IL NUOVO CIMENTO **46 C** (2023) 33
DOI 10.1393/ncc/i2023-23033-x

Colloquia: SOGIN 2023

Automatic object recognition using deep learning for legacy waste treatment

Y. Yoshida

ins:x Decommissioning and Radioactive Waste Management Head Office, Japan Atomic Energy Agency - Ibaraki, Japan

received 7 March 2023

Summary. — JAEA is addressing the back-end issues with the steadfast promotion of sustainable measures. Research and development plans on the back-end are being rationally pursued by considering priorities based on indicators such as bottleneck issues in waste streams, relevance to WAC settings, and effectiveness of cost reduction. In addition, the future vision (JAEA 2050+) has been formulated to promote cross-disciplinary research and development through a new approach that cannot be reached by conventional R&D methods, and active incorporation of information technologies, such as AI technologies. With regard to back-end issues, we are developing intelligent sensing that combines sensing and information processing technologies to realize automatic sorting technology, and non-destructive evaluation technology using high-energy X-ray CT for legacy wastes. The core technology common to all of these technologies is image evaluation technology using deep learning models, which was confirmed to perform very well in the evaluation of waste object recognition.

1. – JAEA's basic policy on backend measures

In pursuit of the potential of nuclear science and technology, Japan Atomic Energy Agency (JAEA) has set forth its future vision (JAEA 2050 + ([1])) to solve the problem of climate change, provide a stable supply of energy, and achieve the objectives of the Realization of Ideal Future Society (Society 5.0 ([2])). JAEA is promoting new initiatives that are not an extension of conventional research and development, as well as cross-disciplinary research and development through the incorporation of information technologies such as AI technologies.

([1]) `https://www.jaea.go.jp/english/about/`.
([2]) `https://www8.cao.go.jp/cstp/english/society5_0/index.html`.

JAEA is steadily promoting and addressing sustainable back-end measures with safety as the top priority. In particular, JAEA's long-term prospect and policies for the back-end measures are compiled as the Back-end Roadmap (2018)([3]), together with the Decommissioning Implementation Policy, which is required to be prepared and published in accordance with the revision of the Nuclear Reactor Regulation Act (Act on the Regulation of Nuclear Source Material, Nuclear Fuel Material and Reactors) in Japan. This roadmap summarizes the planning of a long-term (approximately 70 years) policy on back-end measures for existing facilities in JAEA, relatedly, in IAEA's ARTEMIS Review (2021)([4]), has been evaluated as clearly indicating the future direction of the program and the issues that need to be addressed. Currently, we are considering compliance with standards for waste disposal, establishing a quality assurance system for waste processing, collecting data for waste characterization, and developing facilities and equipment for waste management. Additionally, these projects are being rationally implemented with priority, using indicators such as identification of bottleneck problems in consideration of waste stream, relevance to Waste Acceptance Criteria (WAC), and cost reduction effect.

As a priority for back-end measures, we are developing technologies for non-destructive evaluation of high-energy X-ray computed tomography (CT) for the purpose of identifying the properties of legacy waste, including the presence or absence of harmful matter (fig. 1), intelligent sensing technologies that combine sensing and information processing technologies for the implementation of automatic sorting (fig. 2), and others [1, 2].

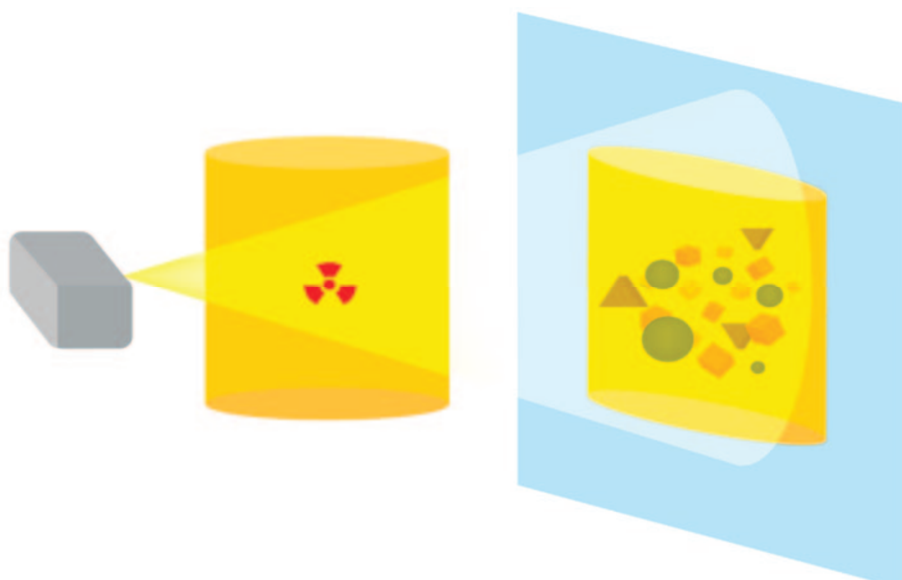

Fig. 1. – Image of non-destructive evaluation of high-energy X-ray computed tomography

([3]) `https://www.jaea.go.jp/english/about/`.
([4]) `https://www.iaea.org/sites/default/files/21/06/artemis_jaea_backend_roadmap_final_report_11june2021.eps`.

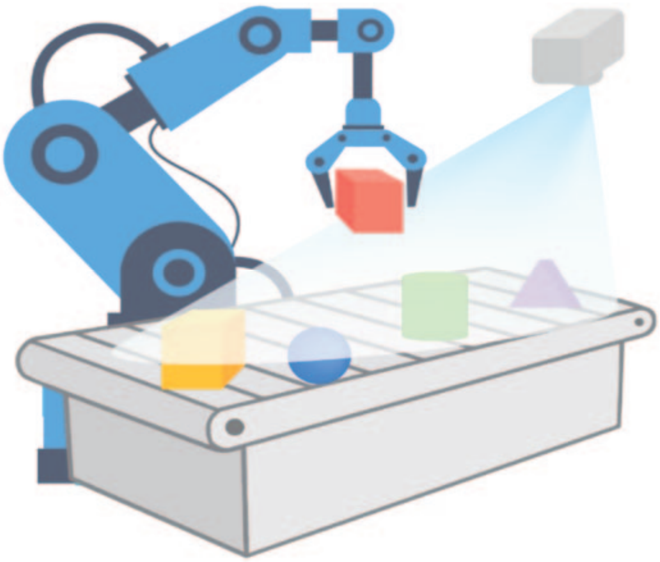

Fig. 2. – Image of automatic sorting technology combining sensing and information processing technologies

This article describes recent efforts to verify the applicability of AI technologies to legacy wastes. In particular, we introduce the image evaluation technology using deep learning models, which is closely related to the non-destructive evaluation technology and the sensing technology for sorting mentioned above.

2. – Legacy waste management and application of AI

Radioactive wastes stored by JAEA are roughly classified into three types based on the characteristics of the waste in terms of the ease of waste disposal, of which Types II and III are legacy wastes [3]. A schematic diagram of each type of waste is shown in fig. 3. Type I waste is generally classified by waste generating facility and type of materials, and have a low variability in radionuclide composition and making it easy to extract materials that would affect waste treatment and disposal in the drums (a scaling factor method is available for verification of waste package radioactivity). Type II waste is a mixture of waste generated from multiple facilities with different nuclide composition ratios, and then compressed and/or solidified. Therefore, this type waste requires a great deal of time for evaluation of radioactivity concentration and removal of undesirable materials. Type III waste is a relatively high dose of waste stored in a sturdy concrete container. Table 1 shows the approximate amount of waste by site and facility where waste is generated and waste type currently stored. There are approx. 200,000 Type I wastes (all waste counts are converted to 200L drums), approx.100,000 Type II wastes, and approx. 20,000 Type III wastes. Type III waste is that the number of storage containers is about 2000 although it is about 20,000 in terms of 200 L drums. In addition, Type III wastes have a very low risk of storage due to sufficient robustness of the shielding containers, and the amount of storage is small. Therefore, JAEA is studying the acceleration of waste treatment for Type II waste, which requires a lot of time and cost for waste segregation.

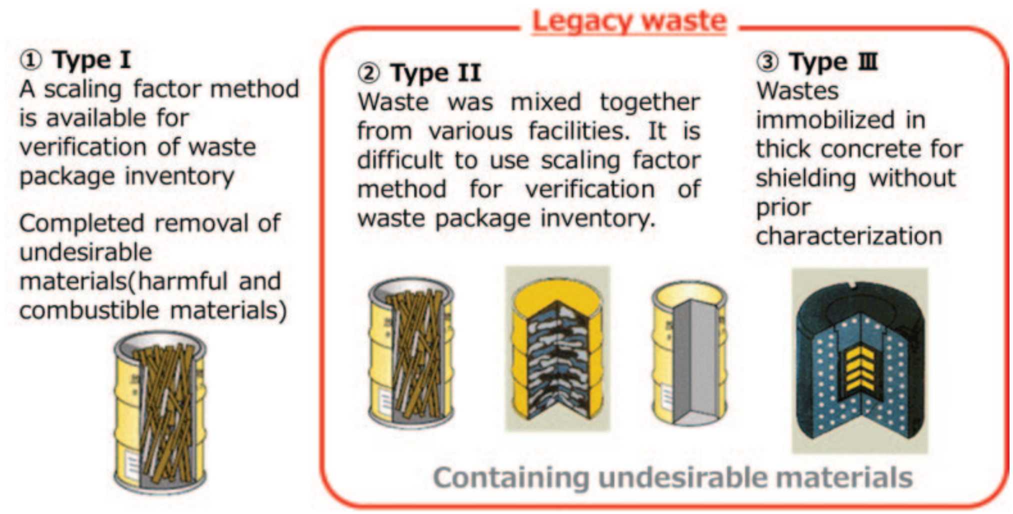

Fig. 3. – Schematic diagram of waste stored at JAEA

TABLE I. – *Approximate amount of waste by site and facility where waste is generated and waste type currently stored*

	Facilities in JAEA					
Waste types	AOMORI R&D Center	TOKAI NSRI	TOKAI NFCEL	OARAI R&D Center	TSURUGA	NINGYO
Type I ∼200,000 drums	Reactor facilities (MUTSU)	Reactor facilities (JPDR etc.) PIE facilities (Hot lab etc.)	Reprocessing, MOX fuel fabrication, Uranium enrichment facility	All facilities	Fugen, Monju	Refining & Conversion Facility, Enrichment Engineering Plant, Uranium Enrichment Demonstration Plant
Type II ∼100,000 drums		Waste treatment facility (Mixed, Compacted waste)		All facilities (Mixed, Compacted waste)		
Type III ∼20,000 drums		PIE facilities (Hot lab etc.)		PIE facilities (MMF etc.) Reactor facilities (JMTR etc.)		

So far, in order to grasp the properties of legacy waste, survey to open drums for Type II waste have been conducted, and it has been revealed that lead and mercury in batteries are contained as harmful matter. According to an evaluation based on statistical analysis of the contents of about 900 cans opened to date, it has become clear that about 10% of the drums contain harmful matter [3]. In light of this background, in JAEA, the procedure for determining the presence or absence of harmful matter in Type II legacy waste is, as the first step, to evaluate the presence or absence of harmful matter by nondestructive evaluation, and as the second step, to open drums that are determined to contain harmful matter and segregate the undesirable materials. To actually evaluate the presence or absence of harmful matter without opening the drum, it is necessary to consider a method that can easily evaluate objects with a diameter of 600 mm scale and

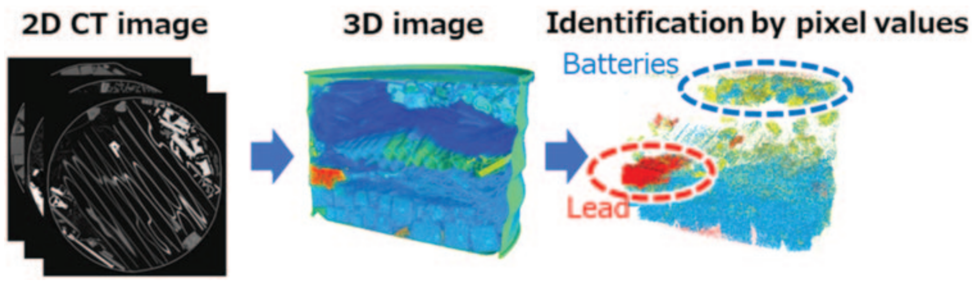

Fig. 4. – CT image of simulated drum waste and harmful matter extraction

an average density of 1 g/cm^3 in the drum. In addition, it is known from the survey to open drums that they contain a large amount of compressed organic matter, and the non-destructive method using high-energy X-ray is effective because the ability to penetrate the material regardless of the object such as organic matter or metal is required to grasp the three-dimensional detailed contents. For example, an X-ray with energies up to 9 MeV can transmit 300 mm of iron. X-ray CT is a non-destructive method to evaluate the three-dimensional structure of a large drum-scale object using such high-energy X-rays [4-6]. The two-dimensional image in the drum can be mathematically reconstructed by synchronously rotating the object to be measured while irradiating it with pulsed X-rays, continuously acquiring multiple transmission images, and obtaining enough information to calculate the tomographic image. By stacking these reconstructed images, a three-dimensional image can be obtained. In order to accurately extract harmful matter from this three-dimensional image, it is necessary to reduce the acquisition height of the two-dimensional image and acquire a large number of transmitted images to obtain a high-resolution image. For the detector, there are line sensors, scintillation detectors, etc., and it is necessary to select one according to the desired resolution [5,6].

The results of the X-ray CT image obtained using a simulated waste material whose actual diameter is on the scale of a drum are shown in fig. 4. From this three-dimensional image, lead and batteries can be extracted by evaluating the image while changing the CT values, but this analysis requires knowledge and skills of a CT image specialist and a great deal of analysis time. There is a need to develop new methods that can automatically and easily evaluate wastes that are in complex contact with various densities in terms of work efficiency.

If a nondestructive evaluation determines that a drum contains harmful matter, the drum must be opened and sorted. This sorting process is a very time-consuming and costly process that must be performed manually in order to completely remove harmful matter. Presently, automated sorting technology is being developed in the field of industrial waste, but it has not yet been realized with sufficient accuracy to be applied to the nuclear field.

A common solution to the two issues mentioned above is to use AI-based object identification technology. This method is a deep learning object recognition technology that has become widely known for its higher performance than other methods in ILSVRC (the ImageNet Large-Scale Visual Recognition Challenge) 2012, an image recognition competition. In ILSVRC2015, it was shown to be able to identify objects with an error rate that exceeds human capabilities, and is now widely used in various fields such as medicine, biology, and materials science [7-15]. Figure 5 shows a schematic diagram of

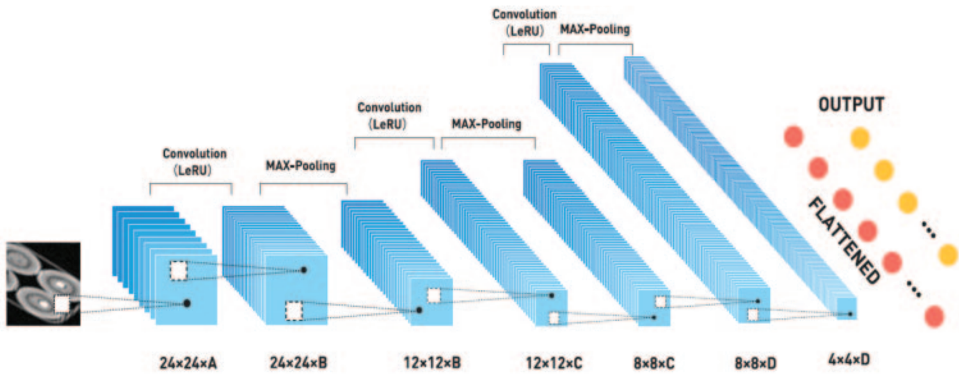

Fig. 5. – Schematic diagram of CNN for image recognition

CNN (Convolutional Neural Network), one of the deep learning methods widely used for image recognition, consisting of an image input layer, a convolution layer for extracting image features and storing location information, an information compression layer for improving robustness against minor image variations, a total coupling layer for classifying images, and a layer for outputting results. We are investigating how effective such AI technology is for waste treatment, the quality and quantity of training data, and what kind of neural network to select to obtain better results from the algorithm's point of view. Figure 6 shows one result of the actual verification, which is the result using a network of SSD (Single Shot Multibox Dtector), and confirms that multiple objects can be identified simultaneously and objects can be identified with high accuracy (mAP > 0.99) with very little false positive establishment [16]. We also confirmed that it is possible to reduce the amount of training data to about 1/100 when images from existing public databases are used for prior learning. This deep-learning-based object recognition technology is expected to be used as a very practical technology in the nuclear field. In addition, as shown in Figure 4, a 3D X-ray CT image is also a superposition of 2D images. We are currently verifying that a 2D image of a drum waste is sufficient for content evaluation using deep learning image identification technology, and are developing a technology to infer 3D objects from a small number of 2D images.

3. – AI accountability and countermeasures

The results of this study on legacy wastes have shown that AI technology is a very useful tool in the field of waste treatment. However, one of the major challenges in general for the implementation of AI technology is how the problem of AI accountability can be solved, especially in the process of a large amount of information and complex objects, which is difficult for humans to understand. This problem becomes even more apparent when considering the application of AI technology, especially in the nuclear field, because accountability is the most important factor in building public trust, which is a major obstacle to the application of AI technology. As a solution to the problem of AI accountability, there needs to be transparency about learning methods and processes, and we need to build AI system that is highly explainable and easy for humans to understand how AI makes decisions. As a countermeasure for the problem, we have developed support technology to improve the explanation of why the decision was made,

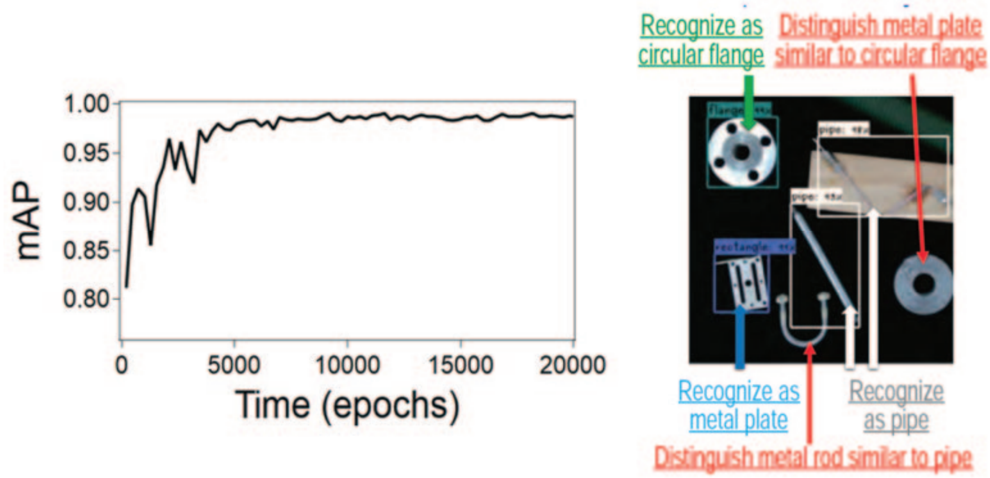

Fig. 6. – Learning curve and object recognition using SSD

by adding objective information that is easy for humans to understand. For example, regarding sensing technology for automatic sorting, in addition to RGB camera imaging information, we are also developing technologies to add material information, such as near-infrared cameras and fluorescent X-ray imaging technology. It is possible to build highly transparent multimodal AI technologies by adding information that is clearly easy for humans to judge. This multimodal approach is expected not only to improve accountability but also to improve the performance of object identification.

AI technology is a field where technological progress are remarkable, and there is a great possibility that new approach related to further improvement of AI accountability will be invented. Particularly, it is vital to continue to update technologies by quickly incorporating new knowledge on issues related to the implementation of AI. In addition, it will be difficult to ignore the development of AI technology in the future, since proactive use of AI technology will improve safety, reduce workload, and lower costs.

4. – Conclusion

To address the issue of legacy waste, we developed a technology that combines information processing technology with intelligent sensing related to automatic sorting technology and nondestructive evaluation technology using high-energy X-ray CT. The object identification technology using deep learning networks utilized in these technologies has been confirmed to exhibit high identification performance and is fully applicable for practical use in back-end issues. Furthermore, as measures related to AI accountability, it has been corroborated that the reliability of AI technology can be enhanced by adding complementary information that enables an objective understanding of AI judgments.

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