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AI-Enabled Paradigms for Non-Intrusive Screening

Use Case Concepts and Considerations

June 2024

Science and
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Executive Summary

On a daily basis, Department of Homeland Security (DHS) personnel conduct high-volume screening missions at land-based ports of entry, maritime ports, airports, federal facilities and presidential events. At these locations, there is a need to screen commercial cargo, passenger vehicles, and personal items for contraband such as narcotics, weaponry, threat materials and devices, and other illicit goods. For border control, this represents an upper limit of 12 million maritime containers at land borders, 12 million containers at seaports, 2.7 million containers via rail, and 100 million passenger vehicles on an annual basis. For transportation security, this represents over 5.5 million screenings per day. And, for federal facilities, this represents the screening of employees and visitors across 9 thousand federal facilities.

To accomplish this, even for a select set of the highest risk concerns, DHS relies heavily on traditional sensing technologies like X-ray portals operating at multiple energy bands, Computed Tomography (CT), and trace chemical sensing to detect contraband without having to perform thorough, time-intensive manual inspections. Today, various forms of Artificial Intelligence (AI) augment the existing paradigms generally with the approach of making better use of the data streaming from the sensors and detectors. In that form, AI is in many cases a back-end appliance that helps manage the full content of given images. But the domains of emerging technologies, coupled with progress in AI, are creating new opportunities to fundamentally rethink these approaches, in some ways turning them inside out, and consequently rethinking the risk models that underpin the historic approaches. Rather than asking what might be in an image based on what has been measured, using AI and machine learning (ML) as tools, we can consider the use of richer foundation models[1] and ask, 'what should you measure'. Rethinking our approaches could provide important advances in how DHS can perform the screening mission with improved accuracy, higher throughput, and less disruption for the stream of commerce (SoC) traffic passing through these checkpoints.

The advancements in what we can detect or image today are closely tied to the data, imaging, visualization, and characterization enabled by AI, and these must be viewed as inexorably connected. Within today's imaging paradigm, a good fraction of the data is not used at all. AI enables new ways of thinking about old problems by fundamentally redefining how data is processed, analyzed, and utilized. Traditionally, workflows in radiological fields have relied on compressing vast amounts of raw sensor data into reconstructed images for human interpretation, a process that inevitably introduces data loss and uncertainty even within the narrow way it is used today. Data is processed and filtered after that to create suitable distillations for human viewing, rather than used in its fuller and richer context. By bypassing or augmenting traditional workflow processes, AI can extract nuanced features directly from raw sensor data—features that may be lost or obscured in the conversion to visual formats. These innovations not only challenge entrenched workflows but also highlight how AI can turn perceived limitations into opportunities.

This report continues the Preparedness Series of papers where we have explored AI, Foundation Models, Adversarial AI, Digital Content Forgeries, and the impacts to DHS missions. It reflects discussions with the private sector, academics, and DHS operational components, as well as technical deeper dives we hosted with Massachusetts Institute of Technology Lincoln Laboratory (MIT LL) on June 27, 2024, on "AI-Enabled Paradigms for Non-Intrusive Screening".[2,3] In this report, we review the technical underpinnings of non-intrusive security screening at an abstract level, introduce non-intrusive screening

[1] Henninger, A., and Kusnezov, D. (2023). Foundation Models at the Department of Homeland Security: Use Cases and Considerations. https://www.dhs.gov/sites/default/files/2023-12/23_1222_st_foundation_models_dhs_paper.pdf

[2] Yaron Rachlin, Y., Elsenbeck, J., Thornton, J., DeAngelus, M., Linnell, J., Liu, J., Kunz, R., Mathews, D., Su, J., and Vaillant, M. Workshop on New AI-Enabled Paradigms for Non-Intrusive Screening Summary Report and Recommendations. Massachusetts Institute of Technology Lincoln Laboratory. June 27, 2024.

[3] Appendix A provides a list of attendees.

concepts in the context of homeland security missions, provide examples of how AI has been used in related applications, and outline opportunities in research and development.

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CONTENTS

1 Introduction

Technologies to help screen for contraband are critical to homeland security missions such as operations at land-based ports-of-entry, maritime ports-of-entry, airports, and in federal facilities or presidential events. In these locations, there is a need to screen commercial cargo, passenger vehicles, and personal items for contraband such as explosives, narcotics, weaponry, threat materials and devices, and other illicit goods.[4] The approaches that are used frame the underlying models of risk that are being employed. Today homeland security missions rely on non-intrusive sensing technologies such as dual-view X-ray portals operating at multiple energy bands, Computed Tomography (CT) operating at multiple energy bands, and trace chemical sensing to detect contraband without having to perform time-intensive manual inspections.

While screening technologies are currently in use, there are many trends motivating a reevaluation of why our current approach to managing risks should be re-imagined, including:

- Evolving and increasingly challenging set of threats and methods for concealment, including small-form-factor but highly damaging threats such as fentanyl, weapons, exothermic materials, high-power explosives, and Special Nuclear Material (SNM),
- Growing stream of commerce volume that exceeds our ability to screen, and
- Significant advances in the field of AI and machine learning, imaging and characterization, data sciences and edge devices, among others, that are opening new possibilities for how one can architect the effective exploitation of non-intrusive screening data to stand up to the spectrum of future threats.

The last trend is central to this report and especially significant, as we hypothesize that coupling new forms of AI with the latest generation of sensing technologies could provide altogether new paradigms that can lead to significantly better accuracy, broader awareness of emerging threats, higher throughput, and less disruption for the SoC traffic passing through these checkpoints.

Because conventional CT security screening processes co-evolved with human driven visualization-centric medical imaging processes, our current screening workflows compress vast amounts of raw data into what is ultimately a human-interpretable format, discarding significant diagnostic information (that is not in a human-interpretable format or simply not measured) along the way. Data science, in conjunction with AI and sensor/diagnostic technologies, has the potential to disrupt this model by enabling a direct pathway from signals to knowledge, asking what should be measured, where, at what resolution and with which capability, to understand and characterize risks that may be of point origin or distributed more broadly across an operational environment in both space and time. For example, even in narrow applications, AI models trained on raw imaging data have demonstrated enhanced diagnostic performance in combination with traditional methods reliant on reconstructed images.[5] Innovations like these highlight the potential for AI and emerging technologies to revolutionize approaches to detection, discrimination, and response, allowing us to leverage data more comprehensively and effectively in the future. Advanced data analysis methods applied on the backend of the workflow, in isolation, are becoming increasingly dated, and utilizing the advancements in large-scale AI, particularly deep learning, provides an opportunity to rethink how we use data to develop risk models and address emerging threats.

[4] For border control, this represents an upper limit of 12 million maritime containers at land borders, 12 million containers at seaports, 2.7 million containers via rail, and 100 million passenger vehicles on an annual basis. For transportation security, this represents over 5.5 million screenings per day. And, for federal facilities, this represents the screening of employees and visitors across 9 thousand federal facilities.

[5] He, B., Guo, Y., Zhu, Y., Tong, L., Kong, B., Wang, K., Sun, C., Li, H., Huang, F., Wu, L., Wang, M., Meng, F., Dou, L., Sun, K., Tong, T., Liu, Z., Wei, Z., Mu, W., Wang, S., Tang, Z., Zhang, S., Wei, J., Shao, L., Fang, M., Li, J., Zhu, S., Zhou, L., Wang, S., Dong, D., Zhang, H. and Tian, J., (2023). From Signal to Knowledge: The Diagnostic Value of Raw Data in the Artificial Intelligence Prediction of Human Data for the First Time, *Engineering*, Vol. 34, pp. 60-69. https://doi.org/10.1016/j.eng.2023.02.013.

This paper frames this discussion at an introductory level and explores the use of AI in homeland security scanning applications,[6] with a focus on how advances in AI and data science could provide new approaches to managing risk.

1.1 What is NII?

As inferred from Figure 1.1,[7] Non-Intrusive Screening includes a number of subcomponent technologies and methodologies. One of these is Non-Intrusive Inspection (NII), a broad category of technologies and methods

Non-Intrusive Screening

What is meant by "non-intrusive screening" technologies?

- Any capability to help rapidly confirm or clear presence of concealed contraband without requiring direct physical inspection
- "Non-intrusive imaging" is typically a major component of this, but not the only one
- Other sensor modes (trace chemical, rad) and information sources (cargo manifests) may play a role as well

AI is critical component of non-intrusive screening to automate data interpretation and inform decisions

Figure 1.1. Non-Intrusive Screening Technologies

that allow officials to confirm or clear the presence of concealed explosives, contraband, weapons, or other threats without physically opening or handling the inspected items. Non-Intrusive Inspection encompasses a range of techniques, with "Non-Intrusive Imaging" being a key component but not the only one. Non-Intrusive Imaging refers specifically to using X-ray, gamma-ray, neutron diffraction, or other technologies to capture data which enables visualization of the contents of vehicles, cargo, or personal belongings. In contrast, Non-Intrusive Inspection also includes additional sensor modes — such as, but not limited to, Nuclear Quadrupole Resonance, trace chemical, and radiation detectors — as well as data from sources like cargo manifests, which provide further context or identification of suspicious items. This combination of imaging and additional sensors enables NII systems to perform scanning and screening at border crossings, ports, airports, and federal facilities.

1.2 Evolution of NII Scanning

Modern NII technology traces its origins to several decades ago. While it is commonly believed that its earliest methods were rooted in medical applications, a chronology by Dr. Fred Roder,[8] a pioneer in explosives detection systems (EDS), reveals that the early development of CT for explosives detection was not simply an extension of medical imaging systems but emerged in parallel, addressing unique challenges in detecting explosive devices. Roder mentions that the two applications, medical and security, "came together" very quickly. In contrast, the earliest forms of X-ray on which CT is based, were discovered in the late 19th

[6] In many cases, we use DHS missions as examples, but these concepts apply broadly to homeland security missions across nations.

[7] Derived from Thornton, J. (MIT LL). "Setting the Stage: Workshop Overview" Presented at the Workshop for AI-Enabled Paradigms for Non-Intrusive Screening. p.4. June 27, 2024. MIT Innovation Center, Cambridge, MA.

[8] Roder, F., (2021). Evolution of Certified Explosives Detection Systems (EDS) A Chronology. Personal Manuscript.

century, specifically for medical imaging purposes.[9] Researchers have traced the earliest forms of "baggage scanning" to this medical imaging invention, with some records indicating that the practice of using X-ray machines to "see through" luggage occurred as early as 1898 in the railway stations of Paris to support customs checkpoints.[10]

The medical imaging capability was initially important, especially to radiologists or doctors, such that they could visualize the results and appropriately diagnose a potential medical condition (e.g., is that cancer, what bone is broken, etc.). However, traditional X-ray imaging has limitations, especially in distinguishing non-metallic threats or items disguised in common shapes. Unlike basic X-ray systems, however, CT scanners use multiple angled X-ray images to generate detailed, cross-sectional 3D images of an object's internal structure. This capability is crucial for detecting unconventional threats (e.g., explosives shaped to resemble ordinary objects) and provide for more accurate results in security screening use cases that are much more complex and include much more uncertainty than medical use cases (e.g., intentionally hidden threat items, cluttered scan, overlapping objects that are of a practically infinite variety, etc.).

While the first use of CT in medical applications occurred in 1971 with EMI's Mark 1, NII work based on CT occurred in parallel.[11] The initial focus was on landmine detection, but the exploration of various techniques for detecting explosives (e.g., gamma-rays, X-ray backscatter, etc.) ultimately led to the recognition of the potential of CT capabilities in screening packages. The conceptual breakthroughs led to the development of systems that could accurately detect explosives by analyzing the physical properties of materials rather than relying on pattern recognition, which was the prevailing method at the time. By 1976, Roder had already patented an approach for using CT to detect plastic explosives in luggage — an invention that would later revolutionize airport security.

The tragic bombing of Pan Am Flight 103 in 1988 accelerated the push for CT-based explosive detection systems. In December 2002, in response to the events of 9/11, the U.S. Government mandated the screening of all baggage and later air cargo at airports. The first certified explosive detection CT scanner was deployed in the mid-1990s, and since then, the technology has steadily improved, moving towards faster and largely automated processes.

Today, modern CT scanners, now enhanced with AI and advanced image-processing algorithms, continue to form the backbone of explosive detection systems in aviation security, providing a much more reliable and automated solution for identifying threats compared to the traditional X-ray systems. One unique challenge in security screening is the increasingly diverse stream of commodities that are subject to X-ray inspection. These systems must account for an array of intentionally hidden threat items, in a cluttered scan, with overlapping objects that are of a (practically) infinite variety in comparison to the relative uniformity of the human body. In summary, while medical CT imaging and security screening technologies share some similarities, the evolution of EDS was driven by a separate, parallel track of development, with unique needs and requirements for detecting hidden and unconventional threats. The early work discussed by Roder paved the way for the use of CT in security, ultimately leading to the automated detection systems we use today.

[9] Babic R.R., Stankovic Babic G., Babic S.R. and Babic N.R., (2016). 120 Years Since the Discovery of X-rays. *Med Pregl*. 2016 Sep;69(9-10):323-330. doi: 10.2298/mpns1610323b. PMID: 29693857.
[10] Colomina, B., (2015). X-Screens: Röntgen Architecture. *e-fluxJournal*. Issue #66. https://www.e-flux.com/journal/66/60736/x-screens-rntgen-architecture/.
[11] Roder's work on using CT for explosives detection predated the widespread application of CT in medical imaging and was not based on an existing medical paradigm.

1.2.1 NII Sensors

Figure 1.2[12] introduces an assortment of sensor and detection technologies relevant to the NII scanning space. Other potential technologies include Muon Tomography, Gravimetry, Electrical Capacitance Tomography, Magnetic Inductance Tomography, Neutron Imaging, Nuclear Resonance, Vibrational Spectroscopy, etc.

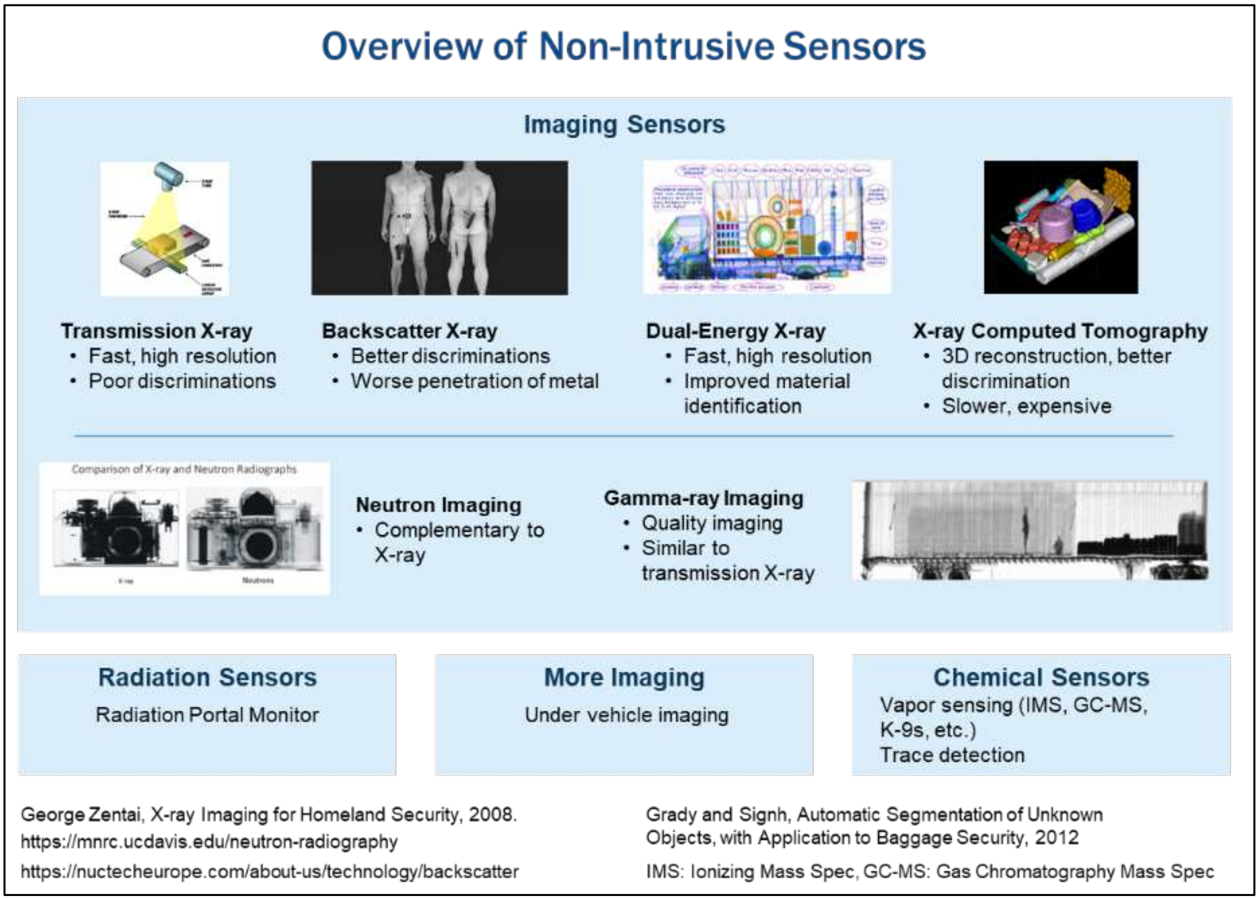


Figure 1.2. Non-Intrusive Sensors

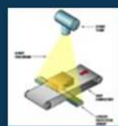
Apart from Neutron Imaging which has potential in screening high density cargo, the other technologies are not suitable due to long detection times, cost, radiation effects, and size constraints. At this point in time, X-ray related detection, augmented in some cases by neutron imaging, is considered the best solution in terms of capability, practicality, and cost for detecting explosives and contraband. As such, this study straddles conventional X-ray transmission and CT, but also recognizes the power of combining additional information such as back scattering. Table 1.1 summarizes their relative strengths and weaknesses. We also acknowledge the potential for information gain from other types of detectors (e.g., X-ray diffraction, refraction, phase changes, etc.) and the potential for cross-correlations in these suites of sensors in security scanning.

1.2.2 Security Applications of CT

The first major security application of CT relates to checked baggage. After the 9/11/2001 incident, following the passing of the FAA Airport Security Federalization Act and the Aviation and Transportation

[12] Derived from Linnell, J. (MIT LL). Non-Intrusive Screening in Operations. Presented at the Workshop for AI-Enabled Paradigms for Non-Intrusive Screening. p.3. June 27, 2024. MIT Innovation Center, Cambridge, MA.

Table 1.1. Relative Strengths and Weaknesses of Technologies in the X-ray transmission and CT Domains [13,14,15]

	Projection  **Transmission X-ray** • Fast, high resolution • Poor discrimination	Backscatter  **Backscatter X-ray** • Better discriminations • Worse penetration of metal	Dual-Energy  **Dual-Energy X-ray** • Fast, high resolution • Improved material identification	CT  **X-ray Computed Tomography** • 3D reconstruction, better discrimination • Slower, expensive
Material discrimination	• Poor discriminations	• Better discriminations	• Material identification	• Better discriminations
Threats detected	• Guns	• Guns • Explosives • Crystalline	• Guns • Explosives • Crystalline	• Guns • Explosives • Crystalline
Precision	• Low	• Medium	• Medium	• High
Scan Speed	• Fast	• Variable	• Fast	• Slow
Costs	• Low	• Medium+	• Medium	• High
Other Important Benefits and Limitations	• **Benefits** - Better image quality • **Limitations** - Only captures shape not structure - Tend to have higher false alarm and overlooked threat rates	• **Benefits** - Distinguish between low Z elements - Generates two images • **Limitations** - Worse penetration of metal - Expensive, especially if 2-sided version needed	• **Benefits** - Improved contrast - Can detect explosives hidden behind object made of heavy materials • **Limitations** - Can't distinguish as effectively between lighter elements	• **Benefits** - Greater spatial resolution and structural information - Looks past/around high-density objects • **Limitations** - Bright metal streaking artifacts and low-resolution impair image quality

Security Act in November 2001, the FAA gave major contracts to L-3 Communications and Invision for the deployment of certified CT-based cargo scanners at scores of U.S. airports, and their integration into corresponding airport baggage handling systems. Though some countries such as Great Britain already had protocols for screening luggage and passengers, this act federalized security at airports. Over a period of years, L-3 and Invision were both acquired several times over by other companies. Many other companies joined the explosive detection system market for checked baggage screening systems and participated in other acquisitions by TSA as well as similar organizations around the world. Some of the current major players are Rapiscan, Smiths, Leidos, and Analogic. These and other companies – many of them small – such as IDSS, Astrophysics, Halo, Micro- X etc., are now supporting developmental efforts using not only conventional CT using projection measurements but also using enhancements such as X-ray diffraction, coded apertures, scatter etc., to improve detection and reduce false alarms (which tend to reduce throughput). These technologies are used both for scanning checked/passenger bags and for air cargo.[16] Other companies such as

[13] Velayudhan, D., Hassan, T., Damiani, E., and Werghi, N. (2022). Recent Advances in Baggage Threat Detection: A Comprehensive and Systematic Survey. *ACM Comput. Surv.* 55, 8, Article 165 (December 2022), 38 pages;
[14] Vukadinovic, D., Anderson, D., (2022). X-Ray Baggage Screening and Artificial Intelligence (AI): A Technical Review of Machine Learning Techniques for X-ray Baggage Screening. Joint Research Council (JRC) Science for Policy Report. https://doi.org/10.1145/3549932;
[15] PEO Detection, (2024). Compare 4 X-Ray Technologies for Baggage Scanners. https://peodetection.com/news/compare-4-x-ray-technologies-for-baggage-scanners/.
[16] Derived from Babu, K., (2023). An Introduction to CT Based Screening for Security, DHS S&T White Paper.

Lumafield, Zeiss, etc., are using CT and AI for examining machine parts and other non-security applications. Some of these efforts are pushing the limits in multiple areas of interest (e.g., resolution, use of data, image reconstruction, etc.). These private sector entities, in industrial and scientific X-ray and CT imaging, are leading breakthroughs in advanced automated defect recognition (ADR) and AI methods being used for defect detection and advanced analysis for a variety of components and materials, and often in high-throughput environments.

Constrained to the investment in legacy systems, the options to improve include:

- Improve the sensors and detectors (e.g., photon counting,[17] multi-contrast/phase contrast imaging,[18] etc.) and the affordability of those,
- Extract more information out of analysis (e.g., non-imaging-centric approaches,[19] anomaly detection approaches,[20] model-based iterative reconstruction,[21] etc.), or
- Do both.

But, more broadly, the entire approach can benefit from thinking anew, as each of those options can be characterized by a host of different approaches. The bulk of this report focuses on how to "extract more information out of analysis", and in some cases we address the third, "both". As a general heuristic, however, we attempt to ideate on innovation applied to conventional systems in development now, in contrast to new sensing modalities.

1.3 Generalized Model of Security Scanning

Figure 1.3 provides a generalized model of security scanning represented at a very high level of abstraction. This is but one implementation of the workflow used for illustrative purposes. Many companies have developed their own proprietary approaches which deviate in some ways from the approach shown in Figure 1.3.

1.3.1 X-Ray Image Acquisition

The X-ray image acquisition process involves passing baggage through a gantry equipped with an X-ray source and dual-energy detectors. X-ray energy beams interact with materials in the baggage at an atomic level through processes such as the photoelectric effect, Compton scattering, and Rayleigh scattering. These interactions vary based on the material's atomic structure and the energy of the X-rays. As X-rays pass through the baggage, their attenuation is recorded by detectors that capture the intensity loss at each energy level. This attenuation is influenced by the material's characteristics, the ordering of materials, and the energy-dependent phenomena such as beam hardening, where low-energy X-rays are more likely to be absorbed by dense materials. The captured signal is converted into digital intensity values, serving as input for future computational processing, including reconstructing material distributions using methods such as CT.

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[17] Ballabriga, R., Alozy, J., Bandi, N., Campbell, M., Egidos, N., Fernandez-Tenllado, J., Heijne, E., Kremastiotis, I., Llopart, X., Madsen, M., Pennicard, D., Sriskaran, V., and Tlustos, L. (2021). Photon Counting Detectors for X-Ray Imaging with Emphasis on CT. *IEEE Transactions on Radiation and Plasma Medical Sciences*, VOL. 5, NO. 4, page 422. JULY.

[18] Miller, E., Campbell, L, Gilber, A., Ivanusa, P. Jensen, S., Kasparek, D., McCall, J., and McDonald, B. (2023). "Gratings-based phase contrast x-rays for security screening", *Proc. SPIE 12531, Anomaly Detection and Imaging with X-Rays (ADIX) VIII*, 125310E. June. https://doi.org/10.1117/12.2664161.

[19] Chung, C., Kalpathy-Cramer, J., Knopp, M., and Jaffray, D. (2020). In the Era of Deep Learning Why Reconstruct and Image at All? American College of Radiology. https://doi.org/10.1016/j.jacr.2020.09.050.

[20] Griffin, L., Caldwell, M., Andrews, J., and Bohler, H. (2019). Unexpected items in the Bagging Area" Anomaly Detection in X-Ray Security Images. *IEEE Transactions on Inferential Forensics Security*, 16, 6 (June 2019), p. 1539-1553.

[21] Hsieh, J., Liu, E., Nett, B., Tang, J, Thibault, J., Sahney, S. (2019). A New Era of Image Reconstruction: TrueFidelity. A Technical White Paper on Deep Learning Image Reconstruction. https://www.semanticscholar.org/paper/A-new-era-of-image-reconstruction%3A-TrueFidelityTM-Hsieh-Liu/d0f8e1e8868e9f8ed22ad5972420139551552e91.

The X-ray imaging acquisition processes employed in security screening systems have often been designed to produce data meant for human interpretation. This may not be ideal for advanced AI models and could hinder their full implementation and impact. Key limitations could include the way analog signals are abstracted during digitization and the inadequate utilization or measurement of primary scatter data, which is a function of energy. These assumptions could constrain the granularity and fidelity of the acquired data, potentially limiting the ability of AI systems to fully leverage the underlying physical phenomena and complex material interactions for enhanced detection or classification accuracy.

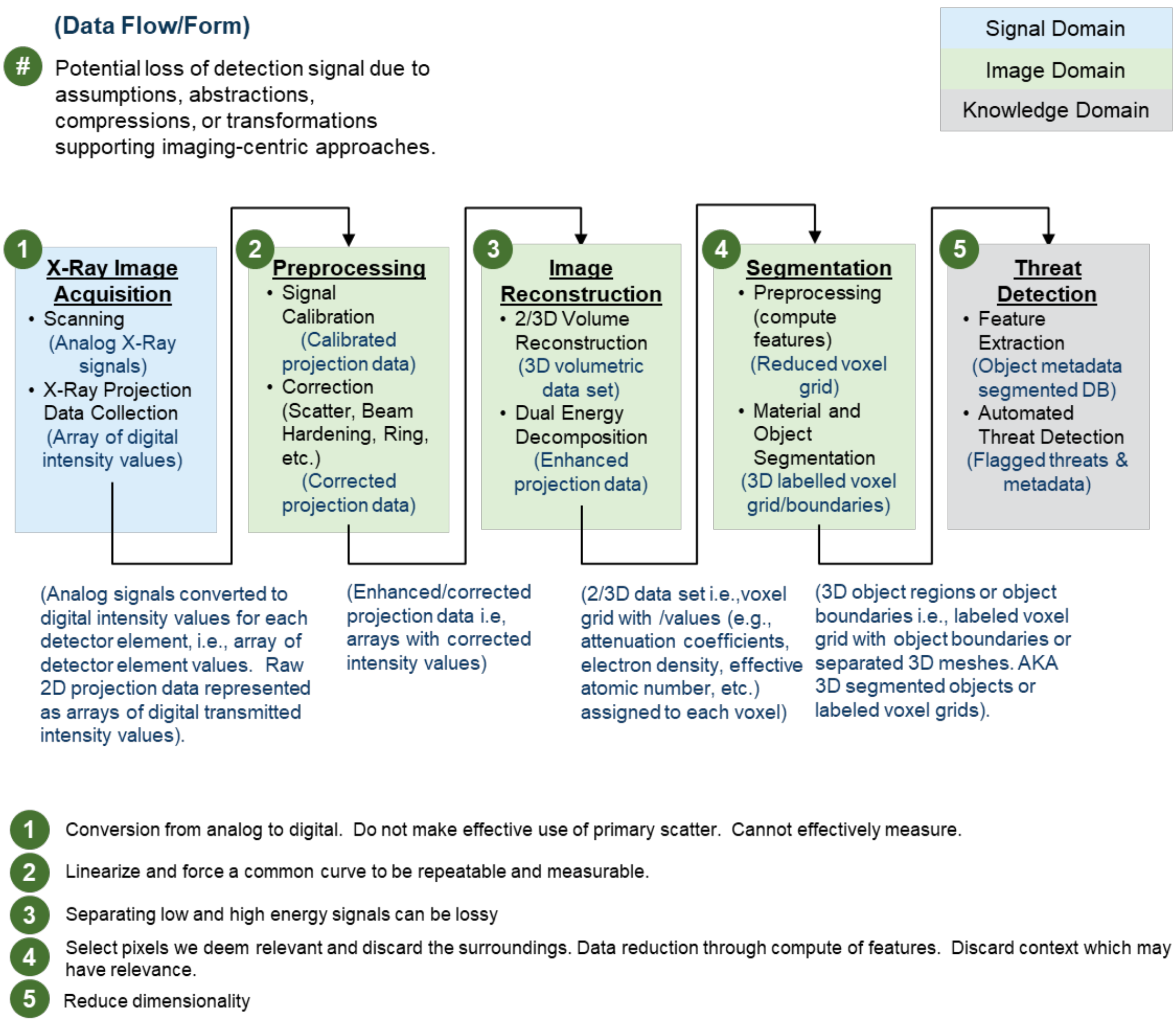

Figure 1.3. Generalized Process for Development of CT Security Screening Models

1.3.2 Preprocessing

Preprocessing X-ray projection data is crucial to enable accurate image reconstruction by correcting for artifacts and inconsistencies introduced during data acquisition. Signal calibration adjusts detector outputs to account for environmental noise, such as electronic fluctuations and temperature variations. This involves offset corrections to remove baseline biases and gain corrections to ensure consistent detector sensitivity. After calibration, various corrections address physical phenomena that can distort the data. Beam Hardening Correction (BHC) mitigates the preferential attenuation of low-energy photons by dense materials, which can cause streaks or false edges in reconstructed images. This is achieved by modeling material-specific

attenuation behaviors and applying linearization curves based on calibration data. However, such linearization assumes that all materials behave uniformly, leading to a loss of detailed information about unique material properties.

Additional corrections refine data quality further. Scatter correction can suppress unwanted scatter artifacts, modeling remaining scatter as blurred signals to be subtracted from the projection data. Other techniques address systematic issues, such as ring artifacts caused by detector defects or mechanical misalignments. These corrections force assumptions such as uniform attenuation curves and scatter approximations that, while effective for producing consistent images, hinder AI-based data-driven approaches by masking subtle, material-specific details that could enhance the accuracy of automated detection and classification systems.

1.3.3 Image Reconstruction

The image reconstruction process converts calibrated and corrected X-ray projection data into meaningful 3D volumetric representations. First, projection data from multiple angles is organized into a sinogram, where each row corresponds to an angular projection and each column represents the offset. Pre-filtering may be applied to reduce noise and enhance spatial resolution before reconstruction begins. Algorithms such as Filtered Back Projection (FBP) use mathematical filters to emphasize high-frequency details while suppressing noise, offering a computationally efficient first-pass reconstruction. For more accurate and artifact-suppressed results, Iterative Reconstruction (IR) employs forward and backward projections to iteratively refine the 3D image, incorporating detailed physical models of the X-ray source, beam, and detector geometry. The result is a voxel grid where each voxel contains a density value derived from the measured attenuation.

In dual-energy imaging, high- and low-energy projection datasets are reconstructed separately and then processed using dual-energy decomposition (DED) techniques. This approach generates material-specific maps, such as electron density or effective atomic number (Z), which enhance material differentiation. Dual-energy reconstruction also enables the creation of advanced datasets, such as effective Z maps or metal artifact-reduced images. However, assumptions made in image-centric screening approaches — such as the reliance on generalized attenuation curves or simplified decomposition models — limit the resolution and fidelity of reconstructed features. These abstractions mask subtle material-specific characteristics, posing challenges for AI-based data-driven systems that rely on nuanced, high-fidelity inputs for advanced analytics and automated decision-making.

1.3.4 Segmentation

Segmentation of reconstructed 2D or 3D data enables the identification of materials and objects to support automated threat detection. Preprocessing reduces the complexity of the voxel grid by computing features such as effective atomic number (Z) and electron density from dual-energy attenuation profiles. These features are used to classify materials into categories such as organic, inorganic, or metallic through techniques such as thresholding, k-means clustering, or Gaussian mixture models. Material segmentation relies on predefined classification schemes and assumes consistent attenuation profiles across varying conditions, which may oversimplify the diversity of real-world scenarios.

Material and object segmentation are often performed together to assign labeled voxel grids to discrete objects. Spatial clustering algorithms such as connected-component analysis and morphological operations are used to define object boundaries, while techniques like watershed segmentation help separate overlapping or nested objects. While effective, segmentation involves data loss: preprocessing reduces the voxel grid's richness, and surrounding contextual data is often discarded. These image-centric assumptions can hinder broader data-driven approaches by excluding subtle contextual details that may be helpful for distinguishing threats in complex environments.

1.3.5 Threat Analysis

Threat detection using segmented data from X-ray projections involves extracting key features from identified objects and analyzing them to flag potential threats. Features such as size, shape, density, and material composition are calculated, with additional data points such as 3D texture patterns or volumetric signatures indicative of specific threats. Advanced algorithms can detect anomalies, such as density contrasts associated with explosives. Rule-based systems apply pre-defined thresholds to classify objects, while machine learning models, such as support vector machines or ensemble algorithms, provide more nuanced threat probability scores. These outputs are critical for operators, especially when enhanced with 3D visualizations that aid in understanding spatial arrangements and object composition.

However, reliance on segmentation assumes that relevant features for threat detection can be accurately isolated from the context, potentially discarding useful surrounding information. Traditional approaches often presuppose that threats possess distinct X-ray attenuation characteristics compared to benign items, which may not always hold true. Additionally, image-centric screening methods emphasize the limitations of standard X-ray transmission data, which depend primarily on density and atomic composition. These assumptions can hinder AI-based, data-driven methodologies, which perform best with comprehensive contextual data and are disadvantaged by incomplete or oversimplified inputs.

2 Major NII Screening Use Cases in Homeland Security Missions

Building on the framework presented in Figure 2.1[22] and expanding it to include small scale systems scanning, the following sub-sections provide deeper insight into the major screening non-intrusive imaging-based use cases in HLS missions.

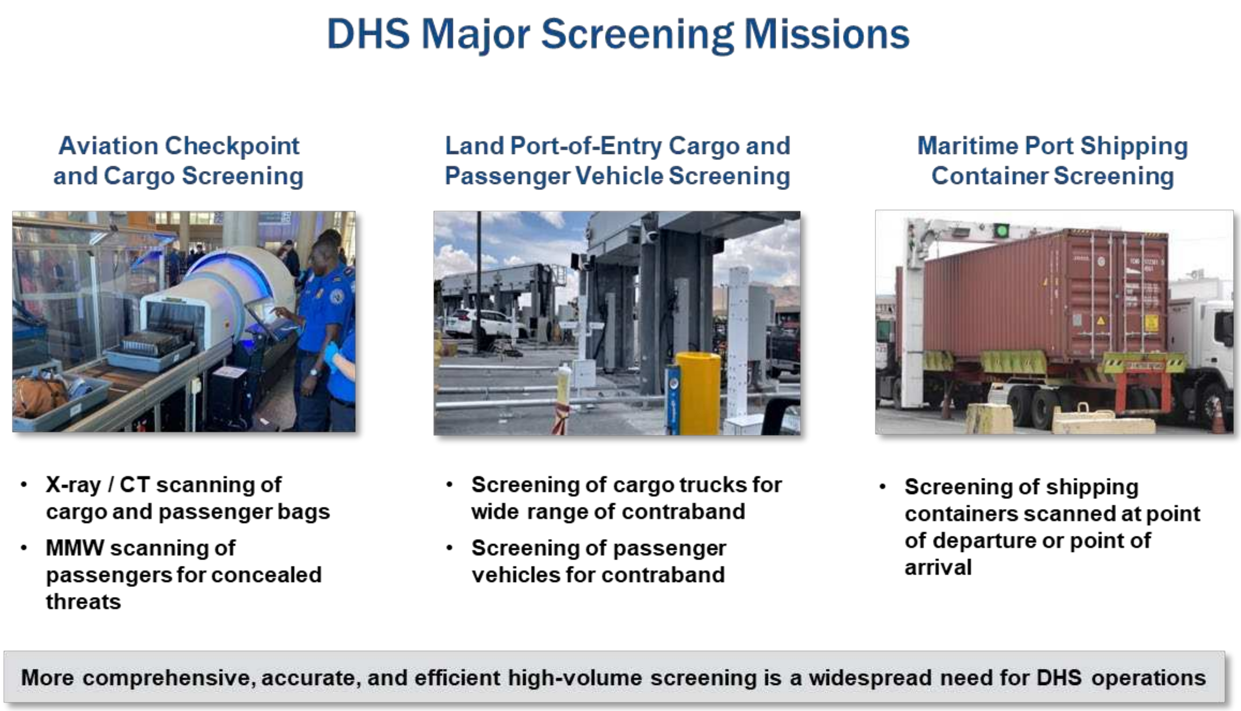

Figure 2.1. Major Non-intrusive Imaging-based Screening Use Cases in DHS Missions. (MMW represents millimeter wave)

[22] Derived from Thornton, J., (2024). "Setting the Stage: Workshop Overview" p.3. Presented at the Workshop for AI-Enabled Paradigms for Non-Intrusive Screening. June 27, 2024. MIT Innovation Center, Cambridge, MA.

2.1 Aviation Checkpoint and Cargo Screening

To prevent terrorist threats, the Transportation Security Administration (TSA) requires all passengers to pass through security checkpoints, where both passengers and their belongings are thoroughly screened to detect and block prohibited items — such as explosives, guns, knives, and other dangerous objects — from entering restricted airport areas or aircraft. TSA relies on a range of screening technologies that combine advanced hardware and software designed to identify potential threats. At airports in the U.S., millimeter wave scanners and metal detectors are used for screening passengers. Their luggage, either hand carried or checked in, is typically inspected using dual-view X-ray or CT scanners. Any alarms are validated using physical inspection or trace equipment. By measuring the X-ray attenuation (at one or more energy levels) and estimating the effective-Z value of the materials, the scanners can detect items that may pose a threat. Figure 2.2[23] shows the screening technologies used in primary and secondary screening for both passengers and checked baggage. Between these and across U.S. airports, TSA generates over 5.5 million images a day through its screening efforts. The following sub-sections provide further detail on these scanning use cases, as well as on air cargo screening, which is another critical but less familiar component of aviation security.

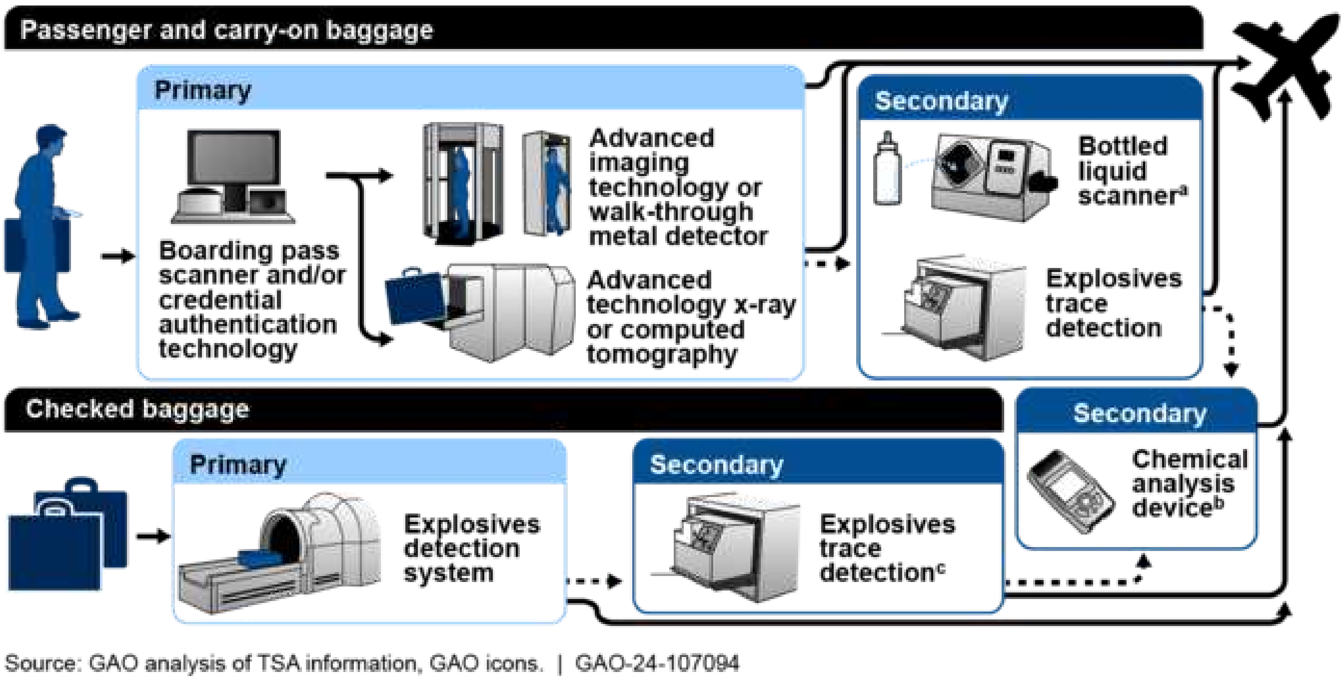

Figure 2.2. Passenger, Carry-on Baggage, and Checked Baggage Use Cases

2.1.1 Passenger Screening

The Transportation Security Administration (TSA) employs advanced imaging technology at airport security checkpoints as a primary method for screening passengers. This technology includes full-body scanners, which can identify concealed threats such as weapons or explosives that might not be detected by traditional metal detectors. As seen in Figure 2.2, if a passenger triggers an alarm on an advanced imaging scanner, TSA protocols require secondary screening, which may involve a targeted pat-down or explosive trace detection to ensure safety.

[23] GAO (2024). Aviation Security: TSA Could Better Ensure Detection and Assess the Potential for Discrimination in Its Screening Technologies https://www.gao.gov/products/gao-24-107094.

Full-body scanners fall into two main categories: millimeter-wave scanners and backscatter X-ray scanners.[24] Millimeter-wave scanners use electromagnetic waves in the frequency range of 30–300 GHz, just above the microwave spectrum. These waves reflect off the body and generate an animated image that highlights potential threats based on their color coding, allowing security personnel to identify areas that may require further examination. In contrast, backscatter X-ray scanners employ low doses of ionizing radiation to reveal objects that are hidden on a person's body. While effective, backscatter scanners are slower and can be perceived as more invasive, which has led to their decreased use in favor of millimeter-wave technology.[25] The choice between advanced imaging technology and metal detectors often depends on specific factors related to each passenger. TSA may direct a passenger to use an advanced imaging booth if they are wearing bulky clothing, have medical implants, or if their belongings raise alarms in a metal detector. On the other hand, passengers without such concerns or passengers with pre-arranged clearances (e.g., Pre-Check, etc.) may proceed through metal detectors, which are generally faster and less intrusive, facilitating a smoother flow through security checkpoints.

2.1.2 Checked and Carry-On Baggage Screening

As seen in Figure 2.2, there are essentially two forms of baggage screening: Checked baggage and carry-on baggage, each using unique technologies designed for threats and distinct security challenges relevant to each. Checked baggage screening is primarily focused on identifying explosives and larger dangerous items that could pose significant threats if detonated in an aircraft's cargo hold. TSA employs advanced screening technologies, including explosive detection systems, to analyze checked luggage for these kinds of hazards. These scanners typically use CT technology to generate 3D images of objects. These CT systems meet classified detection standards. This method allows security personnel to assess the contents for significant threats, primarily related to explosives.

In contrast, carry-on baggage screening addresses a wider variety of threats, including not just explosives, but also items such as knives, firearms, and prohibited liquids that passengers may attempt to bring into the cabin. To accomplish this, carry-on baggage is screened using multiple technologies, including traditional X-ray machines and more advanced imaging systems, such as CT scanners. Again, CT scanners produce three-dimensional images by capturing X-ray data from multiple angles, enabling security agents to identify both metallic and non-metallic threats while allowing passengers to keep most items in their bags during screening.[26]

2.1.3 Air Cargo Breakbulk Cargo

The aviation industry handles a wide variety of cargo, which comes in several configurations. The most common of those configurations is the breakbulk configuration, which includes numerous boxes on skids, homogeneous and heterogeneous. When the items on the skid are homogeneous and not excessively dense, the freight can generally be screened for dangerous items using a large aperture X-ray scanner. If the items on the skid are made up of heterogeneous items, dense items or large numbers of complex items, the screening of the cargo may require breaking the configuration down into single boxes or even possibly breaking the cargo down to separate pieces within the smaller boxes, which then can be screened using large aperture X-ray, explosive trace detection with physical search, or physical search by itself.[27]

Only homogeneous cargo can be screened without breaking the cargo down into individual pieces.

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[24] Accardo, J. and Chaudhry, M.A. (2014). Radiation Exposure and Privacy Concerns Surrounding Full-body Scanners in Airports, *Journal of Radiation Research and Applied Sciences*, Volume 7, Issue 2, 2014, pp. 198-200, https://doi.org/10.1016/j.jrras.2014.02.005.

[25] TSA no longer uses backscatter X-ray in full-body scanning.

[26] The goal is to replace all traditional X-ray systems at checkpoints with CT systems. TSA has provided a billion dollars in contracts to Analogic Corporation and IDSS/Surescan both located in the Boston metroplex. It may be two or three years before all the airports have these systems.

[27] TSA does not mandate any specific requirement for how cargo should be screened. There are four (4) qualification groups and a screening company can decide which option to use.

Density of the items contained in each box needs to be taken into consideration. If the items are dense, more than likely they will create an opaque image, which will require the boxes to be screened individually. With the newer CT cargo scanner technology currently in development, there will be no need to discriminate between homogenous and heterogenous cargo.

The screening company conducting screening will generally use all the information available when deciding which technology is right for the configuration and commodity being screened. The considerations are weight as it relates to size, how large the shipping configuration is, the over packing material of the cargo (e.g., plywood, shrink wrap, cardboard, banding, etc.), the sensitivity of the cargo (e.g., can it be easily be broken or damaged by breaking the configuration down, etc.), and finally can the commodity actually be screened using the chosen technology or method (e.g., liquids and gels, sensitive electronics or peripherals, medical or laboratory tests or items, live animals, machinery or machine parts, construction materials, powdered materials, etc.).

A significant amount of pre-screening work and evaluation needs to go into the process of screening to ensure it is accurate and that TSA procedures are properly carried out and all the cargo which is cleared for transport is free of dangerous items such as improvised explosive devices (IEDs) and other potentially dangerous items. Matching technology or screening method to the commodity to be screened is critical to ensuring this task is completed properly.

2.2 Customs and Border Protection Screening Missions

U.S. Customs and Border Protection (CBP) aims to safeguard the United States from incoming threats by using non-intrusive inspection (NII) and imaging systems to efficiently inspect vehicles, cargo, and personal items at entry points without physical searches. With over 7 thousand miles of border to cover, and roughly 12 million maritime containers entering at land borders, another 12 million at seaports, 2.7 million via rail each year, and 100 million passenger vehicles,[28] CBP generates a host of imagery (e.g., cars, trucks, trains, buses, cargo containers)[29] and relies on inspection systems to enable officials to control the import or export of shipping containers, detect hidden contraband and verify the crossing of legitimate trade items.[30,31] The following sub-sections provide further detail on these scanning use cases.

2.2.1 Land Port of Entry Cargo Scanning and Maritime Port Shipping Container Screening

Land port and seaport cargo scanners are conceptually similar systems.[32] Both aim to scan standard intermodal shipping containers, often called a container or cargo container, which is a large metal crate designed and built for intermodal freight transport, like a boxcar but without wheels. These containers can be used across different modes of transport (e.g., from ships to trains to trucks) without unloading and reloading their cargo. Both use large-scale non-intrusive inspection technologies, such as X-ray and gamma-ray imaging, to screen cargo for contraband, illegal items, and other potential security threats. The goal at both types of ports is to inspect goods efficiently without unloading containers, minimizing disruption to legitimate trade.

However, based on the unique needs of each environment (i.e., land or maritime), there can be differences in scanner deployment and configuration. For instance, land port scanners might be set up for high-throughput

[28] Customs and Border Patrol, (2024). Inbound Traveler and Conveyance Data at Air and Land Ports of Entry. CBP Data Portal. https://www.cbp.gov/newsroom/stats/travel.

[29] CBP processes more than 1 million images per day at ports of entry, and more than 1 billion packages per year.

[30] Transportation Security International (2023). Seeing the Unseeable: Today's Cargo Screening. https://www.tsi-mag.com/seeing-the-unseeable-todays-cargo-screening/.

[31] Jorgic, D., Gottesdiener, L, Cooke, K. and Eisenhammer, S., (2024). How Fentanyl Traffickers are Exploiting a U.S. Trade Law to Kill Americans. https://www.reuters.com/investigates/special-report/drugs-fentanyl-shipping/. Only a fraction of shipping containers are inspected.

[32] But there are some differences, since there could be other types of commercial cargo which are not intermodal containers scanned at land ports of entry.

screening of trucks, while seaport scanners often handle large, stacked shipping containers.[33] In both cases, though, the scanning systems are fundamentally similar in their use of imaging technology to ensure security and verify cargo contents.

As seen in Figure 2.3,[34] the decision to scan with non-intrusive inspection equipment is preceded by an analysis of the shipment's metadata to include manifest data, shipping data, country of origin, etc. These data, in combination with other data (e.g., public records, open sources, etc.), are used by a decision support system, Automated Targeting System (ATS), to determine whether a shipment poses a high risk requiring a NII scan.

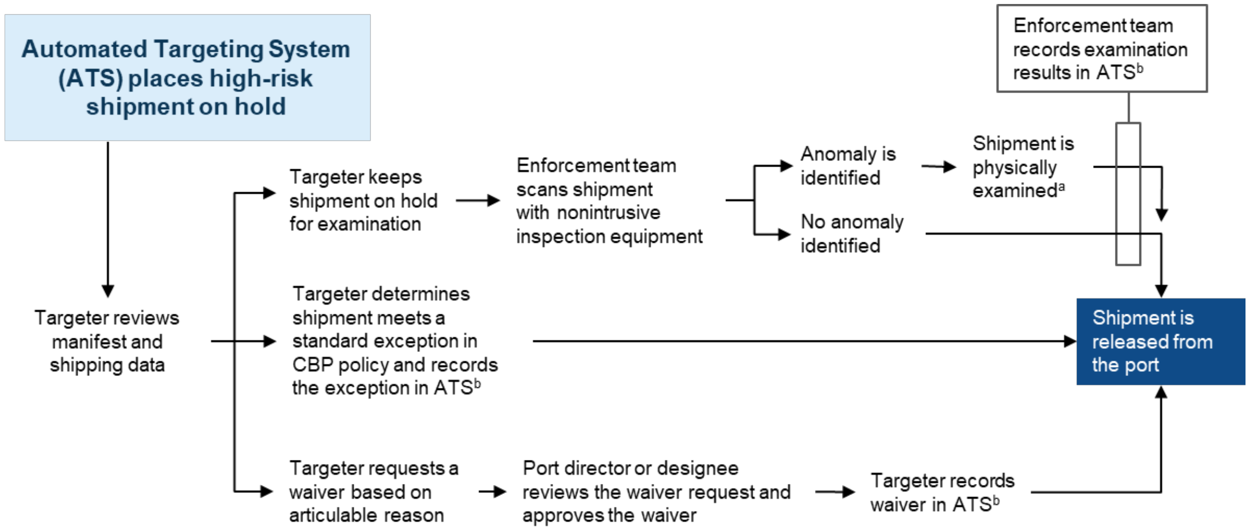

Figure 2.3: Flow Chart Depicting U.S. Customs and Border Protection's (CBP) Targeting Outcomes for High-Risk Shipments. [a]If contraband is discovered during the physical examination, the shipment is to be seized by CBP. [b]Examinations and waivers are recorded in the Cargo Enforcement Reporting and Tracking System (CERTS) – a module within ATS.

Containers selected for non-intrusive imaging are removed from ships and set aside for scanning, a process that is much faster and less disruptive than manual unpacking.[35] These machines use X-rays or gamma rays to create images of the container contents, allowing trained CBP officers to identify any discrepancies between the cargo and its manifest or detect any unusual materials (e.g., dense nuclear components or shielding). Gamma-ray systems are common for air and maritime cargo, producing 3D images and detecting specific materials such as carbon or iron. These systems are easy to operate, quick to deploy in different configurations, and have limited radiation zones.

While legacy gamma-ray systems are still in use, high-energy X-ray systems are now more common due to safety and regulatory advantages. X-rays use linear accelerators to penetrate dense cargo, helping operators spot hidden contraband. Neutron inspection systems further enhance detection by identifying specific threats such as explosives and drugs, using neutron techniques that can reveal an item's elemental composition.

[33] All maritime shipping containers arriving at a U.S. port also go through radiation portal monitors, but radiation monitoring is beyond the scope of this report.
[34] Redrawn from GAO (2015). Supply Chain Security: CBP Needs to Enhance Its Guidance and Oversight of High-Risk Maritime Cargo Shipments. https://www.gao.gov/products/gao-15-294.
[35] X-ray systems generally take a few minutes to scan a standard 40-foot container while some more advanced systems can take only a few seconds. However, total inspection cycle times may range from 7-15 minutes or longer due to image analysis.

There are many commercial systems servicing this use case, such as the OmniView ZBx Gantry, Rapiscan Eagle G60, and HXP-FreightScan, which are highly versatile and can serve both land and maritime ports due to their robust imaging capabilities and flexibility. The Leidos PX 18.18 200 and Safeagle F150180C are optimized for environments handling consolidated or palletized cargo, making them more suitable for seaports and warehouses. The CSIRO Air Cargo Scanner, with its unique neutron-X-ray combination, is best suited for specialized locations, potentially extending to seaports or land ports where high-level material analysis is critical.[36]

2.2.2 Vehicle Scanning System at a Border

At U.S. land border crossings, vehicle screening is essential for detecting contraband, weapons, human trafficking, and other security threats. NII scanning allows CBP officers to inspect vehicles quickly and effectively without the need for manual searches, enhancing efficiency and security. NII technologies, including X-ray and gamma-ray systems, penetrate vehicle to create detailed images of their contents, enabling officers to spot hidden threats and compare these images against manifests. The rapid imaging provided by NII reduces inspection times and streamlines the flow of people and goods across borders.

Under-vehicle scanning systems add another layer of security by offering real-time imaging of a vehicle's undercarriage as it drives over the scanner. This technology provides CBP officers with clear views of hard-to-inspect areas including tire wells, bumpers, and even the trunk, which are often used to conceal illicit materials. Using backscatter technology, these systems allow for immediate analysis before a vehicle clears the checkpoint, making it easier to detect weapons, drugs, cash, or hidden compartments used in smuggling. This undercarriage inspection capability is particularly valuable at high-traffic or high-threat locations, helping officers address security risks with minimal disruption.

Drive-through NII systems have been upgraded with low-energy and multi-energy portals to increase screening efficiency and safety at land border ports of entry. Low-energy portals (LEPs) are used for screening passenger vehicles with occupants inside, reducing the need for secondary inspections. Multi-energy portals (MEPs), on the other hand, screen cargo vehicles by using low energy for occupied cabs and higher energy for the cargo hold, enhancing detection capabilities for various threat levels.[37]

2.3 Secret Service and Federal Protective Services

Individual and small package screening systems are used by the United States Secret Service (USSS) and the Federal Protective Service (FPS) to detect concealed weapons or threats or hazardous items or contraband on persons entering secure areas. The following sub-sections describe these use cases in more detail.

2.3.1 Individual Screening

For the USSS and FPS, advanced imaging technology is critical for screening individuals to ensure the safety of protected spaces and individuals. In FY23, for example, they screened over 1 million people at public White House events.[38] The use of backscatter X-ray scanners, which emit low-dose radiation, allows these agencies to detect concealed weapons or dangerous items under clothing without physical searches. This technology is typically used as a secondary screening measure, triggered only if primary methods indicate a potential threat.

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[36] Excerpted from Transportation Security Industry (2023). Seeing the Unseeable: Today's Cargo Screening. Sep 24, 2023. https://www.tsi-mag.com/seeing-the-unseeable-todays-cargo-screening/.

[37] U.S. Customs and Border Protection (2023). Mobile Nonintrusive Inspection Systems. Fiscal Year 2023 Report to Congress. https://www.dhs.gov/sites/default/files/2023-11/2023_1010_cbp_mobile_nonintrusive_inspection_systems_fy23.pdf.

[38] United States Secret Service (2023). FY23 Report of the Department of Homeland Security's United States Secret Service. p.11. https://www.secretservice.gov/annual-reports/fy-2023-annual-report.

While both agencies prioritize privacy by anonymizing facial features and strictly regulating radiation exposure, the USSS applies these measures specifically to protect high-level officials, including the President and visiting heads of state, focusing on close-contact environments where concealed threats pose a significant risk. The FPS, on the other hand, focuses on securing federal facilities against threats to public and employee safety. For the FPS, scanning individuals with advanced imaging technology helps detect potential weapons or other contraband that could jeopardize federal buildings or their occupants.

2.3.2 Small Scale Systems

Small-scale X-ray and CT scanning systems are critical to the missions of the USSS and FPS as they allow for thorough, non-intrusive screening of packages, personal belongings, and mail entering federal facilities and high-security areas. For FPS, these systems help secure roughly 9 thousand federal facilities by enabling guards to detect and prevent weapons, explosives, or other prohibited items from entering sensitive spaces, a task that directly supports facility safety by complementing manual inspection protocols. [39] The USSS also relies on small-scale scanning to protect individuals in high-risk environments, as it enables rapid inspection of items carried by visitors, reducing the risk of dangerous objects entering protected spaces and supporting their broader mission to protect high-level officials. These technologies provide quick reference images that can be stored for security comparison, enhancing both real-time and retrospective threat detection.

3 Examples of How AI is used in Related Fields

This section considers how AI is being applied in fields related to the NII security screening use case for homeland security missions. These fields include conventional CT imaging, multi-modal foundation models capable of detecting and identifying objects, truth detectors/polygraphs, and command and control systems capable of real-time optimization of operational workflows.

3.1 AI in CT Imaging and Diagnostics

As discussed in section 1.2, AI has been used in X-ray and CT imaging and diagnostic processes for many years. This section reviews some of the more traditional approaches applied, where AI is applied as a back-end appliance to help manage the full content of images, and also some of the more novel approaches that include Large Language Models (LLMs) to support analysis and as a way of representing additional signal lost from source data that gets transformed and compressed to support image-based decision-making.

3.1.1 Conventional Uses of AI in CT Imaging and Diagnostics

As reported in section 1.3.5, AI and ML have been used in the threat analysis functions of conventional X-ray/CT workflows. As a rule of thumb, AI has been applied extensively in industrial and some security CT uses cases in image reconstruction, image segmentation, and automated threat recognition, the last three steps in Figure 1.3. According to Vukadinovic and Anderson (2022),[40] while most automated threat detection methods are for 2D imagery, research is intensifying for 3D threat detection, and the number of 3D object detection methods is growing. The trend of use across both is documented by Velayudhan et al. (2022)[41] who offer a comprehensive analysis of existing literature in 2D and 3D CT X-ray security imaging, describing its use in support of many parts of a classical workflow. Ackay and Breckon (2021)[42] reinforce this analysis with a review of ML and deep learning (DL) applications published in X-ray security imaging. In the context of Figure 1.3, AI can be applied in many processes throughout the security imaging process. AI's application

[39] GAO (2024). Federal Facility Security: Preliminary Results Show That Challenges Remain in Guard Performance and Oversight. https://www.gao.gov/products/gao-24-107599.

[40] Vukadinovic, D., Anderson, D., (2022). X-Ray Baggage Screening and Artificial Intelligence (AI): A technical Review of Machine Learning Techniques for X-Ray Baggage Screening. Joint Research Council (JRC) Science for Policy Report.

[41] Velayudhan, D., Hassan, T., Damiani, E. and Werghi, N., (2022). Recent Advances in Baggage Threat Detection: A Comprehensive and Systematic Survey. *ACM Comput. Surv.* 55, 8, Article 165 (December), 38 pages. https://doi.org/10.1145/3549932.

[42] Ackay, A., Breckon, T., (2021). Towards Automatic Threat Detection: A Survey of Advances of Deep Learning within X-Ray Security Imaging. arXiv:2001.01293v2 [cs.CV] 13 Sep 2021.

to threat analysis has been widely studied in both 2D and 3D-based workflows. Up until 2017, the bulk of AI in NII research in the threat analysis space focused on threat detection and threat classification approaches. With the advent of deep learning, many researchers shifted AI in NII threat identification research to threat segmentation approaches, anomaly detection approaches, and data augmentation approaches (e.g., synthetic data), looking for new ways to improve the workflow and achieve better results in threat identification.

AI has similarly been applied to other parts of the (generalized) workflow. Material segmentation (e.g., distinguishing between the metal frame of a suitcase and the fabric of clothing inside) and object segmentation (e.g., separating a laptop from a book within a bag) both utilize machine learning algorithms to perform these steps, particularly in support of feature extraction and threat classification. Some researchers have explored the application of AI-based methods to improve image reconstruction techniques. Others, though fewer, have used AI-based methods in pre-processing (e.g., boosting the visual quality of X-ray scans) to improve threat identification.[43]

As described throughout section 1.3, however, the type and form of the data used to train the AI have been significantly altered from source imaging to support a visualization-centric approach. This additional signal could be used in combination with current approaches to reinforce the overall signal and reduce false alarms. This theme is amplified and leveraged in the following section.

3.1.2 Innovative Uses of AI in CT Imaging and Diagnostics

In both the private sector and in research, we are starting to see more sophisticated and non-traditional applications of AI. One private sector entity, Lumafield[44] for example, integrates machine learning-driven feature extraction with Large Language Models (LLMs), operating as a reasoning engine that acts as a virtual assistant for engineers. By combining outputs from various ML models (e.g., image transformers, classifiers, object detectors) with institutional and domain-specific knowledge, the Atlas agent automates and enables more sophisticated analyses and decision-support. Most recently, Lumafield released its "Ultra-Fast" CT technology, reducing inspection times by over 99 percent while enabling real-time quality control processes. Finally, with their software-first design philosophy, they have been successful in creating a self-improving ecosystem, reaping the benefits that come from network effects.

Along these lines, several studies evaluating ChatGPT's applicability in various radiology-related domains (e.g., clinical radiology writing, radiology training, radiology report generation, and tailored letters of recommendations, patient education, disease screening, diagnosis, etc.) have been published.[45,46] Other researchers in the medical domain, have focused on extracting more signal from source data, training their AI models with raw scanning data. This approach demonstrated enhanced diagnostic performance in combination with traditional methods reliant on reconstructed images.[19] Similarly, as shown by Zhu et al.,[47] an algorithm that takes in complex magnetic resonance imaging (MRI) measurements can add additional value to the task of image formation, demonstrating the power and feasibility of working with raw complex measurements. Finally, researchers in the medical imaging community have identified the potential for information gain by analyzing the raw source information, free from conformity assumptions, and combining it with the vision-centric data used in conventional CT or MRI processes.[5] The conceptual equivalent of their work, in the context of Figure 1.3, would be represented as a parallel line of effort moving right from the

[43] Unfortunately, the algorithms developed in the baggage security screening domain have not been as successful or rigorously researched as those in general computer vision domain. Reasons for this include: Inherent features of X-Ray scans, extreme clutter and occlusion, limited data sets, class imbalance, image quality, limited prior information, limited generalization, and evolving threats.

[44] Temporal, R. (2023). Lumafield Unveils New AI Co-pilot, Atlas. Manufacturing Quality News. https://www.manufacturing-quality.com/quality-news/lumafield-unveils-new-ai-co-pilot-atlas/.

[45] El Kassem, A. and Smith, A., (2021). Potential Use Cases for ChatGPT in Radiology Reporting. *American Journal of Roentgenoly*;221:373–6.

[46] Cao, J., Kwon, D., Ghaziani, T., Kwo, P., Tse, G., Kesselman, A., et al. (2023) Accuracy of Information Provided by ChatGPT Regarding Liver Cancer Surveillance and Diagnosis. *American Journal of Roentgenoly*; 221:556–9.

[47] Zhu, B., Liu, J.Z., Cauley, S.F., Rosen, B.R. and M.S. Rosen, (2018). Image Reconstruction by Domain Transform Manifold Learning, *Nature* 555(7697), pp. 487-492.

signal domain (blue) to the knowledge domain (gray) without any of the intermediate processing (see Figure 3.2). This could be used in an additive way, additive to the traditional image-based process or in isolation.

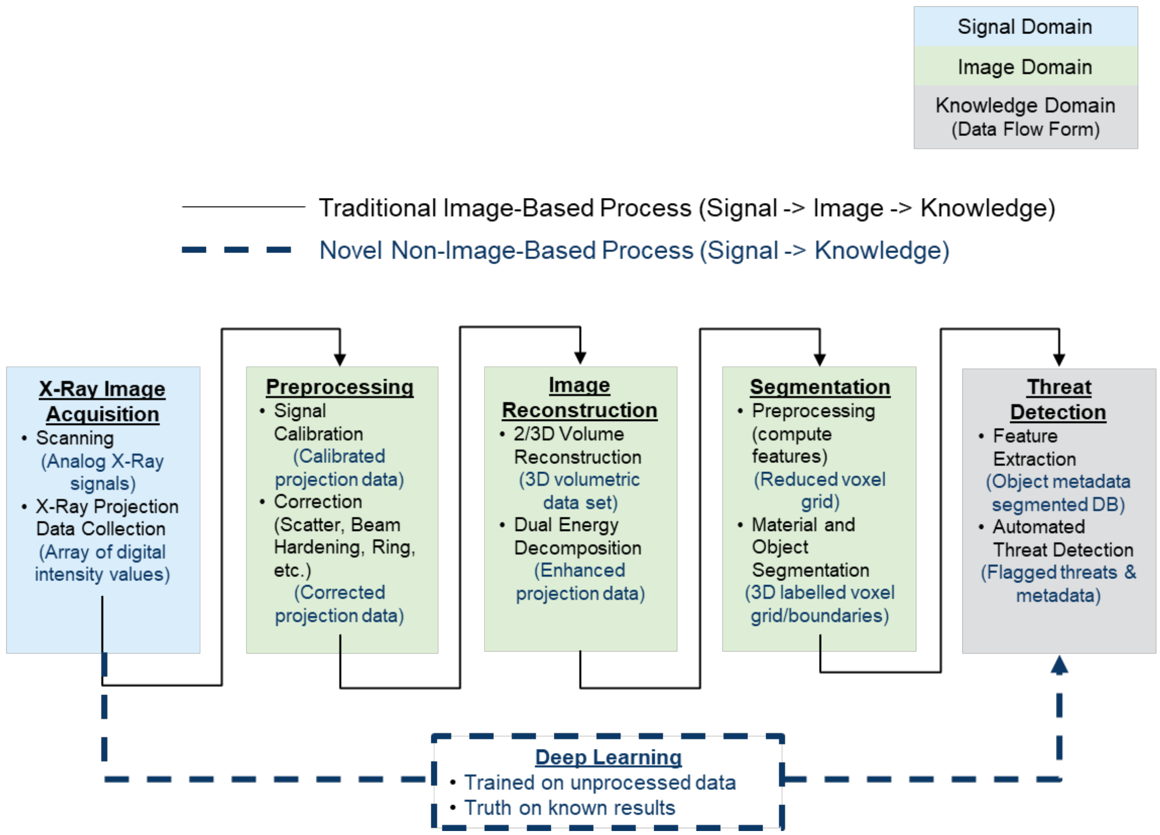

Figure 3.2. CT X-ray Security Imaging Threat Detection Process Recast as Approach in He et al.[5]

3.2 AI Research Concepts in Computer Vision

Many emerging AI techniques in computer vision open new pathways for processing non-intrusive screening data. These include Joint Vision-language foundation models,[48] Fine-grained Object Localization and Segmentation,[49] and Unsupervised Anomaly-Detection Methods.[50]

3.2.1 Foundation Models

As described in Henninger and Kusnezov (2023),[1]a foundation model[51] (FM) is a type of machine learning model that is trained on a broad set of general domain data for the purpose of using that model as an

[48] Li, L., Zhang, P., Zhang, H., Yang, J., Li, C., Zhong, Y., Wang, L., Yuan, L., Zhang, L., Hwang, J., Chang, K. and Gao, J., (2020). Grounded Language-Image Pre-training. The IEEE/Computer Vision Foundation Conference on Computer Vision and Pattern Recognition. June,14-19. Virtual conference.

[49] Kirillov, A., Wu, Y., He, K. and Girschick, R. (2020). PointRend: Image Segmentation as Rendering. In *Proceedings of the IEEE/Computer Vision Foundation Conference on Computer Vision and Pattern Recognition*. June,14-19. Virtual conference.

[50] Roth, K., Pemula, L., Zepeda, J., Scholkopf, B., Brox, T. and Gehler, P. (2022). Towards Total Recall in Industrial Anomaly Detection. The IEEE/Computer Vision Foundation Conference on Computer Vision and Pattern Recognition. June,19-24. New Orleans, LA.

[51] R. Bommasani, D.A. Hudson, E. Adeli, R. Altman, S. Arora, S. von Arx, M.S. Bernstein, J. Bohg, A. Bosselut, E. Brunskill, E. Brynjolfsson, S. Buch, D. Card, R. Castellon, N. Chatterji, A. Chen, K. Creel, J.Q. Davis, D. Demszky, C. Donahue, M. Doumbouya, E. Durmus, S. Ermon, J. Etchemendy, K. Ethayarajh, L. Fei-Fei, C. Finn, T. Gale, L. Gillespie, K. Goel, N. Goodman, S. Grossman, N. Guha, T. Hashimoto, P. Henderson, J. Hewitt, D.E. Ho, J. Hong, K. Hsu, J. Huang, T. Icard, S. Jain, D. Jurafsky, P. Kalluri, S. Karamcheti, G. Keeling, F. Khani, O. Khattab, P.W. Koh, M. Krass, R. Krishna, R. Kuditipudi, A. Kumar, F. Ladhak, M. Lee, T. Lee, J. Leskovec, I. Levent, X.L. Li, X. Li, T. Ma, A. Malik, C.D. Manning, S. Mirchandani, E. Mitchell, Z. Munyikwa, S. Nair, A. Narayan, D. Narayanan, B. Newman, A. Nie, J.C. Niebles, H. Nilforoshan, J. Nyarko, G. Ogut, L.

architecture on which to build multiple specialized AI applications.[52] Foundation models differ from prior work in machine learning that relied on large, labeled data sets such as ImageNet.[53] While such data sets enabled much of the early success achieved in using deep learning methods, they also suffer from limitations such as the difficulty of creating labeled data sets, generalization beyond the data set, spurious correlations, and adversarial attacks as described in a paper by Liu et al. (2021).[54] Instead, foundation models are trained on a large set of unlabeled data via self-supervised learning approaches such as contrastive learning on pretext tasks as described in the survey paper by Jaiswal et al. (2020).[55] The representations learned using this approach have proven useful for a broad variety of downstream machine learning tasks. These downstream learning tasks are solved using a pipeline that leverages representation learned by the foundation models and task-specific data.

The ability to learn representations from unlabeled data has been extended to multi-modal data. This approach can align data from multiple modalities in a common semantic space. For example, Radford et al.[56] introduced a model called CLIP in their recent paper that aligned vision and language by training on captioned images collected from the Internet. Not only did this model enable solutions of vision-language machine learning problems, it also led to compelling performance on pure vision downstream tasks such as object classification.[57] In addition, it has shown promising zero- and few-shot learning performance, which is of particular importance to the problem of screening for new and evolving threats. More broadly, it is becoming apparent that learning representations across multiple modalities can lead to enhanced performance even within a single modality. A more recent example of this type of result is the ImageBind model released by Meta and described by Girdhar et al.[58] This model aligns multiple modalities such as text, sound, and depth images, with conventional visible light images, and demonstrates a path to building a broad multi-modal model, as well as the benefits of building such a model on task performance.

Foundation model concepts include a host of technical considerations and opportunities, some of which are summarized below:

- **Zero-Shot Learning:** The rapidly changing nature of the threat landscape requires the ability to reliably screen for new threats. Certification of a new processing pipeline introduces too much delay, making a compelling argument that a "zero-shot" capability is necessary. Foundation models have shown promising zero- and few-shot performance,[1] which could enable detection of emergent threats while avoiding the need to train or fine-tune new models.
    - **Characterizing Previously Unseen Objects (Zero-Shot Classifier).** Given a verbal description of a new object of concern that has not yet been seen, vision language foundation models can be used to rapidly generate a classifier for this object. This is a remarkable capability, which can also be extended to other combinations of modalities. While performance won't typically match that of a classifier that has been trained with numerous examples, it has been shown in other domains the starting point can be equivalent to a classifier that has seen multiple image examples. This zero-shot

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Orr, I. Papadimitriou, J.S. Park, C. Piech, E. Portelance, C. Potts, A. Raghunathan, R. Reich, H. Ren, F. Rong, Y. Roohani, C. Ruiz, J. Ryan, C. R, D. Sadigh, S. Sagawa, K. Santhanam, A. Shih, K. Srinivasan, A. Tamkin, R. Taori, A.W. Thomas, F. Tramr, R.E. Wang, W. Wang, B. Wu, J. Wu, Y. Wu, S.M. Xie, M. Yasunaga, J. You, M. Zaharia, M. Zhang, T. Zhang, X. Zhang, Y. Zhang, L. Zheng, K. Zhou, and P. Liang, (2022). On the Opportunities and Risks of Foundation Models, Stanford Center for Research on Foundation Models, Stanford University. URL https://arxiv.org/abs/2108.07258

[52] Henninger, A. and Kusnezov, D., (2023). Foundation Models at the Department of Homeland Security: Use Cases and Considerations. https://www.dhs.gov/science-and-technology/publication/foundation-models-department-homeland-security

[53] Deng, J., Dong, W., Socher, R., Li, L.J., Li, K. and Fei-Fei, L., (2009). Imagenet: A Large-scale Hierarchical Image Database, in *Proceedings of the 2009 IEEE Conference on Computer Vision and Pattern Recognition*, IEEE (2009), pp. 248-255.

[54] Liu, X., Zhang, F., Hou, Z., Mian, L., Wang, Z., Zhang, J. and Tang, J. (2021). "Self-supervised Learning: Generative or Contrastive," *IEEE Transactions on Knowledge and Data Engineering* 35(1), pp. 857-876.

[55] Jaiswal, A., Babu, A.R., Zadeh, M.Z., Banerjee, D. and Makedon, F. (2020). A Survey on Contrastive Self-supervised Learning," Technologies 9(1), 2.

[56] Radford, A., Kim, J.W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J., et al., (2021). Learning Transferable Visual Models from Natural Language Supervision, in Proceedings of *International Conference on Machine Learning*, PMLR (2021), pp. 8748-8763.

[57] Notably, and perhaps due to its reliance on a wider data set, CLIP is more robust to distribution shift than ImageNet models.

[58] Girdhar, R., El-Nouby,A., Liu, Z., Singh, M., Alwala, K.V., Joulin, A. and Misra, I., (2023). Imagebind: One Embedding Space to Bind Them All, in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 15180-15190.

capability addresses the challenge of rapidly deploying a threat detection algorithm for an emerging threat for which there is not yet a good set of exemplars.

- **Characterizing Objects Using only a Few Examples (Few-Shot Classifiers).** Given a few examples of an object of interest, potentially across multiple modalities and information sources, one can rapidly generate a classifier to find those objects by using the foundation model representation as a feature space in which to make decisions. Potentially, some fine-tuning could be performed, though it is common practice to also freeze the underlying learned weights of the encoding model, so that only a few weights need to be learned. This approach results in a low-cost training procedure. A few-shot learning-approach provides the ability to rapidly react to new threats by leveraging sparse training data and prior learning to rapidly and efficiently disseminate new classifier capabilities.

- **Unified and Extensible Processing Pipelines:** Existing processing pipelines are single modality, tailored to one task, and typically highly specific to the sensor from which they are ingesting data. A change in sensor or task, a shift in data distribution, and attempts to fuse modalities typically require re-developing or retraining core algorithms in the software pipeline. Foundation models have the potential of providing a representation that enables good performance on a broad array of tasks, that can ingest and align an array of modalities, and that can be efficiently adapted for new sensors, sources of information, and tasks.
- **Physics-informed AI:** Data-driven machine learning has made significant progress on a wide variety of tasks, but can suffer from a lack of robustness, interpretability, and adherence to physical constraints.[59] By incorporating an understanding of the physical mechanisms involved in data collection/generation into machine learning architectures, these issues could be alleviated.[60] Physics-informed machine learning methods can constrain data requirements, reduce training time, and improve model accuracy and generalization,[60] abovebut must be heavily tailored for a specific problem (e.g., solving ordinary or partial differential equations). As foundation models become increasingly multi-modal, integration of physics-informed methods is a logical next step.
- **Multi-Modal Foundation Model:** A multi-modal foundation model can leverage both open data sources as well as DHS-specific data to bring multiple modalities into a meaningful joint space for further processing. These types of models have proven capable in zero-/few-shot scenarios, discussed earlier, enabling detection of emerging threats. This will allow contextual information to be provided alongside corresponding sensor imagery and would aid the model in identifying anomalous regions.
- **Automated Feature Extraction:** By leveraging advanced deep learning techniques, automated feature extraction could identify and prioritize relevant features (e.g., concealed threats, anomalies, structural issues, etc.) without requiring extensive human intervention. This capability ensures consistency, scalability, and efficiency while reducing false positives and improving the workload on officers.
- **Modular Architectures:** Foundation models are proving immensely capable at a wide range of downstream processing tasks but require immense amounts of data and resources to develop. Learned orchestration techniques such as "Mixture of Experts" or "Mixture of Modalities" could potentially accommodate modular pieces, and offer benefits in low SWaP (size, weight, and power) environments as modules can be loaded as needed.

3.2.2 Fine-grained Object Localization and Segmentation

Fine-grained object localization and segmentation can provide precise identification and characterization of objects within scanned data. These techniques enable the systems to differentiate individual items in complex, cluttered environments such as luggage, cargo containers, or vehicles. Advanced segmentation algorithms can isolate specific objects based on shape, density, or material properties, allowing systems to pinpoint suspicious items. Localization further aids in determining the exact position of these objects,

[59] Hao, Z., Liu, S., Zhang, Y., Ying, C., Feng, Y., Su, H. and Zhu, J., (2023). Physics-informed Machine Learning: A Survey on Problems, Methods and Applications, Tsinghua University, https://arxiv.org/abs/2211.08064.
[60] Karniadakis, G., Kevrekidis, I., Lu, L., Perdikaris, P., Wang, S. and Yang, S., (2021). Physics-informed Machine Learning, *Nature Reviews Physics* 3, pp. 422-440.

enabling efficient targeting during manual inspection. By segmenting key features such as voids, anomalies, or unusual densities, these techniques also improve the detection of tampered goods or hidden compartments. Together, fine-grained localization and segmentation reduce false positives, streamline the inspection process, and enhance the detection and identification of emerging or previously unknown threats, ensuring more accurate and efficient operational workflows.

3.2.3 Unsupervised Anomaly Detection Methods

Existing approaches to automated security image analysis focus on the supervised detection of particular classes of threat. However, this mode of inspection is ineffectual when dealing with mature classes of threat, for which adversaries have refined effective concealment techniques. Furthermore, these methods may be unable to detect potential threats that have never been seen before in Stream-of-Commerce (SoC) data. To detect these concealed or unseen types of threat, officers often observe anomalies of shape, texture, weight, feel or response to perturbation. Inspired by the practices of these officers, numerous researchers are developing algorithms to discover visual anomalies, in X-ray images for example, that are historically atypical with respect to expected patterns.[61] This can be used to identify unusual patterns, objects, or behaviors in data streams without relying on pre-labeling training data, and is particularly useful in dynamic use cases where new and evolving threats may emerge unpredictably. By automatically extracting features (e.g., shape, density, material composition, porosity, etc.), the algorithms can flag items that do not match statistical norms of benign items in the training dataset. This can be enhanced with real-time cross-referencing of data (e.g., comparing cargo manifests with CT/X-ray scans), with information that allows tracking SoC data across multiple checkpoints, or other types of multi-modal data available for fusion, and could include data such as:

- **Trace Chemical Sensors:** Trace chemical detection can suffer from a high false positive rate due to interference from benign materials.[62] AI models could be developed, in conjunction with data fusion of orthogonal modalities (i.e., Raman spectroscopy, ion mobility spectrometry, colorimetric methods),[63] to improve trace chemical sensor performance.
- **Manifest Adaptation and Exploitation:** Cargo manifest data could prove a useful information source if the information is rich and accurate. However, current manifest formatting is largely geared for trade and commerce and can contain very coarse labels such as “auto parts” or “mixed goods”. If it could be made easier to enter (e.g., voice transcription, scanning or photographing cargo as it is loaded, mandating descriptive detail on cargo), manifest data could bound the expected set of cargo to aid in threat detection. Computer vision-based labeling could automatically supplement the manifest or decompose general categories such as “auto parts” into more specific items. This type of descriptive contextual information could significantly improve anomaly detection.
- **Orthogonal Sensing:** Fusing disparate sensor data requires careful consideration of orthogonality. If sensors are variants based on similar underlying physics (e.g., backscatter/transmission/dual-energy X-ray, whereas neutron imaging would be complementary to X-ray), measurements are likely highly dependent. This dependence must be accounted for prior to or during fusion to avoid out-sized influence on decision-making. Development of a fusion architecture that includes this consideration will reduce false positives and could potentially improve system performance.
- **Vehicle History:** Maintaining a register of a particular vehicle’s trips, cargo, drivers, etc. could provide a rich source of information for identifying anomalous behavior. This could be associated with a vehicle VIN and trailer DOT ID, and if prior transit sensor data is available, could be compared against to more capably identify anomalies and alterations. If available, shipping companies could share GPS transponder data of the vehicle in question to locate anomalous activity prior to adjudication. This would require a

[61] Andrews, J., Jaccard, N., Rogers, T. and Griffin, L., (2017). Representation-learning for Anomaly Detection in Complex X-ray Cargo Imagery. *Proceedings of SPIE 10187, Anomaly Detection and Imaging with X-Rays (ADIX) II*, 101870E. https://doi.org/10.1117/12.2261101
[62] To, K.C., Ben-Jaber, S. and Parkin, I.P. (2020). Recent developments in the field of explosive trace detection," ACS Nano 14(9), 10804-10833, URL https://doi.org/10.1021/acsnano.0c01579, pMID: 32790331.
[63] Zhang, W., Tang, Y., Shi, A., Bao, L., Shen, Y., Shen, R. and Ye, Y., (2018). Recent Developments in Spectroscopic Techniques for the Detection of Explosives. *Materials*, 11(8), 1364. https://doi.org/10.3390/ma11081364.

non-mutable, secure database (e.g., blockchain) to enable extended temporal records, but could significantly enhance anomaly detection capabilities.

3.3 Behavioral Screening and Sensing[64]

Tel Aviv's Ben Gurion International Airport, considered one of the safest in the world, has layers of security, only partially visible to passengers.[65] A routine part of their security processes includes sophisticated behavior-based analysis, fostered by an aggressive question and answer protocol, administered, and interpreted by security agents. Anybody who has ever taken a polygraph for a security clearance will recognize the similarity in terms of aggressive questioning. For decades, polygraph tests have been used to measure physiological reactions such as heart rate and activity of the sweat glands (Bhamare, et al., 2020).[66] These tests rely on the theory that lying induces heightened physiological arousal, but their accuracy is debated, and experts question their reliability.[67]

A camera-based, AI-based deception-detection system,[68] on the other hand, makes use of multi-modal data such as a voice (e.g., tone, pronoun use, etc.), pupil dilation and eye movement, facial expressions (e.g., engagement of muscles around eyes and mouth), and posture. If detection included even more tactile cues (e.g., heartbeat, perspiration, finger skin temperature, fluctuations in blood pressure, etc.) or other modes of available data (e.g., respiratory rate, facial temperature changes, electrodermal activity, etc.), this would provide a rich multi-modal data set for such an AI-based system. Many examples of promising research in this domain are available in Prome, et al., (2024), who review numerous studies conducted over the last decade. Some of the studies they report on include:

- Fan and Shen, (2021),[69] who demonstrate that computer vision and machine-learned perform well in detecting and analyzing leaked fear facial expressions.
- Amber, et al., (2019),[70] who use CNNs to achieve high accuracy of 99.6 percent in identifying deception.
- Rodriguez-Mesa, et al., (2022),[71] who evaluate a model with 93.69 percent accuracy and assert that we are not that far away from a future where deception detection could be accessible throughout computers or smart devices.

Many research systems,[72] including research funded by DHS,[73] have attempted to develop such a capability while being mindful of important performance parameters surrounding issues of privacy, bias, etc.

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[64] As part of section 3, this subsection simply presents AI research in related domains. This subsection in no way recommends the application of these approaches in homeland security or law enforcement missions.
[65] Liebermann, O., (2016). In Airport Security, Many Say Ben Gurion in Israel is the Safest. https://www.cnn.com/travel/article/ben-gurion-worlds-safest-airport-tel-aviv/index.html.
[66] Bhamare A.R., Katharguppe S., Nancy J.S. Deep neural networks for Lie detection with attention on bio-signals 2020 7th International Conference on Soft Computing & Machine Intelligence, ISCMI, IEEE (2020), pp. 143-147
[67] Shanjita Akter Prome, Neethiahnanthan Ari Ragavan, Md Rafiqul Islam, David Asirvatham, Anasuya Jegathevi Jegathesan. Deception detection using machine learning (ML) and deep learning (DL) techniques: A systematic review, Natural Language Processing Journal, Volume 6, 2024, https://doi.org/10.1016/j.nlp.2024.100057.
[68] Suchotzki, K. and Gamer, M., (2024). Detecting Deception with Artificial Intelligence: Promises and Perils. *Trends in Cognitive Sciences*, Volume 28, Issue 6,2024, pp. 481-483, https://doi.org/10.1016/j.tics.2024.04.002.
[69] Fan J., Shen X. New progress in the paradigm of elicited deception: Application of human-computer interaction in deception detection. 2021 2nd International Conference on Information Science and Education, ICISE-IE, IEEE (2021), pp. 1558-1562.
[70] Amber, F., Yousaf, A., Imran, M., Khurshid, K., 2019. P300 based deception detection using convolutional neural network. In: 2019 2nd International Conference on Communication, Computing and Digital Systems. C-CODE, IEEE, pp. 201–204.
[71] Rodriguez-Meza, B., Vargas-Lopez-Lavalle, R., Ugarte, W., 2022. Recurrent neural networks for deception detection in videos. In: Applied Technologies: Third International Conference, ICAT 2021, Quito, Ecuador, October 27–29, 2021, Proceedings. Springer, pp. 397–411.
[72] Borak, M., (2024). Travelers to EU may be subjected to AI lie detector. https://www.biometricupdate.com/202406/travelers-to-eu-may-be-subjected-to-ai-lie-detector
[73] Muhammad, S., (2024). Project AVATAR: AI Future of Border Security? Center for Aerospace and Security Studies. https://casstt.com/project-avatar-ai-future-of-border-security/.

3.4 AI-assisted Real-time Optimization of Operational Workflows

As with any large-scale detection problem, screening people and cargo is fundamentally limited by the sensing and human resources available. The resources deployed must rapidly rule out threats to allow traffic to flow across borders at a rate that facilitates commerce and does not cause unacceptable delays for travelers. The current approach is to apply the same procedure to each item, person, or vehicle, and then to escalate to secondary screenings if the first screening indicates an issue of concern. Cao and Zheng (2024)[74] show how incorporating AI in the customs process can improve the efficiency of customs clearance inspection. The port environment and customs processes are characterized by dynamic changes, high volume, and complexity. In addition to structured data, there is also a significant amount of unstructured data, including text, video, images, and voice. This requires the utilization of various intelligent services to effectively handle and integrate these different data types into a cogent workflow.[75] To address the complexity of risk screening in customs declaration, AI and big data technologies play a crucial role. These technologies enable efficient and accurate intelligent review of images and accompanying documents, in an adaptive way that optimizes across volume and complexity.

The concept of adaptive screening is to extend this approach by introducing more flexibility into the system, providing new operating points that enable higher throughput at a higher detection rate, for a fixed false alarm rate.

- **Automated Pre-Screening and Dynamic Workflow Adaptation:** To address significant delays at border ports of entry caused by limited agent availability, automated pre-screening systems with tunable false alarm rates can help optimize the flow of goods and people while enhancing detection performance. By leveraging algorithms that dynamically adjust operating parameters based on real-world conditions (e.g., traffic volume, trusted shippers, operator fatigue, etc.), throughput can be improved without compromising detection standards. Unambiguous objects, such as empty trucks or firearms, could be adjudicated without human intervention, further easing bottlenecks.
- **Adaptive Sensing and Context-Aware Processing:** Static screening configurations are inherently inefficient, as they fail to allocate resources dynamically based on initial results or contextual information. Adaptive sensing offers a solution by tailoring subsequent processes to initial screening outcomes. For example, airport security systems can direct luggage to specific sensing modalities based on identified threats, while at border crossings, cameras can classify a vehicle's make and model to adjust screening procedures in real time. Incorporating context, such as anticipated threats or metadata such as shipping manifests, further enhances system performance. Screening methodologies can dynamically adapt based on this information, allowing on-demand model selection tailored to specific cargo or vehicle types — improving anomaly detection and reducing inefficiencies. Emerging technologies, such as multi-modal foundation models, offer promising avenues for implementing adaptive sensing.
- **Semantically Informed Image Displays:** Current image display technologies at border checkpoints lack integration with semantic object labeling or contextual information, such as vehicle make and high-risk compartments. Adapting image displays to align with operator workflows can significantly enhance decision-making efficiency. By analyzing operator behavior through lightweight instrumentation, images can be dynamically adjusted to prioritize critical areas — such as increasing resolution or optimizing dynamic range and color in regions of interest. Adaptive interfaces could also segment vehicles into discrete components for more focused examination, streamlining the review process and reducing cognitive load on agents. These enhancements aim to accelerate human decision-making while maintaining thorough inspection standards.
- **Context-switching for Recognition Models:** Object recognition models are ubiquitous, but typically vendor-locked and infrequently updated. These models could be fine-tuned for specific screening

[74] Cao, Q. and Zheng, X., (2024). Application of Artificial Intelligence Technology in the Supervision of Customs Clearance Machine Inspection. World Customs Journal, 18(2), 51–76. https://doi.org/10.55596/001c.122754

[75] Huang, Z. Y., Zhang, Y. B., Su, F. X., Liu, D., Su, Y., Zhou, Y. H., Cai, X. M. and Wu, W. B., (2024). Discussion on the Application of Artificial Intelligence Technology in Customs. *China Port Science and Technology*, 6(1), 4–9.

scenarios, such as for different geographic regions, modalities, cargo types, or transport containers (e.g., suitcase, shipping container, vehicle), potentially leveraging real-time contextual information. Model selection based on screening context could significantly improve threat detection performance while reducing false positives.

- **Complementary Human AI Teaming:** Evaluate and develop interfaces that better integrate human decision-making with AI models to optimize Human-AI Team performance. Adaptive interfaces could identify and assist fatigued officer performance, learn which data streams are most useful in officer decisions, and recognize when officers are relying too heavily on AI model output in their decisions.
- **Remote Adjudication:** Offloading adjudication to remote analysts would enable parallelization of effort (e.g., multiple ports of entry analyzed simultaneously) and centralize analysis, while easing the cognitive burden of front-line officers. This could also enable or be used to support data labeling for future algorithm development.
- **Adaptive User Experience (UX):** With access to a multi-modal foundation model, context could be used as a semantic prompt input to aid decision-making, potentially highlighting anomalous regions that demand operator attention while de-prioritizing low interest regions. This style of adaptive UX (e.g., segmenting vehicles into sub-parts and emphasizing targeted areas) could be extended to simplify operator workflow and reduce cognitive load.
- **Improving User Interface/UX:** Operators must currently interact with multiple interfaces to gather pertinent data sources (e.g., ATS, manifest, sensor data, adjudication results). Consolidating this information into a unified user interface would greatly improve workflows. Adding new data sources, including AI uncertainty and explainability, could be useful to decision-makers, but care must be taken to avoid degrading adjudication speed. If throughput is severely impacted, operators will skip inspection of a batch of cargo to catch up, meaning those vehicles/containers are not analyzed. AI adjudication could take over in these instances, only referring anomalous items to operators for further inspection, ensuring all cargo is screened.

3.5 Important AI Enablers

Independent of which concept or combination of concepts are explored, there are a host of enabling capabilities that could be, and in some cases must be, employed to operationalize the concept(s). Examples of these include:

- **Data Standards:** Limitations in the availability of raw sensor data will impact the ability to develop modular foundation models operating in measurement domain. Efforts should be made to develop standards facilitating the exchange of raw measurements. Research of measurement domain data augmentation techniques and development of more advanced synthetic data models could supplement raw data access.
- **Learning from Operators:** Development and operation of a lightweight mechanism for observing screening operators could enable AI assistants to learn from operator workflow and enable screening officers a mechanism to provide rapid annotation and labeling of data. Data from this collection would also be able to inform the design of an improved operator user experience. More comprehensive operator feedback on decision-making (beyond a binary threat/no-threat decision) could also be enabled through this mechanism, which would provide valuable contextual information, but careful consideration must be paid on any potential delay caused to operators.
- **Supervised Learning and Synthetic Data:** Most commercially available threat detection algorithms are trained in a supervised fashion, requiring a significant volume of labeled data for threat objects. The availability of threat data in the wild is very limited, and as such advances in synthetic data generation could compensate. Synthetic data generation could also enable more rapid model development on new or emerging threats. This type of approach would likely provide incremental performance gains.
- **Contextual Data Repository:** Context is expected to enhance screening performance but bringing together the various data streams is a challenge. The session identified the critical need for real data and discussed the complexities of sharing data that currently is either dropped or stored in separate domains.

A centralized, contextual data repository could enable training of a foundation model and could also be used to construct a knowledge graph. This graph could form connections over time, across locations, and modalities, and could be used to inform decision-makers of relevant context or relationships during adjudication.

- **Efficient Uncertainty Quantification:** Explainability in AI decision-making is vital for building trust with operators, but quantifying and localizing algorithm uncertainty is computationally expensive and thus not commonly employed. Advances in uncertainty estimation methods and their integration with AI architectures could enable wider adoption, with potential improvements to system trust, robustness, and performance.
- **Model Network Interactions of Entities and Objects Crossing Borders:** Knowledge graphs could be used to capture network connections and spatiotemporal patterns of border crossings. Nodes in the graph could consist of drivers, vehicle make/model/identification number, common shipping routes, types of cargo, and shipping companies. Graph learning methods could then be employed to derive actionable information from these relationships, using patterns associated with prior detected malicious actors to characterize risk for each border crossing.
- **Data Hub:** Establishing a centralized data hub is critical for enabling large-scale AI initiatives, as it consolidates data from multiple sensors and sites, addressing issues of data loss and siloed storage. By providing contextual information, the hub enhances detection accuracy for both human and machine decision-making, enabling precise anomaly identification. It supports human operators through tools such as knowledge graphs and contextual imagery, while also concentrating data needed to train advanced AI models, such as multi-modal foundation models. A data hub is vital for addressing evolving threats, allowing the creation of dynamic models that adapt to changing tactics and improving anomaly detection. Key challenges include developing data-sharing architectures, securing resources, and ensuring compliance with privacy policies through approaches such as federated learning. Initial efforts could focus on limited data integration to demonstrate feasibility before scaling. [76]

4 Synthesis of Opportunities

Given the variety of missions across components and the underlying technologies and systems employed to support those missions, this section provides a holistic view of how advancements in non-intrusive screening in combination with AI can lead to promising research and development directions. As such, this section reviews concepts and considerations, both technological and system-focused, enabling the better handling of unanticipated threats, reducing detection errors and screening latency, utilizing all available data channels to make more informed screening decisions, and fostering effective interactions between operators and screening systems.

4.1 NII Screening Foundation Models (FMs)

Foundation models are key to extracting more information out of the data we have access to already and the key enabler to making FMs work is scale: scale of data, scale of modeling, and scale of computing.[77] Given that DHS NII scanning missions, it follows that the purposeful collection, curation, and use of this data in a foundation model (see Figure 4.1) might be able to mitigate a number of NII security scanning challenges. For example, as described in Bremer, Martz, and Goldmann (2023),[78] existing approaches are highly application specific, scanner dependent, and mostly static once deployed. This has led to a plethora of solutions that are both brittle and non-transferrable, often require significant human oversight, and are

[76] S. Kolokytha et. al., (2017). Improving Customs' Border Control by Creating a Reference Database of Cargo Inspection X-ray Images, Advances in Science, Technology and Engineering Systems Journal, vol. 2, no. 3, pp. 60-66.
[77] J. Kaplan, et al., (2020). Scaling Laws for Neural Language Models, https://arxiv.org/abs/2001.08361. Performance ∝ Data Size x Parameter Size x Compute Size.
[78] Bremer, P.T., Martz, H. and Goldman, M., (2023). Transportation Security Foundation Models. Lawrence Livermore National Laboratory White Paper.

expensive to maintain and operate. At the core of these challenges lies the original definition of the problem as finding a specific type of contraband (e.g., drugs, explosives, nuclear materials, etc.) in a near infinite collection of benign stream-of-commerce (SoC) data. This formulation invariably leads to the need to construct test data containing such objects of interest to drive the development of solutions. Not only are such data collections extremely time consuming and expensive to create, but by their very nature they are highly sensitive and thus cannot be widely shared, and most importantly, they can never adequately represent the enormous variety of real-world data.

Foundation models enable a new approach, aimed at reliably identifying benign cargo rather than directly finding contraband and hypothesized to give rise to a unified, flexible, and continuously improving framework. An FM-based approach exploits the fact that the government has access to large volumes and varieties of SoC in all areas of transportation security. Even considering rare instances of unflagged

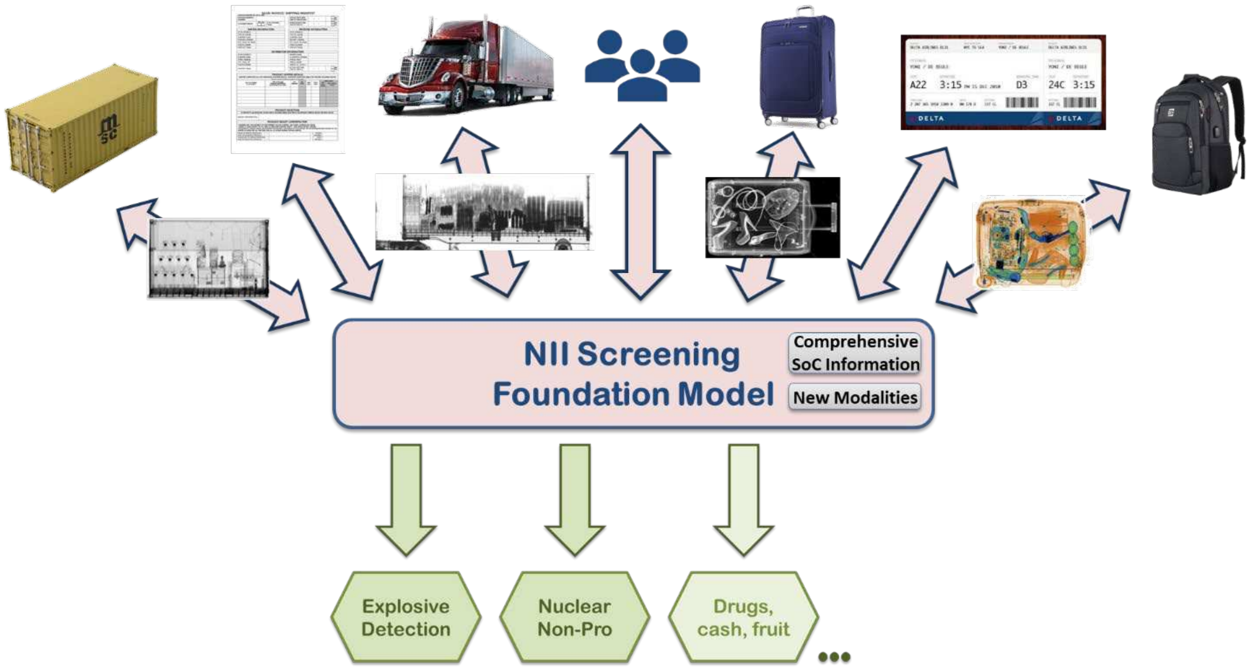

Figure 4.1. NII Security Screening Foundation Model Concept

contraband in the current SoC data, statistically this collection can be considered contraband free and ideally readily shareable barring any privacy concerns. Making use of this data, through a massive, distributed data store populated by X-ray/CT data from all types of scanners, enables the training of an FM that could understand X-ray images the way ChatGPT understands languages. Not only will this model be able to understand all different dialects of X-ray (i.e., data from different physical scanners), but it can continuously learn from data collected each day at all ports of entry. Simultaneously, these data streams provide a continuous source of imminently relevant validation data.

Extrapolating from instances in use now, a FM for NII will solve the scanner and technology dependence, will bolster detection for relatively rare or upcoming scanner technologies (i.e., novel modalities) by exploiting the common ones, and in the future can integrate related information (e.g., shipping manifests, operator feedback, etc.). Where much of the discussion on the use of AI models in science and technology has often stalled at the lack of relevant data and somewhat unclear paths to adoption, DHS has a unique opportunity to leverage existing data streams and a clear path towards a FM for X-ray images that may lead to a transformational improvement in the nation's capabilities.

The Screening Foundation Model (SFM) concept has the potential to transform the way in which we develop and maintain the underlying algorithmic infrastructure that enables screening at scale. It inherently addresses new modalities and fusion of multiple modalities, and new technology such as sensors or sensor applications. It could also enable new technical approaches that address core problems for border screening that are currently under-addressed. These problems include:

- Open world anomaly detection, as described in 3.2.3,
- Rapidly and efficiently deploying a classifier for an object that has not been previously imaged but can be described, or that has been imaged only a few times, and
- A processing pipeline that can be rapidly adapted to incorporate new sensors and information sources.

With these kinds of capabilities, it is feasible to learn from subsets of images, either in context of numbers (e.g., identifying a new type of car) or in context of resolution (e.g., identifying a hidden compartment in a car). The breadth and potential for innovation offered by this paradigm justify its consideration as the methodological underpinning in rethinking how we use data most effectively, what should be measured, where, at what resolution and with which capability, to assess risks, whether isolated or distributed across either space or time.

4.2 Decoupling Image-Centric Assumptions from X-ray/CT Screening Models

One of the modes of data that should be included in the SFM should represent the raw source data, prior to being transformed, compressed, and calibrated to meet assumptions and measurements required to support image-centric visualization approaches. AI model architectures should be modified to train and operate in the measurement space to potentially identify and exploit a larger volume of signal data that is lost post-image formation. As described in section 3.1.2, depending on the structure of the measurement system, data processing and image formation can destroy information and amplify noise;[79] and, along poorly measured dimensions, introduce structured artifacts which can mislead decision-making. In addition, displaying an image requires an allocation of a limited dynamic range, and for complex measurements, phase information is typically completely lost. Finally, image formation, which is accomplished through the solution of an inverse problem, is typically computationally costly. The potential time savings enabled by making decision with fewer measurements or with reduced computation could translate to more rapid screening, enabling increased throughput for a fixed level of detection performance. This increased throughput would directly impact the core screening mission. Limitations such as these motivate the development of algorithms that directly learn the mapping between raw measurements and decisions.

Potential advantages of working directly with raw measurements in the screening context include reduction in computational requirements, the ability to make decisions with low signal to noise ratio measurements that can be taken more quickly, and the ability to make decisions with fewer measurements, which again could reduce overall measurement time. These latter two potential advantages are driven by the fact that the decision problem could be solved directly, without first solving the problem of image formation. Assuming such a pipeline is deployed, high priority items could still trigger an image formation step for human adjudication.

Research areas for this concept include the application of machine learning approaches to the raw measurements of sensing modalities key to threat screening and the characterization of performance relative to traditional measurement processing pipelines. One potential sub-area of research is the identification of neural network architectures that take advantage of the structure of the physical measurements, rather than the existing architectures that have been tuned for high performance on natural images. Even if image formation proves advantageous in some contexts, this research area could also explore learning to form images, with the

[79] Beaudry, N.J. and Renner, R., (2012). An Intuitive Proof of the Data Processing Inequality, *Quantum Information and Computation* 12(5-6), pp. 432-441. https://arxiv.org/abs/1107.0740

goal of improving speed, operating at lower sampling rates, and achieving robustness to a variety of measurement errors.

4.3 AI-assisted Real-time Optimization of NII Screening Operational Workflows: Adaptive Processing, Sensing, and User Experience

As with any large-scale detection problem, screening people and cargo is fundamentally limited by the sensing and human resources available. In addition, the resources deployed must rapidly rule out threats to allow traffic to flow across borders at a rate that facilitates commerce and does not cause unacceptable delays for travelers. The current approach is to apply the same procedure to each item, person, or vehicle, and then to escalate to secondary screenings if the first screening indicates an issue of concern.

The concept of adaptive screening is to extend this approach by introducing more flexibility into the system. The goal of this flexibility is to provide new operating points that enable higher throughput at a higher detection rate, for a fixed false alarm rate.

4.3.1 Automated pre-screening with a tunable false alarm rate

In times of high border port of entry traffic, extensive backups can occur due to the limited number of available agents. Fundamentally, this is due to a mismatch between human resources and the number of screening decisions that need to be made to keep traffic flowing. One way to address this issue is automated pre-screening by algorithms with a tunable false alarm rate. This would enable the system to leverage processing to match the number of human decisions to be made and acceptable queue lengths to the number of agents available. This system will maintain an acceptable flow of goods and people while enhancing detection performance. While there are challenges with conducting pre-screening at the discretion of algorithms, there is precedent for this choice in the use of algorithms in airport security scenarios that rely on Advanced Imaging Technology (AIT) systems.

The performance of an automatic screening algorithm with a tunable false alarm rate could be further improved by leveraging contextual information (e.g., a shipping company's track record) to adjust the sensitivity of the algorithm. Research will be required into how to incorporate various forms of contextual knowledge into the pre-screening processing chain.

4.3.2 Sensor and Processing Adaptation

Static screening and processing configurations are inefficient due to the uniform allocation of resources independent of initial results and context. For example, in an airport, an initial screen can guide luggage to a variety of subsequent sensing modalities tailored to the nature of the threat identified in the initial screen. For border crossings, readily available cameras in front of the crossing can be used to classify the make/model of a vehicle to adapt the processing and sensing in real time to the vehicle structure. Context can also inform adaptation. For example, if a particular threat is anticipated, the processing can be cued to adjust its priors so that there is increased sensitivity to that threat. While doing so is challenging, the advent of multi-modal foundation models provides one technical path to achieving this capability. Research in this area needs to include systems analysis, how to implement adaptive sensing in hardware, and algorithms for controlling the adaptive system and processing sensor measurements, conditioned on contextual information. Such adaptive systems also raise questions about certification, which is a procedure currently tailored to systems with a static configuration.

4.3.3 Semantically Informed Image Display Adaptation

Current image display technology at the border is not informed by the semantic labeling of the objects under observation, or by context such as the vehicle make and compartments that are of highest concern. A

potentially impactful adaptation is to alter the display of the image to facilitate agent workflow. This would be informed by observing operator workflow and decision-making, via lightweight instrumentation.

The image will be presented in a way that makes the human decision-making faster, for example by providing additional resolution in critical areas or making better use of the image dynamic range and color in regions of high interest via adaptive equalization. As an additional example, the adaptive user interface could split up the vehicle into sub-parts that an operator needs to examine as discrete sub-components.

4.4 Innovations in NII Screening Sensors/Detectors

As discussed in section 1.2, there are essentially two large-scale ways of improving the decision-making processes supporting NII screening use cases: Improve the detectors (e.g., photon counting, multi-contrast/phase contrast imaging, neutron diffraction, etc.) and the affordability of those detectors or extract more information out of analysis (e.g., non-imaging-centric approaches, anomaly detection approaches, model-based iterative reconstruction, etc.). We've spent the bulk of this report focused on the latter yet want to also impart the contributions and importance of the former, innovations in the sensor and detector space. These new sensing modalities provide rich new data sources enabling undiscovered relationships and cross-correlations with other parameters in the SFM. For example, adding collectors to measure diffraction or refraction or phase changes can provide much more information, beyond just attenuation, enhancing the signal relative to the noise.

DHS S&T is leading work in Photon Counting Computed Tomography (PCCT). This approach is designed to overcome limitations inherent in conventional CT detectors, delivering improvements in spatial resolution, radiation dose reduction, and energy resolution. Similarly, DHS S&T is also leading research in gratings-based phase contrast X-ray imaging.[80] In contrast to conventional X-ray imaging providing limited means of distinguishing between different materials, gratings-based phase contrast X-ray imaging provides images reflecting three distinct materials signatures: absorption, similar to conventional X-ray imaging; phase contrast, proportional to electron density variations; and dark field, which can be related to material texture. These additional signatures may enhance the ability to distinguish materials in X-ray images, leading to detection improvements.

As we introduced in section 1.2, while perfect detection is scientifically possible, it is not affordable at the scale required to support the scope of homeland security missions. Thus, combinations of innovative sensors/detectors and algorithms/computing infrastructure that provide for the maximum information gain while meeting affordability constraints is the approach we adopt in this study.

5 Summary and Conclusion

As we pursue the next generation of screening technology, the integration and convergence of AI and advanced sensing present an opportunity to fundamentally rethink how we conceptualize and manage risk in non-intrusive screening. Current approaches often rely on static models that compress vast amounts of sensor data into human-interpretable formats, discarding critical diagnostic information and limiting adaptability to evolving threats. By shifting from visualization-centric workflows to AI-driven paradigms, we can enable more dynamic, versatile, and adaptive risk models, better anticipating and addressing a diverse range of threats, reducing the need for manual interventions, and maintaining smoother flows of legitimate travel, while yet handling an ever-increasing volume of commerce. Instead of asking solely what is in an image, AI enables a deeper questioning paradigm: "what should we measure, where, and how", to understand risks across both spatial and temporal dimensions. This shift from asking what is in the image to what should we

[80] Miller, E.A., Campbell, L.W., Gilbert, A.J., Ivanusa, P., Jensen, S., Kasparek, D., McCall, J.D. and McDonald, B.S., (2023). Gratings-based Phase Contrast X-rays for Security Screening, In *Proceedings SPIE, Anomaly Detection and Imaging with X-Rays (ADIX) VIII*, 125310E (14 June 2023); https://doi.org/10.1117/12.2664161.

measure to understand risk enables greater flexibility and precision in our risk assessments. By embracing these innovations, we can reinvent and revolutionize how non-intrusive screening supports homeland security missions in the era of AI. This report highlights those opportunities.

Appendix A: New AI-enabled Paradigms for Non-Intrusive Screening Workshop Major Contributors

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Appendix B. FAQs on CT

Typical questions that are asked about CT scanning for security are enumerated and considered below.

What is the goal of screening?

The primary goal of screening is to detect explosives and prohibited items in checked and carry-on bags, and air cargo. A secondary goal is to screen for contraband which has a very expansive definition. On its website, TSA lists hundreds of items that are prohibited. Most of them apply to carry-on bags but the list for checked baggage and air cargo is also large and keeps growing. Prohibitions for carry-on bags include knives and other sharp objects, guns etc. In addition to explosive materials and devices, incendiary devices and flammable materials are also banned from hold baggage. Among them, lithium batteries pose a significant risk.

What is the nature of the data that is not visualized? Can this un-visualized data be captured to perform other analyses in either real time or as part of a research program?

For operational use, CT EDS (explosive detection systems) can operate in either “Alarms Only” or “All Bags” mode. The mode decision at any station is decided by the concept of operations (CONOPS) that TSA chooses to use at that location. In the “Alarms Only” mode, the scanner will only display the images of bags that its software determines identifies as needing a closer look. In general, since most bags do not have explosives, the percentage of bags visualized in this case would roughly be in the range of the certified false alarm rate. However, the decision to either clear a certain displayed bag, or open it for inspection is made by the operator. In the “All Bags” mode, the images of 100 percent of the scanned bags are presented to an operator. All decisions are taken by the operator. The human-machine interface is very critical to reducing operator error when viewing a projected image. A detailed discussion on this topic is, however, outside the scope of this white paper.

How is X-ray Diffraction used?

Companies, such as HALO, have been funded by S&T to develop X-ray diffraction augmentation of CT screening systems. One approach is to pipeline the output of a conventional CT scanner into an XRD scanner. The conventional scanner provides information about the location and other relevant information of a potential threat object to the XRD scanner which then utilizes that information to focus on the threat to either confirm or dismiss the object as a threat. Very good results for the CT-XRD prototype developmental systems have been obtained in terms of reducing false alarms. Some of the technical details pertaining to XRD are provided on page 3 of this white paper.

Why not use backscatter instead of projection measurements?

As mentioned earlier some of the X-ray photons get scattered (Compton effect). Material that is composed of elements with a low atomic number (such as organic material) scatter more X-ray photons than materials containing elements with a high atomic number (such as metals). Examples of organic material include people, food, cash, plastics, explosives, drugs, etc. In theory, low density items are imaged more clearly in a backscatter system than in a projection only system. Because it is a reflected signal, a backscatter signal will be weak and hence one cannot obtain a practical signal from deeper parts of an object. Thus, a backscatter only system cannot find explosives or contraband that is concealed at a deeper location inside a checked bag or a cargo skid since its penetrating power is very limited. Some EDS manufacturers are using a combination of projection measurements, backscatter, and X-ray diffraction to get the best possible performance out of their CT systems.

What are the differences between security and medical X-rays?

Medical X-ray and security X-ray systems share a common foundation in detecting and interpreting attenuated or reflected electromagnetic radiation, but they differ significantly in purpose, operational requirements, and design. Medical X-ray systems emit higher levels of radiation and are subject to strict safety standards due to their direct interaction with human bodies. Operating these systems requires extensive training; radiologists must undergo years of specialized education to interpret monochromatic images accurately. In contrast, security X-ray systems prioritize efficiency and speed, as inspectors must analyze a wide variety of items — ranging from bags to large cargo — in mere seconds. To aid this rapid evaluation, security scanners incorporate tools like material categorization programs, which assign colors to organic materials, metals, and other substances to enhance threat detection. This contrasts with medical X-rays, which rely solely on black-and-white images due to the uniform organic composition of the human body and the potential for colored overlays to obscure critical details. While both systems rely on similar physics, their operational goals — detailed medical diagnosis versus rapid threat identification — dictate distinct functionalities and training requirements.