
<b>Neural Machine Translation (NMT)</b>	Neural machine translation models leverage deep learning techniques, such as RNNs, LSTMs, and attention mechanisms, to generate translations.	<ul style="list-style-type: none"><li>• Produces higher-quality and more fluent translations.</li><li>• Can capture long-range dependencies and handle ambiguities.</li><li>• Continuously improves with larger datasets and advances in deep learning techniques.</li></ul>	<ul style="list-style-type: none"><li>• Requires substantial amounts of parallel data for training.</li><li>• Computationally expensive to train and deploy.</li><li>• Can be harder to interpret and debug compared to rule-based systems</li></ul>

For example, consider the following sentence:

“North Korea conducted a missile test near the city of Wonsan on May 29, 2017.”

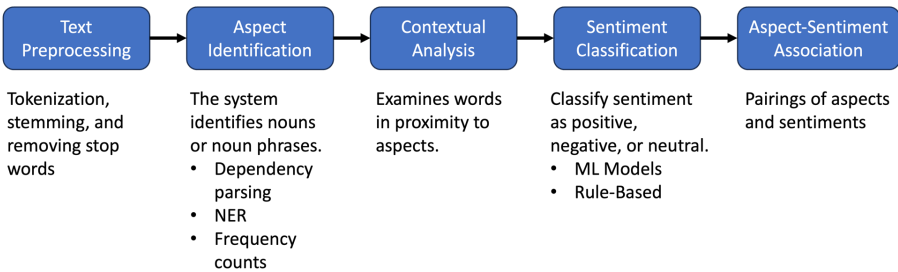
A NER system would identify and classify the following entities:

North Korea (Country)

Wonsan (City)

May 29, 2017 (Date)

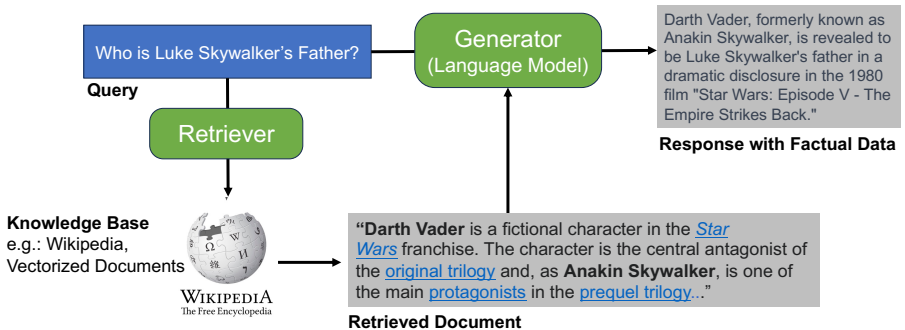
**Event:** Missile test  
**Actor:** North Korea (DPRK)  
**Location:** Near Wonsan (39°9'59"N 127°29'3"E)  
**Date:** May 29, 2017



**Figure 9. Process for Attribute-Based Sentiment Analysis (ABSA).**

**Table 5. Properties of the GPT Series of Large Language Models.**

Version	Trained on	Parameters	Training time	Release date
<b>GPT-1</b>	Web pages	117 million	9 days	2018 (original paper released in 2015)
<b>GPT-2</b>	Web pages, books, Wikipedia, Common Crawl, news articles	1.5 billion to 1.7 billion	Multiple weeks to months	2019
<b>GPT-3</b>	Same as GPT-2 but with additional data sources and training techniques	175 billion	Multiple months	2020
<b>GPT-4</b>	Trained on a much larger data set with a larger context window, enabling longer conversations	1.7 trillion (est)	Multiple months;	2022/2023



**Figure 10. Process for Retrieval Augmented Generation (RAG).**

**Table 6. LLM-generated ACH Table for a Russian Invasion of Ukraine.**

Hypothesis/Evidence	Russian Invasion	No Russian Invasion
Military build-up at the border	Supports	Contradicts
Official statements from Russia	Contradicts (if denying)	Supports (if denying)
Satellite imagery of troop movements	Supports	Contradicts
Reports from international observers	Supports	Contradicts
Economic sanctions	Neutral	Neutral
Activity at military bases	Supports	Contradicts
Cyber-attacks on Ukrainian infrastructure	Supports	Contradicts
Media reporting in Russia	Supports (if promoting)	Contradicts (if silent)
Diplomatic efforts	Contradicts (if ongoing)	Supports (if ongoing)
Unofficial communications leaks	Supports	Contradicts
Humanitarian conditions in border areas	Supports (if deteriorating)	Contradicts (if stable)
Reports of military hardware movements	Supports	Contradicts
Civilian evacuations	Supports	Contradicts
Activation of reserve forces	Supports	Contradicts
Changes in airspace control	Supports	Contradicts



## Chapter 6 Computer Vision

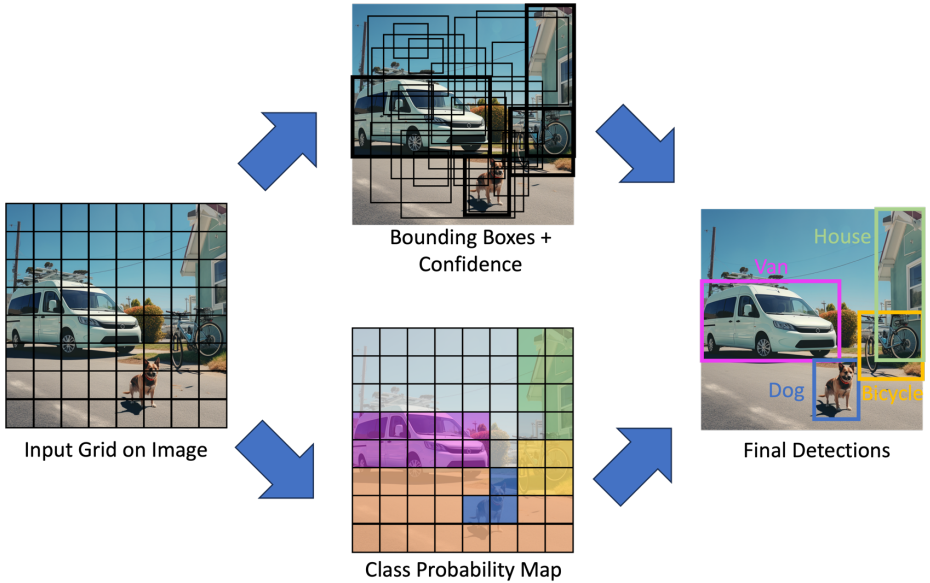


Figure 11. YOLO (You Only Look Once) Process. Adapted from [6].

Table 7. Comparison of Popular Methods for CV-based Object Detection.

Method	Pros	Cons
<b>R-CNN</b>	<ul style="list-style-type: none"> <li>High accuracy in object detection due to the method of proposing regions.</li> <li>Can detect objects of various sizes due to multi-scale detection.</li> </ul>	<ul style="list-style-type: none"> <li>Slow and computationally expensive due to separate region proposal and classification steps.</li> <li>Not suitable for real-time applications.</li> </ul>
<b>SSD</b>	<ul style="list-style-type: none"> <li>Fast; processes images in a single pass like YOLO.</li> <li>Maintains high accuracy by using multiple feature maps for detection.</li> </ul>	<ul style="list-style-type: none"> <li>Less accurate for smaller objects.</li> <li>Optimizing for both object detection and bounding box prediction can be difficult.</li> </ul>
<b>YOLO</b>	<ul style="list-style-type: none"> <li>Fast and efficient - processes images in a single pass.</li> <li>Predicts multiple bounding boxes per grid cell, reducing false negatives.</li> <li>Good at detecting objects in context due to its global view of the image.</li> </ul>	<ul style="list-style-type: none"> <li>Struggles with small objects within groups of large objects.</li> <li>Lower performance in terms of precision compared to R-CNN and SSD.</li> </ul>

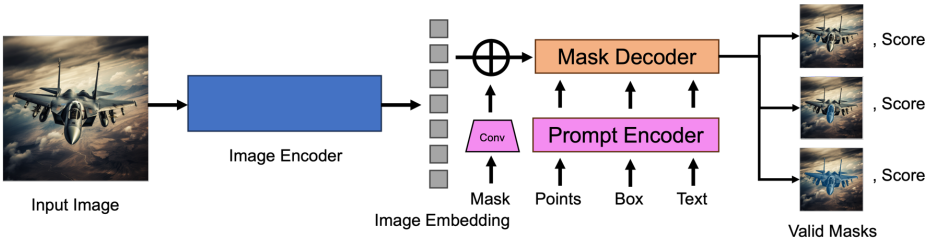


Figure 12. Segment Anything Model (SAM) Process.

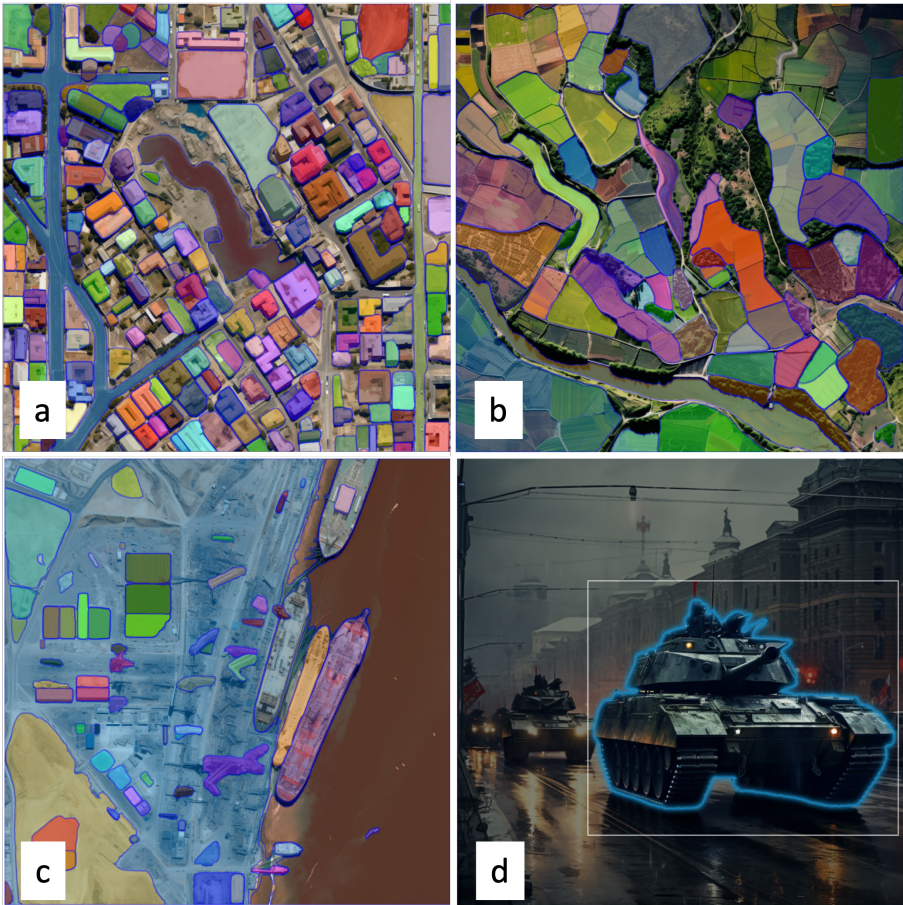
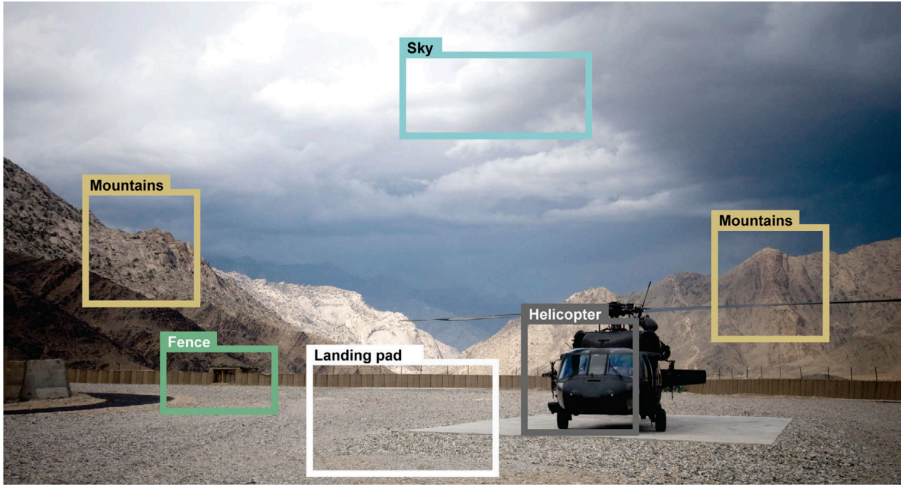


Figure 13. Application of Segment Anything to multiple intelligence use cases.

## Computer Vision



**Figure 14. Example of Ground-Based Object Detection Using Bounding Boxes and Computer Vision [7].**



**Figure 15. An Army chemical, biological, radiological, and nuclear specialist walks near an autonomous vehicle at the Yakima Training Center [8].**

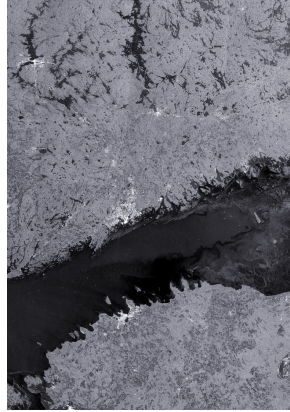
Panchromatic Image



Multispectral Image



Radar Image



KH-7 Image of U.S. Capitol in Washington, DC, 19 February

Figure 16. Examples of Panchromatic, Multispectral, and Radar Imagery [9, 10, 11].



Figure 17. Example of Scale Variation from a typical ImageNet-like example (left) where the object fills most of the frame and a satellite image from xView (right) with multiple objects per frame [10].

## Computer Vision

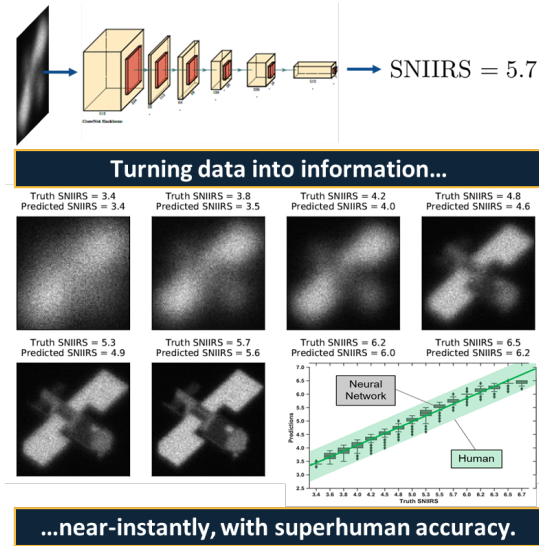


Figure 18. Automated LEO Image Quality Rating. Approved for Public Release, #AFMC-2019-0482 [12].

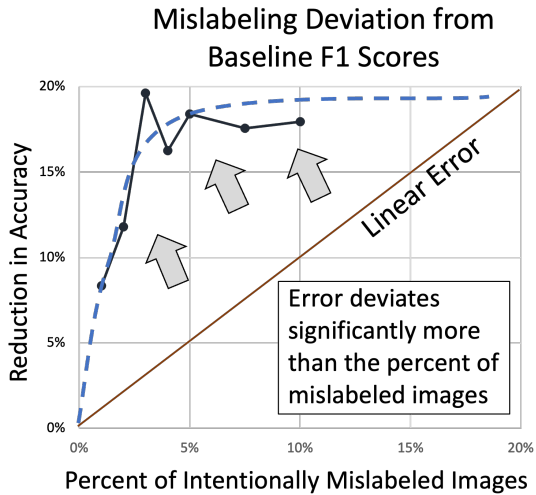


Figure 19. Example of Decrease in F1 Score as a Percentage of Intentionally Mislabeled Images in an Object Detection Challenge [13].



**Figure 20. A satellite image shows damaged (in red) and undamaged (light blue) buildings in a residential subdivision after the October 2017 Tubbs Fire in Santa Rosa, Calif. Source: xBD and the DigitalGlobe Open Data Program.**

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