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Artificial Intelligence for Accelerating Nuclear Applications, Science, and Technology

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DISCLAIMER

Artificial Intelligence for Accelerating Nuclear Applications, Science, and Technology

FOREWORD

Artificial intelligence refers to a collection of technologies that produce systems capable of tracking complex problems in ways similar to human logic and reasoning. Machine learning technologies learn how to complete a particular task based on large amounts of data.

Artificial intelligence technologies are advancing exponentially and can already sort and interpret massive amounts of data from various sources to carry out a wide range of tasks and help tackle many of the world's most urgent challenges. Artificial intelligence has the enormous potential to accelerate technological development in many nuclear fields from nuclear medicine to water resources management to nuclear science and industry.

In 2021, the IAEA hosted a pioneering Technical Meeting on Artificial Intelligence for Nuclear Technology and Applications aimed at providing an international, cross-cutting forum to discuss and foster cooperation in nuclear applications, science, power, radiation protection and nuclear security, and safeguards verification, to reflect on ethical concerns, and to identify priorities for future activities in these fields and how the IAEA can support their accomplishment.

This publication provides an overview of the current state of the art, outlines challenges, and identifies opportunities for accelerating nuclear applications, science, and technology with artificial intelligence.

The IAEA gratefully acknowledges the contributions of numerous experts to the preparation of this publication. The IAEA officer responsible for this publication was M. Barbarino of the Division of Physical and Chemical Sciences.

CONTENTS

EXECUTIVE SUMMARY

Artificial intelligence (AI) and machine learning (ML) methods have had significant impacts in science and technology in recent years. These methods for generating models from datasets or logic-based algorithms that emulate aspects of human performance can similarly accelerate the fields of nuclear applications, science, and technology toward the IAEA goals of contributing to peace, health, and prosperity. In order to accomplish advances with AI in general and ML in particular across these fields, IAEA can play a significant role, as illustrated in Fig. 1, by establishing, hosting and curating centralised resources, including databases, adhering to FAIR (findable, accessible, interoperable and reusable) principles and Open Science best practices, providing stewardship of data sharing, supporting training efforts and development of relevant workforces, as well as enabling connections among the scientific, technology, mathematics, AI and ethics communities.

Many areas can benefit from the use of AI in the realm of nuclear applications. In human health, these areas include clinical research, epidemiology, nutrition, medical imaging, radiotherapy and education of health professionals. AI-based tools are also being used to facilitate different clinical tasks in imaging, computer-assisted diagnosis in mammography and lung cancer screening programmes, and dose prediction in nuclear medicine procedures. ML methods in particular may also increase the efficiency and accuracy of the analysis of computerised tomography and dual-energy absorptiometry scans for body composition and bone analysis. The application of AI methods to nuclear and related technologies in food and agriculture can lead to significant advances and improved efficiency in the optimisation of agricultural production, food product development, management of supply chains, food safety and food authenticity control. In the water and environmental sector, AI can help inform policies to mitigate the world's water problems. The application of AI techniques to hydrology and environmental sciences is expected to improve patterns identification and enable model predictions under a changing climate.

In nuclear science, AI-driven research focuses on the automation of the nuclear data pipeline. These efforts include, for example, the compilation of datasets from publications by using natural language processing applications, and work is ongoing towards using ML methods for robust inference with meaningful uncertainty predictions. Furthermore, AI can assist with validation tasks and the design of experiments for validation. Within the nuclear physics community, AI and ML methods are applied to data analysis and theoretical modelling to improve scientific understanding and to increase the efficiency of data processing and management. Further efforts pertain to the design of future experiments and the optimization of existing setups, and to the operation of facilities dedicated to nuclear physics, such as particle accelerators. Recent successes in applying AI and ML methods to outstanding problems in magnetic and inertial confinement fusion research suggest that such methods have the potential for significant acceleration of fusion R&D. Worldwide efforts in fusion R&D can benefit by enabling broader participation in fusion problem solutions through AI and ML.

In nuclear power, the industry can benefit from AI in areas such as automation, design optimization, data analytics, prediction and prognostics, and insights extraction. Ongoing efforts focus on the transfer of AI technologies from pilot studies to wider applications. In radiation protection, AI applications and their integration into control and monitoring processes (such as individual dosimetry for external exposure) are expected to yield faster, more flexible and more efficient processes with the potential for a deep technological transformation in the field. In particular, AI enables the emulation of human cognition in the analysis, interpretation, and comprehension of complicated work processes including radiation exposure.

In the field of nuclear security, possible applications of AI include analysis of spectroscopic and geospatial data to improve detection of nuclear material outside of regulatory control, enhancements to nuclear material accounting and control systems, and the potential to identify possible insider and external threats at nuclear facilities. On the other hand, the use of AI in nuclear security systems may introduce potential vulnerabilities not immediately recognizable to a human operator or the AI system itself. Significant investigation into the threat of cyber-attacks on AI-enabled technologies is crucial in this area.

Safeguards field activities rely on an ever-growing amount of data obtained with different techniques to detect nuclear materials, including satellite imaging and gamma ray spectroscopy. Combined with the rise of the number of materials under safeguards, the need for more efficient nuclear safeguards processes is evident. Implementation of AI and ML methods would significantly benefit safeguards by increasing the efficiency of these field activities.

Finally, the convergence of AI and nuclear technologies could exacerbate existing ethical concerns in the disciplines as well as give rise to new concerns at their interface. Because both disciplines concern risk and uncertainty and hold huge potential for both benefit and possible serious societal and environmental harm, there is a need for a new discipline on the interface, namely the Ethics of Nuclear and AI Technologies (ENAI). ENAI aims at establishing a non-binary ethics, which could be frontloaded in the design, development, deployment, and use of AI applications in the nuclear field. This would contribute to creating awareness among practitioners about the ethical impact of the convergence of AI and nuclear technologies, while creating mechanisms for robust dialogue with stakeholders. ENAI could further ensure societally accepted and ethically informed decision-making, which ultimately enables responsible governance of the application of AI in the nuclear field.

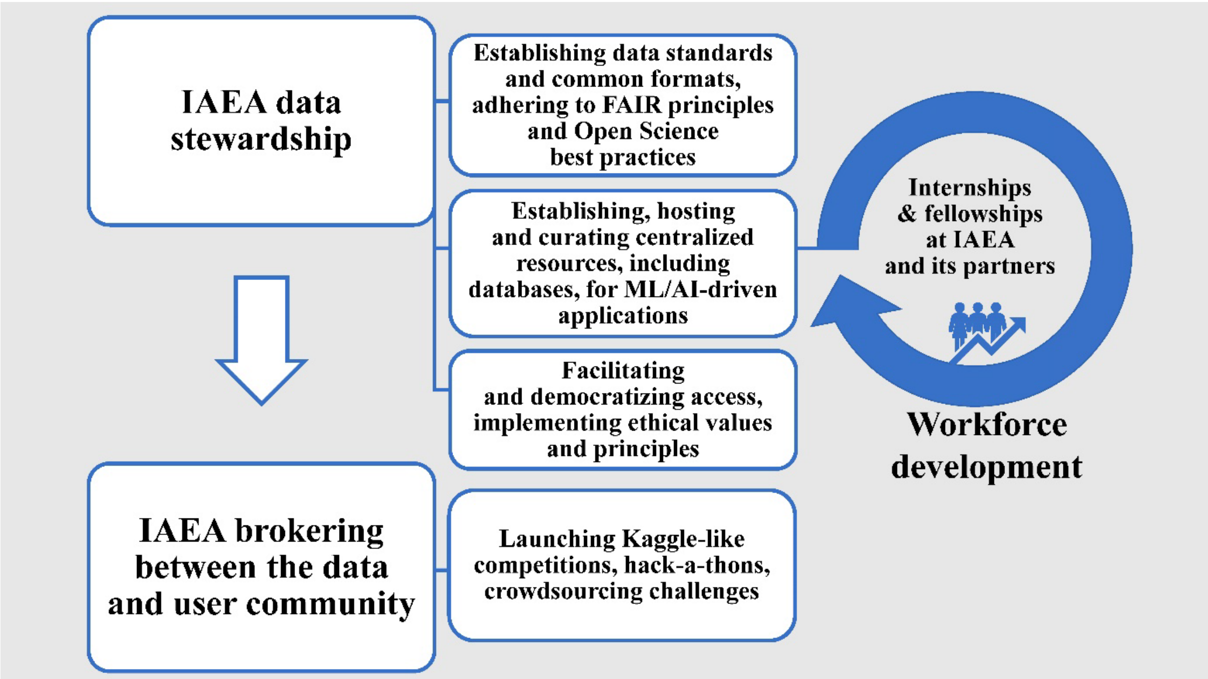

FIG. 1: IAEA's role in accelerating progress in nuclear applications, science, and technology using AI and ML methods.

Chapter 1.

INTRODUCTION

1.1. BACKGROUND

AI falls into logic- or knowledge-based AI and data-driven AI. AI refers to a collection of technologies that produce systems capable of tracking complex problems in ways similar to human logic and reasoning. ML technologies learn how to complete a particular task based on large amounts of data.

AI technology is advancing exponentially and can already sort and interpret massive amounts of data from various sources to carry out a wide range of tasks and help tackle many of the world's most urgent challenges. AI has enormous potential to accelerate technological development in many nuclear fields from nuclear medicine to water resources management to nuclear science and industry. For example, AI's ability to recognize data patterns and analyze high resolution images from satellites, drones, or medical scans can improve responses to humanitarian emergencies, detect global hydro-climatic changes signalling drought or floods, monitor and optimise agricultural productivity, track animal and marine migrations, and help medical professionals identify and treat cancers and other diseases.

Combining isotope science with AI provides an interpretable framework to extract new information from small isotopic variations, offering great potential in a multitude of fields, including isotope hydrology, ecology, forensics and food security. Experts already apply AI-based approaches to water-related isotopic data stored in global networks, such as the Global Network of Isotopes in Precipitation maintained by the IAEA and high-frequency isotope data series. Effective and efficient analysis of these data facilitated with AI helps scientists understand impacts of climate change and population growth on water availability worldwide.

In fusion and nuclear science research, ML can enable optimization of experimental planning and real time control solutions necessary for sustained, safe, and efficient facility operation, by maximising the amount and applicability of information extracted from experimental and simulation data.

AI-based approaches are applied to support nutrition as well as diagnosis and treatment of disease through improved image processing, detection of pathologies, and segmentation. ML plays an increasingly important role in the prediction of an individual's disease course and treatment response. AI will also play an important role in the IAEA's Zoonotic Disease Integrated Action (ZODIAC) initiative to help experts predict, identify, assess, and contain future zoonotic disease outbreaks.

With the advent of powerful computing capabilities and data analysis tools, the nuclear industry is embracing AI and ML techniques for a wide range of visionary activities that could transform the way nuclear systems are being designed, licensed and operated. AI has the potential to enhance the integration of computations and experimental data collected from small-scale experiments or from sensors during operation. This integration, when optimised, allows computational scientists to develop physics models of unprecedented accuracy and helps experimental scientists to minimise the cost and number of validation experiments for first-of-a-kind systems. It also makes it possible for system operators to monitor system states that cannot be directly instrumented. AI methodologies and tools can be applied for physics-based predictive analysis that can be used to perform design, manufacturing, construction, and operation effectiveness optimization; improved new reactor design iterations; model-based fault detection; and for control systems. AI can also bring further benefits to the nuclear industry in terms of reliability, safety, and overall efficiency.

1.2. OBJECTIVE

The objectives of this publication are:

- To provide an overview of the current state of the art, outline challenges, and identify opportunities for accelerating nuclear applications, science, and technology with AI.
- To identify priorities for future AI activities in the nuclear field and determine how the IAEA can support their accomplishment.
- To identify commonalities and synergies between AI research in different applications with a view to facilitating collaborations and cooperation.
- To establish ethically responsible governance of the application of AI technology to the nuclear field and to ensure societally accepted and ethically informed decision-making mechanisms regarding its application.

1.3. SCOPE

This publication encompasses the development and applications of AI in human health, food and agriculture, water and environment, fundamental nuclear data, nuclear physics, fusion, nuclear power, radiation protection, nuclear security, and safeguards verification. It also addresses the ethical impact of the convergence of AI and nuclear technologies.

1.4. STRUCTURE

This publication provides a review of the current state of the art, and outlines challenges and identifies opportunities for accelerating nuclear applications, science, and technology with AI. After the introduction and background information on AI and its use in the nuclear field, Chapter 2 provides a summary of the ethics of AI and nuclear technologies and of the use of AI in nuclear applications, science, power, radiation protection, nuclear security, and safeguards verification.

State of the art, priorities for future AI activities in the nuclear field and the IAEA's role to support their accomplishment[1] are presented in the following Chapters. Chapter 3 addresses the ethical impact of the convergence of AI and nuclear technologies. Chapters 4–12 focus on the applications of AI in nuclear fields corresponding to IAEA's areas of work, including human health, food and agriculture, water and environment, nuclear data, nuclear physics, fusion, nuclear power, nuclear security, and safeguards verification.

[1] Based on input from Agency scientific and technical meetings on the subject matter and through the interaction between the secretariat and expert participants with respect to the theme of this publication and specific parts of the Agency's Programme.

Chapter 2.

SUMMARY OF ARTIFICIAL INTELLIGENCE IN NUCLEAR APPLICATIONS, SCIENCE, AND TECHNOLOGY

2.1. ETHICS

The disciplines of the ethics of AI and the ethics of nuclear technology are well established as separate domains. However, the application of AI technology to nuclear science, technology and applications points to the need for the establishment of a new discipline on the interface of these domains, namely the ethics of nuclear and AI technologies. The raison d'etre for this new domain lies in the facts that both disciplines concern risk and uncertainty and both hold huge potential for benefit as well as for possible serious societal and environmental harm. The ethics of nuclear and AI technologies points to the convergence of already existing concerns in the two subdomains as well as to new concerns arising on their interface. It aims at establishing a non-binary ethics, which could be frontloaded in the design, development, deployment and use of AI applications in the nuclear field. This would contribute to: (i) creating awareness among practitioners about the ethical impact of the application of AI technologies to nuclear science, technology and applications; (ii) putting in place mechanisms for robust dialogue with all identified stakeholders; (iii) ensuring societally accepted and ethically informed decision-making regarding nuclear applications, science, and technology; and (iv) establishing responsible governance of the application of AI technology to nuclear applications, science and technology.

2.2. NUCLEAR APPLICATIONS

There are broad efforts in the human health sector to apply AI in clinical research, nutritional epidemiology, and personalised nutrition. Significant work is ongoing in medical imaging and the potential for AI applications in nuclear nutrition assessments, radiotherapy and education of health professionals is being explored. AI-based tools are being used to facilitate different clinical tasks in imaging such as intra- and inter-modality image registration and fusion, computer-assisted diagnosis in mammography and lung cancer screening programmes, and dose prediction in nuclear medicine procedures. In radiotherapy, AI-based tools have potential to automate repetitive, complex work processes, e.g., segmentation, and automatic generation of beam placement followed by optimization as applied to knowledge-based treatment planning. ML methods may also increase the efficiency and accuracy of the analysis of computerised tomography and dual-energy absorptiometry scans for body composition assessment and bone analysis. Prior to deployment of all AI-based tools into clinical practice, verification of their generalizability, interoperability and robustness, needs to be performed by the health professionals responsible for their implementation.

In the food and agriculture sector, recent implementation of open data policies, innovative data acquisition methods, and enhanced data availability have enabled the use of AI. Furthermore, AI can help improve analytical prediction based on traditional chemometrics, supporting calibration of analytical equipment, and calibrating measurements carried out across the same type of equipment but from different providers, which is essential to create the large datasets needed for AI applications. Collaborative frameworks can provide a mechanism to support the development of AI approaches in food and agriculture science, stimulating progress by interdisciplinary exchange of expertise and experiences across scientific fields and disciplines, to exchange experience and discuss case studies within and outside of the community. AI methods developed within such collaborations can be disseminated widely, leading to further developments, through testing and scaling the developed applications. This can provide significant advantages and efficiencies in optimising agricultural production, food product development, management of supply chains, food safety and food authenticity control, accelerating reaching the sustainable development goals.

In hydrology and environmental studies, the full potential of AI and ML has not yet been thoroughly exploited. Extensive data is available from satellites, unstaffed airborne vehicles, and sensor networks, providing a significant opportunity for AI and ML methods to be applied in conjunction with existing global isotope databases. Application of AI and ML methods to water and environmental studies can be enhanced through extension and quality control of existing isotope databases, spatially and temporally refining relevant datasets, and filling gaps in existing time series data. These databases can further facilitate efficient access to earth-system modellers using AI applications. This way, the combination of isotope techniques, high-frequency data, remote sensing, open-source resources and AI can inform policies for mitigating the world's water problems, as well as issues related to ecology and climate change. Focused connections among data collectors, modellers and water managers can also serve to accelerate progress.

2.3. NUCLEAR SCIENCE

AI efforts in nuclear data aim to automate parts of the nuclear data pipeline. The components of the pipeline that would benefit the most from AI are (i) compilation; (ii) evaluation; and (iii) validation. Currently, a primary barrier to AI advancements in nuclear data is a manual interface with datasets. Developing application programming interfaces is crucial for advancing AI in nuclear data. For the compilation of datasets from publications, natural language processing applications are being explored. Establishing data standards for these compiled datasets will enable faster development of AI for nuclear data. For the evaluation of these datasets, there is work towards using ML methods for robust inference with meaningful uncertainty predictions. Furthermore, AI can assist with validation tasks using integral experiments, and help design future integral experiments for validation.

To accelerate scientific discovery in nuclear physics, there are widespread efforts towards AI applications. These efforts span facility operation, experimental optimisation and design, data processing, management and analysis, and theoretical modelling. Whereas the nuclear physics community has investigated the efficacy of AI methods for more than fifty years, the last five years have seen an exponential increase in the development and use of AI technologies. Looking forward, deeper understanding and utilisation of AI methods that incorporate robust uncertainty quantification will be paramount. Directing efforts towards the integration of AI methods into real-time systems, such as accelerator operations and detector systems, will assist in increasing scientific output from experiments. In order to advance the use of AI in nuclear physics, continued, regular education efforts and curated centralised resources need to be established. In addition, funding opportunities for interdisciplinary positions at the intersection of AI and nuclear physics are required.

In fusion science research, AI and ML have proven highly effective in addressing outstanding problems in tokamak disruption prediction, surrogate models for acceleration of computational tools, and hybrid models that combine physics-based and data-driven models. The success of these efforts in the fields of magnetic fusion energy and inertial fusion energy research suggests that large scale application of such methods has the potential for advancing the realisation of fusion as a commercial energy source. Presently, worldwide efforts in fusion R&D can benefit by enabling broader participation in fusion problem solutions through AI and ML. This broader participation can be facilitated by providing wider access to curated fusion data along with identification of key problems amenable to data-driven methods, providing relevant data standards, expanding the workforce with AI and ML domain expertise to address fusion challenges through education and engagement, and supporting application of technical expertise to fusion by broader domain experts.

2.4. NUCLEAR POWER

The nuclear power industry benefits from AI in areas such as automation, design optimization, data analytics, prediction and prognostics, and insights extraction. Automation via AI leads to an increased reliability and safety risk reduction in high-pressure or demanding situations, thus minimising downtime of common operations due to human error. Examples include automating data analysis of defects of control rods and anomaly detection in nuclear power plants (NPPs) processes. AI-driven optimization can increase NPPs efficiency and could enable the design of complex operations, such as assisting in core-control methods for predictive purposes. Further, advanced statistical modelling via AI-infused physical concepts can provide fitness-for-service assessments, while preserving generalisation to new data. Predictive modelling in NPPs can be leveraged to better inform maintenance activities. However, this is an underutilised tool in the nuclear power industry because standard solutions are currently more broadly adopted. Finally, the large amount of data available on operating NPPs enables discovery of new best practices for improved operating and maintenance efficiencies.

The deployment of AI solutions, however, is often hindered by the difficulty of demonstrating compliance with regulatory standards. The nuclear power community is starting to address these challenges with the creation of dedicated ISO/IEC subcommittees working on promoting a rapid transfer of AI technologies from pilot studies to wide applications. A crucial point remains to protect the trustworthiness and integrity of both models and data used for training and decision-making from potential cybersecurity attacks.

Before the nuclear power industry can effectively adopt AI-based tools, R&D efforts are required in speech and gesture recognition for control room operations, or AI-aided field-testing techniques, such as condition monitoring and automation of predictive maintenance procedures. Most importantly, concrete efforts will be needed to develop a roadmap guiding regulatory investigation, research and positioning on the application of AI systems for nuclear power plants.

2.5. RADIATION PROTECTION AND NUCLEAR SECURITY

The focus of radiation protection is the integration of safety requirements and standards in workplaces subject to radiation exposure. Scoping existing AI applications and their integration in the safety standards is currently ongoing. ML algorithms and virtual reality tools can be exploited to address specific challenges in radiation protection, such as applications for simulation and job planning regarding workers' dose calculations, or dose optimisation during design of facilities and activities including nuclear facilities to comply with regulatory requirements. AI-driven research could enhance radiation protection by producing algorithms and software that emulate human cognition in the analysis, interpretation and comprehension of work processes including radiation exposure. Additionally, by gathering and analysing radiological data across many different machines, faster, more flexible, and more efficient processes for the establishment of radiation protection programmes will be enabled, leading to a deep technological transformation in the field.

There are potential benefits and risks to the use of AI in nuclear security applications. Examples include the potential to improve detection of and response to material outside of regulatory control, the potential to improve nuclear material accounting and control systems, and the potential to identify possible insider and external threats at nuclear facilities. However, the use of AI in nuclear security systems may introduce potential vulnerabilities not immediately recognizable to a human operator or the AI system itself. As a result, there is a need for increased understanding of the limitations of AI applications in nuclear security systems. Significant investigation into the threat of cyber-attacks on AI-enabled technologies is also crucial in this space. In the field of nuclear security, primary efforts need to centre on the analysis of the benefits of AI versus the risks introduced by AI. Experts encourage careful consideration when developing and implementing AI and the establishment of clear objectives and metrics to preserve rather than compromise security. AI also raises a number of ethical and privacy concerns for nuclear security, in addition to questions surrounding data accessibility, intellectual property constraints, and even data sovereignty.

2.6. SAFEGUARDS VERIFICATION

The application of AI is expected to increase the efficiency of safeguards processes, in particular for those that involve classifying data, finding patterns, and identifying outliers in the data. ML methods have been used in the analysis of gamma ray spectra to detect and identify anomalous sources of nuclear materials or to quantify the amount of fissile mass. Furthermore, the verification of spent fuel from gamma ray, neutron and Cerenkov imaging data is an important task within safeguards that can benefit from the application of AI. By combining AI techniques with robotic technology for tasks, such as data collection or calibration, a further increase in efficiency is envisioned. Video surveillance safeguards processes would also benefit from the implementation of AI as their review is both challenging and time-consuming and as conventional algorithms are prone to false alarms. By reducing the number of repetitive tasks that are currently performed by inspectors and experts, the application of AL and ML would increase productivity in safeguards.

At present, however, the accuracy of ML-based predictions is often insufficient to allow for autonomous decisions, and thus requires continued human input. Inspectors and experts will need to work closely with specialists from the AI community to improve the accuracy of AI-based algorithms and to inform their development. This is of particular importance as false alarms affect the trust the users have in the algorithms as well as the trust between the inspectors and the Member States. In addition, false negatives would miss important events with significant consequences for safeguards. As a fraction of the data within safeguards is not open-source, another challenge in the implementation of AI within safeguards pertains to data sharing. Once the discussed challenges are overcome, AI-based algorithms can be established as reliable tools for safeguards processes.

Chapter 3.

ETHICS

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3.1. STATE OF THE ART

3.1.1. Artificial intelligence ethics

While AI technologies have tremendous potential to contribute to the good of humanity, there are some serious concerns about the possibility of these technologies, and their applications, contributing to the transgression of human rights, and human values, such as dignity. Therefore, it is necessary to ensure that these technologies are governed in responsible ways throughout their life cycle including the research, design, development, deployment, use and end of use stages.

Data-driven AI refers to AI research that centres on data classification and deep learning methods. Until around 2000, AI research was mainly focused on knowledge or logic-based research that focused on the nature of knowledge representation and reasoning by formalising natural language and reasoning practises in logic-based systems. There are some notable technical limitations with this kind of approach, especially if one wants to move away from traditional algorithms that prescribe the way in which problems are solved, or logic-based systems behave. Given the advent of the big data era, the focus moved from algorithmic reasoning to finding patterns in data. Many different methods were tested — neural networks, Bayesian networks, support vector machines, evolutionary algorithms, etc. — and one of the major breakthroughs happened in 2012 in the domain of computer vision (image recognition) with Geoffrey Hinton's application of deep learning and other ML techniques [3.1].

ML systems differ from traditional algorithms as there is no given set of rules for solving problems, but rather ML systems learn to solve problems. Thus, the logic of ML systems changes as the way in which algorithms solve problems is not predetermined [3.2]. This property of ML systems raises a host of concerns centring on transparency, explainability, fairness, privacy, and accountability. AI technologies also carry other potential additional threats such as contributing to social and political instability through mis- and disinformation, imperilling the most vulnerable groups in society, changing the quality of human interaction and agency, amplifying inequality, and contributing to threats to the environment and ecosystems. In addition, there are various kinds of harm that can be caused by AI systems that relate to representation of social groupings and allocation of resources based on identity prejudice driven by structural bias in society. Since clearly AI systems are socio-technical systems (e.g., [3.3–3.6]), what is needed to respond to these concerns is inter-, multi-and transdisciplinary input from all stakeholders through-out the life cycle of AI systems (e.g., [3.7, 3.8]), as well as research on responsible AI governance.

AI ethics has exploded into a complex inter-and trans-disciplinary field over the past decade. While there is a distinctive role for computer science on the technical side in this domain, the nature of the ethical concerns raised by data-driven AI applications and technologies is such that there is also an essential role for disciplines in the social sciences and humanities, such as philosophy and anthropology, and for legal disciplines. Ref. [3.8], refers to the "dual advantage of ethical machine learning", which ensures that opportunities for trustworthy and beneficial AI are realized, while, on the other hand, potential harm is minimised. Thus, part of the ethics of AI is asking "difficult questions about design, development, deployment, practises, uses and users, as well as the data that fuel the whole life-cycle of algorithms" (ibid.) as well as asking questions around privacy concerns related to such data.

However, there are also concerns around the scope and actionability of abstract AI policies and regulation (e.g., [3.9–3.11]). There has been a host of policies recently, from the UNESCO global Recommendation on the Ethics of AI, the GDPR, the EU proposal on the identification of high-risk systems, various national policies, and professional regulation, such as the IEEE documents. Ref. [3.9] cautions however in the context of concretising these kinds of policies that

"[i]n order to analyze [AI ethics] in sufficient depth, ethics has to partially transform to 'microethics'. This means that at certain points, a substantial change in the level of abstraction has to happen ……. On the way from ethics to 'microethics', a transformation from ethics to technology ethics, to machine ethics, to computer ethics, to information ethics, to data ethics has to take place" (ibid.).

There is also in the literature a lot of interest in the potential positive impact that bottom-up approaches (e.g., virtue ethics, data-activism) may have on the actionability of policies (see, e.g., [3.7, 3.9, 3.12–3.14]).

In terms of state of the art of AI ethics, some of the main current focus areas include concerns around autonomy and artificial agency (e.g., in military or health situations); robot rights and legal personhood of artificial agents; concerns around fairness (bias), accountability and transparency (including explainability and interpretability) of AI systems; data integrity, ownership and privacy concerns; the need for information and communication literacy; and the need for actionable AI ethics policies. Necessarily, AI ethics is thus a complex field where ethical and epistemic questions are intertwined and it is a field that transforms, adapts, expands, and adjusts as AI technology progresses. This domain needs to be approached in inter-, multi-, and transdisciplinary manners, with broad (bottom-up) stakeholder participation.

3.1.2. Ethics of nuclear technology

Early discussions on the ethics of nuclear technology in the 1960s and 1970s are almost exclusively about nuclear proliferation and nuclear security and about questions such as the moral legitimacy of nuclear warfare [3.15]. The development, possession, and use of nuclear arms were further discussed extensively (e.g., [3.16–3.19]). What is particularly striking about this literature is that it extends beyond philosophy and ethics venues and into international relations, for instance about nuclear deterrence, perhaps one of the most dominating features in international relations literature after World War II (e.g., [3.20, 3.21]).

Since the 1980s, the literature has evolved from a strong emphasis on proliferation and military aspects to the ethics of nuclear energy, focussing on questions of nuclear safety and risk, justice and democracy as well as proliferation aspects associated with dual use technologies. A part of this literature focuses on assessing the moral desirability of nuclear energy by focussing on the longevity and the toxicity of nuclear waste and from the perspective of our duties to future generations [3.22, 3.23], as well as on the radiation risks for both the public and radiation workers [3.24, 3.25]. Kristin Shrader-Frechette did pioneer work in the 1990s discussing the ethical acceptability of nuclear energy because of its inequitable distribution of risk among the current generations (also referred to as environmental justice) but also between the present and future generations [3.26–3.28].

More recent work (the 2000s onward) extends the discussions on ethics beyond the yes/no dichotomy [3.29, 3.30] and elaborates on the specificities of nuclear energy production and waste management, for instance by using criteria of intergenerational justice to reflect on different technological choices for nuclear waste disposal [3.31], or for choosing a fuel cycle [3.32, 3.33]. In the wake of the Fukushima Daiichi accidents, there was a renewed interest in the societal and ethical aspects of nuclear energy. Understandably, there was an interest in better anticipating and dealing with nuclear risks [3.34, 3.35], safety cultures in nuclear power plants [3.36], moral emotions and responsible risk communications [3.37, 3.38], better understanding justice issues (both procedural and distributive) in decision-making regarding waste management and licence renewal decisions [3.39, 3.40], considering nuclear energy as a social experiment whose acceptability needs to be continuously examined [3.41, 3.42], global safety and security implication as a result of new global nuclear energy landscape [3.43, 3.44] and potential role that nuclear energy could play in the future of nuclear energy provision, both for the industrialised and industrialising nations [3.45–3.47].

Issues pertaining to radiological protection have further received ample attention in the literature, but not only with respect to nuclear energy but also the broader nuclear applications (including nuclear medicine) [3.48–3.52]. Considering ethics (and ethical values) in radiological protection has a long standing in the literature [3.53, 3.54] and it has recently been included in the core of thinking about radiological protection. The International Commission on Radiological Protection (ICRP) has recently spelled out the 'Ethical Foundations of the System of Radiological Protection', particularly focussing on the core values including beneficence and non-maleficence, prudence, justice, and dignity [3.55]. ICRP further lists the three procedural values of accountability, transparency and inclusiveness that are ethically relevant in decision-making about radiological protection.

3.2. NEXT STEPS

As explained in the previous section, the applications of nuclear technologies have given rise to certain ethical issues over past decades. AI applications, but also issues pertaining to big data and ML, have also given rise to emerging and constantly progressing ethical issues. The convergence of AI and nuclear science, technology and applications could exacerbate existing ethical issues in the domains of the ethics of AI and the ethics of nuclear science, technology, and applications. In this process, a new domain, namely the Ethics of Nuclear and AI Technologies (ENAI) emerges for the following two reasons: (i) both technologies carry concerns relating to risk and uncertainty, which may be amplified by their interaction; and (ii) both technologies relate to potential for meeting sustainable development goals (strong potential for overall benefit) as compared to both carrying potential negative social and environmental impact.

As a preliminary definition for this new domain, ENAI can be described as research focused on the reflection on, analysis of, and suggestions to mitigate ethical concerns relating to the design, development, deployment and use of AI applications and technology in the nuclear field. Some examples of areas of application where convergent ethical focus is present include the use of AI technologies in the following domains: in assessing risks and decision-making in risk governance; in nuclear reactor control (complementing operator control and automatization) pertaining to better safety assurances; in intergenerational ethics to reason the way future generations would reason; in triage and diagnosis support in medical applications; and in monitoring, dosimetry and health surveillance after a nuclear accident (including links to mobile applications). The methodology of ENAI will include multi-, inter- and transdisciplinary mixed methods as approaches in bioethics, as well as value-sensitive design and design for values as approaches in ethics of technology.

Contexts for reflecting on ethical concerns in AI ethics and ethics for nuclear technology that may also be applicable to ENAI include: transdisciplinary, interdisciplinary, and multidisciplinary research; responsible research and innovation; bottom-up engagement with all stakeholders; and considering the ethical issues of risk acceptability. Reflection on mutual concerns would imply at least safeguarding meaningful human control and human oversight and the complementarity of human and machine decision making; developing methodologies that support the performance monitoring of AI-powered nuclear systems and actively working to mitigate social and environmental justice concerns; raising ethical awareness and literacy concerning these technologies and stimulating public engagement; and considering the problem of accountability and responsibility for the outcomes of these technologies.

New themes to be explored in the context of ENAI will arise as the new discipline evolves, but here are some themes that immediately arise. AI applications can make for better (nuclear) risk assessment and better preparation, better pre-mortem analyzes, better safety and safeguarding. Considering the development of a new, mature and participatory risk-based approach, built on a theoretical model capable of taking into account many factors (e.g., specific use, effects in space and time, populations involved, local cultures, potential injuries, ethical issues involved, and more) and even non-linear correlations would become possible. Concerns around environmental, social and epistemic justice will be a main issue with respect to ethical considerations to be further investigated. The potential contribution of AI technologies to studying the viability of nuclear applications, science and technology to solve climate issues could become an important new theme. AI technology in medical applications can contribute to improving medical care provided appropriate attention is paid to data ethics, medical ethics and research ethics concerns (diagnostics, risk predictions, personalising treatment, triage). The issue of responsibility for possible harm, which is now an even more complex problem if these two powerful technologies are merged, will have to be rethought. Here the debate on epistemic justice and the individualist vs. collective ethics debate will intensify as the harm at issue is often both to individual persons and societies as a whole [3.56]. New dilemmas coming out of the convergence of the two technologies – e.g., dilemma between benefit and harm, ethical vs. technical risk – will arise for ethical consideration. Attention would need to be given to ensuring uptake of ethical considerations: how do we enable all stakeholders to participate actively in such a broad domain? Further epistemic questions that impact ethical considerations, e.g., opacity of AI in nuclear applications, will need to be considered.

There are also some background concerns about the scope and nature of ENAI to take into account. These include the following concerns: Can AI technologies add more risks to nuclear applications? There is an overlap in terms of the presence of risk and the need for risk analyzes. However, on the one hand, there may be divergence in terms of the ethical and technical dimensions of risk in each case, and on the other hand, there may be potential side effects of AI and nuclear technologies and applications and thus the possible transfer or amplification of risks to the combined domain of these technologies needs to be considered as well. Secondly, can the ENAI exacerbate some issues in acceptability of this industry, and usages? Thirdly, is there a risk of negative back propagation effect on the potential of the application of AI technology in nuclear science, technology and applications of the ethical behaviours of professionals. Finally, when are soft laws needed, when do they or should they be allowed to solidify into hard law within the context of the overarching demand to comply with International Law?

3.3. ACCELERATING PROGRESS—IAEA'S ROLE

It is suggested that IAEA could support the following initial endeavours:

1. Establish a new transdisciplinary domain of ENAI:
   i. Facilitate research and collaborations (IAEA supported and acknowledged);
   ii. Assist with organising a trans-disciplinary conference (trans-disciplinary includes inter-disciplinary work and collaborations between academia and industry);
   iii. Assist with establishing an IAEA network on AI for Atoms;
   iv. Promote the domain and awareness about the domain through international challenges focused on humanitarian problems; and
   v. Develop publications on the subject.

2. Provide ENAI training for practitioners:
   i. Develop specific IAEA validated and approved curriculum, module, publications;
   ii. Assist with cultivating respect for trans- and multi-disciplinary research.

3. Facilitate science policy advice:
   i. Assist with ensuring good quality of information and advice in terms of reflexivity and an inclusive and deliberative character;
   ii. Being sensitive and promoting sensitivity to rights-based vs. duty-based approaches and vocabulary in policy-making.

4. Promote responsible research and innovation:
   i. Pertaining to applications of AI techniques in nuclear technology innovations.

5. Formulate ENAI Guidelines:
   i. Assist with creating a repository of best practice;
   ii. Assist with developing impact assessment methodologies, risk analyzes, pre-mortem analyzes, and sharing of best practice;
   iii. Establish a joint observatory with the Human Rights Council.

In order to accomplish the above, attention needs to be paid to at least the following issues: Who is or needs to be part of the dialogue, who are the stakeholders? How do we address concerns about awareness and literacy, problems of public engagement in AI in nuclear technology and applications? How can up-streaming be ensured? What if lay-people do not understand the technologies?

Moreover, context matters in terms of both identifying and addressing ethical concerns. Some known obstacles to effectiveness of AI ethics (and nuclear ethics) regulation may also apply in the ENAI case such as the divide between what members of the technical and scientific community on the ground are concerned with and abstract ethical principles, and subsequent lack of feelings of moral responsibility on the side of those designing and developing these technologies and applications, on the other.

How does one navigate tension between ethical and economic and political concerns in this domain of AI in nuclear technology and applications? How to mitigate exacerbated ethics dumping in both the AI and nuclear field cases in low- and middle-class countries and small island states and exclusion of these countries from regulatory discussions? What suggestions would there be from ENAI to mitigate social and environmental injustice? How can we take sufficient note of the fact that thinking about values change as technologies change and converge? On a related note, how can we take sufficient note of cultural differences in approaching AI in nuclear technology and applications?

Moreover, the applications and technologies are complex systems in both cases – how does one plan for ethical concerns or mitigation of concerns in such a context? Who will determine the readiness of IAEA's Member States for these technologies and for ENAI principles and action? Who is responsible for harm from AI in nuclear technology and applications? Finally, how are human rights impacted on by the convergence of these applications and technologies?

3.3.1. Overarching concerns and way forward

The ethical issues mentioned above have the potential to increase and intensify as AI and nuclear technologies and applications develop and further converge. ENAI has a huge and diverse scope given the proliferation of domains in which AI technologies are applied to nuclear applications e.g., medical contexts will be different from power plant contexts. While here it is argued that ethics needs to be mostly considered in a non-binary mode, the question is legitimate whether (from an ethical point of view) there are situations in which the convergence of nuclear applications and AI should not be applied at all.

Given these concerns, it would be advisable to respect the need for joint development of the research agenda on this topic. This would support and help grow co-creation of ethics approaches, which would inform an understanding of the making of ethics concurrent with the making of AI and nuclear technologies and applications in an integrated way. It would also facilitate scoping of remits and supporting and growing societal input to the remit and scope of ENAI considerations.

3.4. EXPECTED OUTCOMES

Support for the endeavours discussed in the previous section will result at least in:

- Providing societally accepted and ethically informed decision-making regarding nuclear science, technology and applications.
- Establishing responsible governance of the application of AI technology to nuclear science, technologies and applications.
- Creating and improving awareness among practitioners (from early age) about ethical implications of AI, nuclear technologies and the convergence of both fields.
- Enhancing dialogue with important societal stakeholders.

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Chapter 4.

HUMAN HEALTH

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4.1. STATE OF THE ART

Use cases of AI in the human health sector can be divided into four separate areas: (i) radiotherapy and medical physics; (ii) medical imaging and nuclear medicine; (iii) nuclear-related nutrition assessment; and (iv) health education. Medical physics aspects are relevant to (i) and (ii).

4.1.1. Radiotherapy

Scientific exchange and publications on AI have grown exponentially in the past few years, but AI-based tools are not widely used in radiotherapy, including medical physics aspects. Growth in the area of personalised medicine is converging with the developments of AI methods, opening up new possibilities, while pushing the ethical and quality assurance boundaries of conventional practices. The scientific community is aware that — although AI has transformative potential — there are risks of unintended consequences. Challenges exist in the clinical implementation of AI-based tools and in technical, ethical and legal domains (including patient data privacy). Several relevant international and national organisations have recently provided guidance in these domains [4.1–4.5].

4.1.2. Medical imaging and nuclear medicine

AI applications are used in medical imaging to facilitate different clinical tasks such as image processing, computer-assisted diagnosis (CAD) for detection of pathologies, image co-registration, patient-specific dosimetry, or prediction of clinical outcomes. AI algorithms have already shown great promise in breast and lung cancer screening programmes. For lung cancer screening, AI applications have been implemented as a research tool, in particular screening with computed tomography (CT) including restaging [4.6]. AI has been successfully used as a second reader for the detection of lung nodules. Multimodality AI imaging models have been developed commercially to rule out various pathologies not limited to cancer, especially on chest CT. Imaging AI applications for the detection and evaluation of COVID-19 complications have been developed, mainly but not uniquely to recognize pneumonia patterns, sometimes pathognomonic. Furthermore, AI is also used to improve radiology workflow [4.7] and for optimization studies, e.g., in the form of virtual imaging trials for optimization of design and use of imaging equipment.

At the global health level, the first medical imaging applications making use of AI are devoted to tuberculosis (TB) and chest X rays [4.8, 4.9]. This also forms the basis of the interagency Special Programme for Research and Training in Tropical Diseases (TDR), which is already implementing a research toolkit for the calibration of CAD score thresholds and other parameters of TB on chest X rays [4.10, 4.11].

Another potentially impactful development, in particular for LMICs, is at the intersection of AI with teleradiology [4.12–4.16]. In the near future, this could include cancer imaging, and in particular lung cancer (both screening and (re)staging), and TB. In fact, previously unseen constellations of patient imaging findings were observed at the outset of the COVID-19 pandemic, i.e., notable recognizable factors such as new pneumonia patterns and associated complications, including cardiovascular ones.

AI also has tremendous prognostic capacity when combined with, for example, radiomics [4.17, 4.18]. However, relevant clinical decision-making support is based on multiple reliable imaging biomarkers. To achieve the desired outcome, standardized protocols for image acquisition, feature extraction, and analysis have to be considered when utilizing these AI-based tools.

Multidisciplinary collaboration will be required in continued development of AI-based medical imaging applications. Target areas of quality assurance and safety include standardized image reconstruction protocols, patient-specific optimisation of radiation doses, and validation of AI tools. To ensure quality and safety in medical imaging, the current quality assurance programmes need to be extended to the relevant aspects of AI tools used in clinical practice. The quality assurance should address the performance and safety of AI tools and the involvement of imaging medical physicists is of paramount importance.

4.1.3. Nuclear nutrition assessments

The use of AI in the field of nutrition is increasing, particularly in the areas of clinical research, nutrition epidemiology and personalised nutrition. The main use cases of AI with respect to nuclear techniques are imaging techniques, such as dual energy X ray absorptiometry (DXA) and CT, which provide body composition and bone health data. Manual analysis of scans can be time consuming, thus limiting the application in a clinical setting. The use of ML could automate the process, facilitating more accurate and feasible data collection in clinical settings. The challenge of AI in nuclear nutrition assessment techniques is that performance is only as good as the quality of the data that informs the process.

4.1.4. Health education

AI applications have long been associated with education, which is referred to as AI in education (AIED). Its continuing development saw the adoption of intelligent tutoring systems as well as dialogue-based tutoring systems, a version of ITS developed in the 1980s for medical education [4.19]. Modern developments in AIED include the use of exploratory learning environments, learning applications, chatbots, collaborative learning, student forum monitoring, and continuous assessment [4.19]. More recently, AI has also been used as a backend technology for interfaces such as virtual reality, augmented reality, and serious games.

Innovation in education is needed to prepare people for an AI-driven world [4.20]. Although doubts linger regarding the educational value of AI, several AI systems demonstrated to have positive impacts on student learning in the last decade [4.20]. However, whereas AI may have various applications and substantial potential for health education, its adoption in this field has been limited and relevant research is still scant [4.19, 4.21].

4.2. NEXT STEPS

4.2.1. Radiotherapy

The routine use of deployed AI-based technologies in radiotherapy, including medical physics aspects, is expected to grow over the next 5–10 years. AI tools will mainly be implemented for task replacement (in which repetitive work processes such as image segmentation is automated, with subsequent validation by the responsible clinical professional), and decision support systems (which facilitates and supports complex work processes by the responsible professional taking clinical actions or decisions, including treatment planning and computer-assisted diagnosis). Decision support systems in particular require clear interpretability of AI-based tool outputs, avoiding black-box modelling approaches.

Clinical deployment of AI-based technologies needs to consider that the need for educated and trained radiotherapy professionals, e.g., radiation oncologists, medical physicists, and radiation therapy technologists, is likely to increase, and that AI methods cannot be used to substitute adequately trained radiotherapy professionals.

The roles and responsibilities of radiotherapy professionals need to be clearly defined and retained as AI tools are deployed. A core team is needed for implementation of AI, with radiation oncology and medical physics professionals leading the process. Broader expertise and participation from IT personnel, data scientists, knowledge engineers, data protection and ethics officers will likely be needed in varying degrees to support the implementation process, depending on the application.

New training for radiotherapy professionals, driven by the expansion of domain knowledge requirements, must enable them to organise services and departments with integrated AI based tools, effectively select and implement AI applications in the clinic, appropriately define the input for AI, and competently evaluate the output of AI based tools.

4.2.2. Medical imaging and nuclear medicine

Substantial opportunities exist for applications of AI to advance and support medical imaging and nuclear medicine in the clinical setting. There are active proposed areas of research and development, including inter-regional coordinated research projects on CT imaging and COVID-19 as part of efforts towards pandemic preparedness and the use of AI to detect TB from chest X rays. In parallel, efforts towards standardization and quality assurance of various AI-based tools are necessary to improve their performance and reproducibility.

4.2.3. Nuclear nutrition assessments

The next steps for AI in relation to nuclear nutrition assessment techniques include the more efficient and accurate analysis of CT scans and DXA scans for body composition or bone analysis, which will make these techniques more accessible and standardized in the clinical setting. It is expected that advances in the next decade for AI and nutrition in the research and development phase will involve the use of body composition data to predict clinical outcomes of diet-related non-communicable diseases (NCDs) and all-cause mortality.

4.2.4. Health education

As AI technologies develop and continue to be used to improve the learning experience, their application in health education is also expected to become more prevalent in the future [4.19, 4.20]. Well-designed AIED has the potential to improve learning effectiveness and reduce implementation costs as well as teaching-related workloads of health education practitioners [4.19]. The learning sciences have the role of informing the design, development and adoption of educational AI [4.20], ensuring that AI technologies are used to tackle learning problems. Therefore, a stronger tripartite collaboration among researchers, education practitioners and technology developers will be needed to implement AI in health education.

While AIED initially focused on attempts to create systems as perceptive as human education practitioners, modern educational applications have been exploring the use of AI in non-autonomous systems used by education practitioners to support their practice [4.22]. Whereas machine learning research may aim to create fully autonomous systems that could fundamentally replicate human cognition, AIED concerns itself more with augmenting the cognition of education practitioners and learners, enabling them to make more informed decisions [4.22]. Such is the case with the use of AI-based multimodal learning analytics in educational contexts to provide explicit and comprehensible means of information presentation to teachers and learners [4.23]. In the future, a change of focus may be expected on AIED research and development towards Human-AI hybrid systems for intelligence augmentation and enhancement of learning experiences with high human agency. This needs also to be reflected in the use of AI in health education.

4.3. ACCELERATING PROGRESS—IAEA'S ROLE

4.3.1. Radiotherapy

Practices using AI-based technologies that involved radiation medicine need to adhere to the International Basic Safety Standards [4.24]. The IAEA may support its Member States in providing guidance on:

- Education and training of health professionals for utilisation of AI-based technologies in radiation medicine;
- Selection, specification and evaluation of AI-based tools;
- Clinical implementation, commissioning and quality assurance of AI-based technologies;
- Aspects of data curation for the definition of the inputs to the AI-based technologies;
- Evaluation and validation of the AI-based tool output (e.g., accuracy, reproducibility, bias avoidance); possible 'tuning' of the AI-based tool, previously trained and validated on a standardised data set or with data from another context;
- Harmonisation in the use of AI-based tools.

Technical support in the field needs to be based on the principle that the use of any AI-based tool in the clinical practice is safe, effective, and efficient, with the output of the AI-based tool being interpretable, vendor neutral, and ethically and legally compliant.

4.3.2. Medical imaging and nuclear medicine

As there is currently no long-term prospective validation of AI solutions for medical imaging, the IAEA is uniquely poised to conduct inter-regional coordinated research projects. To date, the primary area of interest of AI in medical imaging is thoracic imaging for several clinical indications: particularly tuberculosis, lung cancer, identification of emerging infections, and a spectrum of cardiovascular conditions. Improvements in workflow, quality and safety are other target AI medical imaging categories already being appraised longitudinally and within frameworks of ethics and good governance.

4.3.3. Nuclear nutrition assessments

The opportunities for IAEA to support the progress of AI in relation to nuclear nutrition assessment techniques include the research and development of AI in using body composition to predict clinical outcomes of diet-related NCDs and to improve analysis of body composition from CT and DXA scans. To advance the area, it is important to have quality data; therefore, the IAEA can have a role in supporting Member States to collect and curate quality data obtained using nuclear techniques. To accelerate progress, AI could be incorporated into regional capacity building efforts, related to the benefits and appropriate use of AI in nuclear nutrition assessment techniques.

4.3.4. Health education

As educational and training activities continue to be fundamental to advance IAEA's Human Health programme, so too does it become important to maintain them aligned to the introduction of emerging technologies such as AI as an enabling infrastructure with the potential to improve learning and, consequently, the impact of these activities. As R&D in AIED and especially in AI for health education builds in the next decades, the IAEA may play a role in keeping abreast of such development, assessing the possibility of its design, development and use in its own education and training activities.

Firstly, the added value of AI in health education activities needs to be periodically assessed in terms of its impact, costs, and human resources needed. The use of AI in the learning design of educational technology activities in health education, while promising, may not be considered as a first option in the upcoming years. Nevertheless, in preparation for a potential adoption of the technology, special attention needs to be given to the ethical and legal framework as required for data collection in educational settings, since this may play a role in the future for the adoption of AI solutions in educational technology activities within the IAEA.

4.4. EXPECTED OUTCOMES

Expected outcomes of the activities discussed in the previous section include:

- Safe, effective and efficient deployment of AI-based technologies based on guidelines and training material developed in critical areas through IAEA expert meetings and in ongoing technology assessment activities.
- Ensuring inclusive and representative sets of curated data for AI applications from IAEA's global data collection, stewardship activities and inter-regional research projects.
- Increased capacity in Member States in using DXA and CT scans for body composition assessment.

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Chapter 5.

FOOD AND AGRICULTURE

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5.1. STATE OF THE ART

Some of the global challenges currently facing the food and agriculture sector are so multifaceted that they cannot readily be solved by human expert knowledge alone. As AI and ML techniques mature, the opportunities to implement these new methods in numerous scenarios within the domain of nuclear techniques in food and agriculture will arise. Applications may include food fraud detection, predicting food safety incidents, remote sensing data for agricultural soil management, optimising remediation of radioactively contaminated land, and development of new food and beverage products.

Extensive information at all scales is needed in decision-making processes for agriculture and food production. Enhanced data availability through the implementation of open data policies and innovative data acquisition methods, have enabled the use of AI in the food and agriculture sector. Variation in sampling, sample preparation and analysis are often bottlenecks for data sharing, but AI could assist in dataset standardisation. Furthermore, AI can help by improving analytical prediction based on traditional chemometrics (e.g., infrared spectroscopy, nuclear magnetic resonance), or by supporting calibration of analytical equipment. Regarding the latter, AI can further assist in calibrating measurements carried out across the same type of equipment but from different providers, essentially leading to the creation of large datasets needed for AI applications. In addition, AI can play an essential role in bringing data together from different sources, resolutions or scales, and lastly, the Internet of Things combined with AI and decision-support is a fast-growing domain. However, legal constraints and ethical concerns around security, trust and issues of transparency and explainability are limiting the applications of AI methodologies in food and agriculture, as in other fields.

It is important to remember that even with the full potential of AI unleashed within the food and agriculture domain, data-driven decision-making is only as good as the data used. Properly coupling available data requires state-of-the-art and validated solutions that focus on harmonising data access, analytics and predictive modelling.

5.2. NEXT STEPS

Food and agricultural sciences are typically characterised by limited data availability compared to other scientific disciplines, due to expensive and labour-intensive data collation and annotation, and analysis which often needs specialised field-based or remote sensing devices and expertise. Furthermore, agronomic experiments often take years to assess outcomes accurately and so data collection takes place on long time scales. Several approaches can be used to meet these challenges. High-throughput analytical systems could rapidly increase data availability, while other useful example applications could include automatic data collation, data generation from satellite imagery, data mining from online datasets, or inclusion of more classical data streams (e.g., papers, newspapers, reports, social media, etc).

Major principles to further improve data availability are known as FAIR. This set of principles ensures that the data are shared in an effective way that enables and enhances reuse by humans and machines. Furthermore, metadata may be used to connect datasets through AI. But even with FAIR data, one major challenge is the human factor. It is still a decision made by scientists or policymakers, not machines, to make data accessible. To solve this challenge, people need to be made aware about the significant advantages of data sharing. However, the legal framework for data sharing, including ownership and intellectual property, can be extremely difficult to navigate and needs to be carefully considered as well. A solution to encourage data sharing is federated learning, which may be a basis for sharing knowledge instead of sharing and moving data. Federated learning brings the model to the datasets (training the model from one database to another database without necessarily revealing its contents).

An additional step where AI can support food and agricultural sciences is in the field of laboratory analysis. While high-throughput analytical systems are a way forward for increasing data availability, in particular low-cost systems (e.g., spectral analysis on dry matrices that do not need extensive sample preparation), another promising way forward is the development of calibration transfer methods for analytical instruments. Such calibration transfer is essential to develop large uniform datasets across different laboratories using different equipment for a similar type of analysis (e.g., spectral analysis). One such major initiative is the currently initiated ring-trial by Soil Spectroscopy for Global Good [5.1], which allows the development of an advanced yet intuitive, open-source, web-hosted platform to predict various soil properties from mid-infrared spectra collected on any spectrometer anywhere in the world.

Furthermore, when data is collected from a wide range of sources, such as online available datasets or geographical data of different scale and resolution, data fusion and integration are topics that will need major attention, from both the theoretical and practical side, before the data can be widely applied. Other fields in the food and agriculture sciences use data mining already, including applications to crop yield data, prediction of zoonotic diseases, impact of climate change on diseases, etc. Many of these applications need careful follow-up to avoid bias in the data collection, leading to questions on the ethics of using AI in this field.

Interpretable ML is a field of increased interest and importance, but applications in food and agricultural sciences have been limited to date. Such applications can benefit from increased interpretability in models to support enforcement or policymakers and improve end-user understanding in different contexts. Although applications of AI are progressing slowly in the field of food and agricultural sciences, AI is starting to be included in curricula of universities and faculties for agricultural sciences, at PhD, but also at master's degree level. However, also high schools (secondary schools) need to play a role in education in the field of AI to ensure capacity and interest from students later in their academic careers.

More interdisciplinarity and cross-domain interaction is required to allow theoretical and practical AI to be more connected to applied sciences, and in food and agriculture in particular. For instance, in the soil spectroscopy field, AI applications are carried out by soil scientists as domain experts, and not mathematicians or computer scientists, so many opportunities for improvement may be missed.

5.3. ACCELERATING PROGRESS—IAEA'S ROLE

IAEA CRPs can provide mechanisms to support the development of new AI approaches in food and agriculture science. Progress needs to be stimulated by interdisciplinary exchange of expertise and experience across scientific fields and disciplines, case study sharing within the community, and enhancement of connections with other fields. Case studies can be used as a basis for exchanging experiences while connecting theory and application. Significant progress is often made on the theoretical, mathematical, and information technology side, which often does not get rapidly translated into practical applications.

AI approaches developed within an IAEA CRP can be disseminated to all Member States through technical cooperation projects and IAEA capacity building programmes. Such dissemination will also lead to further developments, through testing and scaling the developed applications.

5.4. EXPECTED OUTCOMES

The expected outcomes of the activities outlined in the previous section include:

- Fusing and integrating data and datasets from local to global scale;
- Innovative model development for enhanced decision-making and enforcement in a scientific and ethical way, based on Open Science and FAIR principles;
- Improved use of nuclear and isotope data.

AI will provide significant advantages and efficiencies in optimising agricultural production, food product development, management of supply chains, food safety and food authenticity control, accelerating reaching the sustainable development goals.

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Chapter 6.

WATER AND ENVIRONMENT

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6.1. STATE OF THE ART

AI has been transformative across all scientific disciplines [6.1], but the potential of modern data science techniques has not yet been fully exploited in hydrology. AI tools can in fact accelerate the use of isotope techniques for better management of water and environmental resources. With the increasing availability of data from satellites, unstaffed airborne vehicles, and sensor networks, there is a large quantity of data available to couple and explore in conjunction with the IAEA's global isotope databases. Initiated in 1960 by the IAEA in cooperation with the World Meteorological Organization, the Global Network of Isotopes in Precipitation (GNIP) has become the world's most comprehensive collection of isotope data in atmospheric waters. The network has collected around 140 000 isotope records from ca. 1100 stations (350 active) in collaboration with many contributors from around the world. New efforts to systematically collect isotope records, e.g., rivers (GNIR) and lakes (GNIL), along with continuous growth of the existing GNIP databases, increasingly drive the field into the era of big data.

The IAEA's continually expanding global isotope databases provide significant opportunities to benefit from the innovations in treating large amounts of complex data with ML algorithms. In some cases, ML outperformed traditional statistical tools and process-based hydrologic models with regard to the predictivity of hydrological variables or created new insights into the relationships of certain variables [6.1–6.3]. The latter is possible because ML, and in particular deep learning, are able to account for highly non-linear and non-homogeneous models, and to operate in non-stationary environments. In comparison with process-based models, there are advantages and disadvantages for both approaches. Caution needs to be used when using ML for extrapolation: there is a high potential for over-fitting of highly uncertain data or data with unknown uncertainty and it is difficult to assess the predictive capability beyond the range of the training and validation data set. This is a strength of physical models. Advantages and disadvantages, as well as opportunities stemming from integrations of these approaches in predictive modelling contexts, are extensively discussed in [6.4].

In the direction of exploiting innovative ML features, the IAEA has applied random forest methods to disentangle the relationships between lake evaporation and catchment characteristics of the IAEA's collection of isotopes in lakes [6.5]. Such explanatory ML methods enable us to explore imperfect physical observations and discern signals that were overlooked in the past [6.6] and, hence, have their own role in delivering scientific insights and discoveries in natural sciences [6.7]. Moreover, unsupervised ML (comprising, among others, principal component and clustering analysis) can uncover relationships between variables that are not detected by multivariate statistics [6.8].

One of the largest challenges in using AI technologies for water and environment applications is to provide long-term systematic observations with adequate process representation. AI can help to spatially (and temporally) refine datasets [6.9–6.13], to fill gaps [6.14] and to extend existing time series [6.2]. These are common problems in isotope hydrology, since isotope data generation still relies on a high input of manual labour.

6.2. NEXT STEPS

Water isotopes are applied in hydrological studies to provide information on when and where water was recharged, where it is stored, and how it is partitioned. These isotopes also act as environmental tracers and baseline spatial surfaces that can be applied to track migratory animals, food origin and past growth conditions of plants. Hence, knowing the isotopic composition of water sources with high temporal and spatial resolution is critical for several fields of environmental sciences and beyond. ML approaches applied to environmental isotope data include random forests, XGBoost, support vector machines, genetic programming, self-organising maps, and long short-term memory (LSTM) recursive neural networks. LSTMs improved time series simulations of isotopes in a stream against previous process-based models and helped to confirm some processes not integrated into the models previously [6.3]. This suggests that we can expect to extract hidden information in isotope time series, as more researchers become able to use ML tools for their data analysis. The ML algorithm XGBoost provides a time series of isotopes in precipitation for any place in Europe [6.2]. However, Europe is a data rich region, not only regarding isotopes, but also the environmental variables needed to train the algorithm. Getting this information on a global scale is difficult. In the future, we hope to identify regions and variables that are needed to provide this kind of information with a high degree of accuracy globally. Application of these AI tools at a regional or local level for different sites can be the first step to using them accurately before they are applied globally.

Currently, AI applications are more widely used in other fields of hydrology. For example, the compelling performance of super learning (a type of ensemble learning combining several ML algorithms) was shown for streamflow forecasting [6.4]. Moreover, super learning using several base models might overcome some common problems in applying ML approaches to isotope hydrology problems [6.15]; spatial data is often geographically biased, and some geographic areas or temporal events are not sampled at all. Some limitations of ML models are their weakness in extrapolation and statistical inference [6.16]. Steps to improve AI tools and integrating other mechanisms that improve these limitations are of interest to the field of (isotope) hydrology. The community is just starting to explore these possibilities and, consequently these efforts need to be supported.

Environmental isotope data is part of many process-based hydrological models [6.17, 6.18]. Although predictions by ML methods are often more accurate than physically based models, they are usually restricted to single components of the hydrological cycle. Embedding ML methods into process-based hydrological models to represent individual processes showed promising results and the synergy between these modelling approaches is superior to either approach individually [6.19]. Future work entails combining the understanding of environmental processes with the ability of ML for extracting patterns and information directly from data [6.3, 6.20]. This is especially so regarding the integration of process-based and ML models for providing probabilistic predictions and forecasts in a straightforward way [6.4].

With improvements in satellite data availability, sensor technology and rapid transfer of data, along with improved computational power, AI will play an increasing role in environmental sciences. An example is the use of AI in the flood forecasting initiative from Google [6.21]. There is a need to couple isotope data with the output of findings from AI enabled extraction of patterns from satellite images for the classification of distinct hydrological modes, which would enable us to do more meaningful intercomparisons. An example could be the prediction in un-sampled catchments via similarity detection and information transfer using e.g., neural networks.

6.3. ACCELERATING PROGRESS—IAEA'S ROLE

6.3.1. Data hub

Data-driven approaches require robust datasets – availability, quality, and quantity of data are of utmost importance. ML tools require large amounts of data for training and testing to achieve an accurate output. However, obtaining isotope data is still a laborious task that requires substantial human and laboratory resources. The IAEA hosts GNIP and GNIR and has established isotope hydrology as part of the toolbox of researchers and water managers in more than 100 IAEA's Member States through technical cooperation projects. This establishment has been accompanied by training and expert advice, providing standards and inter-laboratory proficiency tests and comparisons [6.22–6.24]. Therefore, the IAEA can accelerate and drive R&D progress in the use of AI for isotope hydrology and ecology by picking up on what has been already established and is part of the mandate: facilitating and ensuring high-quality data. Hence, any effort in improving, maintaining, extending and — maybe most importantly — grating easy access to these global networks accelerates the application of AI in water, environment, ecological, and climate sciences. The opportunities that AI offers to tackle important environmental questions in the face of climate change requires the support of expanded measurement and observation data collection and to ensure the continuity of long-term monitoring.

The IAEA can strengthen their role in organising the database structure, source attribution, data contribution, coordination, and sustainability of databases and networks by implementing a permanent competence team. This competence team needs to be accompanied by a consortium of people allocated from IAEA and its Member States to participate on a longer time frame ensuring continuity of monitoring stations and guiding expansion of the network. Data quality can be improved through advertising the IAEA's existing tools, such as sampling guidelines and the inter-laboratory comparison exercises for stable isotopes (WICO) and tritium in water (TRIC).

Vice versa, these networks can benefit from progress in R&D by applying AI technologies to ensure the quality and consistency in the data sets themselves. Hence, there is an opportunity for the IAEA's databases to benefit from these data analysis tools. For example, ML algorithms can be used to identify potentially faulty data or processes (sampling, lab, data treatment), and in this way, to automate certain parts of quality control, to link data with publications, and to interpolate data temporarily and spatially (e.g., [6.2, 6.25]). Furthermore, AI can be used to identify key regions of interest, as well as to optimise sampling and monitoring efforts (e.g., where additional GNIP stations are needed). Here, the IAEA can act as a global facilitator of the adoption of AI through integration of ML tools to improve the quality of the data and data products that it provides to Member States.

6.3.2. Connecting stakeholders

Three important groups of stakeholders were identified:

1. Potential data providers, mostly researchers who collect the data for a specific study or want to understand and forecast a specific system.
2. Modellers and data analysts who have the capacity to use different AI models to gain a deeper understanding of the system or achieve accurate predictions.

3. Water managers who need to make decisions based on the models provided by the first two groups.

Obviously, the first two groups are not always segregated. Significant overlap between the first two groups is desirable and can be encouraged by offering training and engagement through the IAEA. To many isotope hydrologists, the perceived lack of interpretability of AI model outputs and difficulties in accessing data discourages them from exploring this opportunity. However, it has been shown that decision of which AI model to choose and what training data to use is a trade-off between interpretability and predictivity [6.3, 6.4]. Hence, the IAEA can help to overcome these misconceptions and to identify which of the many options to approach a research question is most applicable to the problem being tackled. Furthermore, the integration of AI based models into water management plans will be carried out by the third group and can be encouraged by the IAEA through technical cooperation projects. Integrated training is needed that combines process-based understanding with strong numerical and theoretical skills. In this sense, isotope hydrology is becoming an increasingly interdisciplinary field that requires training from experts from different fields to translate this developments and benefits from advances in other fields of science.

The IAEA has specifically supported this interaction among stakeholders through several mechanisms including via CRPs and workshops. The COVID-19 pandemic speeded up engagement in the virtual space and this supported further opportunities to discuss advances in data analysis and develop courses on this. For example, a data analysis training course was offered online in 2021 with 88 participants from 50 Member States. Data analysis using AI needs to be integrated as a module in this type of course in the future. With regard to community building, a mechanism is suggested that goes beyond a typical CRP in terms of duration and needs to be able to respond to the technical developments in both isotope data availability and advances in AI. This mechanism can be in the frame of a technical group with regular online and hybrid meetings, with specific projects targeting the challenges of AI applications. These specific projects can include the production of guidelines, papers, consultancy reports, for example, the design of the GNIP network, the expansion of monitoring networks to other water isotopes, hackathons-like events that address a specific question or bundle of data etc. Eventually, projects also need to target a fourth group, which might be defined as the largest group of stakeholders, because it refers to the water consumers. These can be engaged through citizen science, public outreach, school projects and public discussions that will be necessary to use AI tools within ethical frameworks.

6.3.3. Providing training and guidelines

Training and the production of guidelines have been mentioned multiple times and this reflects the fact that training is one of the core mandates of the IAEA. In the field of isotope hydrology, this includes correct sampling, storage, analysis, the treatment of raw data, the correct use of statistical methods and models for data interpretation. The application of AI complementing isotope data interpretation and modelling will need guidelines and best practice as well. For example, Ref. [6.26] proposed a checklist for reporting ML models for chemistry that guides how to report data sources, cleaning, representation, as well as model choice, training and validation and finally, code availability. While the IAEA currently does not provide guidelines for this, these could be provided by a consortium of experts under the coordination of the IAEA, either in conjunction with other groups or specifically for isotope hydrology.

6.3.4. Making isotopes parts of earth science and climate models

Isotopes help to improve model parametrization and can validate local, regional and global models in earth sciences; these can be hydrogeological, ecological (soil-water-plant-atmosphere), climate models, etc. In climate change studies isotopes can verify and improve atmospheric circulation models. However, a caveat here is that — as for the previously mentioned reasons — isotope data is often not available at the resolution needed for this type of model. The solution can be to interpolate data or assume in the case of precipitation that these samples integrate for longer time periods and larger spaces. Noticeably, doing so requires extra work and a thorough understanding of isotope hydrology (incl. data treatment) from the modeller. By the same token, filling gaps in the isotope series requires isotope hydrology knowledge and thorough testing of the approach. The IAEA can cooperate with experts to provide this type of data to modellers, thereby promoting the inclusion of isotopes in the models and evaluating which data gaps need to be filled. For this purpose, ML algorithms can be used, as they have shown good predictivity in modelling time series or in the construction of isoscapes. This paves the way to combine high-frequency and high spatial resolution data with isotopes and will allow the inclusion of isotopes in large scale models, for example, global climate models.

6.4. EXPECTED OUTCOMES

6.4.1. Data hub

The IAEA's efforts on providing and ensuring reliable data need continuous and sustainable structures. As the host of the GNIP and GNIR networks, the IAEA plays a central role with regard to the consolidation and expansion of these networks. This means that the IAEA is expected to supply the necessary data repository to be used in ML models, as well as to be integrated into global hydrological models and other environmental research activities. However, the IAEA not only play the role of a host, but also as a safeguard of data quality, which starts in the laboratory. Here, the IAEA is expected to continue and expand the efforts of quality control of isotope analysis in Member States laboratories. Expected outcomes in this regard are:

- Continued long-term systematic observations.
- Guidance and coordinated efforts to build databases and monitoring networks (including quality control), i.e., manuals, guidance, best practices.
- Advertised data quality activities to laboratories producing isotope data and groups providing isotope databases;
- Facilitated data sharing among experts and stakeholders;
- Established a standing competence group for the coordination of databases and networks with the goal of a common isotope data base.

6.4.2. Connecting stakeholders

Specific projects in the area of AI and big data need to be developed to support stakeholders on database coverage, quality, and sharing with central coordination, considering the integration of national and international network activities into the IAEA's network. Further coordinated activities on ML techniques for water issues as well as contributions for publication on using AI tools to understand hydrological processes are foreseen. Progress on integrating AI into isotope data analysis and exploring the opportunities can be done in the framework of a CRP or in the scope of technical meetings. A CRP can explore the frontiers of applying ML to refine data sets, fill gaps and acquire new insights into processes that have been hidden from hypothesis driven science.

6.4.3. Providing training and guidelines

Training courses that specifically incorporate AI and ML under the IAEA's Water Resources programme will be developed. Integrated training ranging from data quality assurance, over process understanding to analytical skills in applying ML will be provided, as well as guidelines for reporting ML models in isotope hydrology.

6.4.4. Making isotopes parts of earth science and climate models

The IAEA can continue playing its role as a guardian for good scientific use, and increase its engagement with the earth-system modelling community and other United Nations entities working on this topic.

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Chapter 7.

NUCLEAR DATA

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7.1. STATE OF THE ART

The production of high-quality atomic and nuclear data involves compilation, evaluation and validation. Nuclear and atomic reaction and transport models are an essential part in the evaluation and validation process. The section discusses how ML is already being used to support these activities.

In the compilation process, publications with relevant measurements need to be identified, the data extracted from text and tables, and added to nuclear databases. For instance, the EXFOR library [7.1] is a prominent nuclear database that contains cross section data and other nuclear reaction quantities, along with their metadata and uncertainties. This database is maintained and developed under the auspices of the IAEA by the International Network of Nuclear Reaction Data Centers (NRDCs). At present, these activities are performed manually. However, the use of natural language processing to find relevant literature and facilitate data extraction is under development. An example in the general nuclear domain is given in Ref. [7.2]. Obstacles to automation are the specific vocabulary used in nuclear physics, such as the notation to identify reaction systems, e.g., 181Ta(n,2n) and reports written in various languages. Furthermore, some historical reports need to be made text-searchable first by using Optical Character Recognition software and errors are usually introduced in the conversion process.

In nuclear and atomic data evaluation the aim is to provide comprehensive collections of estimates with associated uncertainties of nuclear and atomic quantities, such as cross sections, half-lives, and energy level schemes of nuclides. To this end, relevant experimental data are retrieved from databases or manually extracted from publications, and combined by using statistical methods, as well as nuclear and atomic models. It is essential to provide application programming interfaces (APIs) to automatically retrieve data feeding into ML algorithms and other advanced nuclear data processing. Therefore, several attempts have been made to address this issue for the EXFOR library, such as the creation of a Python package called x4i, a prototype of a document-oriented database [7.3] and a JSON output option in the EXFOR database retrieval system hosted at the IAEA [7.4]. More recently, a working group (SG50) under the umbrella of the Working Party on International Nuclear Data Evaluation Cooperation (NEA/WPEC) was established. The goal of SG50 is to create a prototype of an automatically retrievable, comprehensive and curated experimental database based on EXFOR. This database is user-driven and aims to speed up the evaluation process by automating steps done by evaluators (e.g., re-normalizing, identifying missing uncertainties, etc.), while it also provides interpretable input for ML algorithms by casting metadata available in existing databases into a unique format.

Unknown errors present in nuclear databases (caused by errors in the experiment itself or introduced during compilation) [7.5] can lead to biases in the results of a statistical analysis and underestimated uncertainties. The Generalized Least Squares (GLS) method, which is the commonly used method in the nuclear data field, is sensitive to wrongly specified uncertainties and outliers. As demonstrated in [7.6], ML methods can assist humans in identifying problematic data and features of an experiment. Such ML assisted evaluation workflows can accelerate evaluation work and act as a helpful tool for quality assurance, as well as point experimentalists to features that need to be explored in future experiments to understand biases.

Once the experimental data are retrieved, assessed and, if possible, corrected, a statistical method is used to either fit a physics model or apply a generic mathematical fitting function, such as a Padé approximation, to the data. For model-based evaluations, Monte Carlo procedures, such as BMC [7.7], BFMC [7.8], UMC-B/G [7.9], realisations of importance sampling, have gained traction over the last decade thanks to the steady increase of computing power. Some techniques developed in the field of statistics and engineering have been recently brought to the attention of the nuclear data community, such as [7.10], which may help to make Monte Carlo evaluation procedures more efficient. Over the last few years, Gaussian process regression, a non-parametric Bayesian method, has been used in evaluations that do not rely on nuclear physics models [7.11], and in model-based evaluations to account for imperfections of the physics models [7.12, 7.13]. Bayesian networks have been recently suggested as a flexible framework for nuclear data evaluations [7.14], as they link different sources of information within a probabilistic framework. GLS and gaussian process regression (GPR) rely on the assumption of a multivariate normal distribution and that reliable uncertainties are available. Bayesian hierarchical models [7.15] and different notions of uncertainty Ref. [7.16] may be incorporated in the future to relax these assumptions.

In the resolved resonance region, the R-matrix formalism is employed to obtain fit data. This formalism depends on parameters such as spin assignments and poles, which cannot be observed directly. Due to the non-linear nature of this formalism, finding manually the correct assignments is often an intractable problem and thus ML methods have been explored to automate and facilitate this task [7.17, 7.18].

Finally, if enough data are available and the predictive power of a physics model is insufficient, ML may be used to learn a model from the available data. Different ML methods, such as neural networks for the prediction of fission fragment mass yields [7.19] and nuclear masses [7.20, 7.21] have been applied. ML methods, such as random forests, neural networks and GPR may be employed to quantify model bias and extrapolate model parameters to reaction systems without data [7.22].

Once an evaluation has been completed, it needs to be validated by assessing its performance in simulations of integral experimental responses, e.g., an iron sphere with a californium source in its centre. It has been shown how random forests can be leveraged to assist humans in identifying problematic features of experiments [7.23]. Besides using the existing integral experiments for validation, new ones can be constructed with a larger sensitivity to specific features of an evaluation. As the design of integral benchmarks relies on computationally expensive transport codes, Bayesian global optimization can help to find good strategies [7.24].

The sequence of activities required to go from the experimental campaigns to data libraries ready for use in applications is sometimes referred to as nuclear data pipeline. Compilation, evaluation, and validation are steps in this pipeline. It should be noted, however, that this process is not as linear as the term pipeline may imply. For instance, based on validation results, an evaluation may need to be adjusted. Moving and transforming data from one stage of the pipeline to another involves human effort. APIs to databases and model codes can help to automate parts of the pipeline, e.g., to make an evaluation reproducible [7.25], and to streamline experimentation with ML methods applied to nuclear data [7.26].

7.2. NEXT STEPS

AI in general, and ML in particular, will play an increasingly important role in the creation, evaluation and exploitation of nuclear, atomic and molecular data over the next decade. As described in the previous section, ML methods are already applied at various stages of the atomic and nuclear data pipeline.

An important issue that needs to be addressed is data accessibility and data quality. The development of APIs to retrieve experimental data will be essential to applying machine learning techniques. Databases with experimental data, such as EXFOR, contain the data as reported by the experimenters or as extracted by compilers (humans) from papers. In addition to databases which aim to record uncorrected and possibly flawed experimental data, curated databases are required for ML applications. Because of this, the creation of curated databases may also benefit from the application of ML methods, for instance, for outlier detection and to identify data with wrongly assigned metadata. The creation of curated databases can be achieved gradually by creating prototypes for a subset of the data types stored in original experimental databases and then subsequently broadening the coverage. Such databases must have clearly defined and well-documented APIs to be easily usable by the atomic and nuclear data community. Proper documentation must therefore not be an afterthought but part of the process of creating these databases and APIs.

Physics models can be regarded as human knowledge which has been condensed to a mathematical and quantitative form and may serve as valuable input for ML methods. Fast and programmatic access to model predictions that are easily comparable with experimental data is therefore important. The creation of unified APIs to obtain model predictions without the need to expose the details of compute infrastructure to users will also be beneficial.

Containerization solutions, such as Singularity/Apptainer [7.27, 7.28], can facilitate these developments on a technical level, as the orchestration of databases and model and simulation codes with different dependencies across different computer and cluster architectures is complex without them.

Regarding methodology to curate experimental databases, e.g., by using outlier detection algorithms, and to evaluate atomic and nuclear data, different approaches going beyond standard practice are being explored until firm recommendations can be provided.

7.3. ACCELERATING PROGRESS—IAEA’S ROLE

In support of its programmatic activities concerning fundamental data for nuclear applications, the IAEA aims to facilitate the development and deployment of AI approaches where these can improve data quality, availability and use.

The IAEA hosts several prominent databases (e.g., EXFOR, RIPL, etc.) with global recognition and widespread use. Its Networks, CRPs and technical meetings can bring together an international community of researchers, database maintainers and ML developers to improve the accessibility of these resources with respect to future AI activities.

Specific areas in which the IAEA can support AI include:

- Continuing to identify important open questions and issues that could benefit from the application of ML, see section 7.1.
- Enriching experimental databases (e.g., EXFOR, ALADDIN) with well-documented APIs and rich metadata: this is considered essential for the development and testing of ML algorithms exploiting the data.
- Draft a document laying out a standard approach for data handling (based on so-called FAIR principles) and collaborative open-source practices with a focus on EXFOR and potentially others. This document needs to consider input from nuclear data users, ML developers and database maintainers
- Hosting repositories with reference datasets for domain-specific ML studies.
- Defining diverse test sets with domain-specific data to validate ML models for comparison studies. The curation of test is important for the impartial assessment of ML algorithms and to define the relevant physical quantities to which they are applied to.
- Supporting educational and outreach activities, including workshops, to teach ML methods and the relevant nuclear physics knowledge, as well as organising meetings for comparison exercises and training.
- Initiating and administering crowd-sourcing campaigns and open science challenges to improve the quality and quantity of data in relevant databases and to develop new ML models and algorithms. This can include hackathons, competitions using Kaggle or a similar platform, or direct engagement with universities.

7.4. EXPECTED OUTCOMES

As documented above, the IAEA can play an active supporting role in the adoption of AI approaches in nuclear, atomic and molecular data compilation, evaluation and validation.

One of the major outcomes of the IAEA's involvement alongside Member States will be the creation of curated reference test sets to validate ML models. The correct evaluation of ML models is strongly dependent on the test sets chosen. The IAEA can host a repository of curated test sets and associated APIs to retrieve the data, offering the nuclear, atomic and molecular data community a dependable and robust platform for benchmarking.

A related outcome to the above would be a focus on methodologies and tools for detection of application-specific issues in data and models, which impede scientific progress in the area. Such issues could include, but are not limited to, systematic measurement errors or other sources of bias in the data, but also in the models themselves.

Furthermore, by supporting educational and outreach activities, as well as organising meetings and workshops on the use of ML for nuclear, atomic and molecular data, and crowd-sourcing campaigns, it is expected that the quality and quantity of data will increase, and that the compilation, evaluation and validation workflows will be significantly optimised via the application of ML techniques.

Another major outcome of the IAEA's involvement will be clear licensing of data in databases and repositories. This will facilitate the general use of data for training and testing ML models. The current landscape of data repositories makes it sometimes unclear how certain data can be used, which causes researchers to create test sets from scratch, making the comparison of ML models difficult. Clear licensing and improved accessibility would solve this problem and will promote the re-use of data sets across different international projects.

By identifying open questions and issues that could benefit from the application of ML, the IAEA is in a unique position to create a roadmap for future theory and measurement needs. It is anticipated that this roadmap will be very useful for aligning international nuclear, atomic and molecular data efforts and channelling the available resources towards impactful projects.

ML methods may be used in the regular evaluation work at IAEA, in neutron data standards and within the International Nuclear Data Evaluation Network (INDEN), to obtain a better understanding of the data, as well as to improve quality assurance and increase efficiency.

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Chapter 8.

NUCLEAR PHYSICS

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8.1. STATE OF THE ART

Nuclear physics is a broad, distributed field that investigates nuclear structure and reactions across a wide range of energy and size scales. This involves advanced theoretical work involving advanced modelling, as well as experimental efforts at various types of facilities across the globe. AI is currently in use or under investigation for use across these experimental and theoretical areas of nuclear physics research. For the purpose of this Chapter, these efforts are grouped into four areas to best disseminate the current work being done in AI and ML in nuclear physics:

- Data analysis and modelling;
- Data processing and management;
- Experimental design and optimization; and
- Facility operation.

The work represented in this Chapter is not exhaustive. A comprehensive summary of the current state of AI in nuclear physics is given in Ref. [8.1].

8.1.1. Data analysis and modelling

ML methods are currently employed in theoretical nuclear physics and data analysis to facilitate scientific discoveries. By speeding up computational bottlenecks in theoretical computation and simulation as well as data analysis, the workflow of scientific research is expedited. For example, ML is used to rapidly extract useful information for the determination of α-clustering in nuclei [8.2]. ML is also being used to investigate theoretical models and build highly non-linear and correlated models, which are difficult to tackle with conventional methods. For example, Ref. [8.3] uses Bayesian model averaging to predict the existence of nuclei at the neutron dripline. This method incorporates uncertainty quantification for extrapolated predictions, which is essential to inform experimental efforts. Additionally, Ref. [8.4] uses Bayesian neural networks to predict β-decay half-lives with uncertainties.

8.1.2. Data processing and management

Experimentally, data processing and management requires software decision-making to extract useful information for data analysis. ML is currently employed to both speed up data processing and to improve the quality of recorded data. Hierarchical clustering is used to find tracks of products from a nuclear reaction in a time projection chamber [8.5], and neural network architectures are used to identify reaction types [8.6]. Ion-beam analysis uses nuclear signatures to identify elements in samples for a broad range of applications. For example, Particle-induced X ray emission is a common technique for non-destructive analysis of materials. ML-based clustering methods can be used to improve the statistics, and thus the accuracy of quantification of trace elements [8.7]. Neutron scattering experiments are used for crystallography imaging. Neural networks are shown to improve characterization of Bragg peaks, which in turn improves calculations for crystallography structure [8.8, 8.9].

8.1.3. Experimental design and optimization

AI-based single-objective optimization has been utilised for the design of the dual-radiator Ring Imaging Cherenkov detector [8.10] at the future Electron Ion Collider (EIC). This detector is a proposed component for particle identification of the collision products. Similar efforts are being made at the EIC Comprehensive Chromodynamics Experiment, where an AI-based multi-objective optimization has been employed to design the tracking system [8.11, 8.12], which consists of multiple sub-detectors to measure and reconstruct the trajectories of charged particles.

8.1.4. Facility operation

Significant efforts are underway for AI-based control and operation of particle accelerators. AI-based operations have the potential to increase beam time and improve the quality of beams, as well as rapidly detect faults during the operation of accelerators [8.13]. For example, model-informed Bayesian optimization is shown to tune beams faster with fewer samples [8.14]. Reinforcement learning can rapidly tune beams with model-independent decision-making policies [8.15]. AI-informed accelerator operations have been tested on systems of varying beam and facility types across the world. Additionally, multi-objective optimization can be used for accelerator design [8.16].

8.2. NEXT STEPS

Advancing the use of AI in nuclear physics within the next decade will require focusing efforts on nuclear physics drivers, concerted education efforts and acquiring interdisciplinary funding.

8.2.1. Nuclear physics drivers

Key drivers for AI applications in nuclear physics are uncertainty quantification and real-time systems. Although efforts in these areas have already commenced, they are in an early stage of development. For example, predictions in nuclear effective field theories rely on a finite number of terms of an infinite sequence. To this end, Ref. [8.17] quantified the uncertainty associated with this truncation using Gaussian processes. In addition to quantifying the uncertainty, evaluating the quality of this estimate will be crucial for developing trustworthy AI.

Another decisive factor for the uptake of AI in nuclear physics is its application in real-time systems from accelerator operation to data collection in detectors. One example for the former is the optimization algorithm reported in Ref. [8.18] that performs real-time feedback on the beam-driven plasma wakefield accelerator AWAKE, minimising the transverse size of the electron beam while maintaining a design orbit.

8.2.2. Education efforts

A pillar of the accelerated use of AI in nuclear physics rests on concerted education efforts for researchers at all levels. In this regard, several summer schools and workshops with a focus on AI techniques have been held, but these need to become established, long-term training opportunities, ideally providing the ability to interact with scientists who specialise in AI or AI applications in related fields. Past events include, for example, an online course on Machine Learning and Data Analysis for Nuclear Physics as part of ECT*'s TALENT programme [8.19] or a summer school on Machine Learning Applied to Nuclear Physics organised by the Facility for Rare Isotope Beam Theory Alliance [8.20]. ML in nuclear physics was also part of the 2021 IAEA Workshop on Computational Nuclear Science and Engineering [8.21]. The virtual or hybrid events increased the accessibility and reach of the education efforts, and providing established, wide-reaching events will enable advances in nuclear physics by creating broad AI literacy.

8.2.3. Interdisciplinary funding

To foster collaboration with adjacent areas of research, and in particular with computer or data scientists with a research background in AI, the need for interdisciplinary funding opportunities is evident. Joint positions (cross-departmental and cross-institutional) need to be created to establish synergies between different areas of nuclear physics, as well as with related fields and to initiate and maintain collaborations. Facilitated and structured communication between the experimental and theoretical nuclear physics communities, as well as between the wider nuclear physics community and adjacent ones, such as high-energy physics, would benefit R&D as well as production and deployment efforts of AI applications.

8.3. ACCELERATING PROGRESS—IAEA'S ROLE

In order to accelerate progress in the field of nuclear physics through the advanced use of AI, the following areas could be supported by the IAEA:

- Hosting and curating central resources;
- Sponsorship of community efforts;
- Workforce development and providing of funding opportunities; and
- Interdisciplinary coordination.

8.3.1. Hosting and curating central resources

The engagement of nuclear physicists with AI could be increased through a website hosted and curated by the IAEA with input from the community. Inspired by efforts in high-energy physics [8.22, 8.23], this resource could provide a comprehensive and continuously updated list of relevant publications in the field. This list could be complemented by an overview of the different available algorithms and by highlighting examples, where the advantages of AI over more conventional approaches are particularly apparent. For researchers, who are beginning to familiarise themselves with the concepts of AI, simple benchmarks that include manageable datasets could be provided. In addition, the website could also give details on events related to the use of AI in nuclear physics – from the aforementioned workshops and summer schools to conferences and webinars. Should this central resource be well received by the community, it could be upgraded to include either a forum or a communication channel.

8.3.2. Sponsorships and community efforts

Direct means to support the uptake of AI in the nuclear physics community are data challenges and hackathons. In 2019, the IAEA organised a data visualisation challenge [8.24] for the IAEA International Conference on Climate Change and the Role of Nuclear Power. Similar challenges focussing on AI in nuclear physics could be set up to promote AI and in particular ML.

The IAEA could organise or sponsor competitions, such as Kaggle competitions [8.25] or hackathons, which can be built around open questions in nuclear physics that could benefit from the application of AI-based methods. Events like hackathons and Kaggle-like challenges have been discussed at the first workshop on AI for the EIC [8.26] with events planned for 2022. Hackathons were held at the AI for Nuclear Physics Workshop that took place at the Thomas Jefferson National Accelerator Facility [8.27]. The IAEA could also introduce prizes for these events and poster prizes for AI-related nuclear physics workshops, schools or conferences. Community guidelines on ownership of work and publication rights for such projects need to be discussed and agreed upon.

8.3.3. Workforce development and providing funding opportunities

The IAEA offered its first online workshop that contained ML lectures and lessons dedicated to nuclear science and engineering in 2021 [8.21]. A similar annual, dedicated AI workshop would enable an AI-literate workforce in nuclear physics that can advance the IAEA's scientific goals by leveraging state-of-the-art computational technologies. Virtual opportunities would extend the reach of the workshops while in-person experiences can provide strong training through one-on-one interactions and assistance. Hybrid events allow participants from all IAEA's Member States to engage in a way that is most accessible for them.

In addition to providing education opportunities to nuclear scientists, collaboration with AI scientists is essential to work at the cutting-edge of AI technologies. The IAEA can facilitate collaboration with AI scientists through positions that support hybrid AI and nuclear physics activities. These could be IAEA internships or fellowships with defined support for AI activities.

A position for an AI expert, who is interested in the intersection of AI with nuclear physics, would create a point of contact for scientists beginning to work with AI methods and provide a connection with the ML and AI fields. If such a position is created, clear authorship guidelines need to be defined for the role and publications in AI conferences — the premier publication outlet for the computer science community — needs to be encouraged and valued.

8.3.4. Interdisciplinary coordination

Available resource structures within the IAEA to foster regional or international collaboration on specific topics are CRPs [8.28] and Networks [8.29].

CRPs typically involve 10 to 15 institutes that work together over a period of 3 to 5 years. The participating institutes at which the research is conducted agree upon a set of objectives and activities with predetermined outcomes and foreseen outputs. The IAEA acts as the coordinating body, assigning a member of its technical staff as project officer of the CRP, and sponsors the CRP. For example, one of the ongoing CRPs within nuclear physics on Facilitating Experiments with Ion Beam Accelerators [8.30] aims to increase the impact of accelerator-based techniques in developing IAEA's Member States.

One of the key limitations hindering effective international collaboration are national legal regulations on foreign trade and export control. To overcome this challenge, the IAEA could sponsor a CRP for the standardisation of non-export-controlled research relevant for AI in nuclear science. Such standards would facilitate international scientific collaboration. In addition, the nuclear physics community would benefit from common data and reporting standards for AI results, such as model architecture and hyperparameters; an example checklist is provided by NeurIPS [8.31].

Networks, on the other hand, aim to strengthen international cooperation and dialogue and facilitate cooperation between participants. A common denominator of many existing networks is education, for example in the Latin American Network for Education in Nuclear Technology or LANENT network [8.32], whose goal is to preserve, promote and share knowledge as well as to foster knowledge transfer on nuclear technology within the region.

8.4. EXPECTED OUTCOMES

All of the IAEA activities proposed in this Chapter look towards the acceleration of scientific discovery in nuclear physics. This acceleration is envisioned via three tangible outcomes:

- Establishment of training avenues for nuclear scientists;
- Development of community standards; and
- Development of scientific output.

The establishment of annual training opportunities for nuclear scientists in AI methods will build an AI-literate workforce in nuclear physics, which equips personnel with the expertise necessary for expedited discovery and scientific output.

The proposed activities would produce defined community standards with respect to publications, datasets, and non-export controlled research. This creates reproducible research that enables the community to utilise AI research for applications in one's own subfield of nuclear physics.

The above outcomes would lead to increased research output in AI for nuclear physics with impacts expected in the quality of data for analysis, the quantity of data collected at experiments, and improved analyzes in both processing time and accuracy.

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Chapter 9.

FUSION

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9.1. STATE OF THE ART

Nuclear fusion holds the promise of delivering clean, virtually endless energy for humankind to meet the world's energy demand. To this aim, fusion scientists, and increasingly engineers, are tirelessly working to overcome the scientific and technological challenges emerging from the difficulty of recreating fusion conditions at temperatures hotter than the Sun's core in a fusion device at an industrial scale, while regulating pressure and magnetic forces for a stable confinement of the plasma (a hot, charged gas made of positive ions and free-moving electrons with unique properties distinct from solids, liquids or gases) and to sustain fusion reactions long enough to produce a net energy output. Several plasma confinement strategies aimed at energy production from fusion are currently being researched and developed. This Chapter focuses on magnetic fusion energy (MFE), which uses magnetic fields to confine the fusing plasma (like in a tokamak or a stellarator device), and inertial fusion energy (IFE), which employs high energetic laser or particle beams to heat and compress a fuel pellet (target). R&D activities on both MFE and IFE produce extensive amounts of experimental and simulation data, providing an opportunity for the application of ML and AI approaches. In the last decade, AI and ML have increasingly been adopted as advanced statistical tools to accelerate fusion science discovery and optimise simulation workflows.

This Chapter aims at briefly discussing the state of the art in AI and ML applications to fusion science and provides some examples from both MFE and IFE communities.

9.1.1. Examples from magnetic and inertial fusion energy research

Some of the main outstanding challenges in MFE are the development of scenarios to design and predict experimental conditions and to actively control the magnetically confined plasma. Integrated whole device modelling requires complex multi-scale physics simulations, which are extremely time consuming for achieving active, timely predictions. ML models are employed to aid experimental MFE operations [9.1], by combining simulations and experimental data to inform control room decisions, i.e., regarding the operational space that needs to be probed in subsequent experiments. As plasma exhibits strongly non-linear behaviour even when using these models to predict operations, active control algorithms are necessary to avoid the sudden and uncontrolled loss of the plasma's thermal energy and magnetic confinement on timescales of milliseconds. These uncontrolled plasma terminations are called disruptions and their avoidance is crucial to the development of MFE next step devices based on the tokamak concept. Over the last decade, substantial effort has gone into investigating the role of ML algorithms in developing disruption prediction models (for a partial review see Refs [3–28] in Ref. [9.2] of this Chapter). Overall, the MFE community routinely leverages AI to address limitations in experimental measurements, physical models, or computational solutions.

Similarly, in IFE R&D, AI is employed at different stages of the science discovery workflow, from simulation loops to experimental optimization [9.3]. Both inertial and magnetic confinement fusion involve complex multi-scale, multi-physics systems whose accurate modelling in high-dimensional integrated simulations is extremely expensive [9.4]. ML-based surrogate models are therefore more frequently used as proxies for simulation tools or as models for codes, providing fast results for exploration of designs or in combination with other tools for uncertainty quantification. As an example, AI can enhance analysis of instrumentation data, especially imaging, and potentially extract inferred quantities using accelerated models or surrogates [9.5]. Additionally, while pushing the methodological development of ML algorithms, a productive integration with state-of-the-art computing solutions is needed, e.g., hardware accelerators, high-performance computing resources, etc. AI representations of physics packages can lead to much faster computation when deployed on next-generation computational hardware.

9.2. NEXT STEPS

This section focuses on providing examples from MFE and IFE communities of ongoing development and envisioned advances in the next decade for AI-driven fusion.

9.2.1. Real-time magnetic confinement energy system behaviour prediction, identification and optimization

AI will become an intrinsic component of MFE workflows for plasma performance optimization, event and anomaly detection, plant operation monitoring [9.6]. For example, next generation fusion devices will need to take advantage of AI-driven predictive modelling for real-time monitoring of the proximity to different boundaries of plasma stability [9.7–9.10]. To develop such data-driven solutions, model interpretability needs to be preserved. In fact, black-box models, providing no explicit possibility of being validated against physics-based ones, cannot extrapolate to new regimes for which no existing data is available for training. A well-behaved output with a defined validity region and extrapolability boundary is required, while uncertainty quantification is essential to verify the reliability of ML algorithms.

AI can assist and accelerate progress in fusion materials science for example by providing an alternative approach to develop accurate and robust interatomic potentials [9.10]. Given a database of electronic structure calculations, a ML-based regressor is trained to learn the most general model form for the interatomic potential, thus providing a multiscale link between quantum and classical atomistic simulations.

Related to the optimization of next generation fusion facilities, recent efforts have led to outstanding examples of collaboration with AI experts to either discover operational regimes for plasma performance optimisation [9.11], or to design advanced feedback controllers [9.12].

Fusion scientists are strongly motivated to employ or develop state-of-the-art AI solutions, given the stringent requirements to any integration with plasma operation and control systems, although progress is limited by several challenges that are discussed in the next section.

9.2.2. Inertial fusion energy physics understanding through simulation, theory and experiment

Similarly to the MFE case, more computing power combined with AI-driven solutions, continues to allow IFE scientists to elevate their predictive frameworks to improve modelling for both traditional simulations and ML-accelerated models. For example, an experimental prediction pipeline [9.13] can correct simulation models using the last decade of fusion-related experiments carried out at the National Ignition Facility (NIF) at Lawrence Livermore Laboratories, USA [9.3]. The development of this pipeline entails the design of transfer learning solutions that can remove simulation bias and better match experimental data, thus improving prediction accuracy.

ML algorithms, such as genetic programming, random forest, Bayesian inference frameworks and neural networks, can also be used to accelerate the design of drive pulse and target structure for inertial fusion experiments. Additionally, the IFE community widely adopts open-source hydrodynamic codes such as FLASH [9.14], MULTI-2D and MULTI-IFE [9.15], which are commonly used in both laser and Z-pinch fusion experiments and validation [9.16]. New directions for these methods and tools have also been adapted for the exploration of new, more efficient fusion designs. For example, Ref. [9.5] demonstrates that an AI surrogate could enable the search of complex design spaces to deliver designs that are quite robust, but that humans had not considered. To aid AI-guided design exploration, fusion simulation codes will need to be further accelerated. Researchers have shown that AI surrogates embedded within these simulation codes can greatly accelerate expensive microphysics packages, leading to ten times faster simulation time [9.17]. AI tools are also transforming the ways that scientists combine and synthesise data. Representation learning (autoencoders or contrastive learning methods) can be used to combine image, spectral, and scalar data to create a distilled representation of physical models, reducing the amount of data needed while maintaining essential physics correlations [9.18]. IFE scientists have also shown that multi-physics AI methods can be coupled to high-performance computing to build deep learning models at the scale of the largest supercomputers on the planet [9.19]. And finally, with a scientific mission that has grown to span from microphysics to multi-physics, and from simulation to experiment, investigators have developed complex steering tools to drive AI workflows. These tools are essential for building the large and complicated data sets necessary to train the most informative AI models for applied science [9.20]. The data sets and models that are produced by these evolving and complicated projects are invaluable, but their cost is beyond reach for many in the field — especially academics and researchers in less developed countries. One example on how to help democratise these assets is the Open Data Initiative [9.21].

The future of IFE R&D will include an integrated combination of the technologies, methods and sharing practices described above. This future will include accelerated simulation with hybridised AI and numerical physics systems, next-generation computation hardware optimised for hybrid workloads, high data rates from repetition-rated experimental facilities, distributed computing spanning from the edge to the data centre, simulation-driven experiments and experiment-driven simulation, AI steering for optimization of both experiment performance and model predictive capability, and levels of integration not yet explored.

The community is developing new ways of working to accelerate discovery and innovation, including strong public-private partnerships like those modelled by AI3 [9.22]. Such partnerships need to be expanded to fully realize the AI-driven fusion research ecosystem of the future, while also democratising resources. The community, especially in less developed countries, needs to be able to access shared data, predictive models (or codes), and analysis tools to fully accelerate progress. Lastly, there exists a fundamental need for shared computer resources to execute fusion science investigation. New partnerships and consortia, brokered by independent parties, but funded by public-private consortia, could provide access to that.

9.3. ACCELERATING PROGRESS—IAEA'S ROLE

AI is playing an increasing key role in fusion science discovery: by exploiting large experimental and simulation datasets, AI can bridge gaps in our path to fusion energy. However, current development of ML applications for fusion often encounters obstacles common to both MFE and IFE communities. Examples include the fact that data ecosystems differ across different laboratories, therefore extrapolating pure data-driven models clashes with computationally challenging validation of multi-scale physics systems, and the lack of sharing analysis information often leads to duplicating efforts. This section discusses the major challenges in MFE and IFE, preventing the adoption of AI-driven fusion science discovery at its fullest potential, and where the IAEA can play a key role in addressing them. These major challenges are:

1. Data and data access:
   i. Data return rates for IFE;
   ii. Infrastructure to share data (MFE, potentially IFE); and
   iii. Analysis routines to create, curate and share data (IFE and MFE).

2. Community engagement and workforce development:
   i. Coupling of relevant expertise and resources;
   ii. Minimising duplication of effort in MFE and IFE communities.
   iii. Education background for ML and AI of existing and incoming scientists is limited; and
   iv. Competitive salary and job compared to industry.

How can we address these bottlenecks and accelerate progress in fusion? In this Chapter, a number of data-centric enabling activities are suggested, such as the development of open data repositories, the creation of cross-disciplinary initiatives, the development of workshops and schools that combine computational and data science elements for fusion research, and new ways to actively engage the community — for example with Kaggle-like competitions or hackathons.

Hidden in plain sight is the real need of a data steward to act as a broker or ambassador between the data and the user community — a role that the IAEA already plays in other areas and that would be the ultimate enabler to accelerate fusion R&D with the help of AI.

9.3.1. Data accessibility and the need for open science

Large open access databases are required for ML models training and validation. However, there is hesitancy to share experimental or simulation data due to institutional policies, security or intellectual property issues, or the fear of being scooped. While some efforts within the fusion community over the years have started to build such databases, they are still limited in scope (e.g., tokamaks [9.23] and stellarators [9.24] in MFE), complexity (global 0-D quantities) and accessibility [9.25] and may use a variety of formats and data standards [9.26]. The IAEA can help enhance large-scale accessibility by hosting common data sites, i.e., playing a data stewardship role, improving connectivity among fusion data source institutions and nations, and providing standards for both general access and specific domain data types. Each of these forms of support will enable broader participation in fusion problem solving via AI applications.

Most importantly, open access repositories of fusion data need to be made available beyond national and institutional barriers to fully boost AI-based research. The status quo sees fusion databases hosted at different facilities in different formats, behind firewalls or with limited access provided through data agreements. AI for applied science requires teamwork, as problems are growing more complex and interdisciplinary, and progress will require diverse skills in order to design solutions impossible to accomplish as individuals or even small teams. Moving to centralised repositories of experimental, simulation, or plant operation data with standardised metadata, will attract AI experts to pivotal fusion projects, and open participation to fusion communities worldwide. This effort needs to be accompanied by the education of the fusion community to adhere to Open Science (OS) best practices [9.27] and principles known as FAIR [9.28] — serving to guide data producers on sharing not just the data but also the algorithms, tools, and workflows to allow all components of the research process to be made available, fostering transparency, reproducibility, and reusability.

Hence, the IAEA playing such a data stewardship role can be of key importance. This role would be facilitated by the extensive in-house experience in maintaining databases in several areas, from fundamental atomic, molecular and nuclear data to isotopic data and measurements [9.29–9.32], and thus enable AI applications in fusion science and accelerate progress. Specifically, the IAEA is well-positioned to establish and host new databases of experimental fusion data to study phenomena such as disruptions in tokamak plasmas, where first-principle models cannot provide comprehensive predictive solutions. These databases could be developed within an IAEA framework for cooperation, such as CRPs [9.33] or Networks [9.34], aimed also at supporting data standards definition and implementation of FAIR and OS principles to help enhance large-scale accessibility across different communities.

9.3.2. Community engagement and workforce development

Common frameworks are needed to create one community of practice focused on AI for fusion science, inclusive of IFE, MFE, and basic plasma science. IAEA can lead cross-domain initiatives, like workshops or technical meetings that could bring together fusion scientists to increase collaboration on ML applications to common research challenges, for example, image data classification, advanced surrogate models, and improved optimization techniques.

By adhering to OS principles, the fusion community can better leverage the growing worldwide interest in fusion research participation by non-fusion scientists, diversifying the knowledge and skill base. Open data access is a fundamental standard in the ML community and will be a fundamental requirement for fusion to fully leverage those capabilities. Additionally, open databases can be used for training purposes of current and future fusion scientists to engage in ML and AI activities through outreach activities, training workshops and schools – including relevant training activities IAEA carries out in partnership with, for example, the International Centre for Theoretical Physics (ICTP) — development of e-learning resources or launching Kaggle-like competitions, hackathons and similar crowdsourcing challenges and initiatives. IAEA could lead these activities that would allow the fusion community to expand engagement and to energise and integrate many diverse communities, e.g., the private sector, ML and AI experts, students, science researchers, other relevant cross-field researchers, and private entities.

Furthermore, expanding fusion databases to embrace OS principles would offer opportunities for internships or fellowships dedicated to related tasks (like database development and curation) at IAEA, partner institutes, organisations, private companies, thus contributing to capacity building and workforce development. Finally, by incentivizing the integration of the MFE and IFE communities, IAEA can further connect AI initiatives scattered across many different working groups worldwide, thereby engaging a broader community. This will result in reduced duplication of efforts in certain research areas, increased cross-pollination, and would allow fusion subject matter experts to exploit cross-domain synergies in order to accelerate progress in fusion research.

Last but not least, hybrid curricula are needed to fully leverage AI in fusion science. Fusion subject matter experts usually have no or little background in AI methods and need access to educational opportunities to develop the necessary skills. Training tools and outreach initiatives aimed at educating fusion subject matter experts can provide a connection with the AI community that could attract and enable participation. The fusion community also needs to recognize the need to actively connect with ML scientists and the necessary technical support to create and maintain large datasets. In general, a diversification of the workforce and their skill sets is necessary. IAEA coordination on capacity building development, as well as on facilitating and enhancing collaboration among domain experts and students through technical meetings and workshops, can aid substantially in growing the worldwide workforce in these areas.

9.4. EXPECTED OUTCOMES

The activities described in the previous section would produce the following outcomes:

- Improved data accessibility (adhering to FAIR/OS principles), acting as fusion data steward, establishing data standards and common formats;
- Improved cross-domain community coordination on projects with cross-domain entities (e.g., atomic data workshops, EOS community, transport coefficients workshop, ML and fusion scientists' meetings);
- Enhanced community engagement through data contests and competitions;
- Developed and increased a diversified workforce through outreach and education initiatives, such as summer schools, internships and fellowships, but also production of cross-domain training materials, and publication of educational material.
- Accelerated technical advancement through public-private partnerships. These can:
  - Bring rapid technology advancements to public fusion science while bringing essential needs of public science to those advancing tech solutions; and
  - Help establish shared resources (e.g., computational resources) managed by an independent oversight body.

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Chapter 10.

NUCLEAR POWER

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10.1. STATE OF THE ART

In broad terms, the main opportunities for AI to achieve a positive impact on the nuclear power industry can be grouped in the areas listed below. In all of these, AI offers the capability of leveraging massive amounts of complex data in ways that were previously impossible to do by humans or with more traditional techniques. In addition, AI enables the capture, codification and retention of human expertise to support robust, repeatable and explicable machine-led decisions. For each group, a brief description of the topical area with generic application examples is given, followed by more specific examples. These are most definitely not exhaustive, as there are many other applications under each topic; rather, they are provided to help solidify the main idea behind each topic and provide concrete examples of the types of work and benefits they can entail.

10.1.1. Automation, to increase reliability and reduce time of common operations

Various common activities in nuclear plants place staff in high-pressure or demanding situations, increasing the chance of human factor errors and personal safety risk. Many of these issues can be reduced by leveraging data science technologies for automation. In some situations, activity time can be diminished, possibly reducing radiation exposure and critical downtime. Other tasks may be repetitive but time consuming. Examples here include analysis of non-destructive evaluation data and work management processes.

The wide range of established ML techniques allows automation of very different processes ranging from automated analysis of complex process data to facilitating decision making and improving work processes. Many of these applications are already well developed.

Applications that focus on automating analysis of complex data can be illustrated by a range of defect or anomaly detection solutions. Examples include in-service inspection and control rod drive mechanism (CRDM).

In-service inspection is a critical part of safe operation of nuclear power plants. However, analysing inspection data is laborious, time consuming and prone to human errors. Using ML, this analysis can be automated to a significant degree [10.1, 10.2]. Automating data analysis will improve inspection reliability and efficiency. It will also allow extracting more information from the inspection data and improve predictability. The current models have shown good performance and recommended practice for qualification is in place [10.3].

CRDMs are used in pressurised water reactors (PWRs) to insert or withdraw control and shutdown rods into the reactor. CRDM coil currents have been shown to indicate certain types of anomalies including late latches and rod slips due to the build-up of metallic deposits, commonly referred to as CRUD. In CRDMs, CRUD can prevent the grippers from fully closing and cause the CRDM to inadvertently drop rods, which can result in significant plant downtime [10.4]. However, identifying these types of anomalies automatically is difficult and often involves evaluation of thousands of coil current measurements by multiple human experts that can take hundreds of man-hours to perform. ML is shown to detect CRDM coil current anomalies with approximately 96% accuracy in near real-time. Before deployment, more CRDM measurement examples need to be used to cover the breadth of available CRDM data and improve the overall accuracy.

Other significant applications deal with automating and facilitating some areas of anomaly detection, decision making and report analysis. A process or equipment anomaly growing in a plant often results in states of which the operator is not aware until the anomaly results in a significant change, enough to be detected by the operator. ML methods can learn data trends. They have the potential to augment the operator state awareness and detect anomalous conditions. Recently, methods of semi-supervised ML [10.5] and the use of physics-based models to complement or assist the typical data-driven approach of anomaly detection [10.6] were found to potentially improve the performance of anomaly detection methods and are therefore of continuous research interest.

A significant part of NPP operation relates to staff walking around the plant to inspect the plant condition and environment and collect needed information. Hence, in the area of work process improvement, computer vision and ML enables drones to recognize features of their surrounding environment, eliminating or reducing the need for human rounds [10.7]. Some of these examples are currently in field testing. The main challenge highlighted is the lack of access to training data.

Human-computer interaction in the nuclear power plant's main control room (MCR) is the basis for efficient operator perception and control of the operating status of the plant. Speech recognition and gesture with high correctness and fast response time can simplify the operation process and help improve the efficiency of the operator. Such multimodal interaction can be used to reduce the operator's workload and achieve the effect of reducing human errors. Initial research on such systems have been completed and further work on method optimization and training data is needed.

For every event occurrence at an NPP, a typical work process encompasses several steps and cycles of reviews and analysis. Several human-based decisions are made regarding how to address each individual report before it goes to planning and scheduling, if needed, for it to be executed. This human-based decision is not only time consuming but also prone to human error. Natural language processing (NLP) methods coupled with ML can be developed to replicate the human decision-making processes of analysing the event reports and generating resulting documents and outcomes. This area of research is rapidly advancing into task-specific tools that the nuclear power industry is gradually leveraging. Those tools continue to expand in their functionality as new opportunities emerge for NLP and ML.

10.1.2. Optimization, to increase efficiency and design of complex operations

Nuclear power can leverage data science techniques to optimise complex processes, plans and strategies such as inventory management, outage scheduling and fuel cycle parameters. This will improve operations, plans, strategies and decision drivers. Some examples of such applications are shown below.

Outage scheduling optimization can be improved using current ML techniques, and wider plant history databases can be used by ML to optimise radiation mitigation strategies.

During the design phase of a nuclear power plant, AI systems can be used, e.g., to help optimise configuration management, requirement management, building information modelling, verification and validation. Many of these tasks can be addressed using current established AI technologies. Successful implementation of AI in the design engineering process can significantly improve the safety of nuclear power plants, as well as reduce the time and the cost of design. It also could provide cost-effective design solutions for other stages of the life cycle (construction, operation, decommission, etc.). Some elements of automatization and AI have already been implemented in several Building Information Modelling (BIM) software. The main challenge of AI adoption is the lagging regulation for AI application in the design engineering process of NPPs and available machine-readable requirements and data. In addition, research is needed to make existing methodologies and design algorithms more accessible for AI.

A nuclear reactor is a complex system, and its comprehensive control is not trivial. Besides well-known control of thermal power and coolant temperature, reactor controllers take care of plenty of other aspects such as operational safety permitting operation only within given limits, homogenization of burnup, burnup compensation, compensation of the poisoning, shaping of the power density distribution, support of flexible electricity production, operation economy, etc. Machine learning based techniques can be used to improve the traditional core-control methods and to allow improved predictive control of NPPs. AI allows consideration of an arbitrary large number of goals even if quite different in nature. In the case of reactor governance, safety, ergonomics, operation economy and grid services can be processed simultaneously in accordance with each other.

For optimal in-core fuel management, designers attempt to solve a 'combinatorial optimization' problem by utilising expert judgement, nuclear design principles, and physics-based tools. However, the search space size of combinatorial problems grows dramatically with the size of input space and therefore this process is quite demanding in terms of human time and computational resources. AI can quickly search for a candidate optimal loading plan before final evaluation with licensed codes.

10.1.3. Analytics, to increase the quality of current models and understanding of the used systems

AI techniques can also support further research for longer-term benefits. AI methods can, for instance, be leveraged to expedite the characterization and validation of materials for newer generation designs, reducing the time and cost of the necessary materials research, as well as help develop new quality assurance practices for additively manufactured components for small and microreactors and optimise the design of experiments to reduce uncertainties or experiment costs, and developing advanced dispatch and control methods for nuclear reactors for both energy and heat process applications and optimise strategies for hybrid nuclear energy systems.

In some cases, existing analytical models are overly simplistic in order to be mathematically tractable and fail to describe the process of interest in sufficient detail or accuracy to inform decision making. In such cases, AI approaches can be leveraged to develop such complex models and provide more accurate predictions. One example is the use of AI models to describe the critical flow that can occur in light water reactors in automatic depressurization systems and safety relief valves or in a loss of coolant accident (LOCA) or main steam line break, as presented during the consultancy meeting.

AI models can be leveraged for complex and time-consuming statistical modelling that are likely suboptimal, as for fitness-for-service (FFS) assessments. The advantage of such traditional models is their higher generalisation to new data given the explicitly defined relations between features and target. This explicit, direct relationship is typically lacking in AI models, impacting their performance on new data. This shortcoming can be overcome by incorporating physical concepts into the AI model, showing that expert knowledge can be used in conjunction with AI techniques to improve current modelling capabilities.

AI techniques can be leveraged for model validation, especially for advanced computer simulations that have proliferated over the last years and generate large amounts of data. Such approaches can support, for instance, digital twin applications.

10.1.4. Prediction and prognostics, to better inform maintenance activities

Data science approaches can be leveraged to predict events, including failures, and assess current asset conditions, such as remaining useful life. Asset owners can use these tools to plan their maintenance and outage strategies, potentially reducing unexpected downtimes and minimising periodic inspections. Examples of potential applications include leveraging the monitoring operation data streams for abnormal conditions and informing adequate timing of maintenance or inspection activities.

Despite the proliferation of advanced simulation tools developed over the past two decades, their true value is not yet fully realized by end-users. Many questions remain unanswered such as why should the industrial practitioners believe that the new advanced tools will provide more accurate predictions as compared to those obtained with legacy tools which have been heavily calibrated based on decades of operational experience? How can the industry leverage these advanced tools to better communicate with the regulator on upgrading their validation standards when applied to first-of-a-kind reactor designs or new fuel concepts? How to confidently integrate new operational data with the models to continually improve their predictions? All these questions remain difficult to answer, often requiring experts to determine whether and how the advanced tools could provide a quantitative edge over legacy tools. AI provides a natural approach to addressing these goals by providing mathematically rigorous and explainable algorithms to measure information content available in the simulation and the experimental data using information theory principles. The existing methods again are heavily influenced by classical statistical methods such as Bayesian inference theory and the Generalized Least Squares methodology [10.6]. In their standard implementation, these methods are designed to assimilate available measurements with simulation predictions to improve future predictions for similar or closely relevant systems. Because of the numerous assumptions made, such as linearity and Gaussianity, the effectiveness of these methods remains limited and has not seen wide adoption in the nuclear industry. Motivated by AI principles, nuclear researchers are pursuing the development of inference methods that do not suffer from the limitation of classical methods, however no application-ready implementations currently exist. These methods provide clear value of AI to improving the predictions of complex systems, because they provide clear quantitative metrics on characterising the information footprint across multiple sub-systems, time, and space, allowing for reliable generalisation of the predictive results.

10.1.5. Insights, to extract lessons from experiments and operating experience

The nuclear industry has accumulated thousands of reactor years of operating experience and amassed huge libraries of validation experiments used in support of model validation. Data science technologies can leverage this rich experience in unprecedented ways to unlock new best practices and better inform future decisions on the various stages starting from conceptual design to licensing and operation. These new trends and observations can lead to improved operating and maintenance efficiencies for near-term implementation.

Some specific practical applications for which AI can be leveraged in the industry include holistic assessment of maintenance records and practices, and of corrective action programs, to assess trends and extract lessons to inform future operations. As another example, AI technologies could identify the best types of sensor and arrangement for a given class of nuclear reactors that can be correlated with various sources of process anomalies, currently undetected with existing equipment-specific sensors. In general, methods are in early stages of development or adaptation to the nuclear industry; they are currently exploring how to glean insight from nuclear power plant data. A key challenge to this is the level of language specificity: not only are these methods language specific, but they can also be jargon-specific, and methods need to be informed by an industry ‘dictionary’.

10.1.6. Deployment challenges

At present, it is sometimes challenging to provide interpretability, confidence, and robustness measures of performance for AI. If expected to perform autonomous functions, additional concerns must be addressed, including cybersecurity concerns to ensure trustworthiness and integrity of models and data used for training and decision-making, and regulatory concerns which require an assessment of system vulnerability, e.g., data source malfunction or deliberate falsification.

The development of AI technologies for safety critical applications could present a challenge to regulators, as many traditional assurance approaches might not be easily applicable. For example, the limited transparency of AI and ML products may make their actions difficult to interpret, their biases unclear and their malfunctions mysterious. Moreover, it is sometimes difficult to fully specify the requirements for AI and ML products, as they may involve responding to novel situations.

Demonstration of compliance with standards is challenging due to the fast-moving nature of AI and ML technologies, and the time lags introduced by work to codify good practice into those standards. Security also poses unique challenges through data management and threats of adversarial attacks. Taking the challenges posed by the complexity and potential obscurity of AI and ML technologies, high level regulatory safety assessment principles and guidance may need to be developed to ensure that the full benefits of AI and ML can be accrued, particularly where there may be significant consequences of failure or maloperation.

Standards have always been important for the adoption of new technologies with AI being no exception. IEC and ISO have already created a dedicated subcommittee, ISO/IEC JTC 1/SC42, to develop AI standards. Recognizing the potential of AI and its current applications in the nuclear industry, IEC/SC45A started to prepare a Technical Report with the objective to help promote rapid transfer of AI technologies from pilot studies to wide applications.

Standardisation is the basis for conformity assessment. In order to enable acceptance of AI in safety-related applications standards, especially with regard to safety and security, existing standards would need to be adapted or new standards developed. Depending on the safety-relevance of an AI application, third party testing could be carried out by conformity assessment bodies (e.g., based on the ISO/IEC 17000 series of standards) in order to ensure independence from AI developers.

The attacks used against AI systems differ from the kinds of attacks we are accustomed to against other systems. The goal of these attacks is to have the model make poor decisions — either globally, lowering overall reliability, or under very specific conditions, so that given tailored samples can trigger specific, attacker desired outcomes. Learning systems are uniquely updated over time and have models that in many cases require extensive and ongoing retraining. This leads to a large attack surface distributed over time, as attackers can target these systems in the design phase, during initial and ongoing training, and when deployed on operational systems.

Being a different approach, AI will bring new specific challenges not faced before. AI specific cybersecurity concerns, explainability, the higher need for data, new considerations from the regulatory bodies (to whom AI is also new), etc. are some of them. It is important to proactively address these as adequate. Whether AI is used autonomously or with human supervision, a considerable level of assurance is needed.

10.2. NEXT STEPS

10.2.1. Technology development

These are activities which relate to further developing technologies that are in an earlier stage of maturity. Examples include:

- Further development of speech and gesture control software system;
- Development of anomaly detection from plant monitoring data;
- Core monitoring techniques and experimental validation and demonstration (CORTEX) need to be brought to a sufficient level of maturity before utilities can use it for routine core monitoring to inform operation and maintenance decisions;
- Having been trained to determine fuel core loading plans that meet safety requirements, neural networks can be further leveraged to guide the optimization of fuel loading.

10.2.2. Technology deployment

In some specific areas, the industry has the technological means to start practical adoption of ML. For these cases, field implementation of the applications, initially on a test basis, need to be pursued to start building trust in the systems, as well as their gradual adoption. One example is the automated analysis of non-destructive evaluation examinations. Applications for radiography and ultrasonic examinations are ready for field testing that can be carried out in parallel with the regular inspections to provide an assessment of field performance. Other examples include condition monitoring and automation of predictive maintenance procedures.

10.2.3. Enabling technologies

Enabling technologies refer to capabilities that need to be built in order to enable the successful development or deployment of AI technologies. They can be technical, such as developing an industry-specific NLP dictionary to support the activities listed in section 10.1.5, or more programmatic, such as interfacing with regulatory bodies to gain acceptance of the technology, as applicable. For example, for the successful and safe implementation of AI in the design engineering process of nuclear power plants, it is reasonable to conduct R&D and their deployment in the following areas:

- Development of legal regulation for AI application in the engineering design process of nuclear power plants;
- Development of common database requirements (safety, security, etc.);
- Development of accessible and understandable to AI requirements (optimization, simplification, specification, etc.) when framing common database requirements;
- Adaptation of existing methodologies in accordance with process approach;
- Development of design algorithms that are accessible and understandable to AI.

The development of a roadmap to guide regulatory investigation, research and positioning on the application of AI systems for nuclear power plants is also extremely valuable to pursue.

10.3. ACCELERATING PROGRESS—IAEA’S ROLE

In this section, a summary of beneficial IAEA assistance is provided, followed by one or more IAEA implementation mechanisms which could deliver the suggested support.

10.3.1. Data and information management systems

The availability and quality of data is highlighted as a challenge for several application areas. The nuclear data tends to be sensitive, which imposes limits to its use. In addition, accurate labelling and data sanitation is a significant undertaking. A few things enabled recent advances in ML, but the availability of standard data sets for research and performance evaluation was arguably the most impactful. Training and testing data availability would enable worldwide research into this area. Thus, increased data sharing and finding ways to make data more accessible would accelerate the development and adoption of ML methodologies. Potential beneficial actions include:

- Developing and maintaining a library of synthesised datasets (of similar pedigree to those collected in nuclear power plants) for hypothetical or representative reactors serving as benchmark datasets for comparing and evaluating performance of various AI algorithms [10.8, 10.9].

- Guiding development and deployment of privacy-preserving methods for data anonymization to alleviate concerns over exchange of nuclear systems operational data leading to their adoption by stakeholders. The method must conceal the identity of the data source while providing full access to all mathematical features employed by AI algorithms.
- Creation of a repository facilitating the exchange and sharing of data for representative projects to promote the value of AI to the IAEA's Member States.

10.3.2. Networks fostering longer-term collaboration around a specific topic

Identifying common solutions and successful application areas across the industry would help leverage working solutions, as for example, identifying application areas of common interest, such as the practical use of AI in NPPs. The IAEA could play a role by facilitating a network with subgroups for each of the main application areas. Each application can have a small working group for close discussion who meet periodically. Each of these working groups can report and share to a combined larger technical meeting (all working groups), where all can learn from their experiences. The IAEA can help identify world leading expertise with an aim of working in a more cross-sector way. Also, strengthening liaison relationships with relevant national or international organisations to better coordinate global efforts in standardising AI applications in the nuclear industry so as to speed up adoption and meanwhile save R&D and deployment costs.

10.3.3. Training workshops

Model transparency and making the ML systems understandable for both the people that interface with them and for the people that oversee them is required. While the users may not need full understanding of the ML techniques applied, they need to build a working understanding to facilitate effective interaction with the system. Training workshops (courses development and hands-on training) are typically implemented to assist with capacity building in Member States. They might be used to assist with the development of needed competencies and, for example, to train the instructors.

10.3.4. Coordinated research projects

CRPs bring together research institutes in Member States to collaborate on research topics of common interest. Results of the CRPs are disseminated to all Member States through scientific and technical publications, and other communications media

For the regulated nuclear environment, field trials and gaining acceptance of the utilities is crucial. For some of the use cases this is easier, and they may help introduce AI and ML to the industry. For some use cases, more evidence is required to gain acceptance. Lack of consideration of potential blockers for deployment at the concept stage could prevent timely and effective deployment. Facilitating this process and experience sharing would accelerate and facilitate adoption of AI and ML. CRPs could be implemented to facilitate this, including AI reliability, with IAEA mediated field testing, round-robin exercises and peer review of AI and ML solutions. Specific examples include the facilitation and promotion of field testing or comparative, round-robin testing of technologies as they become available. IAEA could develop and maintain one or more Standardised Test Suites for validating performance of AI algorithms in a round-robin demonstration or other contexts.

10.3.5. Publications on safety or security

Another area of work can be reviewing the impact of AI and ML on existing IAEA guidance and standards and provide commentary on their applicability, especially in the safety and security area. Regulatory acceptance is indeed required for the final application in power plant environments. While the exact regulatory needs depend on the specific country and on the ML application, the present lack of a clear route to the licensing of AI applications, where this may affect safety or security, has the potential to prevent deployment on active plants, and for the benefits of AI to be lost. Common but flexible principles and guidelines addressing the most common challenges met with gaining regulatory acceptance for AI and ML would help development and adoption. The guidelines need to highlight the benefits of AI and ML but also address the need to safely deploy and utilise the technologies and provide an independent view of standardisation activities and their role, as well as highlight the need for validation of the standards and monitoring of their obsolescence.

10.3.6. Nuclear Energy Series, Technical Reports, TECDOCS, non-serial publications

Another area of work can be considering development of principles and guidance for AI and ML systems, including best practices. In addition, IAEA topical reports on AI technology and or the practical use of AI in a nuclear power context would be beneficial. Examples include: core design and monitoring, and diagnostics and load optimization; predictive maintenance and outage optimization; improvement of NDT/ISI results through evaluation, interpretation, and analysis; material ageing management; condition monitoring; autonomous monitoring; anomaly detection; elaboration and improvement of models; automating operations and work processes; streamlining work management process; reliability analysis and risk assessment, as well as data modelling and simulation.

10.4. EXPECTED OUTCOMES

Examples of outcomes the IAEA could support AI use in the field of nuclear power include:

- Increased data availability for AI applications to achieve their potential systems and to facilitate and accelerate the application of AI technology.
- Improved modelling and simulation capabilities relevant to AI applications.
- Bridging the gap between the AI community and the industry to identify specific generic applications of interest.
- Capacity building to develop workforce competencies (students and practitioners) highlighting the value, mechanics and limitations of AI techniques
- Increased confidence in the adoption of AI in existing and future plants by providing guidance on the deployment of the technology.
- Streamlined licensing processes of designs comprising AI solutions (through the increased confidence).
- The availability of specific recommendations to NPP utilities, regulatory bodies, research and design organisations, as well as vendors with respect to the application of AI technologies.

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Chapter 11.

NUCLEAR SECURITY

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11.1. STATE OF THE ART

AI can have varied impact depending on how it is applied within different areas of nuclear security, including radiation detection for material outside of regulatory control, cyber and information security, forensics, material and facility security, and insider threats.

11.1.1. Radiation detection, analysis, and decision support

Data collection and interpretation are large components of any nuclear security activity. AI is being explored as an opportunity to provide not only improved data analysis, but to support complex and variable data processing, in addition to decision making support in order to increase the effectiveness and efficacy of nuclear security activities.

Research in AI applications for detector data analysis has indicated the potential for machine learning algorithms and deep learning models to be use for radioisotope identification in high efficiency but low-resolution plastic scintillator detectors. This can expand the capabilities of detectors used in nuclear security applications by providing additional information for decision making and response if detectors alarm. The expanded capabilities potentially offered by AI in radiation detection may reduce nuisance alarms, and aid in assessing complex and variable data streams to better focus resources and provide real-time situational awareness [11.1, 11.2].

This is also true for nuclear forensics, where AI is being used to enhance the systematic approach used to draw conclusions in an investigation. As no single parameter will allow drawing conclusions with high confidence, it is typical that several parameters will be included in an evaluation, creating a multi-dimensional problem to analyze. Supervised learning techniques have been applied to complex data sets, including such processes as image analysis, colorimetry, and spectra to conduct classifications of material. Increased attention is being paid to deep learning techniques and the evaluation of non-numerical information to enable high confidence conclusions with smaller learning sets. [11.3, 11.4].

11.1.2. Cyber and physical defence

AI has significant potential for cutting-edge computer security techniques for NPPs, detecting and responding both current attacks and future unknown attacks. AI techniques provide various ways to learn from data and operations, including identifying patterns and anomalies in the vast quantities of information related to the sensing and control of nuclear processes. Cyber-attacks on instrumentation and control (I&C) systems can cause physical damage to facilities and may be targeted within acts of sabotage, indicating the need for both physical and computer security solutions that can detect evidence of both adversarial actions and the progressive process impacts that may be indicative of an ongoing cyber-attack.

Due to the large aggregate sum of information and the comparatively small, detailed examples of adversarial actions much of this data may need to be processed within unsupervised models.

An autoencoder is an example, a neural network intended to ingest large amounts of data to produce an internal representation that allows the identification of patterns or features [11.5].

Such examples of AI have been shown to support the detection anomalies in I&C network traffic, these types of machine and deep learning algorithms hope to compensate for the lack of abnormal data and also benefit from the abundance of normal data from day to day operations.

Other applications of AI for computer security may seek to observe the state of the process itself. An Extended Kalman Filter (EKF) is a nonlinear state estimation technique that has been deployed for this purpose, to generate estimates of process state variables and provide for a prediction of the future state of the system allowing the identification of anomalies that may be indicative of cyber-attacks.

A greater benefit may be obtained through combining the dual approaches to network traffic and process variable anomaly detection. Such an example would be extending the EKF anomaly detection with a Kalman Filter deployed to produce an independent and concurrent model of the control network traffic. The output of both applications of EKF and KF may then be combined through a fuzzy model (or other application of a human-like decision process) allowing anomalies to be appropriately weighted and identified through comparison to both models simultaneously forming an even strong indicator to support the detection of cyber-attacks [11.6].

In order to add additional insight into potential attacks, the development of explainable AI models provide information about which component is under attack and how much it deviates from normal operation. Such an explainable AI computer security solution platform may enhance the detection, analysis, and response to computer security incidents within nuclear facilities as the output or results of the AI model may be readily interpreted by human operators and emergency responders ensuring greater integration of the AI solutions into existing organisational management systems and decision making processes [11.7].

AI may also be used to identify vulnerabilities and compromised employees, operations, and missions, providing insight to detect anomalous behaviour or patterns. As with detection data and cyber systems, pattern and anomaly detection can offer analysis of human behaviours to aid in defending again insider threats. AI technologies can be developed to understand the requirements for rule compliance and evaluate image data and other data streams to verify if the rules and measures are being followed or disregarded [11.8].

11.1.3. Blockchain

Blockchain, a subset of Distributed-Ledger Technology (DLT), is not ordinarily included within AI, however there are opportunities for it to be coupled with AI for nuclear security activities.

DLT is the use of a decentralize, synchronized database shared across multiple ‘nodes’ to track the transaction of assets. Blockchain adds cryptographic techniques to protect and authenticate data, building trust and data consistency across activities. Blockchain has been demonstrated and adopted in a variety of industry sectors to manage risk and aid in the tracking of high value assets, including origination. Case studies on cobalt supply chains, the diamond industry, and food supply chains, among others, offer examples for the potential for integrating AI and blockchain technologies for nuclear security [11.9, 11.10].

11.1.4. Considerations

Though there are many positive implications for AI in nuclear security, there are limitations, risks, challenges, and considerations which must be explored.

Explainable AI is an important consideration for applications of AI that rely on transparency and replicability. Nuclear forensics findings may be presented as evidence in court, where the expert witness need to outline to the judge or the jury on what grounds the conclusions have been reached, and so transparency of the analysis process may be crucial.

AI-enabled technologies require a certain level of infrastructure, including computational needs and data requirements to properly develop and train AI models. Too much or too little information, incomplete information or data sets, absence of key data or bias, can be challenging for realistic application. Not enough abnormal data available or massive quantities of ‘normal’ data could create errors (one-class classification problem). AI solutions may also be limited despite available data due to technologic and infrastructure inequities around the globe [11.11].

AI, like other technologies, is not immune to vulnerabilities or risk. Aggregated information could result in threats to information security, while potential cyber-attacks against AI models and against the computing infrastructure could lead to a compromise of future AI-supported functions or decision-making systems in uses of AI across all nuclear fields. Dialog on uses of AI need to balance this increased risk, keeping in mind the additional susceptibility to cyber-attack, potential exposure of sensitive information, and the consequences of compromise of AI supported functions.

Adversarial AI is also a consideration for nuclear security. While AI technologies are useful for the enhancing of nuclear security activities, adversaries with AI capabilities may post risk, and thus countermeasures must also be considered [11.12, 11.13].

AI is not a magic solution to solving all challenges and so careful consideration is necessary when developing and implementing AI. Technology should be deployed intelligently for well-defined challenges, preserving rather than compromising security. AI raises a number of ethical and privacy concerns, in addition to questions surrounding data accessibility, sharing, intellectual property constraints, and even data sovereignty.

11.2. NEXT STEPS

There is a need for more investigation on the positive and negative impact and implications of AI in nuclear security. Research into specific AI applications for nuclear security topical areas is needed to understand its use, limitations, and vulnerabilities. AI research focused on developing or expanding understanding will also be key to enabling future research avenues.

11.3. ACCELERATING PROGRESS—IAEA’S ROLE

The IAEA can have a supporting and transformative role in aiding progress towards the realization of the impacts of AI in nuclear security, whether they are positive impacts or negative. IAEA Webinars, Technical Meetings, and CRPs can provide mechanisms to support the development, awareness, and application of AI, as well as countermeasures and defence against, in nuclear security. These information exchanges and collaborative opportunities can address Member States’ needs in nuclear security, including more investigation on the positive and negative impact and implications of AI in nuclear security.

These activities can be disseminated and even enhanced by the IAEA's development of guidance on terminology, implementation, training, testing, and regulating AI capabilities for nuclear security.

11.4. EXPECTED OUTCOMES

The expected outcomes of the activities outlined in the previous section include:

- Increased confidence in the utilization of AI technologies within nuclear security functions, without compromising defence in depth.
- Enable the exchange of information to support a common understanding of the design, implementation, and functionality of AI models assuring they do not affect the capacity to provide adequate nuclear security.
- Expanded cross-cutting and interdisciplinary cooperation internationally since AI impacts multiple stakeholders within the nuclear community.

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Chapter 12.

SAFEGUARDS VERIFICATION

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12.1. STATE OF THE ART

The IAEA conducts various safeguards inspection field activities to ensure states are using nuclear material for peaceful purposes and the material is not diverted for the production of nuclear weapons. These field activities are sometimes complex, and many safeguards' inspections produce a large amount of heterogeneous instrumentation data, as these inspections are difficult operations. Driven by the increase of material under safeguards and the introduction of new measurements techniques and sensors expanding global nuclear fuel cycle activities, the amount of data and number of inspections has been steadily growing, calling for the need to increase the efficiency of nuclear safeguards processes [12.1].

An extensive range of safeguards data could be used to train ML algorithms. For example, the volume of available satellite imagery and open-source data has increased dramatically over the past several years and is expected to keep growing in the near future. Additionally, video cameras have also been installed by the IAEA, along with various sensor technologies, that are generating a complex and growing amount of information in the form of data which can be utilised for various purposes, including AI.

With this rise in the amount of generated data, many tasks are becoming increasingly labour intensive. However, these larger datasets can be used for different applications: classifying data, finding patterns, and identifying outliers in the data. These are the domains in which AI could significantly improve efficiency and effectiveness within safeguards. If AI is appropriately paired with input from experts and inspectors, the amount of time they spend on tedious or repetitive tasks will decline, increasing their ability to work within their core expertise.

Key Applications that would be a natural fit for AI are gamma spectroscopy, verification of spent fuel, robotics, surveillance, and productivity, which are discussed in detail below.

12.1.1. Gamma spectroscopy

ML algorithms look like a promising tool for improving the sensitivity of radiological searches. An algorithm developed using neural networks and trained using source and spectra data successfully detected anomalous sources, identified the source type, and located the closest detector. A more complex dataset is planned for future use to progress the algorithm further and improve radiological search methods [12.2].

Research performed at the IAEA demonstrated that AI can also be used for fissile mass quantification, specifically mixed oxide fuel verification. Impure mixed oxide (MOX) fuel verification is difficult to perform with neutron multiplicity counting and therefore, gamma spectroscopy was explored as an alternative. Spectra were obtained from Monte-Carlo models, covering a wide variety of sample parameters and inhomogeneities. These gamma spectroscopy measurements were then utilised to train a neural network and autoencoders. Once the models are trained, a sample could theoretically be measured in the field and using this ML algorithm, the fissile material's mass, concentration, alpha value, and multiplication could be obtained as a result of the analysis with the neural network [12.3].

12.1.2. Spent fuel verification

Spent fuel makes up a large portion of the material under safeguards and their inventories are continually increasing. Spent fuel is measured by utilising the neutrons and gamma rays emitted by spent fuel, and these inspections generate a large amount of data. Spent fuel verification can also be performed using Cerenkov imaging data. These data sets can be utilised for AI algorithms, and numerical simulations can supply training and test datasets for the model.

Several ML models have been examined to determine if models can successfully distinguish between complete fuel assemblies and defect fuel assemblies. Initial results are promising, demonstrating the models can detect fuel replacement and further classify spent fuel based on the percentage of replaced pins [12.4]. ML models can also potentially be used to analyze spent nuclear fuel inventory data to verify burn-up, cooling time, and initial enrichment [12.5]. Additionally, these models can be utilised to measure the bias of the spent fuel measurement. Bias is the difference between calculations and measured performance of spent nuclear fuel properties. These biases can be predicted with ML models and are similar to the observed biases [12.6]. By utilising AI and ML, inspectors could have the ability to verify spent fuel assemblies in the field more efficiently.

AI was also used to improve the processing of data obtained from the neXt Generation Cerenkov Viewing Device (XCVD) with a support vector machine to classify blurry XCVD images, which may require further image processing [12.7]. Different image improvement techniques for XCVD image processing were investigated. Although this algorithm is promising, more investigation is required before it can be used regularly in the field.

Overall, the technology’s accuracy is sometimes on par with traditional instruments, but it is not mature enough to make autonomous decisions. It still requires improvement and inspector and expert input to make decisions.

12.1.3. Robotics

Spent fuel verification can also be performed more efficiently with the use of robotics and AI. For example, robotic technology, such as the RCVD, can assist with spent fuel verification. Robotics can be implemented within safeguards to increase operational efficiency by collecting data, performing 3D mapping, calibrating data, etc. By utilising robotics to assist with safeguards tasks, the efficiency of operations can be increased, particularly in difficult areas, where data is hard to gather because of inspector safety. AI can be used with robotics to identify objects and anomalies, provide the robot with autonomous sensor fusion, and improve the human/machine interface [12.8].

12.1.4. Video surveillance

Implementing AI for video surveillance would allow for significant productivity gains in safeguards. Surveillance review is challenging and time-consuming for safeguards inspectors. Classical algorithms currently used for surveillance review are prone to false alarms, leading to decreased review productivity. AI-based algorithms have the potential to drive down these false alarms, while more specifically and accurately identifying objects and actions of safeguards relevance.

There have been several recent developments in the use of AI for surveillance review at IAEA. One area of research is the review of surveillance data to detect and track safeguards relevant objects, operator declarations, and anomalous activities in the data. Surveillance data could also be used with learning-based algorithms to detect and count objects.

However, further improvements to AI implementation could be made by providing larger video datasets to train the models better. Image and video data can be acquired from similar facilities under surveillance, from simulations, and digital twins. Different safeguards objects and activities could also be added to expand the image datasets and improve the training. An open challenge for the limited resources at IAEA is the effort needed to annotate training datasets. Techniques that will help automate the annotation process as well as reduce the overall amount of training data are required. AI and video surveillance will expand from identifying spent fuel casks to other safeguards-relevant objects and activities to flag [12.9].

These areas are promising for implementation and require further development and expert input.

12.1.5. Productivity

AI can be used to increase productivity in many areas of safeguards, and it is important to examine how AI will impact human performance. When ML was used in conjunction with human input to detect objects, it helped improve user performance in identifying important items in images, particularly with novice users [12.10]. AI can assist in identification tasks, but it may need to consider the expertise level of its user, and different algorithms need to be utilised for expert vs. non-expert users.

The use of AI in developing a digital safeguards assistant for different field activities was examined. These digital assistants could decrease the cognitive and physical burden placed on experts in the field and help mitigate human error [12.11] when performing field activities.

With the current status of AI, there are concerns with the accuracy of the models and the models producing false alarms. False alarms affect the trust the users have in the algorithms and the trust between the inspectors and the IAEA's Member States. False negatives miss important events, with grave consequences for safeguards. Therefore, before implementing AI in safeguards processes, it is necessary to improve output accuracy.

More work needs to be done to determine how best to merge AI with inspector perception and experience. Inspector knowledge will be an asset to AI and AI will help inspectors by cutting down on time and energy spent on repetitive tasks. With AI and inspector perception and experience merged, nuclear safeguards processes will increase inefficiency.

Overall, safeguards can significantly benefit from implementing AI, but further development and exploration into critical applications are necessary before widespread use.

12.2. NEXT STEPS

A crucial aspect will be the merging of inspector expertise with AI and ML development. AI will not replace inspectors, but it will need to implement safeguards inspectors' expertise to be useful for them in the field. It can become an essential aid for inspectors to utilise during various safeguards operations. IAEA has many experts and inspectors to influence the merging of AI and safeguards. These experts and inspectors will need to work closely with AI experts outside of the IAEA to produce practical solutions.

IAEA has access to safeguards datasets from inspections and can share these large datasets to facilitate the training of various ML models. There is also an opportunity to make use of digital twins in safeguards. Digital twins are a virtual environment populated by data obtained from sensors applied to the physical object that use simulation, reason, and ML to help make decisions. Digital twins could be used in safeguards to supply data to train ML models.

12.3. ACCELERATING PROGRESS—IAEA’S ROLE

Successful implementation of AI requires a blend of data science and physics throughout the lifecycle of the nuclear material. IAEA safeguards has a pool of specialists, whose expertise will be valuable for developing AI algorithms. IAEA safeguards could become a leading use case or client for specific fault-proof AI research and development. Safeguards require a high degree of accuracy from inspection results, and AI in safeguards is no different. The development of greater accuracy AI could greatly benefit other industries outside of safeguards.

IAEA could become involved in a more moderating or stewarding role to help guide the development of AI instead of being directly involved in its development. Standing up the capability to develop AI and ML within IAEA would require many resources. Therefore, it would be more beneficial for the IAEA safeguards group to advise the Member States instead of directly developing these algorithms.

Additionally, because the future of AI is open-source, the IAEA may need to adapt its policy frameworks to provide this data. While some safeguards data is open-source, there is a portion of data IAEA receives and securely analyzes. This structure may need to be adapted to allow for specific instances of providing data. IAEA’s legal framework and those of its Member States may also need to be altered to enable data sharing.

12.4. EXPECTED OUTCOMES

The development of ML and AI will improve inspector output and increase the efficiency of safeguards operations in the field. These developments in AI will decrease the repetitive tasks necessary for inspectors to perform and increase the ease of inspection. IAEA inspectors and experts will need to work closely with AI developers to improve the efficiency and accuracy of AI for future use within safeguards. Implementing AI within safeguards will require a change in how certain datasets are shared, particularly as open-source data is the future of AI. Improvements in AI for safeguards purposes will help foster development in other industries.

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LIST OF ABBREVIATIONS

AI	artificial intelligence
CRP	coordinated research project
ENAI	ethics of nuclear and AI technology
FAIR	findability, accessibility, interoperability and reusability
ML	machine learning
NPP	nuclear power plant

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