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DATA MAYHEM VERSUS NIMBLE INFORMATION: TRANSFORMING HECTIC IMAGERY INTELLIGENCE DATA INTO ACTIONABLE INFORMATION USING ARTIFICIAL NEURAL NETWORKS

by

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Disclaimer

Table of Contents

List of Figures

Page

List of Tables

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Abstract

The current Processing, Exploitation and Dissemination (PED) process does not satisfy the demands for intelligence to warfighters. Data production rate from Imagery Intelligence (IMINT) sensors far exceed the current capacity to process and analyze it, making the PED process a choke point for intelligence reaching combat forces in a timely manner. The demand for intelligence is, and will continue to be, on the rise for the foreseeable future. Artificial Neural Networks (ANN), allows for faster data processing and analysis, leveraging technology in favor of the IMINT analysis process. This paper answers the question of how can ANN effectively transform IMINT data into reliable and timely intelligence for combat commanders. The purpose of this work is to open the appetite for a material solution that can be implemented. Using technical explanations with a problem/solution framework and focus, this paper articulates the solution to the research question. Conclusions express how ANN systems evolve, signaling a suitable solution for the problem of handling big data. Recommendations are to explore the implementation of ANN at the core of the PED process in order to make it more agile in processing and analyzing data. Due to the complexity of designing and deploying ANN, the scope of this research is limited to conceptual technical details. This paper is not intended to provide a technical solution for implementation.

Introduction

National-level military and civilian leaders recognize the need for agiler, better-integrated intelligence to warfighters to meet operational requirements. Advances in sensor technology, added to a vast diversity of sources, produce Imagery Intelligence (IMINT) raw data in enormous quantities. The capacity within the military to process and exploit such massive amount of data is not sufficient to satisfy the ever-growing demand for actionable intelligence.[1] To further compound the problem, manpower shortage and constraints make it very difficult to allocate sufficient intelligence technicians and analysts to expedite the processing of all that IMINT data. Intelligence is time-sensitive; hence, processing data in a timely fashion is of paramount importance. Those restrictive conditions warrant due diligence in finding solutions to compliment and supplement human analysts' capacity, so intelligence and information can reach operators and end-users at the speed of need.

Technological advances have proven to be a force multiplier in the military and the commercial sector alike, where automated data processing is a prime example. The Air Force has been a technology champion since inception, where introducing a new state-of-the-art technology will not represent a drastic change for the force. Commercial implementations of Artificial Neural Network (ANN) have demonstrated its ability to transform very large amounts of complex data, comparable to IMINT, into usable information.[2] Employing ANN for IMINT data processing can increase exploitation throughput and efficiency, bringing more intelligence products to the field at a faster rate.

Overview of the Study

Neural networks can process an enormous amount of data while becoming smarter as they do it, recognizing and "remembering" patterns, eventually "inferring" information out of raw data—hence evolving and becoming more intelligent with time.[3] Deep-learning systems mimic the human brain; they associate and connect common patterns, creating smart connections leading to effective learning.[4] In a layered neural network, each module in a chain processes a specific type of data, which in turn becomes an input to the subsequent layer, resulting in usable information as the final product.[5] Similar studies and commercial applications have demonstrated how ANN can process and interpret massive amounts of complex data, resulting in information readily available and presented to humans in an intuitive form, as showcased on the System of Systems Analysis (SoSA) concepts on law enforcement forensic work.[6] Likewise, the Process, Exploitation, and Dissemination (PED) process can benefit by implementing ANN in order to bridge the gap between constant data generation and intelligence production.[7] The end state would be an enhanced PED process by ANN, leaving IMINT analysts as the final authority in the information creation cycle with the approving and vetting authority for the products created by ANN.

Human analysts can modify, supplement or discard all products created by ANN. Organization processes and procedures, such as standard operating procedures (SOPs), will determine the type and depth of human intervention for ANN products. Implying that every single ANN product will require human intervention signals an ineffective technical solution to the main problem. In order to implement ANN effectively, products will bear an accuracy confidence index based on how smart ANN is of the specific factors evaluated; the higher the index, the more accurate the product is likely to be. Based on such rating, added to other mission requirements such as level of fidelity desired and timelines, operators can develop SOPs containing ANN products' prioritization schema.

The Nature of the Problem

The United States (U.S.) military is required to maintain a high state of readiness by being able to respond and adapt rapidly to any potential threat, anywhere in the world. The National Military Strategy (NMS) formalizes that requirement and empowers agility and integration with other instruments of power.[8] Satisfying that difficult obligation depends greatly on robust intelligence, surveillance, and reconnaissance (ISR) capabilities.[9] One pillar of the broader ISR capability group is IMINT. As part of the Geospatial Intelligence (GEOINT) family and as the name implies, IMINT collects, processes analyzes and distributes intelligence and information derived from or interpreted from imagery.[10] The nature of IMINT calls for the tremendous amount of raw data generated from a multitude of sensors, on the ground, in the air and space-based. The issue is the great disproportion between the vast amount of IMINT data produced, contrasted with the relatively meager ability to yield actionable intelligence and usable information to the field. Military operators have an unquenchable thirst for intelligence and information, which is more than justified by military operations and mission requirements. The problem is that current processing capability for IMINT, and other disciplines within the intelligence world, such as Signal Intelligence (SIGINT), can barely satisfy demand. In principle, SIGINT can also benefit from ANN as a solution proposed in this work, however; the scope of this research is limited to IMINT. Processing capacity shortfall calls for innovative solutions and a more agile way to generate intelligence and information.[11]

Purpose of the Study

The purpose of the study is to provide an option—in the form of technology—to accelerate the processing of IMINT data into actionable intelligence. The goal is to process, analyze and distribute verified products, as accurate and as fast as possible. Products from IMINT enable or directly support other core military functions such as, navigation and timing, intelligence indications and warning, Command and Control (C2) and Operational Environment Awareness.[12] The inequality between the IMINT data production capability sharply contrasts with the ability to analyze and process data into actionable intelligence. The study seeks to provide an option to balance these two factors by increasing the IMINT processing capability employing ANN in order to accelerate the PED process, aiding analysts in the overall effort.

The Research Question

Commanders at all levels need relevant, accurate and timely intelligence on hand to plan, execute and assess military missions. The U.S. possesses incredible capabilities to collect a wide array of imagery data, but the processing throughput is not on par with data production. Therefore, the research question for this study is how can Artificial Neural Networks effectively transform IMINT data into reliable and timely intelligence for combat commanders?

Definition of Terms

Active Electronically Scanned Array (AESA) radar. This type of radar uses solid-state transmitting elements that generate pulses, versus a rotating antenna. Modern AESA radars use many modular elements to scan wide angle using phase delay. That means no moving parts, faster scan rates and better reliability by generating several frequencies and pulses simultaneously, which allows for multi-spectrum echo returns. Not only more targets can be monitored, but higher fidelity is achieved by interpolation and correlation of the echoes received by the radar processor.

Area of Responsibility (AOR). This refers specifically to reconnaissance missions' AOR and it is not necessarily equivalent to combat operations' AOR. Reconnaissance missions can take place within designated military operations’ AORs but often times they cover areas beyond those especially when employing space assets.

Exploitation. According to JP 1-02, exploitation is interpreting imagery by technical, experience-based skills and measuring methods in order to make the results available for dissemination.

Interoperability. This is the characteristic of a weapon system or a capability to operate in harmony and synchronized with other weapons systems, in accordance with the established military standards and expectations.

Imagery. Joint Publication 2-03 defines imagery as the representation in a graphical fashion of any natural or man-made object or activity related to such. Imagery is for the most parts the product of sensors, such as cameras and radars, depicting the characteristics of the objects captured. Sensors include but are not limited to airborne platforms such as airplanes and unmanned aerial vehicles, as well as satellites. Other platforms also produce imagery such as ground-based platforms not including concealed photography means.

Sensor/Radar revisit rate. The rate a radar or camera samples a particular target; the higher the rate, the more scans (hence more images returns) the sensor produces. All things being equal, faster rates produce more and higher resolution images, however, it also increases the rate of false returns (echoes or ghosts images). Most modern sensors have adjustable revisit rates capability, allowing sensor operators and mission crew to change the type of imagery that will be produced by sensors.

Visualization. Representation of data in visual form, such as annotated images and maps.

Research Methodology

This research used the problem/solution framework. As stated before, the key problem addressed is the relative sluggishness of the current PED process to generate actionable intelligence and information, derived from IMINT data. The audience will have enough background information for context and education about the problem before explaining the proposed solution. The paper examines joint criteria, such as agility, adaptability and interoperability requirements for the solution as listed on the NMS. Interoperability is closely related to platform security, which are implied and inherent requirements for all military systems, including information and automation systems. The research also examines multi-phase processing and exploitation capability, a set of criteria derived from IMINT doctrine. The paper examines alternate solutions, such as more human analysts and additional smart sensor technologies, in tandem with ANN in order to provide contrasting perspectives while answering the research problem. The goal is to show that ANN is a viable answer for the research question.

LITERATURE REVIEW

As primary sources, the paper refers to the latest version of the NMS[13] in order to validate the topic relevance and military necessity. Additionally, joint doctrine serves as primary source within the paper; doctrine provides context with regards to intelligence as a function of the military and the requirements associated with it.[14] [15]

Given the strong technical nature of this work, a number of secondary sources provide explanation, clarification, context, and legitimacy of the assessments and conclusions exposed in the research. For instance, the articles "How Does The Human Brain Work?..."[16] and "What is Deep Learning?"[17] introduce and explain the main technical concept to the audience, going from how natural learning occurs to a simplified description of the artificial learning process.

Furthermore and as the research promotes, multi-layered Artificial Neural Networks (aka Deep-learning) can significantly aid decision-making by transforming raw sensor data into actionable intelligence with little to no human intervention. This revolutionary claim calls for a trustworthy rationale as explained by Adam Svendsen.[18]

The research narrows its scope and application specifically to IMINT. Based on that focus, the paper refers to sources like “An 'object-use fingerprint': The use of electronic sensors for human identification,”[19] and “Designing Future Processing, Exploitation, and Dissemination Support Systems Using Simulation”[20] tying the discussion specifically to implementing the technology to IMINT. While ANN implementation can be applied to other intelligence disciplines such as SIGINT, the scope of the research limits the discourse to IMINT. Additional secondary and a limited amount of tertiary sources will be used during the research. Tertiary references serve as a way to compare previous research in this area. Due to the nature and level of sensitivity of IMINT, most primary and secondary sources containing IMINT information are classified or at least For Official Use Only (FOUO). All documents used as reference in this research are unclassified.

ANALYSIS, CONCLUSIONS AND RECOMMENDATIONS

Anytime a new process or system is proposed, fundamental questions require answers such as what are the alternatives compared to maintaining the status quo; how much would it cost to implement such alternative; can the new process meet or exceed requirements and is it cost-effective? Specific criteria include IMINT processing and exploitation accuracy and throughput and multi-phase processing and exploitation. An alternate option could be to develop smarter sensors, capable of processing enough data on-board with the correct level of accuracy and fidelity without the need of analysts.

Analysis

It is very important to understand the current PED process first before exploring changes or alternatives. A diverse set of ISR platforms such as aircraft and satellites collect still images and/or videos (raw data) and transfer them to a processing center. Once the data leaves the sensor (sensing) and enters the processing stage, the PED process begins. Human intelligence analysts are the heart of the PED process since they have to translate actual intelligence and information out of the raw data received. As Figure 1 below shows, the current model is linear in nature; here the human element becomes the limiting factor at every stage of the process.

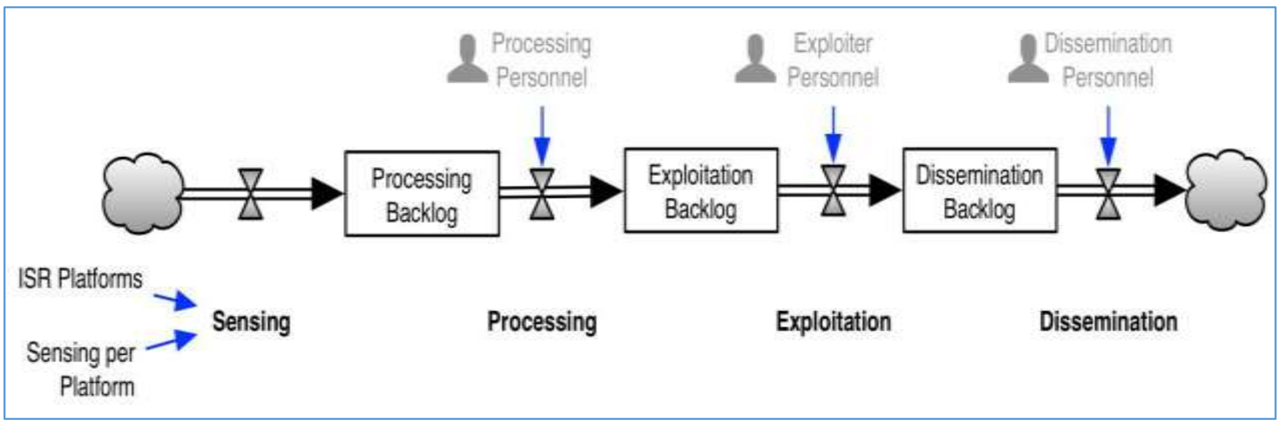

Figure 1. The Current PED Process (Reprinted from "Designing Future Processing, Exploitation, and Dissemination.")

Overview of the PED Process

A number of ISR platforms (aircraft, satellites, etc.) constantly collect data, initiating that way the PED process. Platforms employ sophisticated camera sets and radars to collect raw IMINT data. These sensors produce high-resolution imagery and full-motion video at staggering rates, ranging from single to hundreds of images per-minute or several thousands of video frames per minute as well. For instance, the Multi-Platform Radar Technology Insertion Program (MP-RTIP) is an Active Electronically Scanned Array (AESA) radar system, employed as an airborne sensor on RQ-4 Global Hawks and E-8 Joint STARS. The MP-RTIP can generate still images and objects' tracks (radar reference points of moving targets on the ground) simultaneously. The resulting data stream is transferred from aircraft to ground stations terminals via line of sight or satellite links. [21]

Once the data generated by the sensor reaches the servicing ground station terminal, it is re-packaged and transported to the designated processing center—usually one of the many Distributed Ground Stations (DGSs)—via terrestrial communication networks. From the moment sensors capture imagery to the time it reaches the processing center as raw data, it all happens in seconds. Depending on resolution and sensor revisit rate settings, a single minute worth of mission data can contain between one to hundreds of still images, thousands of tracks plus the associated meta-data.[22] Certainly, the volume of data sourced to DGSs is enormous.

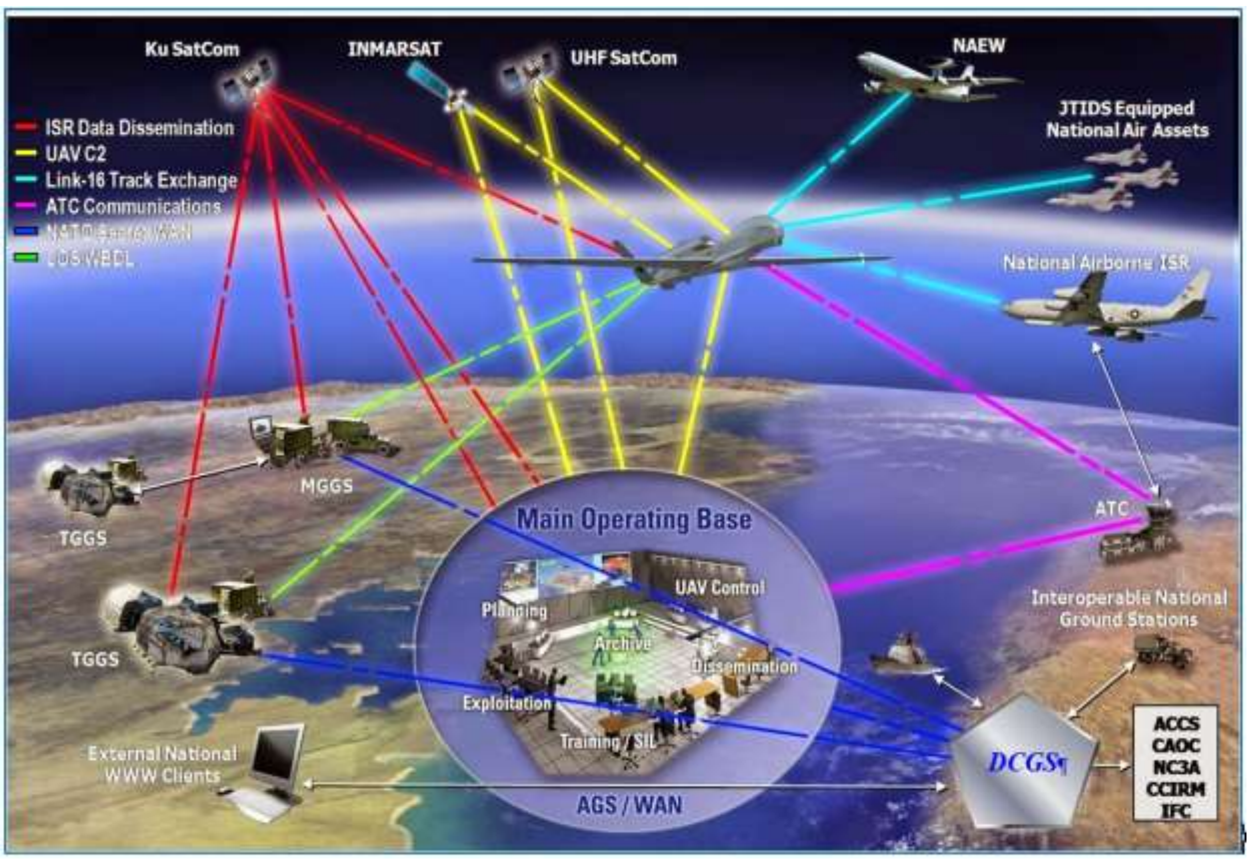

Figure 2. Remote Piloted Aircraft (RPA) Command, Control, and Communications (C3) systems (Reprinted from uaventures.blogspot.com)

Airborne platforms such as the RQ-4 Global Hawk and JSTARS have long flight endurance, which allows them to perform long single-mission sorties or several missions within a single flight. For example, a typical RQ-4 operational tasking usually ranges from 24 to 30 hours in a single-mission sortie, where the actual collection time could be from 12 to18 continuous hours. By using the lower end of that spectrum, it is easy to ascertain that just a single RQ-4 mission can produce tens of thousands of files that require processing and analysis. In contrast, the processing and analysis of such data to transform it into actionable intelligence are not as effective.

Advances in science and technology such as improved sensors, space-based communications, and high-speeds terrestrial communication systems make today's ISR platforms nimble collection agents. Technology has played a crucial role in enhancing the ability to observe, capture and transmit raw IMINT data however; it sharply contrasts with the capacity to process such data. Analysts leverage technology at DGSs around the world but not as much as sensors do for collection. Technicians and analysts invest considerable amount of time and effort processing and analyzing data, which is not commensurate with the rate of data production.

Effective Imagery Analysis Prerequisites: Proficiency, Expertise and Ingenuity

Using the RQ-4 background above as a reference, effective IMINT analysts need to have additional skills and knowledge, on top of being IMINT experts. They need to know the area of operation (AO); they need to be proficient with the particular sensor employed (MP-RTIP in this case, which has many possible configuration modes) and need to be experts about the particular target(s) (such as pattern-of-life, terrain features and well-known artificial objects). That collateral expertise provides context—a critical element in transforming data into intelligence.

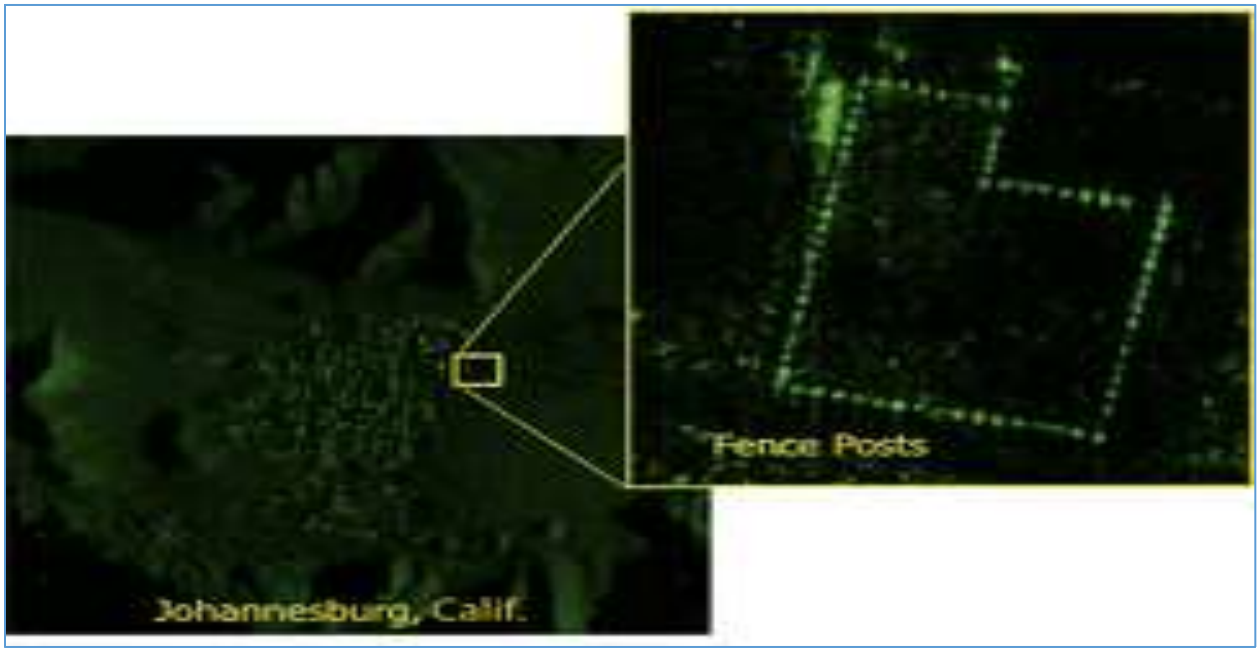

Figure 3. At 45,000 ft., the MP-RTIP sensor concurrently collected a large spot image of Johannesburg, Calif., and an image of fence posts on a property there. (Credit: Northrop

Formal IMINT analysis training requires constant progress. Air Force Specialty Code (AFSC) 1N1 Career Field Education and Training Plan (CFETP) is the imagery analyst chief training framework for Airmen.[23] Glancing at the 1N1 CFETP, it is evident that IMINT analysts have a very wide and diverse formal training needed to master to become proficient. Such intensive training added to the supplemental training discussed above, represents a complex knowledge matrix that military analysts need to nurture to be effective interpreters of raw data. For instance, the SAR graphic depicted in Figure 3 requires expert interpretation to identify the fence posts properly, as labeled in the post-analysis image, and to distinguish them from similar objects like building foundations or posts from a corral. Experienced sensor operators and/or analysts can discern subtle differences displayed on images that show the difference between a wooden post and metal for example, as shown in the figure above. The level of subjectivity required to differentiate how sensors "view" different materials and object types make it incredibly difficult to automate such interpretation accurately.

Air Force IMINT analysts undergo a very intense technical school, where they receive core training common to intelligence professionals in the military. Once the 1N1s are trained on core skills, they are vectored to be either Imagery Analysts or Targeteers. Once Airmen are formally assigned to the Imagery Analyst track (1N1A), they are required to complete significant IMINT-specific training before they are fully qualified to interpret operational data.[24] This training starts with Initial Qualification Training (IQT) at a designated Formal Training Unit (FTU). The main 1N1 training site for 1N1s is at Goodfellow Air Force Base, Texas.

In spite of the location, IQT is usually comprised of a compressed and intensive training curriculum that prepares Airmen for Mission Qualification Training (MQT). The purpose of IQT is to familiarize 1N1s with the system they will be working with, such as the main PED weapon system, the Distributed Common Ground Site (DCGS). Consequentially, MQT certifies analysts on the weapon system, indicating they are ready to employ the sensors during operational missions.[25] For example, analysts operating the MP-RTIP sensor (also called “sensor operators”) go through IQT and MQT—for that sensor in particular—after technical school at Grand Forks Air Force Base, North Dakota, home of the 69th Reconnaissance Group (69 RG). The 69 RG operates and maintains the RQ-4 Block-40 fleet—the version of Global Hawk with the MP-RTIP sensor as payload. The 69 RG also has an FTU not only providing IQT and MQT for analysts performing the mission, but it also provides MQT for RQ-4 pilots. One of the inherent advantages of RPA communities is that analysts and pilots must work very closely, effectively complimenting each other’s skills with an all-inclusive crew mindset. Synchronized efforts are required to comply with time-sensitive mission tasks. Initial steps of IMINT processing frequently begin right at the crew level in the RQ-4 world, effectively shorting the timeline of first-phase exploitation.

The objective of the ISR community is to provide actionable intelligence to combat forces as fast as possible. The planning and execution of military missions directly depend on time-sensitive information. For tactical purposes, intelligence value is proportional to time, where the operational and strategic value is not as diminished with time.

Table 1. Phases of Imagery Exploitation (Extracted from Joint Publication 2-03)

Exploitation Phase	Category	Time factor (Needed by)	Purpose and Description
First-phase Exploitation	Time-dominant exploitation	As soon as possible but NLT 24 hours within receipt of imagery	To meet time-critical requirements, usually from on-going combat operations and tactical in nature. The intelligence and information derived from imagery are critical to mission success. The timeline starts when analysts receive the raw imagery data from the platform(s) to the time its interpretation is delivered.
Second Phase Exploitation	Non-time dominant exploitation	One week within receipt of imagery	Provides more detailed and organized intelligence with a comprehensive account of the information derived, validated by intelligence requirements tasking.
Third Phase Exploitation	Non-time dominant exploitation	Not defined; usually, exceed one week after receipt of imagery.	Extensive analysis is devoted to third-phase, including all available imagery sources and other intelligence sources, such as SIGINT and human intelligence. This phase is suitable for strategic analysis and authoritative products.

As Table 1 above shows, exploitation of IMINT data is categorized in three phases to allocate the adequate priority of resources for exploitation and analysis. Combat forces determine the priority of given missions by communicating how time-sensitive the expected analysis is needed at the field.[26] Even for data originally destined for time-sensitive analysis, as time passes and the collected data age increases, the non-time critical analysis is applied such as strategic planning and shaping of the battlespace preparation. For instance, if a particular ISR platform such as an RQ-4 is tasked to collect on a very specific area during a very specific timeframe, in support of ground operations to identify, detect and/or capture a high-value target (HVT), the IMINT data analysis request is submitted by combat forces usually as a first-phase exploitation requirement. The specific location, number of enemy forces, time of the day and the type of weapons present in the area are all factors that are time-sensitive used as planning and execution parameters needed to track, capture and/or kill a HVT. While the data becomes tactically irrelevant with time, the overall value of the data is not necessarily diminished; the process can continue under non-time dominant exploitation and analysis framework. To maximize efficiency, data is cataloged from time-dominant to non-time dominant category dynamically and that way the exploitation process continues in a seamless fashion.

Data collected and already ingested by the DCGS can be very valuable for operational and strategic purposes. In essence, analysis of IMINT data can be re-initiated at any given time for any given purpose; hence, IMINT data has no expiration date. Regardless of the conditions under which data is exploited and analyzed, time-dominant conditions or otherwise, the challenge is to extract and deliver relevant intelligence at the speed (response time to combat forces) and at the rate (amount of actionable intelligence) of need. The human mind is extraordinarily good at producing intelligence and information from raw data, even if the data is abstract in nature. Intuition, perception, knowledge, and experience are examples of characteristics not easily replicated by technology or automation, where the human mind is the master of all. These traits are paramount in producing actionable intelligence, especially under time-sensitive conditions. The human brain is the prime model to use in order to develop artificial solutions to aid military IMINT analysts in expediting the production of intelligence.

Artificial Neural Networks Explained

The human brain is so complex that it continues to elude the human race's understanding on how it really works. Biologically speaking, the brain's construct is an incredible work of nature, containing more cells than any other organ in the body. As many as 100 billion neurons make up the brain each with the ability to connect to each other constantly. These connections occur at the chemical and biological level, where minerals act as conductive agents that enable the links between neurons. Electro-chemical signals enabled by sodium, potassium and ionized chloride, create an electrical current that serves as a carrier wave for messages between neurons. Organically speaking, the brain is a smart dynamo that not only generates electricity but also generates smart signals that enable communication between neurons.[27]

The electrical charges the brain creates carry messages between neurons, allowing them to communicate with each other within this very complex network. Neurons communicate on a one-to-one basis as well as one-to-many mesh, which is why neurological activity can forge extremely complex and efficient associations that lead to what humans call experience, memory, and knowledge. Another very unique ability for humans provided by the brain is intuition; the capability to deduce information from raw data, as perceived by the senses.[28] Ambitious research like the EyeWire project seeks to map the human brain's neurons in an effort to gain a better understanding of how it really works.[29]

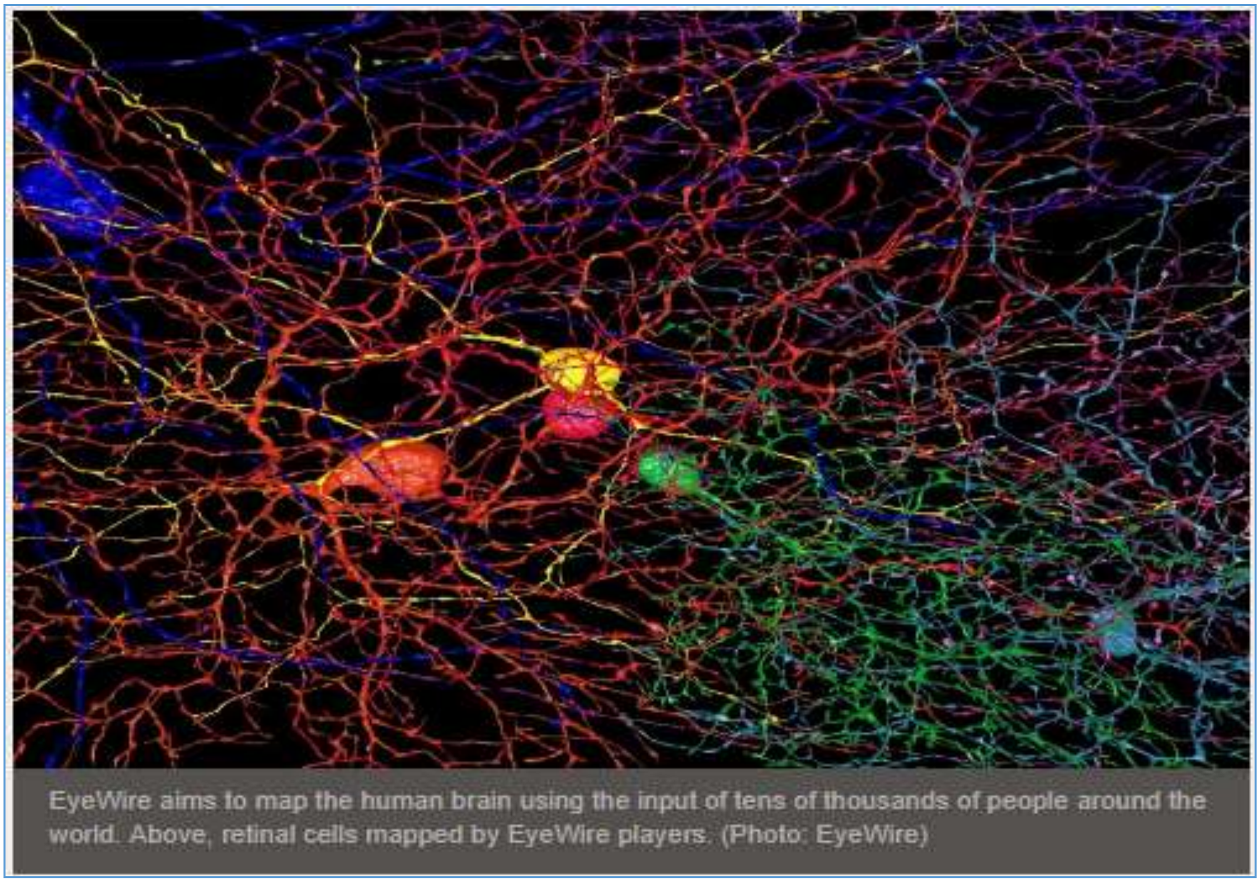

Figure 4. Graphical Map of the Human Brain (Reprinted from iScience.com with permission from EyeWire)

Understanding how the human brain functions helps in the understanding of what ANN is and how it works. As the name implies, ANN is a combination of hardware and software designed to mimic the behavior and functionality of the human brain. Deep-learning systems, another term used interchangeably for ANN, have the capability to make complex associations, accumulating knowledge and "intelligence" with the ability to apply it in solving problems. As the neuron is the brain's basic unit of intelligence and knowledge building, algorithms (a mathematical procedure used to solve complex problems) are the core ANN component and the most basic core component of its design.[30] In artificial neural networks, algorithms reside as embedded hardware code or within the multitude of programs and programming logic in the software architecture that makes-up the entire system. Advances in microchip technology added to solid-state circuitry and memory, allows for programming, storing and executing algorithms at the hardware level (embedded or firmware-based programming). A simplistic example of how algorithms work is a handheld calculator.

A simple calculator machine employs one of the simplest algorithms sets—logic gates combinations—which are hard-coded in its integrated microcircuit microchips. Logic gates compute the value of two or more variables, yielding a discrete mathematical result. Calculators and modern computers employ logic gates as the main computational backbone to process data input and output. Embedded logic gates within the circuitry allow the calculator to "know" how to solve arithmetic problems. The calculator's user interface invokes and runs the particular algorithms required by the command code inputted to the system by the user.

By design, the computer accepts integers as data and any arithmetic operations symbols, like add, subtract or the square root as commands (these commands invoke the algorithms), where the equal sign acts as the execute command (analogous to the "Enter" key on a desktop computer) for the calculator computer system.[31] Algorithms running at the hardware level increase computational performance and throughput and simultaneously expand system scalability while minimizing footprint and complexity. Minimizing algorithm architecture and design complexity, such as common hand-held calculators[32] do, is of vital importance in highly complex ANN systems. Streamlining architecture design facilitates message exchange among algorithms, which is a must-have functionality for ANN systems.

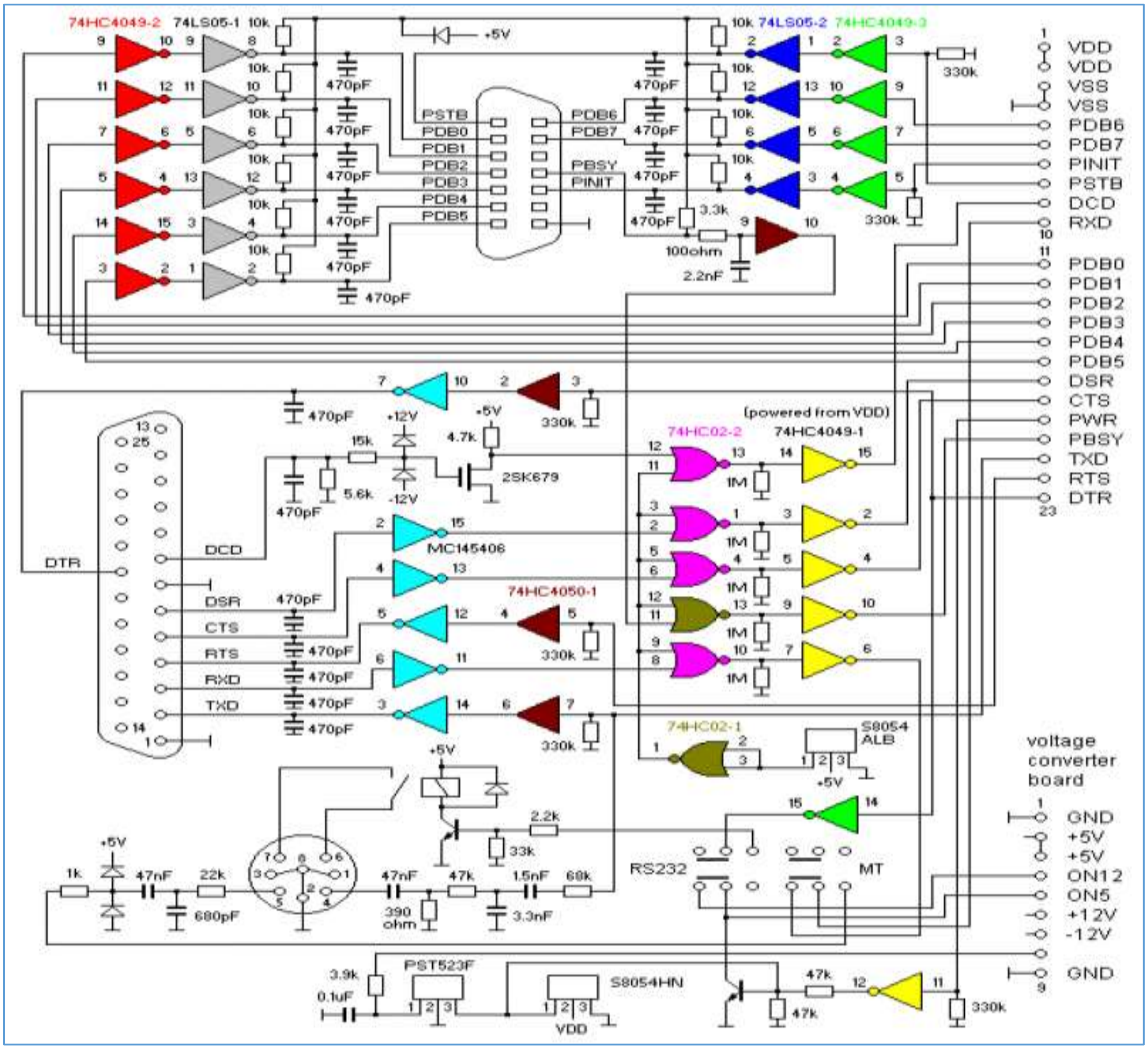

Figure 5. Logic Diagram of a Calculator - Logic gates are depicted in a color-coded and shaped fashion, according to their particular functions. (Reprinted from readingrat.net)

In terms of complexity, sophistication, and level of intelligence, comparing a handheld calculator to a modern ANN system is equivalent to comparing a unicellular organism to a bird or a horse. Deep learning systems have a wide range of algorithms, going from relatively simple ones, such as those based on applied mathematics (linear algebra for example) to extremely complex, deep-nested heuristics algorithms. For instance, two common linear algebra-based algorithms used in ANN systems are vectors and matrices. Matrices are suitable for computing lists of variables that will produce discrete values. Conversely, computing variables that require multiple characterizations and deeper levels of analysis require more complex algorithms, such as Logistic Regression (used in decision-support systems) or naïve Bayes (employed to separate legitimate messages from spam emails).[33]

Deep learning systems rely on what type of data and how it is presented as input and the flexibility to manipulate data without violating data integrity. A simplified illustration of that concept would be an enterprise email server running a naïve Bayes algorithm to detect spam emails. For text messages, discrete preset characteristics and parameters (filters) are employed to distinguish between legitimate emails and spam; keywords or phrases blacklists are common practice. In contrast, that same task becomes far more difficult if the spam content is embedded in graphic files attached to emails, even if the graphics have the same blacklisted keywords. In this scenario, neither the email servers nor the algorithm may "knows" how to properly characterize graphics, unless an algorithm capable of performing such a task is used.[34] Fortunately, computers "view" text and graphics the same way … a series of binary numbers to process. That facilitates the creation of smarter algorithms that can be used to characterize process and analyze graphical inputs, such as images and video. Modern ANN system takes full advantage of implementing many algorithms simultaneously, resulting in a more powerful and efficient overall system.

Understanding that data representation can build or break the functionality or usability of a given ANN platform is important. A way to enhance the versatility of artificial intelligence designs is to allow it to ingest several data types and presentation forms. The logical conclusion then is to transform data presented as input into other forms that can be consumed, interpreted and analyzed by ANN, increasing that way the numbers of possible data presentations that can be processed. That is exactly what deep learning systems accomplish via Multilayer Perceptron (MLP). In a platform implementing MLP, mathematical formulas map input data presentation as output, effectively presenting data in different forms, allowing that way for such data to become valid input to the processing ANN core.[35]

Using the email scenario above as a reference, filtering the expression “001” on a text email only requires exclusion of binary value “00000001” for example, anywhere it is detected in the email server. In the case of a picture file, however, “001” is not its binary value but a large set of pixels, each containing a binary value on its own, where the number of pixels is proportional to the size of the picture. Assuming the size, color and shape of “001” displayed in a graphic are known (at least a feasible range of possible specifications) discrete discriminators (or even a set of discriminators) can be identified. Hence a filter can be crafted. In essence, this effect is the equivalent of adding senses to a relatively primitive computer that only “knew” how to compute discrete values mainly by addition, subtraction and comparison.

Humans have the ability to interpret data, regardless of the fidelity or data layer visibility. Neural networks with deep learning have to use MPL (or MPL-like) processes in order to ingest and process data foreign to them. Humans are inherently capable of adapting data presentation, seamlessly and instantaneously, so the brain can process and analyze it. Data processing and interpretation are done by cognitive skills at the basic layers (knowledge and experience) or by perception and intuition at the different levels of hidden layers. For instance, symbols and markings are used to communicate basic messages at the cognitive level; understanding the meaning of a red traffic light does not require much analysis. Conversely, understanding why a traffic light takes too long to change from red to green requires more reasoning and analysis.

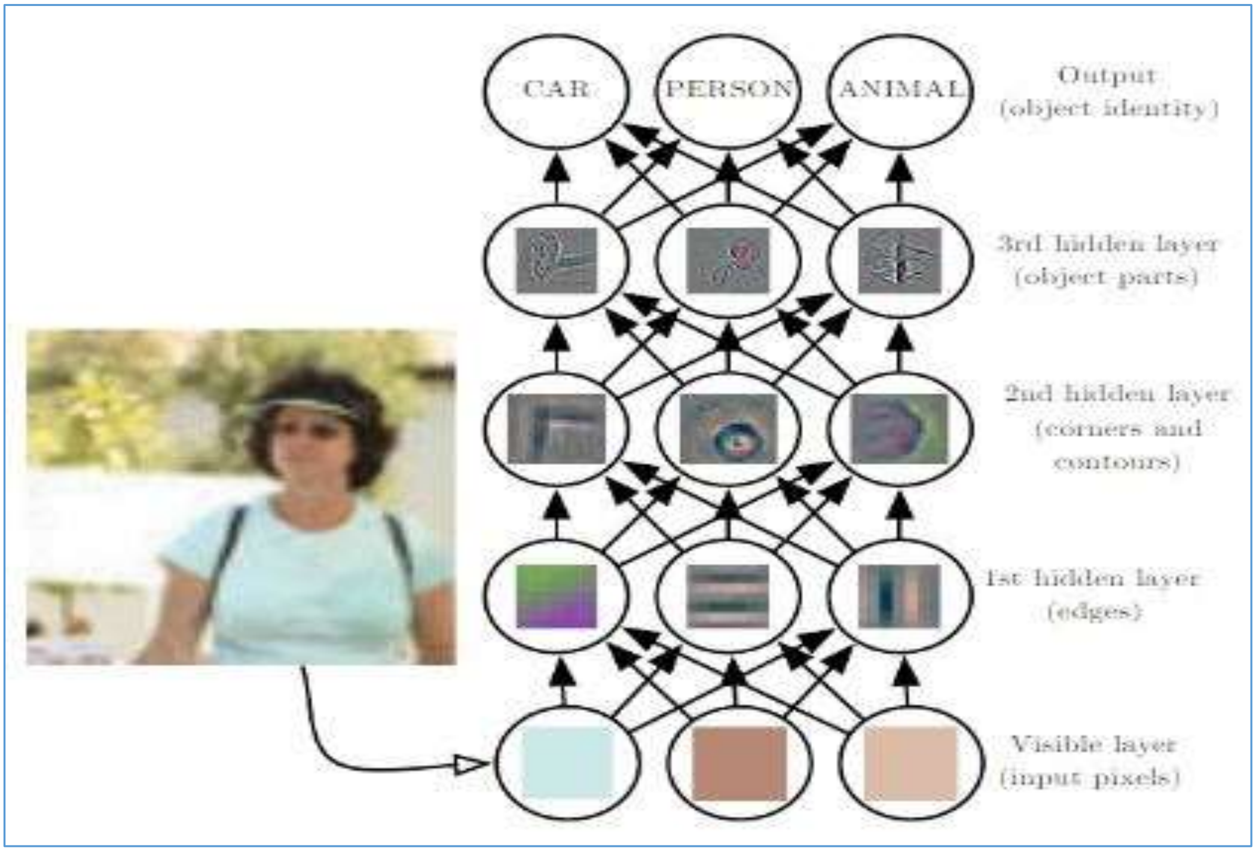

Figure 6. Illustration of a deep learning model (Reprinted from deeplearningbook.org)

Regardless of how data is presented to humans, a MPL-like process is initiated upon data exposure. Figure 6 shows how the cognitive layer (visible layer) provides the known facts. What humans see as colors and general shapes, for example, a deep learning system ingests as pixels or pixel groupings. Following the logical association matrix up to the subsequent hidden layers, the ANN system can eventually "deduct" the image as a person and not as a car or an animal. Adding more variables to each layer and adding more layers could yield higher fidelity in the interpretation of data. In the above figure for example, if the system had deeper and more layers, it could identify sex, age (approximation) and possible ethnicity. Agile data characterization is one of the benefits of employing ANN, where stacked layers can identify very specific attributes from raw data. Characterization is one of the key features to exploit from ANN in order to make the IMINT PED process more responsive to demands from combat forces.

Processing, Characterizing and Visualizing IMINT Data with ANN

Combatant commanders (CCMDs) usually originate IMINT operational requirements (taskings) via their corresponding GEOINT cells. One of the primary responsibilities of the GEOINT cell is to coordinate the assessment, correlation, and processing of GEOINT data by converting it into formats suitable for consumption of end-users. In that context, users include IMINT analysts tasked to exploit the data at the DGSs. Processing IMINT data involves automated, semi-automated or manual procedures in order to integrate and/or fuse data.[36] The power and versatility of ANN can streamline data processing and exploitation, starting at the GEOINT cell level for example and all the way throughout the PED process.

In order to maintain interoperability standards, ANN can be added to existing DoD communications infrastructure in a non-disruptive fashion. Embedding ANN to ubiquitous platforms—such as the web—can effectively transform IMINT data into reliable and timely intelligence. A web-based ANN interface can offer a front-end processor capability IMINT analysts to interact with, supported and complimented by a more robust and more powerful back-end processing systems. That method allows for the implementation of relatively lighter, yet powerful, algorithm-based analysis and response, providing faster processing of data, plus more agile characterization and data visualization. A good example of a successful ANN implementation in industry is Google, starting as a web search engine and evolving to a full set of web applications all fueled by ANN.[37]

Google is a System-of-Systems (SoS), where each major functional area (system) is a rendition of ANN or ANN-like technology. The PageRank engine within Google assigns a numerical value to webpages (rank), indicating their relevance index level, in context with the search parameters (query). PageRank evaluates, in real time, users' queries against all records and instantiations of similar queries within the entire Google platform.[38] PageRank also performs characterization of webpages using content analysis, a number of page visits and how many references or links point to the page by other webpages. The sum of all these factors results in the overall page relevance index as calculated by the PageRank function.

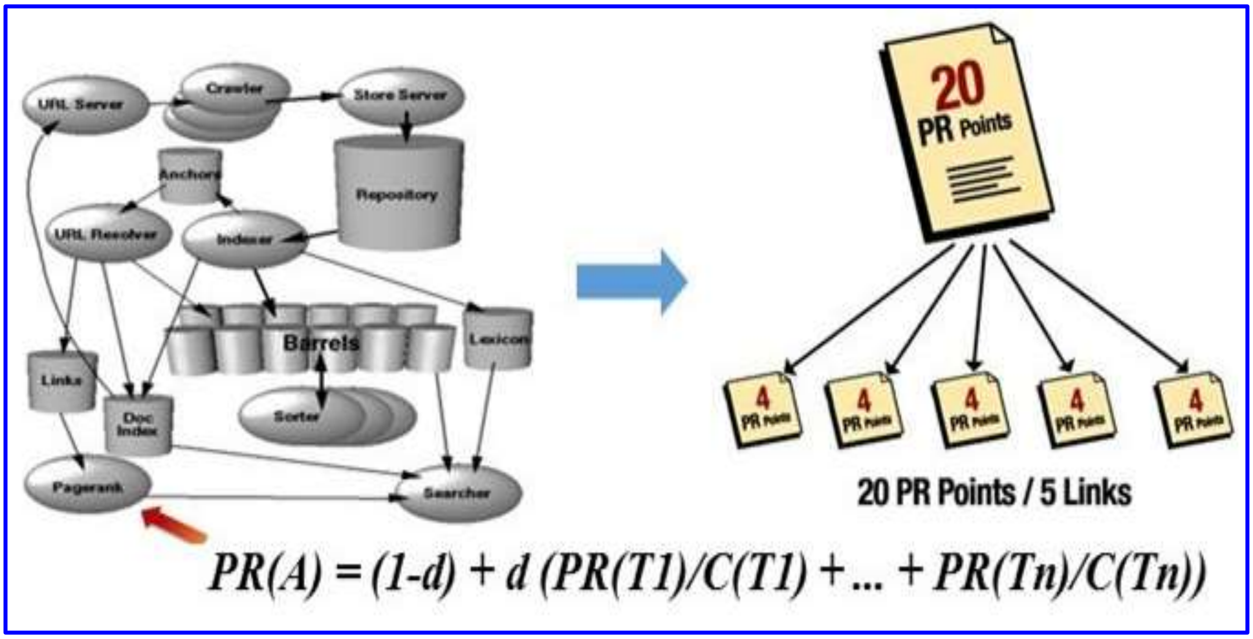

Figure 7. Google's Architecture Showing PageRank interconnectivity and Effects (Reprinted and extrapolated from "The Anatomy of a Large-Scale Hypertextual Web Search Engine.")

In a similar manner, ANN can be used to characterize IMINT data and to perform crosscheck simultaneously, in near-real time and without disrupting the flow of data to DGSs for further analysis. It can generate imagery annotations (commonly referred as "call-outs" by analysts) in seconds, and even milliseconds, using automatic image annotation algorithms. Because the data forwarded to the DGSs would have ANN-bound call-outs, the DGS analysts would also expedite their work using these early indicators and aids provided by ANN. Based on known parameters provided by meta-data (data about data), sensor status, telemetry and external data sources (such as trusted intelligence databases), a system running automatic image annotation can label imagery with relevant keywords, adding context appropriate for interpretation. Analogous to Google's PageRank, the Ranking-Oriented Neighbor Search Mechanism (RNSM) automatically assigns relevant text annotations to images by correlating several layers of data applicable to and related to the image being annotated. The particulars on how RNSM works is beyond the scope of this research and while automatic image annotation, in itself, is not necessarely artificial intelligence, it is an illustration on how the aggregate of capabilities like that builds ANN. In this example, the combined use of RNSM with other algorithms, such as Learning-to-Rank (LTR)—a label ordering mechanism—and Learning-based Keyword Propagation Strategy (LKPS), produce automatic imagery annotations, minimizing and/or eliminating human intervention. Facebook and Flickr run RNSM, within their respective ANN architectures, for content and photo tagging.[39]

The same principles can also be applied to IMINT data processing and analysis, where ANN would ingest the data directly from ISR platforms and without interfering with the rest of the PED process. To illustrate this point, the MP-RTIP sensor for example tags each SAR image file with meta-data such as sensor altitude, date and time stamp, geographical location (coordinates), objects' dimensions and view angle, to name a few. Using ANN running RNSM algorithms, imagery call-outs can take place in seconds versus analysts' annotations which can take several minutes, even for a skilled IMINT technician. That plus the added benefit of having optional simultaneous data crosschecks capability. Data analysis corroboration with "neighboring" data sources from sensors, local data sources or even from DGSs' data repository can strengthen the fidelity of the short-term products. Imagery analysts would only need to validate the accuracy and relevance of tags generated by ANN versus interpreting the images, add contextual meaning to them and editing/to add the actual call-outs manually. Even correcting erroneous annotations would be faster than constructing them manually.

Another way of expediting the transformation of IMINT data into actionable intelligence is by accomplishing data visualization in real-time (or near-real time, depending on available computing processing backbone architecture) with ANN. Employing Content-based Image Retrieval (CBIR) technology for example, ANN can perform salient edge characterization, transforming data and text-based parameters into visual products. Research in this area has shown how ANN systems running CBIR perform searches on existing meta-data and/or databases loaded with physical descriptions, resulting in the production of histograms or vignettes.[40] Another key capability enabled by an ANN system running the CBIR algorithm is query-by-image; an intuitive way of performing searches and data crosscheck, based on graphical interface input instead of text queries. This technology allows users to input images (pictures, maps or even rudimentary hand-drawn sketches) as parameters for searches versus having to type complicated and cumbersome text-based queries.[41] As a result, ANN executes comparison and checksums with existing imagery and text data conforming to the required parameters submitted by the users, producing an annotated graphical depiction of the search.[42] Using high-end computer processor architecture, these computations only take seconds, making this model suitable for near-real time data visualization of IMINT data.[43] [44] A recent example of a revolutionary and successful implementation of artificial intelligence for visualization is the Facebook’s “Visual N-Grams from Web Data” project. This system not only uses graphics as inputs for searches but also can predict text phrases and other images, such as avatars, emoticons and icons, to serve as annotations. The ANN infrastructure uses big data sources and seamless performs analysis and visualization for users.[45]

Conclusions

Modern technology offers many alternatives to handle and manipulate data. The abundance of IMINT data, while compared to intelligence throughput, calls for a solution that leverages technology in solving that problem. A deep-learning system running ANN as the core can serve as a suitable capability gap filler to expedite actionable intelligence and information production from the huge IMINT data constantly produced. Implementing a SoS, where each sub-system (layer) would process data with a specific set of algorithms, such that the product becomes the input for the next layer. For example, a notional ANN system destined to process IMINT data could have as the outer layer a set of CBIR functions, where basic data characterization and visualization is to be performed and simultaneously be available for time-phase exploitation. In turn, this data can be passed to the next layer of ANN running additional analytical algorithms, such as an LKPS and RNSM sets. Following that model, each layer feeds on precedent ones, further refining the analysis and extraction of information and intelligence. As demonstrated by industry leaders like Facebook and Google, the potential benefits of ANN cannot be ignored by DoD, especially when similar problems with big data analysis have been handled with great rate of success.

Recommendations

A robust ANN system, integrated within the current IMINT PED architecture and process, can yield enormous benefits in processing and analyze IMINT data at a faster pace. That would effectively provide actionable intelligence and information to combat forces at the rate of need. Using existing ANN implementations as a model to follow can save time and resources in developing such system within DoD. The core platform hosting this ANN system should be not less than super-computers (or equivalent) due to the intense demands for processing power and high-speed communication networks. The deployment strategy is best using a distributed construct, where all and any customer can access the system for any particular operational need. The layered construct of deep learning systems allows for access of information at all layers. Time-sensitive information could be accessed at the outer layers without sacrificing the capability of more exhaustive data analysis at deeper layers of the system. Recent successful employment of ANN systems, such as Facebook's Learning Visual N-Grams project described above, showcase the potential for the IMINT PED process to benefit from such technology in a similar fashion. A layered deep learning system could provide access to time-sensitive intelligence to field units at the outer layers, such as GEOINT cells, while operational and strategic analysis information could reside at the inner layers, similar to how Facebook does.[46] This approach may require a shift in the current framework of the PED process but flexibility is one of the multiple benefits of ANN.

The current demands for timely and relevant intelligence require diligent and innovative solutions; ANN provides a viable option to solve this problem. That demand will continue to increase in the foreseeable future. Combat commanders and military forces in general need relevant intelligence, at the right time, in order to plan and execute missions worldwide. The application of ANN technology can leverage automation to fulfill a military necessity, otherwise accomplished by slower methods. The US military cannot afford to delay the implementation of a more agile way to deliver intelligence and information to combat commanders.

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