BIG DATA MINING AND ANALYTICS
ISSN 2096-0654 06/06 pp140–160
Volume 5, Number 2, June 2022
DOI: 10.26599/BDMA.2021.9020027

Deep Learning in Nuclear Industry: A Survey

Chenwei Tang, Caiyang Yu, Yi Gao, Jianming Chen, Jiaming Yang,
Jiuling Lang, Chuan Liu, Ling Zhong, Zhenan He, and Jiancheng Lv*

Abstract: As a high-tech strategic emerging comprehensive industry, the nuclear industry is committed to the research, production, and processing of nuclear fuel, as well as the development and utilization of nuclear energy. Nowadays, the nuclear industry has made remarkable progress in the application fields of nuclear weapons, nuclear power, nuclear medical treatment, radiation processing, and so on. With the development of artificial intelligence and the proposal of "Industry 4.0", more and more artificial intelligence technologies are introduced into the nuclear industry chain to improve production efficiency, reduce operation cost, improve operation safety, and realize risk avoidance. Meanwhile, deep learning, as an important technology of artificial intelligence, has made amazing progress in theoretical and applied research in the nuclear industry, which vigorously promotes the development of informatization, digitization, and intelligence of the nuclear industry. In this paper, we first simply comb and analyze the intelligent demand scenarios in the whole industrial chain of the nuclear industry. Then, we discuss the data types involved in the nuclear industry chain. After that, we investigate the research status of deep learning in the application fields corresponding to different data types in the nuclear industry. Finally, we discuss the limitation and unique challenges of deep learning in the nuclear industry and the future direction of the intelligent nuclear industry.

Key words: nuclear industry; Artificial Intelligence (AI); Deep Learning (DL); research status; development trend

1 Introduction

Nuclear industry generally refers to a comprehensive emerging industry engaged in the production, processing, and research of nuclear fuel, as well as the utilization and development of nuclear energy. As a high-tech strategic industry, the nuclear industry involves nuclear raw materials, nuclear fuel, Nuclear Power Plants (NPPs), nuclear power, nuclear weapons, and so on. For national defense and security, nuclear weapons with mass destruction are the basis of modern military strategies of some countries[1]. For the national economy, the nuclear industry can convert nuclear energy into electric energy, thermal energy, and mechanical power, so as to obtain safe and clean energy. Nuclear power, as clean energy, actively responds to the consensus of the Paris Agreement[2] and the Chinese plan for peak carbon dioxide emissions[3]. In addition, the nuclear industry can also provide radioisotopes for radiation processing, food preservation, medical diagnosis, geological exploration，and other fields[4,5]. In the field of nuclear medicine, nuclear technology can be used to diagnose and treat diseases by the common imagining equipment, e.g., Positron Emission Tomography/Computed Tomography (PET/CT) and Single-Photon Emission Computed Tomography (SPECT)/CT[6–8]. Figure 1 shows that specific application fields are covered by the nuclear industry. From Fig. 1, we can find that nuclear technology has penetrated into various fields and has a significant impact on national development, social progress, scientific research, and so on.

• Chenwei Tang, Caiyang Yu, Yi Gao, Jianming Chen, Jiaming Yang, Jiuling Lang, Chuan Liu, Ling Zhong, Zhenan He, and Jiancheng Lv are with the College of Computer Science, Sichuan University, Chengdu 610065, China. E-mail: tangchenwei@scu.edu.cn; {yucy, gaoyi, chenjianming, yangjiaming1, langjiulin, chuanliu}@stu.scu.edu.cn; linda.zhong.abc@gmail.com; {zhenan, lvjiancheng}@scu.edu.cn.
* To whom correspondence should be addressed.
Manuscript received: 2021-12-08; accepted: 2021-12-15

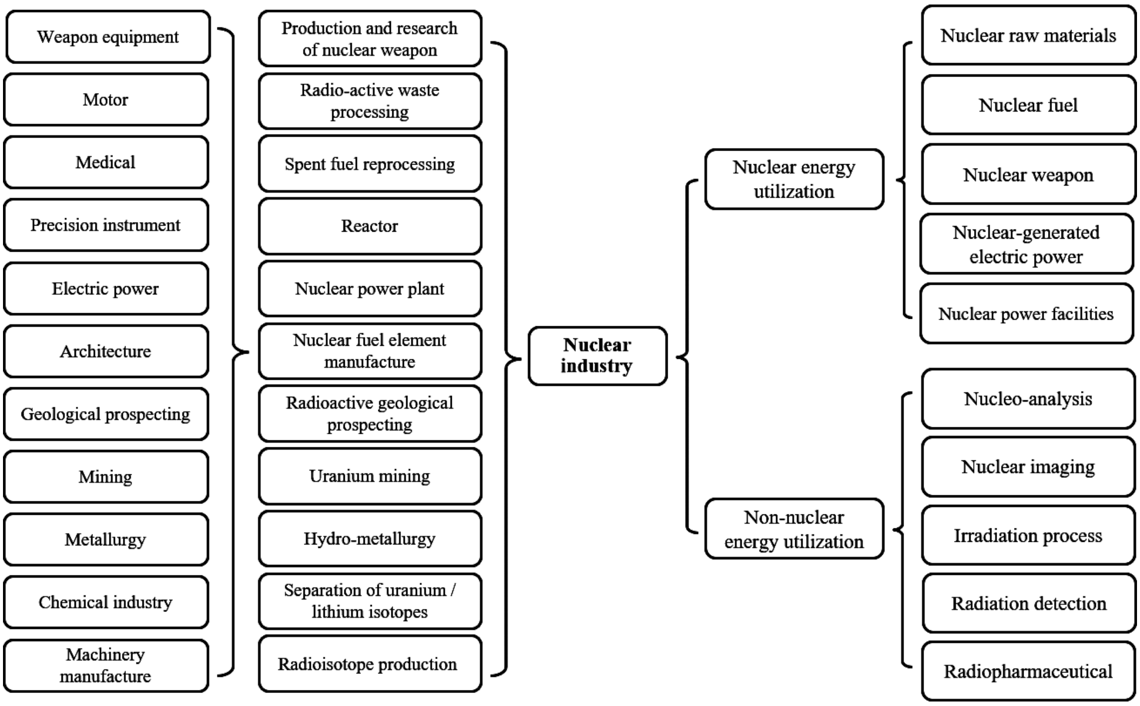


Fig. 1 Common application fields of the nuclear industry. The first column on the left represents the weapon equipment, motor, medical, chemical industry, and other disciplines involved in the nuclear industry. The second column on the left lists the manufacturers, as well as the Research and Development (R&D) institutions related to the nuclear industry. On the right side of the figure, nuclear industrial applications are divided into nuclear energy utilization and non-nuclear energy utilization. Among them, nuclear power converts nuclear energy into electric energy by controllable nuclear reaction belonging to nuclear energy utilization, and nuclear medical belongs to non-nuclear energy utilization.

With the promotion and development in the fields of nuclear power and nuclear medical, the nuclear industry has gradually formed a complete industrial chain structure, and its demand for intelligent manufacturing is becoming increasingly urgent. The utilization of Artificial Intelligence (AI)[9] technologies can improve the quality and efficiency of the nuclear industry production and reduce the operation cost at each operation stage of the nuclear industry chain[10]. Moreover, the nuclear industry will produce radioactive waste, and there is also the risk of nuclear energy leakage caused by the failure of nuclear reactor. The introduction of AI technologies can assist the nuclear spent fuel reprocessing, the treatment, storage, and disposal of the radioactive waste, as well as the accident relief of NPPs, so as to ensure the safe operation of the nuclear industry and reduce the risk of human operators to a great extent[11]. Furthermore, with the rapid development of AI technologies and their deep integration with manufacturing, aviation, military, medicine, transportation and so on, cross fields, such as smart city[12–14], intelligent transportation[15–17], intelligent medical system[18–20], industrial intelligence[21–23], have emerged like bamboo shoots after a spring rain. It is worth mentioning that Tsinghua University defines the "industrial intelligence" as the use of AI and other theories and methods to solve the technical problems of operation, management, research and development, production, and service in the process of industrial manufacturing*. The United States, Germany, China, and other countries have used AI technologies to realize industrial intelligence, in order to improve the competitiveness of national industry through industrial intelligence, so as to take the lead in the new round of the industrial revolution, i.e., the "Industry 4.0"[24–29].

The development of AI is inseparable from the accumulation of massive data and the increasing improvement of computing power, as well as the proposal and in-depth research of Neural Networks (NNs) methods[30–32]. In 2006, Hinton and Salakhutdinov[33] published the pioneering work of Deep Neural Networks (DNNs) in the journal *Science*, and put forward the concept of Deep Learning (DL), which set off an upsurge of academic research on

* https://www.au.tsinghua.edu.cn/kxyj/xkfx.htm.

DL. In 2015, Lecun, Bengio, and Hinton[34], the three giants of DL who won the Turing Award, published a review article on DL in the journal *Nature*, which further promoted the theoretical research and application development of DL. Moreover, the improvement of mass storage technology enables researchers to design large-scale network models and solve more complex problems. The emergence of high-performance Graphics Processing Unit (GPU) also greatly improves the speed of numerical and matrix operation, and significantly shortens the running time of DL algorithms[35]. At present, DL has made amazing achievements in Computer Vision (CV) tasks such as image classification and object detection[36, 37], Natural Language Processing (NLP) tasks such as natural language generation and machine translation[38, 39], speech recognition[40, 41], and multi-modal learning[42–46]. As an important technical means of AI, DL methods have also been widely used in the nuclear industry with the upsurge of industrial intelligence concept recently, and great progress has been made in theoretical research and application research in the field of the intelligent nuclear industry[30, 47–49].

As shown in Fig. 1, the complete nuclear industry chain is based on nuclear resources and integrates exploration, development, research, application, service, and so on. Nuclear fuel production, reactor construction, nuclear spent fuel reprocessing, nuclear weapon manufacturing, and other scenarios require system design, equipment manufacturing, construction, commissioning, and operation[1, 50]. It has the ability to standardize, serialize, mass produce, research, and develop a new generation of the intelligent nuclear industry. Therefore, applying DL technologies to all segments of the complete nuclear industry chain can promote the development of informatization, digitization, intelligence of the nuclear industry[51–53]. Among them, the nuclear power industry involves nuclear fuel supply, nuclear power equipment manufacturing, nuclear power engineering design and construction, nuclear power technical service and guarantee, nuclear spent fuel reprocessing, radioactive waste disposal, etc. Nuclear power is the most common nuclear industry system, and the most extensive application field of the nuclear industry combined with DL technologies[54–57].

In this paper, we first analyze the upstream, midstream, and downstream segments that are able to introduce intelligence in the whole industrial chain of nuclear power industry in Section 2. Among them, we describe the intelligent demand scenarios for AI in detail in Subsection 2.1. Then, we sort out the data types involved in each segment of the nuclear industry chain in Subsection 2.2. After that, we present the theoretical research status and application development of DL technologies in the nuclear industry chain corresponding to different data types in Section 3. Moreover, considering that nuclear medicine is quite different from the nuclear industry chain using nuclear energy, such as nuclear power, we also introduced the research status of DL in the field of nuclear medicine in Subsection 3.4. In Section 4, we discuss the limitations and unique challenges of DL in the nuclear industry and the future direction of the intelligent nuclear industry. Finally, we provide the conclusion in Section 5.

2 Nuclear Industry Chain

As the most common and complete nuclear industry system in the nuclear industry, the nuclear power industry chain involves all segments, such as mining, manufacturing, development, research, and processing, as well as requires a certain degree of supervision and capital investment in all segments[58]. Thus, deep learning can be applied to many segments of the nuclear power industry chain and generalized to other nuclear industries, so as to promote the development of the nuclear industry intelligence. Figure 2 shows the nuclear power industry chain with three basic segments, i.e., upstream, midstream, and downstream. Among them, the upstream segment is mainly nuclear fuel supply and raw material production, including the mining of natural uranium materials, nuclear fuel processing for manufacturing nuclear fuel elements, and nuclear fuel cycle. The midstream segment is mainly the manufacturing of nuclear power core components, mainly including nuclear island equipment, conventional island equipment, and auxiliary systems, as well as the manufacturing of corresponding instrument control. The downstream segment is mainly the design and construction, operation, as well as maintenance of NPPs. In addition, the downstream segment of the nuclear power industry chain also involves spent fuel reprocessing, which is closely related to the fuel cycle in the upstream segment of the nuclear industry chain[59].

2.1 Intelligent demands in nuclear industry

Aiming at the upstream, midstream, and downstream segments of the nuclear power industry chain, we

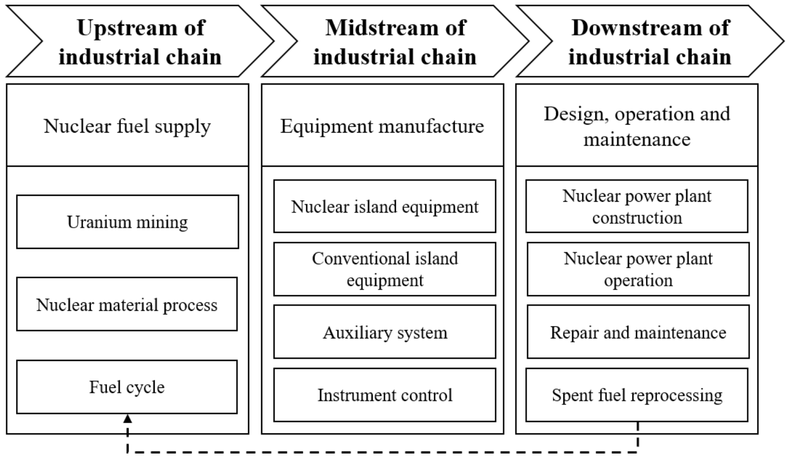


Fig. 2 Nuclear power industry chain with upstream, midstream, and downstream segments. Among them, the upstream segment is mainly nuclear fuel supply, the midstream is nuclear equipment manufacturing, and the downstream is nuclear power plant design, operation, and maintenance.

summarize some nuclear industry application scenarios that can introduce DL technologies as follows.

• **Upstream of nuclear industry chain.** In the nuclear fuel supply of upstream segment, the DL methods can be utilized to construct the knowledge graph related to the natural uranium[60, 61]. Then, the constructed knowledge graph is able to guide the organic combination and interconnection of natural uranium exploration, mining design, mine production, and other uranium mining links, so as to improve the exploration efficiency, reduce the mining time, and resolve the high-risk and high hazard elements in the mining process. In the nuclear material process link, the DL method can also be introduced to manage and analyze the massive processing data for the real-time monitoring and adjustment of processing equipment[62]. Furthermore, DL methods based on multi-objective optimization can be used to optimize the parameters of the processing operation for improving the yield and quality of nuclear fuel elements, as well as the manufacturing efficiency[63].

• **Midstream of nuclear industry chain.** In the nuclear equipment manufacturing of midstream segment, DL methods can be used to analyze and process the massive structured, unstructured, and semi-structured data generated by design, production, and operation of the nuclear island, conventional island, auxiliary system, and instrument control equipment, so as to provide intelligent analysis and decision-making system[64]. Moreover, in nuclear equipment manufacturing, high labor costs and low labor productivity exist side by side, and the working and operation environments of equipment production are difficult to control. Thus, the DL methods can be introduced to detection, classification, clustering, and other simple tasks that need a manual repeated operation.

• **Downstream of nuclear industry chain.** In the design and construction, operation, and maintenance of NPPs of downstream, DL methods can be introduced to create an integrated, digital, intelligent, and life-cycle NPPs platform. Moreover, a big-data analysis GPU computing platform based on DL can also be built to support a multi-physical field coupled and multi-parametric digital reactor design suite. In the operation and maintenance stage, special industrial robot embedded with DL models can be widely used to complete equipment regular inspection, environmental detection, underwater welding, emergency rescue, and other operations in hard-to-reach areas with strong radioactivity, so as to realize the long-term, safe, and economic operation of the nuclear industry[52, 65, 66]. In the spent fuel reprocessing stage, DL methods can be used to study the highly nonlinear relationship between operating conditions and uranium resource utilization efficiency, so as to realize the real-time optimization of operating parameters and improve the efficiency of spent fuel recycling.

In general, DL and other AI methods can be introduced into many links in the whole nuclear power industry chain to speed up the pace of the nuclear industry towards Industry 4.0[62, 67]. The most intuitive and common applications are to use various DL methods to manage, analyze, and predict the massive production data, operation data, external data, prediction data, and other big-data in the whole nuclear industry chain, so as to realize the data-driven intelligent decision analysis system, as well as assist nuclear power operators and researchers in the intelligent management of the whole nuclear industry chain.

2.2 Data types in nuclear industry chain

Recently, with the development of big-data technology and Internet of Things (IoT) applications, various data types will be involved in the whole nuclear industry chain. In addition to the basic data types (e.g., equipment data, industrial informatization data, and industrial chain related data), the user behavior data, social relationship data, periodic data collected by sensors, Internet data obtained by web crawlers, and other potentially meaningful data are covered in the nuclear industry chain. It is very necessary to effectively utilize and analyze these diversified data in the nuclear industry chain. As the most popular Machine Learning (ML) method studied and applied at present, DL technologies realize AI by Artificial Neural Network (ANNs)[33,34]. DL methods carry out feature extraction and expression through unsupervised, semi-supervised, and fully-supervised learning. The low efficiency and subjective problem of feature engineering in traditional ML methods, as well as the generalization dilemma of the single static model are solved well by DL methods[68]. Thus, DL methods have immeasurable application potential in the nuclear industry. Due to the deep mining of data values in the nuclear industry by DL methods, the development of data-driven intelligent innovation in the nuclear industry is unstoppable.

At the same time, more and more deep neural networks used to analyze different data types (e.g., image, video, text, speech, and multi-modal data) have been proposed with the deepening of deep learning research. Most DL models are based on Deep Belief Network (DBN)[69], Convolutional Neural Network (CNN)[70], Recurrent Neural Network (RNN)[71], Long Short-Term Memory (LSTM)[72], and General Advantageous Net (GAN)[73], etc. Variants of these models are widely used in CV, speech recognition, NLP, and other industrial applications, as well as achieve excellent results. As shown in Fig. 3, in order to more clearly and intuitively summarize the application research of deep learning in the whole nuclear industry chain, we first analyze the data types in the nuclear industry chain. Then, for each data type, we briefly introduce the development of deep learning in these data types and corresponding applications.

- **Graphic/image/video data.** In the construction and operation of the nuclear industry, it will involve traditional engineering drawings (e.g., designed computer aided design drawings), as well as a large number of images and video data for monitoring the operating environment and equipment working conditions. Because of powerful visual feature extraction ability, CNNs models have been widely used in the field of CV[34,74]. With the expansion of problem scale, more and more variants of CNNs (e.g., VGGNet, GoogLeNet, ResNet, DenseNet) have been proposed and successfully applied to object detection, semantic segmentation, image caption, and other complex CV application scenarios[36,75,76]. Applying CNNs-based models in the nuclear industry are able to quickly and effectively analyze the graphics, images, and videos, which can strengthen the automatic operation monitoring of key equipment and improve the safety of operation.

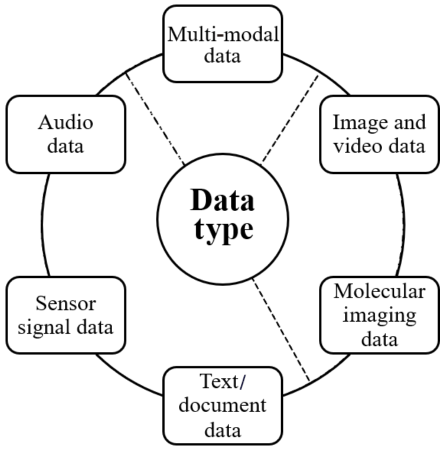


Fig. 3 Common data types of the nuclear industry chain. Among them, the audio data, sensor signal data, and text/document data can be divided into sequence data. The image and video data, and molecular imaging data belong to visual image data. The multi-modal data refers to data from multiple sources or forms.

- **Text/document data.** In the nuclear industry, text and document data (e.g., equipment parameters, professional references, and simulation data) are also often involved. The NLP technologies enable computers to understand the meaning of natural language. The LSTM and word2vec are successful in many simple NLP tasks, such as text classification. The transformer models[77] with attention mechanism make achievements in the natural language generation tasks, such as machine translation. After that, the Bert model[78] is designed to pre-train the unlabeled text data for deep feature representation. Then, the fine-tuned Bert model can achieve state-of-the-art results in various NLP tasks. Applying NLP technologies in the nuclear industry can model text/document data to make the computer have the ability to understand and analyze natural language, which can further realize the automation of the nuclear industry construction and the intelligent operation[79].

• **Audio data.** The nuclear industry has high requirements for safe management. The simulation of NPPs in the personnel training plan must reproduce the situation faced by operators in the actual operation. One purpose of the simulation is to support the design of new control systems or ergonomic evaluation of existing control systems, so as to improve man-machine interaction and operation safety[80]. When an abnormal situation occurs, the operators must quickly judge the accident situation from the corresponding variables and alarm indications. In these scenarios, the corresponding automatic speech recognition system can be developed based on DL to recognize speech commands and perform the required tasks without the manual intervention of the operator. Moreover, speech recognition can also be studied based on DL[81], so as to improve the security of management, as well as solve the problems of multi-level access control and industrial robot authentication.

• **Sensor sequence signal data.** The nuclear industry is composed of many complex components. Various sensors (e.g., humidity, gas, pressure, and temperature sensors) have been developed for online real-time monitoring of the operation state. The sensors' sequence signal data are sparse, but the frequencies are extremely high. In case of abnormal conditions, the parameters of the sensors will change dramatically. Most of the current nuclear safety management methods are based on the principle of "Detection-Response", i.e., the safety control systems make action responses only after abnormal conditions are detected. The principle makes the safety control system slow to feedback the reactor data and fail to make real-time decisions. On the other hand, the traditional statistical methods are difficult to solve the prediction problem of nonlinear processes in abnormal working conditions of the nuclear industry. For the data characteristics of sequence signals and the problem of the "Detection-Response" principle, DL methods can be designed to learn massive historical data and predict the trend of operating conditions. Then, the principle of "detection-response" can be changed as "prediction & advanced interfere", so as to solve the situation that "abnormal working conditions are inevitable" faced by passive control in the past[10]. Considering that both sensor signals and text data belong to sequence data, NLP technologies combined with context information are generally used to extract the feature of sequence data and apply to the safety prediction of the nuclear industry.

• **Multi-modal data.** In addition to the data type mentioned above, the nuclear industry chain also involves the structured data stored in a relational database, interface type data generated by information systems (e.g., TXT, JSON, and XML), audio and video data in an industrial environment, as well as other data (e.g., atmospheric flow field monitoring data, remote sensing information, and 3D elevation information). For these different modal data, the DL methods based on multi-modal learning are able to process and learn multi-source and multi-modal information, as well as analyze the states of systems, equipment, environment, and personnel in the nuclear industry from multiple angles[82, 83]. Compared with single-modal representation learning where information is expressed as numerical feature vector, the multi-modal learning aligns the features of different modes and eliminates the modes redundancy[84–86].

• **Molecular imaging data.** Nowadays, nuclear molecular imaging is the hot-spot of medical imaging technology. Due to the wide spectrum of biological targets, there are many kinds of molecular images. The PET, SPECT, optical imaging, and Magnetic Resonance Imaging (MRI) also increase the diversity of molecular images. With the rapid development and wide applications of DL technologies in biomedical data, more and more researchers pay attention to the DL technologies in the acquisition and interpretation of nuclear molecular imaging[87]. It is worth mentioning that it is difficult to collect large-scale molecular imaging data sets. In addition, DL is difficult to be applied to small-scale, multidimensional, and heterogeneous molecular imaging data. Recently, the proposals of small-sample learning and transfer learning make DL technologies achieve good results in the field of nuclear medicine[85, 88–90]. DL methods can be used to realize the image reconstruction, denoising, segmentation, and fusion of molecular imaging. Many researchers also use DL technologies to extract deep feature representation from molecular imaging to realize personalized medical treatment.

The above are some common data types in the whole nuclear industry chain. Among them, both graphics/images data and molecular imaging data belong to the visual image data. The CNNs models are often used for computer vision tasks, e.g., image classification, object detection, semantic segmentation. Thus, the CNN-based DL methods are often utilized for computer vision applications in the nuclear industry. Then, by the CNN-based DL methods, the safety management, operation, and maintenance of the nuclear industry, as well as nuclear medical diagnosis can be intelligent. Text/document data, sensor signal data, and audio data belong to sequence data. The RNN and LSTM are often used for signal processing and sequence feature extraction, which can be further used in intelligent operation and safety prediction of the nuclear industry. Multi-modal data not only includes all types of data mentioned above but also involves other structured or unstructured data. Using multi-modal learning, we can understand and use these complex data, so as to better serve the intelligent management of the nuclear industry.

3 Deep Learning in Nuclear Industry

As shown in Fig. 4, we introduce the research developments of deep learning in the nuclear industry from four fields, i.e., computer vision (Section 3.1), sequence data processing (Section 3.2), multi-modal learning (Section 3.3), and nuclear medicine (Section 3.4). Among them, text document data, audio data, and sensor signal data all belong to sequence data. Therefore, in the sequence data processing of Subsection 3.2, we introduce the research developments of NLP, speech recognition, and sensor sequence signal processing in the nuclear industry.

3.1 Computer vision in nuclear industry

Due to the special operating environment of the nuclear industry, the corrosion, fatigue, and wear problems of nuclear equipment are very serious. If these problems are not found and handled in time, it may affect the nuclear equipment construction, installation, operation, and other stages. It may even cause major potential safety hazards and huge economic losses to the nuclear industry. In 2011, a nuclear accident occurred in Fukushima, Japan, which was classified as the most serious Level 7 in the international nuclear event classification table[91]. The Fukushima nuclear accident in Japan sounds a safety alarm for all countries deploying nuclear programs. Among them, periodic inspection of equipment components[49] and prediction of Remaining Useful Life (RUL)[92] are important means and common ways to ensure the safe operation of the nuclear industry chain. However, there are many hard-to-reach areas with strong radioactivity in the working environment of the nuclear industry, which means that there are great potential safety hazards by manual periodic inspection. In addition, the working conditions of the nuclear industry are very complex, which makes the accurate inspection of equipment and prediction of RUL very difficult. Therefore, utilizing deep learning technologies to realize real-time automatic detection of equipment defects[49,93–95] and accurate prediction of RUL[96–98] is a key development direction for the nuclear industry to

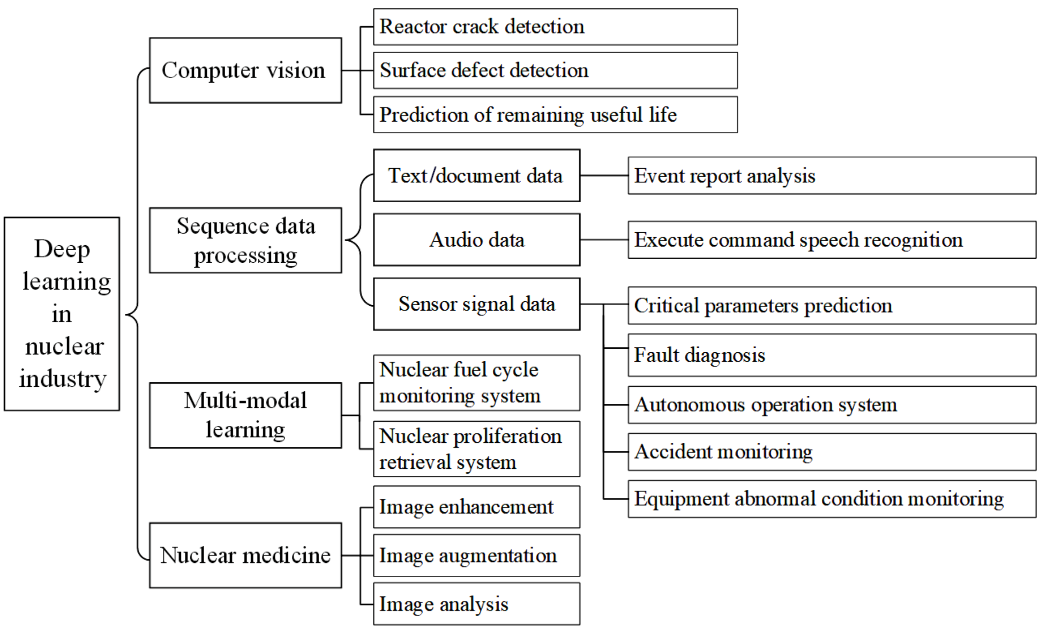


Fig. 4 Research status of deep learning in the nuclear industry. There are four research directions, i.e., computer vision, sequence data processing, multi-modal learning, and nuclear medicine. Among them, sequence data processing includes text document processing, audio processing, and sensor sequence signal processing.

improve operational efficiency and realize intelligent management.

The nuclear reactors are submerged in water to keep cool, and their high temperature and radiation hazards make it impossible to carry out direct manual periodic inspection of reactor components. Therefore, in the traditional regular inspection of reactor cracks, technicians generally conduct a remote review and manual detection on the video records of underwater reactors, which is time-consuming, cumbersome, and subjective[75]. With the development of AI, many crack detection methods of nuclear reactors based on traditional machine learning have been proposed[76, 99–102]. However, because the tiny cracks with low contrast and variant brightness are hardly visible, the crack detection methods based on machine learning often misreport non-crack traces such as scratches, welds, and wear marks[52]. Researchers carried out a series of researches on DL-based crack detection of nuclear reactors[52, 75, 102–104]. Specifically, in 2017, Chen and Jahanshahi[52] proposed a cracks detection method based on Naive Bayesian data fusion scheme and CNN (named NB-CNN) for nuclear reactors. The proposed NB-CNN method utilizes CNN to extract the visual features of individual video frames captured in nuclear reactor videos, and the naive Bayesian data fusion scheme to aggregate the information extracted from each video frame. The NB-CNN method achieves a 98.3% hit rate against 0.1 false positives per frame. In 2019, Chen and Jahanshahi[103] proposed an NB-FCN method based on Full Convolutional Networks (FCN) and Naive Bayes (NB) probability for detecting reactor cracks from inspection videos in real-time with high precision, which achieves 98.6% hit rate. Table 1 shows the comparison results of hit rate and processing times (T) of reactor crack detection methods based on machine learning and DL. Compared with LBP-SVM[99] based on traditional machine learning, NB-CNN[52] and NB-FCN[103] based on DL have a great improvement in the hit rate of reactor crack detection. Moreover, the NB-FCN[103] achieves the best performance on the processing times, and requires only 0.02 s for a 720×540 frame and 0.10 s for a 1920×1080 frame. Experiments demonstrate that the reactor crack detection methods based on DL take an important step towards accurate and real-time video processing for autonomous NPP inspection.

The Laboratory of Data Intelligence, Sichuan University, Chengdu, China, and Nuclear Power Institute of China (NPIC) also carried out DL technology researches on computer vision in the nuclear industry[49, 105]. They sorted out the equipment overhaul inspection reports and daily inspection reports of an NPP from 2014 to 2017. And, they screened 4446 images including 2039 defective equipment surface images and 2407 non-defective equipment surface images. They marked the category labels and locations of rust, peeling, blistering, and cracking on the defective equipment surface images. Based on the collected surface defect images data of nuclear equipment, Lang et al.[49] proposed a multi-scale feature fusion mechanism[106] to improve the deep visual features extraction ability, and a real-time defect detection method based on the fully convolutional one-stage object detector[107]. Most DL-based models are difficult to trade-off high performance and low power consumption, which limits their deployment and application in edge devices. Therefore, many current DL-based methods with high-performance fail to be directly applied to practical industrial application scenarios. In Ref. [49], Lang et al. introduced the knowledge distillation[108] to make a simple student network imitate the complex teacher network for model compression. The proposed method improves the defect detection accuracy and maintains high real-time performance, simultaneously. Figure 5 shows some results of the method proposed in Ref. [49] on surface defect detection of nuclear equipment. Moreover, Gao et al.[105] proposed an end-to-end edge detection method based on swin transformer[109] to realize intelligent analysis of high-temperature oxidation of zirconium alloy[110]. The proposed edge detection method can automatically detect the oxide film boundary of the microscopic image of zirconium alloy, as well as segment the α and β phases. Figure 6 shows the detection results of oxide film boundary and segmentation results of α phase and

Table 1 Comparison of hit rate and processing times of reactor crack detection methods based on machine learning and deep learning. "Hit rate + NB" refers to hit rate results of methods with Naive Bayes.

Method	Hit rate (%)	Hit rate+NB (%)	T (for frame 720×540) (s)	T (for frame 1920×1080) (s)
LBP-SVM[99]	69.0	79.0	1.87	12.58
NB-CNN[52]	93.8	98.3	2.55	17.15
NB-FCN[103]	94.8	98.6	0.02	0.10

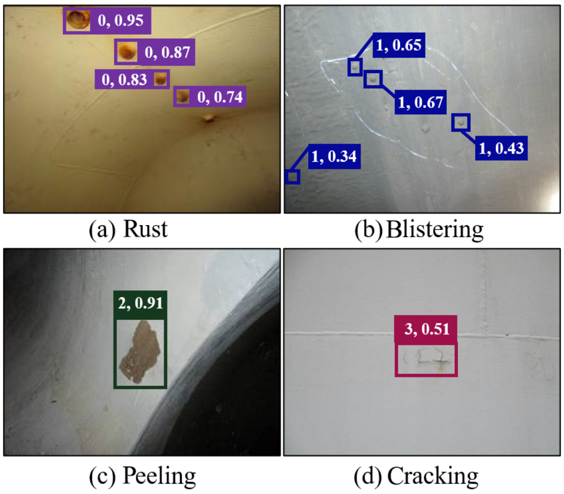


Fig. 5 Detection results of the surface defect detection method of nuclear equipment based on deep learning proposed in Ref. [49]. The two numbers next to each bounding box in four subfigures represent the defect category, where 0 is rust, 1 is blistering, 2 is spalling, and 3 is cracking, and the corresponding confidence, respectively.

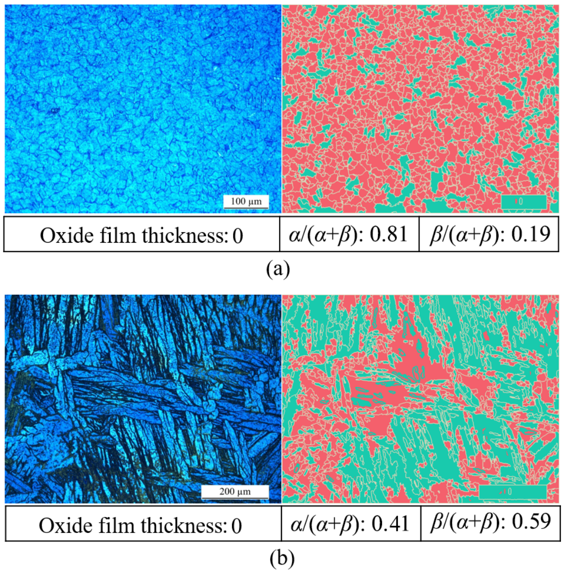


Fig. 6 Detection results of oxide film boundary and segmentation results of α phase and β phase by the edge detection method based on deep learning proposed in Ref. [105].

β phase by the edge detection method proposed in Ref. [105]. The images in the first column of Fig. 6 are the original microscopic image of zirconium alloy. The images in the second column of Fig. 6 are the semantic segmentation results, where the red blocks and green blocks are α phase and β phase, respectively. As shown in Fig. 6, we can see that the edge detection method based on DL proposed in Ref. [105] provides an effective technical means for material principal component analysis. In the future, this laboratory will further analyze the area of surface defects of the nuclear industry equipment by using DL-based semantic segmentation methods. By the intelligent analysis results, the operators can adopt different maintenance schemes for different degrees of defects, so as to realize long-term, safe, and economic operation management of the nuclear industry.

In addition to defect detection, risk assessment and monitoring of key components of equipment are also very important for the safe operation of the nuclear industry. The common risk assessment and monitoring methods are to avoid the failure of key components by RUL prediction[92, 97], so as to realize the safety and health management of the nuclear industry. Figure 7 shows the illustration of the RUL prediction†. The DL technologies with strong feature extraction capability are more and more widely used in RUL prediction of key components in the nuclear industry[96, 111, 112]. Key Subject Laboratory of Nuclear Safety and Simulation Technology, Harbin Engineering University, Harbin, China studied the RUL prediction of electric valves in NPPs based on DL models[96, 111, 112]. The aging and degradation of electric valves are mostly caused by the uneven lattice of valve body, uneven fluid impact, fluid corrosion effect, and radioactive material irradiation[97]. Wang et al.[96, 111, 112] made some reasonable assumptions and approximate design for the aging parts of electric valves by adjusting the tightness of screws, referring to the experimental process and data collection method of simulating valve aging proposed in Ref. [113]. Then, considering the sequential characteristics, they pre-processed and reshaped the original 2D image data collected to 3D stacked data block. In addition, Ref. [96] also introduced signal acquisition devices, e.g., acoustic emission sensor, pressure sensor, temperature sensor, and flow sensor, to obtain rich relevant features. Based

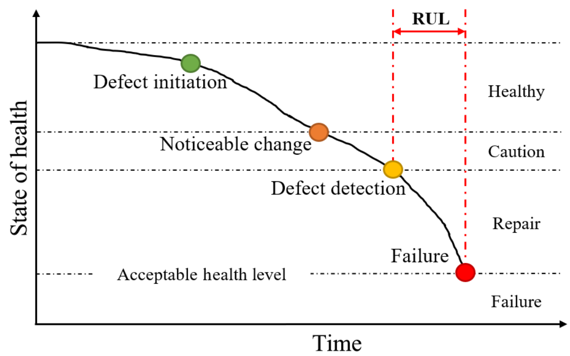


Fig. 7 Illustration of the RUL.

† https://medium.com/it-paragon/remaining-useful-life-predictive-maintenance-5b78a17f7d10.

on the previous pre-processing works, Wang et al.[111] proposed DL methods based on LSTM with convolution kernel, improved temporal convolutional network[96] and Convolutional Auto-Encoder (CAE)[112], to extract the sequential visual features of electric valves, so as to realize the prediction of RUL. Experiments demonstrate that these DL-based methods can predict RUL more accurately and quickly than other typical machine learning methods. In the future, the DL-based methods can be broader applied in other critical components, and the maintenance efficiency of all nuclear industries will be further improved.

3.2 Sequence data processing in nuclear industry

In the whole nuclear industry chain, sequence data include text document data, such as event reports, audio data, and sensor sequence signal data. Among them, the signal data generated by various sensors are the most common sequence data. The researches of DL in the field of sequence data processing in the nuclear industry mostly focus on analyzing and processing all kinds of sequence data using NLP technologies, e.g., LSTM, for prediction and classification.

In terms of text document data in the nuclear industry, DL models can be used for analysis of event reports. In the nuclear industry, there are a large number of event reports generated by licensed employees. The comprehensive analysis of the reports can provide valuable insights into the safe operation of the nuclear industry equipment. However, the extensive event reports in various text formats pose a great challenge to the comprehensive analysis. Based on the Stanford's CoreNLP API[114], Zhao et al.[115] proposed a rule-based expert system called Causal Relationship Identification (CaRI), to identify the causal relationship between events by analyzing the abstract section of the reports from the U.S. Nuclear Regulatory Commission Licensee Event Report database[116]. Experiments on the CaRI system show that most causality relationships can be captured and analyzed automatically.

In terms of audio data in the nuclear industry, DL models can be used for speech recognition in the man-machine interaction interface of the nuclear industry control platform. Previously, the operators could only interact with the virtual physical console through the computer keyboard and mouse to simulate the judgment of abnormal conditions and the identification of alarm indications in the actual operation process. Jorge et al.[80] developed an automatic speech recognition system and integrated it into the man-machine interaction interface of developing virtual NPP console. The developed automatic speech recognition system can be used for command execution in the control room, as well as navigation and interaction in the virtual environment. In the pre-processing stage of the developed automatic speech recognition system, Jorge et al.[80] utilized the cepstrum analysis[117] to extract relevant parameters from speech signals for isolated words recognition. Then, the isolated words were input into the Feedforward Neural Network (FNN) for automatic speech recognition. Moreover, Jorge et al.[118] also introduced other DL models for automatic speech recognition system. They proposed an automatic speech recognition system based on deep FNN and General Regression Neural Network (GRNN). By these developed automatic speech recognition systems, the operators can navigate and operate the virtual console in front of the computer display or projection screen through voice commands without manual intervention, such as keyboard and mouse. In the application of speaker recognition, Ramgire and Jagdale[119] proposed a speech control pick and placed robotic arm with a flexiforce sensor. They introduced Mel-Frequency Cepstrum Coefficients (MFCC) algorithm to extract features for speech recognition and speaker recognition. Then, the speaker automatic recognition can be used for security authentication, and speech automatic recognition can be used for machine control. With the development of DL technologies, many effective speech recognition models and speaker recognition models are proposed and make remarkable achievements[40,41]. The researches mentioned above provide a potential application field for speech recognition and speaker recognition based on DL in the nuclear industry.

In terms of sensor sequence signal data in the nuclear industry, DL models are often used in the processing and analysis of sequence signals to realize the intelligent diagnosis and prediction of various sensor abnormalities. The operating conditions of the nuclear industry are changeable and complex. When devices in the nuclear industry fail, there will be a large number of alarm parameters. The prediction of key parameter values can help operators judge the changing trend of system parameters in advance and then effectively improve system security. Chen et al.[120] proposed an LSTM-based model for predicting critical parameters of NPP. Chen et al.[121] proposed a fault diagnosis method of NPP based on Deep Belief Network (DBN), which is trained on numerous original time-domain signal data of process parameters in NPPs. Moreover, Lee et al.[122] proposed an autonomous operation algorithm based on LSTM and Function-based Hierarchical Framework (FHF) for NPP safety systems. The proposed autonomous operation algorithm has a superior ability to monitor, control, and diagnose nuclear safety systems. In the accident monitoring, She et al.[123] proposed a DL model based on LSTM to predict the abnormal working conditions of the nuclear industry safety system. The proposed model makes full use of the advantages of LSTM for long-time sequence data processing and realizes the prediction of core parameters under abnormal working conditions through historical operation dataset and rolling update training method. The experimental results show that the LSTM-based model proposed in Ref. [123] is able to effectively predict the changing trend of core parameters under accident conditions. At the same time, in the simulation condition prediction of small Loss Of Coolant Accident (LOCA), the accurate condition trend prediction for the same kind of accident shows the good generalization ability of the LSTM-based method. Radaideh et al.[124] proposed a prediction model based on deep FNN and LSTM to predict coolant failure accidents for safe operation monitoring of NPP. They simulated extensive sequence data of four key sensors, i.e., temperature, pressure, flow rate, and water level sensor. Then, they used the DL methods to model the NPP accident, so as to help the operators grasp the accident situation quickly and accurately. Moreover, Choi and Lee[125] proposed an LSTM-based sensor error detection model for an emergency situation, e.g., reactor trip, which can immediately detect sensor errors and specify the particular sensor with errors. In the equipment abnormal condition monitoring, Zhang et al.[126] proposed a state prediction method based on LSTM for state monitoring of main pump winding temperature, which is an important parameter reflecting the operating state of nuclear power devices. They utilized a large number of sequence data collected by the sensing and detection system for model training and took the steam pressure sensing data collected by the real-time parameter system of an NPP as the test object. The excellent prediction performance of the proposed model verifies the applicability of the DL-based method in the field of the nuclear industry operation safety assurance. Mandal et al.[127] also proposed an online fault detection and classification method based on DBN for thermocouples monitoring in NPPs, and validated its performance by composite statistical hypothesis test on field data obtained from thermocouple sensors of the fast breeder test reactor. Liu et al.[128] proposed an outlier detection strategy based on Bayesian hypothesis testing, and established the signal prediction model based on LSTM for mechanical condition anomaly monitoring of pump station and nuclear power turbine. In addition, Wang et al.[129] proposed a real-time intelligent prediction method based on Back Propagation (BP) neural network. The proposed method can be used for the real-time prediction of nuclear critical safety parameters in the nuclear fuel reprocessing, so as to rapidly evaluate the operation status and safety performance of the processing system. The prediction accuracy of the proposed method is more than 99%, and the calculation speed is more than 2000 times faster than that of traditional simulation method.

As shown in Fig. 8, there are many applications of DL models, e.g., LSTM, FNN, and DBN, in sensor

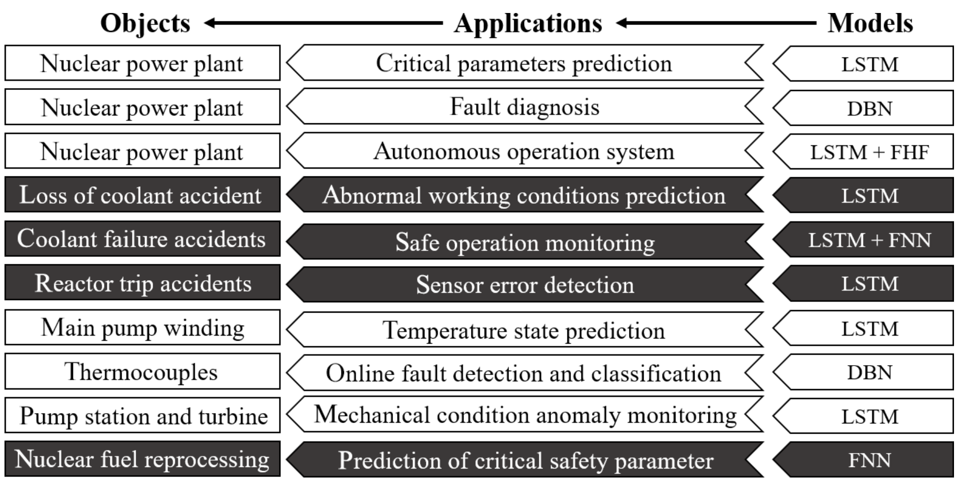


Fig. 8 Sensor sequence signal data processing based on deep learning in the nuclear industry.

sequence signal data processing in the nuclear industry, which can be roughly divided into four categories, i.e., critical parameters prediction, fault diagnosis, accident monitoring, and equipment abnormal condition monitoring. These important explorations of DL-based methods in the related fields of sequence data processing in the nuclear industry have broad application scenarios, and have great referential significance for the application of AI in the industry.

3.3 Multi-modal learning in nuclear industry

The Additional Protocol approved in 1997 introduced the use of commercial satellite imagery to verify nuclear materials and facilities against use in clandestine military activities. Specifically, the commercial satellite imagery can verify the information provided by countries involved in nuclear researches, and observe changes in facility activities during the nuclear fuel cycle, so as to identify undeclared activities[130]. The Cube Satellites (CubeSats) equipped with abundant sensors and data analysis capabilities, proposes a multi-modal global monitoring method to predict and describe the local surface of the earth on demand. It is worth mentioning that most of the data analysis technologies are based on DL models. Then, based on the CubeSats, Mendoza et al.[130] proposed a new data analysis method based on multi-modal DL models, and developed a corresponding monitoring system for phenomena related to the nuclear fuel cycle. Once a sensor on the CubeSats collects the data of target, the on-board computer will apply the feature extraction method based on multi-modal DL models before transmitting the information to the ground station. The DL-based data analysis capability attached to CubeSats can quickly detect the potential sensitive phenomena and reduce the pressure of data transmission. In the phenomenon detection tasks, the recall rate of the proposed DL-based analysis method is between 89.7% and 99.3%, and the accuracy is between 92.3% and 99.9%. However, with the increase of available data, the ability of the system to analyze data becomes very tight. In order to meet this challenge faced by nuclear non-proliferation analysts, Feldman et al.[131] proposed a large-scale multi-modal retrieval system based on DL models to help nuclear non-proliferation analysts search open-source scientific, technical, and news data, as well as find indicators of nuclear proliferation capabilities and activities. The proposed multi-modal retrieval system relies on a set of trained DNNs to evaluate the conceptual similarity of data patterns, e.g., text, image, and video. Then, according to the nuclear fuel cycle process template, these DNNs can map conceptually related words, sentences, and images to adjacent points in the multi-modal feature space, and realize the intra-modal and inter-modal retrieval of seed query points through nearest neighbor algorithm. The quantitative and qualitative results for text-to-image, image-to-image, and image-to-video retrievals on nonproliferation-specific multi-modal data sets verify the effectiveness of the DL-based multi-modal retrieval method proposed in Ref. [131].

3.4 Deep learning in nuclear medicine

In the nuclear medicine community, there are several essential topics, i.e., improvement of images quality, image processing, image augmentation, and image analysis. In terms of nuclear medicine molecular image reconstruction, many DL models, e.g., CNN and FNN, have been used to improve PET image resolution and improve the noise characteristics of PET scanners with large pixel crystals[89]. Similar works have been done in Refs. [90, 132], and they also integrated the DNNs models into the iterative process of image reconstruction to improve the final image quality. Moreover, the DL methods for attenuation correction and registration in PET/CT and PET/MR have also been proposed in Refs. [133–135], and the experimental results proved that these DL methods can generate high-precision attenuation maps. In terms of image denoising and other image processing, a large number of DL methods have also been proposed for the generation of full-dose PET images based on low-dose images[136]. In addition, there are some researches devoting to solving the problem of limited number of molecular images. On the one hand, the full-scale molecular images are cut into multiple image blocks through semantic cutting method based on DL models[87, 137]. On the other hand, there are also studies on data expanding by data enhancement technologies, e.g., image rotation and flipping[138, 139]. In terms of image analysis, more and more methods based on DL models have been proposed to realize the automatic and high-precision detection and classification of lesion objects in molecular images. Wang et al.[140] utilized the AlexNet[141] as the image feature extraction model to distinguish mediastinal lymph node metastasis of lung cancer from PET/CT of FluoroDeoxyGlucose (FDG). Moreover, the automatic lesion detection and segmentation methods based on DL frameworks[142, 143] lay a theoretical foundation for the development of DL-based automatic solutions for nuclear medicine. As a data-driven AI method, DL technologies learn features of data through model training, and their decision-making processes can be completed with minimal human-computer interaction. Therefore, DL technologies are very suitable for the field of nuclear medicine related to radiology, especially in the hot issues of cancer imaging. Noting that relevant research publications on radionics and DL increase sharply in recent years[144].

4 Future of Intelligent Nuclear Industry

Although DL technologies have made impressive achievements in many links of the whole nuclear industry chain, the theory and application of DL in the nuclear industry still need to be further explored and developed. On the one hand, current DL technologies mainly focus on theoretical research and application exploration in the fields of image processing and NLP. However, the data structures generated in the nuclear industry are extremely different from the familiar data structures. In addition, data collection and annotation in special fields have always been great challenges. Thus, there are still many difficulties and problems to be solved in applying DL technologies directly to the corresponding fields of the nuclear industry. On the other hand, the nuclear industry attaches great importance to safety and environmental protection, so there are high requirements for the accuracy, fault tolerance, interpretability, and real-time performance of the algorithm. However, there is still a lot of space to explore the interpretability of the existing DL methods, which poses a challenge to the credibility of key control and decision-making in the nuclear industry.

It is worth mentioning that many corresponding methods have been proposed to solve the shortcomings of DL, and experiments have proved the effectiveness of these methods. For example, the previous DL models deal with a relatively single data type, which can not fully mine the useful information hidden between different data types. The proposals of multi-modal learning[86] make full use of the information of different modes. Moreover, the amount of data required for the DNNs training is large, but the cost of obtaining and labeling training data samples is very high, especially in special scenarios, e.g., the nuclear industry. The proposals of small-sample learning, few-shot learning, and zero-shot learning[88, 145, 146] enable the neural network model to obtain a learning ability of knowledge transfer after learning a small amount of data. In addition, the proposals of incremental learning[147] allow the neural network models to have the ability to continuously acquire and adjust, as well as learn novel data, so as to realize the dynamic change ability of the model to deal with environmental changes. These technological developments of DL have brought more research ideas and application possibilities for the intelligent development of the nuclear industry, and DL will continue to deepen in the field of the nuclear industry. Next, we list some future development trends of DL in the whole nuclear industry chain:

- **DL for the upstream link of the nuclear industry chain.** The upstream link of the nuclear industry chain mainly involves the supply of nuclear fuel. DL technologies are able to be used to process and deeply analyze the multi-dimensional and heterogeneous data generated in the process of nuclear fuel mining and processing. DL methods have strong representation ability and excellent fitting ability in dealing with the big data analysis problems with challenges, e.g., multi-modality, high sparsity, low similarity, feature redundancy, dimensional disaster, and so on. Therefore, DL technologies are very suitable for this kind of multi-objective optimization tasks in nuclear fuel mining and processing, so as to improve the efficiency of the processes of uranium exploration and nuclear fuel processing, as well as reduce the risk, simultaneously.
- **DL for the middle link of the nuclear industry chain.** In the nuclear equipment manufacturing link in the middle of the nuclear industry chain, special robots can be developed based on DL technologies to realize the automatic manufacturing operation of the nuclear island, conventional island, auxiliary system, and other equipment. Especially in some high-precision and high-difficult production processes, fine robots can be used to replace people's work. The DL-based special robots can not only achieve high quality and high yield, high-speed stability, safety, and reliability, and save materials, but also achieve the precision that is difficult to be completed by manpower, so as to liberate people from tension and difficulties. The introduction of DL technologies is expected to comprehensively improve the efficiency and quality of robots dealing with complex and diverse tasks in complex unstructured environment, as well as promote the roboticization and automation of the nuclear industry robotics and nuclear equipment manufacturing technology.
- **DL for the downstream link of the nuclear industry chain.** The downstream link of the the nuclear

industry chain mainly involves the design, operation, and maintenance of the nuclear industry. DL technologies can be used to realize the intelligent operation and management with few or even no people in the nuclear industry process. The nuclear leakage accident in Fukushima, Japan, has always reminded us that the safety of the nuclear industry is very important. On the one hand, in the process of construction, operation, and maintenance, various data in the process can be collected. Then, the intelligent analysis can be carried out by using artificial intelligence technologies such as DL models, so as to carry out intelligent safe operation management in each nuclear industry process. On the other hand, with a large number of NPP reaching the retirement age and the urgent demand for land resources due to population growth, how to realize the reuse of retired nuclear facilities and the reprocessing of spent fuel has become an issue of great concern to the nuclear industrial powers all over the world. The introduction of DL technologies and robotics in Nuclear Facility Decommissioning and nuclear fuel cycle operation will greatly reduce the risk of human operators, improve the efficiency and reliability of operation in the nuclear technologies environment, as well as provide a safer and reliable solution for Nuclear Facility Decommissioning and nuclear fuel cycle.

• **DL for nuclear medicine.** In the field of nuclear medicine, DL technologies can be combined to simulate and predict nuclear medicine related experiments, so as to promote the common development of nuclear medicine and artificial intelligence. The DL methods can also be used for intelligent diagnosis of PET, SPECT, and other molecular images. In addition, the DL methods can be used to predict the mutation results of virtual seed DNA in radiation breeding, and then carry out the verification of real experiments after obtaining the desired results, which will help to control the cost, speed up the experimental process, and effectively reduce the workload of experimental personnel.

• **Special DL technologies for nuclear industry.** Special neural network models and learning algorithms for the nuclear industry are also the development trends. Taking the CNNs in DL field as an example, the CNNs are easy to fail under the small disturbance, and the misjudge the images that could have been correctly classified with high accuracy. However, in the field of the nuclear industry, safety is very important. Therefore, it is necessary to study the deep neural networks dedicated to the nuclear industry to ensure the robustness of the DL models in the special application environment of the nuclear industry and the stability of the model against attack samples. In addition, the data generated by some equipment in the field of the nuclear industry is limited, and some data are generated continuously. Directly using some existing learning algorithms often can not converge the model well. Therefore, it is also necessary to carry out frontier research such as small-sample learning, zero-shot learning, continuous learning, and incremental learning in the field of the nuclear industry application.

• **Solution of differential and partial differential equations based on DL technologies.** It is worth mentioning that using deep neural networks to solve the differential and partial differential equations is also the current development hot-spot. The whole industrial chain of the nuclear industry involves the solution of many differential and partial differential equations, such as electromagnetic hydrodynamics, chemical hydrodynamics, dynamic meteorology, ocean dynamics, groundwater dynamics and so on. Solving differential equations is a very difficult and time-consuming work, especially the solution of partial differential equations involving high-dimensional derivation in nuclear reactors. Using the DL methods to solve the differential equations involved in the whole nuclear industry chain can effectively solve the rapid solution of the differential equations in the high-dimensional case, and ensure the accuracy of the final results. Moreover, using deep neural networks to solve differential equations and partial differential equations is not only a development trend of deep learning theory, but also a hot application direction of deep learning method in industrial intelligence and other cross fields involving physics or mathematics. We believe that many other frontier researches of DL technologies will also intersect with the nuclear industry, so as to promote each other's development to a great extent.

5 Conclusion

The fourth generation industrial revolution (Industry 4.0) with the application of a new generation of information technology in the industrial field as the core technology driving force is quietly coming. With the development and progress of the nuclear industry in recent years, as well as the development of AI, big data, cloud computing, IoT, and 5G technologies, the development of digitization, informatization, networking, and intelligence of the nuclear industry has become an inevitable trend. Based on the most common and complete nuclear power industry chain in the nuclear industry, this paper excavates the application scenarios of intelligent demand in the upstream, middle, and downstream links of the whole nuclear industry chain, and further analyzes the data types in these demand scenarios. Then, aiming at the graphics, images, video data, text document data, voice data, sensor sequence signal data, multi-modal data, and molecular image data in the field of nuclear medicine, the research statuses of the corresponding applications of deep learning in the field of the nuclear industry, such as computer vision, sequence signal processing, multi-modal learning, and intelligent nuclear medicine, are summarized. It can be found that DL technologies play an important role in the intellectualization of R&D and design, production and manufacturing, operation and maintenance management of the nuclear industry. In addition, combined with the development trend of DL and the industrial characteristics of the nuclear industry, this paper puts forward the future development trend of DL technologies in the whole industrial chain of the nuclear industry. It is believed that with the continuous promotion of intelligent manufacturing and the in-depth development of DL technologies, DL technologies are expected to fully penetrate the whole industrial chain of the nuclear industry, and the nuclear industry intelligence will also usher in major development opportunities.

Acknowledgment

This work was supported in part by the State Key Program of National Science Foundation (No. 61836006), the National Natural Science Fund for Distinguished Young Scholar (No. 61625204), the National Natural Science Foundation of China (Nos. 62106161 and 61602328), as well as the Key Research and Development Project of Sichuan (No. 2019YFG0494).

References

[1] N. Egel and R. L. Hines, Chinese views on nuclear weapons: Evidence from an online survey, *Res. Polit.*, vol. 8, no. 3, p. 20531680211032840, 2021.

[2] FCCC, *Report of the Conference of the Parties to the United Nations Framework Convention on Climate Change (21st Session, 2015: Paris)*. Geneva, Switzerland: FCCC, 2015.

[3] F. H. Zhu, Y. S. Wang, Z. Xu, J. Z. Li, Y. H. Dong, H. Li, X. L. Li, Y. Hu, X. L. Sun, and Y. Ding, Research on the development path of carbon peak and carbon neutrality in China's power industry, (in Chinese), *Electric Power Technol. Environ. Prot.*, vol. 37, no. 3, pp. 9–16, 2021.

[4] R. J. Woods and A. K. Pikaev, *Applied Radiation Chemistry: Radiation Processing*. New York, NY, USA: John Wiley & Sons, 1993.

[5] Z. Zimek, G. Przybytniak, and I. Kaluska, Radiation processing of polymers and semiconductors at the institute of nuclear chemistry and technology, *Nukleonika*, vol. 51, no. S1, pp. S129–S132, 2006.

[6] P. E. Christian and K. M. Waterstram-Rich, *Nuclear Medicine and PET/CT: Technology and Techniques*. St. Louis, MO, USA: Mosby, 2007.

[7] W. W. Lie, B. Jiang, and W. J. Zhao, Obstetric imaging diagnostic platform based on cloud computing technology under the background of smart medical big data and deep learning, *IEEE Access*, vol. 8, pp. 78265–78278, 2020.

[8] C. Aktolun, Artificial intelligence and radiomics in nuclear medicine: Potentials and challenges, *Eur. J. Nucl. Med. Mol. Imaging*, vol. 46, no. 13, pp. 2731–2736, 2019.

[9] S. Russell, Artificial intelligence: The future is superintelligent, *Nature*, vol. 548, no. 7669, pp. 520–521, 2017.

[10] X. Q. Yang, J. Guo, H. Tang, and Z. Liao, Application prospect analysis of big data and artificial intelligence in the field of nuclear industry, (in Chinese), *Inf. Commun.*, vol. 2, pp. 266–268, 2020.

[11] Z. Y. Kong, Development trend of robot application in nuclear industry, (in Chinese), *At. Energy Sci. Technol.*, vol. 14, no. 5, pp. 645–649&625, 1980.

[12] K. Zhang, J. B. Ni, K. Yang, X. H. Liang, J. Ren, and X. S. Shen, Security and privacy in smart city applications: Challenges and solutions, *IEEE Commun. Mag.*, vol. 55, no. 1, pp. 122–129, 2017.

[13] J. Mabrouki, M. Azrour, D. Dhiba, Y. Farhaoui, and S. El Hajjaji, IoT-based data logger for weather monitoring using arduino-based wireless sensor networks with remote graphical application and alerts, *Big Data Mining and Analytics*, vol. 4, no. 1, pp. 25–32, 2021.

[14] A. Guezzaz, Y. Asimi, M. Azrour, and A. Asimi, Mathematical validation of proposed machine learning classifier for heterogeneous traffic and anomaly detection, *Big Data Mining and Analytics*, vol. 4, no. 1, pp. 18–24, 2021.

[15] J. P. Zhang, F. Y. Wang, K. F. Wang, W. H. Lin, X. Xu, and C. Chen, Data-driven intelligent transportation systems: A survey, *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 4, pp. 1624–1639, 2011.

[16] L. Figueiredo, I. Jesus, J. A. T. Machado, J. R. Ferreira, and J. L. M. De Carvalho, Towards the development of intelligent transportation systems, in *Proc. ITSC 2001. 2001 IEEE Intelligent Transportation Systems*, Oakland, CA, USA, 2001, pp. 1206–1211.

[17] Y. N. Malek, M. Najib, M. Bakhouya, and M. Essaaidi, Multivariate deep learning approach for electric vehicle speed forecasting, *Big Data Mining and Analytics*, vol. 4, no. 1, pp. 56–64, 2021.

[18] J. H. Kamdar, J. J. Praba, and J. J. Georrge, Artificial intelligence in medical diagnosis: Methods, algorithms and applications, in *Machine Learning with Health Care Perspective*, V. Jain, J. M. Chatterjee, eds. Springer, 2020, pp. 27–37.

[19] W. L. Bi, A. Hosny, M. B. Schabath, M. L. Giger, N. J. Birkbak, A. Mehrtash, T. Allison, O. Arnaout, C. Abbosh,

I. F. Dunn, et al., Artificial intelligence in cancer imaging: Clinical challenges and applications, *CA: Cancer J. Clin.*, vol. 69, no. 2, pp. 127–157, 2019.

[20] K. K. Singh and A. Singh, Diagnosis of COVID-19 from chest X-ray images using wavelets-based depthwise convolution network, *Big Data Mining and Analytics*, vol. 4, no. 2, pp. 84–93, 2021.

[21] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, Intelligent manufacturing in the context of industry 4.0: A review, *Engineering*, vol. 3, no. 5, pp. 616–630, 2017.

[22] G. Lampropoulos, K. Siakas, and T. Anastasiadis, Internet of things (IoT) in industry: Contemporary application domains, innovative technologies and intelligent manufacturing, *Int. J. Adv. Sci. Res. Eng.*, vol. 4, no. 10, pp. 109–118, 2018.

[23] J. Mabrouki, M. Azrour, G. Fattah, D. Dhiba, and S. El Hajjaji, Intelligent monitoring system for biogas detection based on the internet of things: Mohammedia, morocco city landfill case, *Big Data Mining and Analytics*, vol. 4, no. 1, pp. 10–17, 2021.

[24] J. W. Veile, D. Kiel, J. M. Müller, and K. I. Voigt, Lessons learned from industry 4.0 implementation in the German manufacturing industry, *J. Manuf. Technol. Manage.*, vol. 31, no. 5, pp. 977–997, 2019.

[25] J. Habánik, A. Grencíková, and K. Krajco, The impact of industry 4.0 on the selected macroeconomic indicators in Slovak republic, Germany, the USA and Japan, *J. Int. Stud.*, vol. 14, no. 2, pp. 26–37, 2021.

[26] J. M. Müller and K. I. Voigt, Sustainable industrial value creation in SMEs: A comparison between industry 4.0 and made in China 2025, *Int. J. Precis. Eng. Manuf.-Green Technol.*, vol. 5, no. 5, pp. 659–670, 2018.

[27] L. Jay, X. Li, Y. M. Xu, S. J. Yang, and K. Y. Sun, Recent advances and prospects in industrial AI and applications, (in Chinese), *Acta Automat. Sin.*, vol. 46, no. 10, pp. 2031–2044, 2020.

[28] T. Y. Chai, Development directions of industrial artificial intelligence, (in Chinese), *Acta Automat. Sin.*, vol. 46, no. 10, pp. 2005–2012, 2020.

[29] Y. Yuan, Y. Zhang, and H. Ding, Research on key technology of industrial artificial intelligence and its application in predictive maintenance, *Acta Automat. Sin.*, vol. 46, no. 10, pp. 2013–2030, 2020.

[30] Y. Yu, M. Li, L. L. Liu, Y. H. Li, and J. X. Wang, Clinical big data and deep learning: Applications, challenges, and future outlooks, *Big Data Mining and Analytics*, vol. 2, no. 4, pp. 288–305, 2019.

[31] J. C. Lv, M. Ye, and Z. Yi, Convergence analysis for Oja+ MCA learning algorithm, in *Proc. Int. Symp. on Neural Networks*, Dalian, China, 2004, pp. 810–814.

[32] J. C. Lv and Z. Yi, Convergence analysis of Chauvin's PCA learning algorithm with a constant learning rate, *Chaos, Solitons Fractals*, vol. 32, no. 4, pp. 1562–1571, 2007.

[33] G. E. Hinton and R. R. Salakhutdinov, Reducing the dimensionality of data with neural networks, *Science*, vol. 313, no. 5786, pp. 504–507, 2006.

[34] Y. LeCun, Y. Bengio, and G. Hinton, Deep learning, *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[35] S. Moazemi, Z. Khurshid, A. Erle, S. Lütje, M. Essler, T. Schultz, and R. A. Bundschuh, Machine learning facilitates hotspot classification in PSMA-PET/CT with nuclear medicine specialist accuracy, *Diagnostics*, vol. 10, no. 9, p. 622, 2020.

[36] K. M. He, X. Y. Zhang, S. Q. Ren, and J. Sun, Deep residual learning for image recognition, in *Proc. 2016 IEEE Conf. Computer Vision and Pattern Recognition*, Las Vegas, NV, USA, 2016, pp. 770–778.

[37] R. Girshick, Fast R-CNN, in *Proc. IEEE Int. Conf. Computer Vision*, Santiago, Chile, 2015, pp. 1440–1448.

[38] T. Mikolov, K. Chen, G. Corrado, and J. Dean, Efficient estimation of word representations in vector space, arXiv preprint arXiv: 1301.3781, 2013.

[39] I. Sutskever, O. Vinyals, and Q. V. Le, Sequence to sequence learning with neural networks, in *Proc. 27th Int. Conf. Neural Information Processing Systems*, Montreal, Canada, 2014, pp. 3104–3112.

[40] F. Seide, G. Li, and D. Yu, Conversational speech transcription using context-dependent deep neural networks, in *Proc. of Twelfth Annual Conference of the International Speech Communication Association*, Florence, Italy, 2011, pp. 437–440.

[41] G. E. Dahl, D. Yu, L. Deng, and A. Acero, Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition, *IEEE Trans. Audio, Speech, Lang. Process.*, vol. 20, no. 1, pp. 30–42, 2012.

[42] K. Xu, J. L. Ba, R. Kiros, K. Cho, A. Courville, R. Salakhutdinov, R. S. Zemel, and Y. Bengio, Show, attend and tell: Neural image caption generation with visual attention, in *Proc. 32nd Int. Conf. Int. Conf. Machine Learning*, Lille, France, 2015, pp. 2048–2057.

[43] J. C. Lv, Z. Yi, and K. K. Tan, Global convergence of GHA learning algorithm with nonzero-approaching adaptive learning rates, *IEEE Trans. Neural Netw.*, vol. 18, no. 6, pp. 1557–1571, 2007.

[44] N. Srivastava and R. Salakhutdinov, Multimodal learning with deep Boltzmann machines, in *Proc. 25th Int. Conf. Neural Information Processing Systems*, Lake Tahoe, NV, USA, 2012, pp. 2222–2230.

[45] W. Zhong, N. Yu, and C. Y. Ai, Applying big data based deep learning system to intrusion detection, *Big Data Mining and Analytics*, vol. 3, no. 3, pp. 181–195, 2020.

[46] C. W. Tang, J. C. Lv, Y. Chen, and J. X. Guo, An angle-based method for measuring the semantic similarity between visual and textual features, *Soft Comput.*, vol. 23, no. 12, pp. 4041–4050, 2019.

[47] S. Suman, Artificial intelligence in nuclear industry: Chimera or solution? *J. Clean. Prod.*, vol. 278, p. 124022, 2021.

[48] H. A. Saeed, M. J. Peng, H. Wang, and B. W. Zhang, Novel fault diagnosis scheme utilizing deep learning networks, *Prog. Nucl. Energy*, vol. 118, p. 103066, 2020.

[49] J. L. Lang, C. W. Tang, Y. Gao, and J. C. Lv, Knowledge distillation method for surface defect detection, in *Proc. 28th Int. Conf. Neural Information Processing*, Bali, Indonesia, 2021, pp. 644–655.

[50] J. Li, *Contemporary China: Nuclear Industry*, (in Chinese), Hong Kong, China: Contemporary China Press, 2009.

[51] S. Mandal, B. Santhi, S. Sridhar, K. Vinolia, and P. Swaminathan, Nuclear power plant thermocouple sensor-fault detection and classification using deep learning and generalized likelihood ratio test, *IEEE Trans. Nucl. Sci.*, vol. 64, no. 6, pp. 1526–1534, 2017.

[52] F. C. Chen and M. R. Jahanshahi, NB-CNN: Deep learning-based crack detection using convolutional neural network and Naïve Bayes data fusion, *IEEE Trans. Ind. Electron.*, vol. 65, no. 5, pp. 4392–4400, 2017.

[53] V. H. C. Pinheiro, M. C. Dos Santos, F. S. M. Do Desterro, R. Schirru, and C. M. D. N. A. Pereira, Nuclear power plant accident identification system with "don't know" response capability: Novel deep learning-based approaches, *Ann. Nucl. Energy*, vol. 137, p. 107111, 2020.

[54] D. C. Chen, Z. Wang, D. Guo, V. Orekhov, and X. B. Qu, Review and prospect: Deep learning in nuclear magnetic resonance spectroscopy, arXiv preprint arXiv: 2001.04813, 2020.

[55] J. P. Langstrand, H. T. Nguyen, and R. McDonald, Applying deep learning to solve alarm flooding in digital nuclear power plant control rooms, in *Proc. Int. Conf. Applied Human Factors and Ergonomics*, San Diego, CA, USA, 2020, pp. 521–527.

[56] H. J. Zhao, H. Tang, B. Xiao, J. Zheng, Y. W. Li, and X. Q. Yang, Application research of artificial intelligence and big data in the field of nuclear power, (in Chinese), *China Nucl. Power*, vol. 12, no. 3, pp. 247–251, 2019.

[57] X. M. Xiao and R. Sha, Application of artificial intelligence in nuclear energy industry, (in Chinese), *China Informatization*, vol. 12, pp. 10–12, 2017.

[58] M. Schneider and A. Froggatt, The world nuclear industry status report 2019, in *World Scientific Encyclopedia of Climate Change: Case Studies of Climate Risk, Action, and Opportunity Volume 2*, J. W. Dash, ed. Singapore: World Scientific, 2021, pp. 203–209.

[59] S. L. Zhang and Q. Li, The development and scale of the nuclear power in China under the restraint of low carbon, (in Chinese), *China Popul., Resour. Environ.*, vol. 25, no. 6, pp. 47–52, 2015.

[60] F. M. Salman and S. S. Abu-Naser, Expert system for castor diseases and diagnosis, *Int. J. Eng. Inf. Syst.*, vol. 3, no. 3, pp. 1–10, 2019.

[61] R. P. Martin and B. Nassersharif, Deep knowledge expert system for diagnosis of multiple-failure severe transients in nuclear power plant, in *Artificial Intelligence and Other Innovative Computer Applications in the Nuclear Industry*, M. C. Majumdar, D. Majumdar, and J. I. Sackett, eds. Boston, MA, USA: Springer, 1988, pp. 281–288.

[62] M. A. Al-Garadi, A. Mohamed, A. K. Al-Ali, X. J. Du, I. Ali, and M. Guizani, A survey of machine and deep learning methods for internet of things (IoT) security, *IEEE Commun. Surv. Tut.*, vol. 22, no. 3, pp. 1646–1685, 2020.

[63] A. Hedayat, Developing a futuristic multi-objective optimization of the fuel management problems for the nuclear research reactors, *Kerntechnik*, vol. 85, no. 1, pp. 26–37, 2021.

[64] R. Seifert, M. Weber, E. Kocakavuk, C. Rischpler, and D. Kersting, Artificial intelligence and machine learning in nuclear medicine: Future perspectives, *Semin. Nucl. Med.*, vol. 51, no. 2, pp. 170–177, 2021.

[65] O. Tokatli, P. Das, R. Nath, L. Pangione, A. Altobelli, G. Burroughes, E. T. Jonasson, M. F. Turner, and R. Skilton, Robot-assisted glovebox teleoperation for nuclear industry, *Robotics*, vol. 10, no. 3, p. 85, 2021.

[66] D. Lee and J. Kim, Autonomous algorithm for safety systems of the nuclear power plant by using the deep learning, in *Proc. Int. Conf. Applied Human Factors and Ergonomics*, Los Angeles, CA, USA, 2017, pp. 72–82.

[67] M. Elsisi, M. Q. Tran, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, Deep learning-based industry 4.0 and internet of things towards effective energy management for smart buildings, *Sensors*, vol. 21, no. 4, p. 1038, 2021.

[68] P. Ongsulee, Artificial intelligence, machine learning and deep learning, in *Proc. 2017 15th Int. Conf. ICT and Knowledge Engineering* (*ICT&KE*), Bangkok, Thailand, 2017, pp. 1–6.

[69] G. E. Hinton, Deep belief networks, *Scholarpedia*, vol. 4, no. 5, p. 5947, 2009.

[70] Y. LeCun, LeNet-5, convolutional neural networks, http://yann.lecun.com/exdb/lenet, 2015.

[71] L. R. Medsker and L. C. Jain, *Recurrent Neural Networks: Design and Applications*. Washington, DC, USA: CRC Press, 2001, pp. 64–67.

[72] S. Hochreiter and J. Schmidhuber, Long short-term memory, *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.

[73] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, Generative adversarial nets, in *Proc. 27th Int. Conf. Neural Information Processing Systems*, Montreal, Canada, 2014, pp. 2672–2680.

[74] K. O'Shea and R. Nash, An introduction to convolutional neural networks, arXiv preprint arXiv: 1511.08458, 2015.

[75] A. Veit, M. J. Wilber, and S. J. Belongie, Residual networks behave like ensembles of relatively shallow networks, in *Proc. Advances in Neural Information Processing Systems*, Barcelona, Spain, 2016, pp. 550–558.

[76] K. M. He, X. Y. Zhang, S. Q. Ren, and J. Sun, Identity mappings in deep residual networks, in *Proc. 14th European Conf. Computer Vision*, Amsterdam, The Netherlands, 2016, pp. 630–645.

[77] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, Attention is all you need, in *Proc. 31st Int. Conf. Neural Information Processing Systems*, Long Beach, CA, USA, 2017, pp. 6000–6010.

[78] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, BERT: Pre-training of deep bidirectional transformers for language understanding, arXiv preprint arXiv: 1810.04805, 2018.

[79] S. K. Patnaik, C. N. Babu, and M. Bhave, Intelligent and adaptive web data extraction system using convolutional and long short-term memory deep learning networks, *Big Data Mining and Analytics*, vol. 4, no. 4, pp. 279–297, 2021.

[80] C. A. F. Jorge, A. C. A. Mól, C. M. N. A. Pereira, M. A. C. Aghina, and D. V. Nomiya, Human-system interface based on speech recognition: Application to a virtual nuclear

power plant control desk, *Prog. Nucl. Energy*, vol. 52, no. 4, pp. 379–386, 2010.

[81] G. Chauhan and P. Chaudhari, Robotic control using speech recognition and android, *Int. J. Eng. Res. Gen. Sci.*, vol. 3, no. 1, pp. 1210–1216, 2015.

[82] H. Choi, Deep learning in nuclear medicine and molecular imaging: Current perspectives and future directions, *Nucl. Med. Mol. Imaging*, vol. 52, no. 2, pp. 109–118, 2018.

[83] L. Sun, C. Zhao, Z. Yan, P. C. Liu, T. Duckett, and R. Stolkin, A novel weakly-supervised approach for RGB-D-based nuclear waste object detection, *IEEE Sens. J.*, vol. 19, no. 9, pp. 3487–3500, 2019.

[84] C. J. Wang, Z. H. Li, and B. Sarpong, Multimodal adaptive identity-recognition algorithm fused with gait perception, *Big Data Mining and Analytics*, vol. 4, no. 4, pp. 223–232, 2021.

[85] C. W. Tang, X. Yang, J. C. Lv, and Z. A. He, Zero-shot learning by mutual information estimation and maximization, *Knowl.-Based Syst.*, vol. 194, p. 105490, 2020.

[86] J. Gao, P. Li, Z. K. Chen, and J. N. Zhang, A survey on deep learning for multimodal data fusion, *Neural Comput.*, vol. 32, no. 5, pp. 829–864, 2020.

[87] H. R. Roth, L. Lu, A. Farag, H. C. Shin, J. M. Liu, E. B. Turkbey, and R. M. Summers, DeepOrgan: Multi-level deep convolutional networks for automated pancreas segmentation, in *Proc. 18th Int. Conf. Medical Image Computing and Computer-Assisted Intervention*, Munich, Germany, 2015, pp. 556–564.

[88] C. W. Tang, Z. A. He, Y. X. Li, and J. C. Lv, Zero-shot learning via structure-aligned generative adversarial network, *IEEE Trans. Neural Netw. Learn. Syst.*, doi: 10.1109/TNNLS.2021.3083367.

[89] X. Hong, Y. L. Zan, F. H. Weng, W. J. Tao, Q. Y. Peng, and Q. Huang, Enhancing the image quality via transferred deep residual learning of coarse PET sinograms, *IEEE Trans. Med. Imaging*, vol. 37, no. 10, pp. 2322–2332, 2018.

[90] K. Gong, J. H. Guan, K. Kim, X. Z. Zhang, J. Yang, Y. Seo, G. El Fakhri, J. Y. Qi, and Q. Z. Li, Iterative PET image reconstruction using convolutional neural network representation, *IEEE Trans. Med. Imaging*, vol. 38, no. 3, pp. 675–685, 2019.

[91] L. Huang, Y. Zhou, Y. T. Han, J. K. Hammitt, J. Bi, and Y. Liu, Effect of the fukushima nuclear accident on the risk perception of residents near a nuclear power plant in China, *Proc. Natl. Acad. Sci. USA*, vol. 110, no. 49, pp. 19742–19747, 2013.

[92] X. S. Si, W. B. Wang, C. H. Hu, and D. H. Zhou, Remaining useful life estimation–a review on the statistical data driven approaches, *Eur. J. Oper. Res.*, vol. 213, no. 1, pp. 1–14, 2011.

[93] Z. P. Guo, Z. W. Wu, S. Liu, X. Ma, C. Y. Wang, D. J. Yan, and F. L. Niu, Defect detection of nuclear fuel assembly based on deep neural network, *Ann. Nucl. Energy*, vol. 137, p. 107078, 2020.

[94] Q. S. Jiang, D. P. Tan, Y. B. Li, S. M. Ji, C. P. Cai, and Q. M. Zheng, Object detection and classification of metal polishing shaft surface defects based on convolutional neural network deep learning, *Appl. Sci.*, vol. 10, no. 1, p. 87, 2020.

[95] X. Y. Suo, J. Liu, L. C. Dong, S. F. Chen, E. H. Lu, and N. Chen, A machine vision-based defect detection system for nuclear-fuel rod groove, *J. Intell. Manuf.*, doi: 10.1007/s10845-021-01746-7.

[96] H. Wang, M. J. Peng, R. Y. Xu, A. Ayodeji, and H. Xia, Remaining useful life prediction based on improved temporal convolutional network for nuclear power plant valves, *Front. Energy Res.*, vol. 8, p. 584463, 2020.

[97] H. Li, W. Zhao, Y. X. Zhang, and E. Zio, Remaining useful life prediction using multi-scale deep convolutional neural network, *Appl. Soft Comput.*, vol. 89, p. 106113, 2020.

[98] F. Calivá, F. S. De Ribeiro, A. Mylonakis, C. Demazière, P. Vinai, G. Leontidis, and S. Kollias, A deep learning approach to anomaly detection in nuclear reactors, in *Proc. 2018 Int. Joint Conf. Neural Networks*, Rio de Janeiro, Brazil, 2018, pp. 1–8.

[99] F. C. Chen, M. R. Jahanshahi, R. T. Wu, and C. Joffe, A texture-based video processing methodology using Bayesian data fusion for autonomous crack detection on metallic surfaces, *Comput.-Aided Civ. Inf. Eng.*, vol. 32, no. 4, pp. 271–287, 2017.

[100] Y. J. Jeon, J. P. Yun, D. C. Choi, and S. W. Kim, Defect detection algorithm for corner cracks in steel billet using discrete wavelet transform, in *Proc. ICCAS-SICE*, Fukuoka, Japan, 2009, p. 276973.

[101] Y. J. Jeon, D. C. Choi, S. J. Lee, J. P. Yun, and S. W. Kim, Defect detection for corner cracks in steel billets using a wavelet reconstruction method, *J. Opt. Soc. Am. A*, vol. 31, no. 2, pp. 227–237, 2014.

[102] J. P. Yun, Y. Park, B. Seo, S. W. Kim, S. H. Choi, C. H. Park, H. M. Bae, and H. W. Hwang, Development of real-time defect detection algorithm for high-speed steel bar in coil (BIC), in *Proc. 2006 SICE-ICASE Int. Joint Conf.*, Busan, Republic of Korea, 2006, pp. 2495–2498.

[103] F. C. Chen and M. R. Jahanshahi, NB-FCN: Real-time accurate crack detection in inspection videos using deep fully convolutional network and parametric data fusion, *IEEE Trans. Instrum. Measure.*, vol. 69, no. 8, pp. 5325–5334, 2020.

[104] F. C. Chen and M. R. Jahanshahi, ARF-Crack: Rotation invariant deep fully convolutional network for pixel-level crack detection, *Mach. Vis. Appl.*, vol. 31, no. 6, p. 47, 2020.

[105] Y. Gao, C. W. Tang, J. L. Lang, and J. C. Lv, End-to-end edge detection via improved transformer model, in *Proc. 28th Int. Conf. Neural Information Processing*, Sanur, Indonesia, 2021, pp. 514–525.

[106] L. Qi, J. Kuen, J. X. Gu, Z. Lin, Y. Wang, Y. K. Chen, Y. W. Li, and J. Y. Jia, Multi-scale aligned distillation for low-resolution detection, in *Proc. 2021 IEEE/CVF Conf. Computer Vision and Pattern Recognition*, Nashville, TN, USA, 2021, pp. 14438–14448, 2021.

[107] Z. Tian, C. H. Shen, H. Chen, and T. He, FCOS: Fully convolutional one-stage object detection, in *Proc. IEEE/CVF Int. Conf. Computer Vision*, Seoul, Republic of Korea, 2019, pp. 9626–9635.

[108] G. Hinton, O. Vinyals, and J. Dean, Distilling the knowledge in a neural network, arXiv preprint arXiv: 1503.02531, 2015.

[109] Z. Liu, Y. T. Lin, Y. Cao, H. Hu, Y. X. Wei, Z. Zhang, S. Lin, and B. N. Guo, Swin transformer: Hierarchical vision transformer using shifted windows, arXiv preprint arXiv: 2103.14030, 2021.

[110] H. G. Kim, I. H. Kim, Y. I. Jung, D. J. Park, J. Y. Park, and Y. H. Koo, High-temperature oxidation behavior of CR-coated zirconium alloy, in *Proc. of LWR Fuel Performance Meeting/TopFuel*, Charlotte, NC, USA, 2013, pp. 842–846.

[111] H. Wang, M. J. Peng, Y. K. Liu, S. W. Liu, R. Y. Xu, and H. Saeed, Remaining useful life prediction techniques of electric valves for nuclear power plants with convolution kernel and LSTM, *Sci. Technol. Nucl. Install.*, vol. 2020, p. 8349349, 2020.

[112] H. Wang, M. J. Peng, Z. Miao, Y. K. Liu, A. Ayodeji, and C. M. Hao, Remaining useful life prediction techniques for electric valves based on convolution auto encoder and long short term memory, *ISA Trans.*, vol. 108, pp. 333–342, 2021.

[113] E. Madar, R. Klein, and J. Bortman, Contribution of dynamic modeling to prognostics of rotating machinery, *Mech. Syst. Signal Process.*, vol. 123, pp. 496–512, 2019.

[114] C. D. Manning, M. Surdeanu, J. Bauer, J. R. Finkel, S. Bethard, and D. McClosky, The Stanford CoreNLP natural language processing toolkit, in *Proc. 52nd Ann. Meeting of the Association for Computational Linguistics*, Baltimore, MD, USA, 2014, pp. 55–60.

[115] Y. F. Zhao, X. X. Diao, J. Huang, and C. Smidts, Automated identification of causal relationships in nuclear power plant event reports, *Nucl. Technol.*, vol. 205, no. 8, pp. 1021–1034, 2019.

[116] W. B. Cottrell and R. B. Gallaher, Licensee event report sequence coding and search procedure workshop, *Nucl. Saf.*, vol. 22, no. 2, pp. 162–164, 1981.

[117] A. V. Oppenheim, *Discrete-Time Signal Processing*. Upper Saddle River, NJ, USA: Pearson Education India, 1999.

[118] C. A. F. Jorge, M. A. D. C. Aghina, A. C. D. A. Mól, C. M. D. N. A. Pereira, Man machine interface based on speech recognition, in *Proc. of the 2007 International Nuclear Atlantic Conference*, http://carpedien.ien.gov.br:8080/bitstream/ien/1690/1/Man%20machine%20interface%20based%20oj.pdf, 2021.

[119] J. B. Ramgire and S. M. Jagdale, Speech control pick and place robotic arm with flexiforce sensor, in *Proc. 2016 Int. Conf. Inventive Computation Technologies* (*ICICT*), Coimbatore, India, 2016, pp. 1–5.

[120] Y. S. Chen, M. Lin, R. Yu, and T. S. Wang, Research on simulation and state prediction of nuclear power system based on LSTM neural network, *Sci. Technol. Nucl. Install.*, vol. 2021, p. 8839867, 2021.

[121] Y. S. Chen, Y. H. Yang, M. Lin, and R. Yu, Fault diagnosis technology of nuclear power plant based on deep learning neural network, (in Chinese), *J. Shanghai Jiaotong Univ.*, vol. 52, no. S1, pp. 58–61, 2018.

[122] D. Lee, P. H. Seong, and J. Kim, Autonomous operation algorithm for safety systems of nuclear power plants by using long-short term memory and function-based hierarchical framework, *Ann. Nucl. Energy*, vol. 119, pp. 287–299, 2018.

[123] J. K. She, S. Y. Xue, P. W. Sun, and H. S. Cao, The application of LSTM model to the prediction of abnormal operation in nuclear power plants, (in Chinese), *Instrumentation*, vol. 26, no. 12, pp. 39–44, 2019.

[124] M. I. Radaideh, C. Pigg, T. Kozlowski, Y. J. Deng, and A. N. Qu, Neural-based time series forecasting of loss of coolant accidents in nuclear power plants, *Expert Syst. Appl.*, vol. 160, p. 113699, 2020.

[125] J. Choi and S. J. Lee, Consistency index-based sensor fault detection system for nuclear power plant emergency situations using an LSTM network, *Sensors*, vol. 20, no. 6, p. 1651, 2020.

[126] S. Y. Zhang, T. Y. Lu, H. Zeng, C. Xu, Z. Zhang, Q. Y. Huang, Y. Y. Zhang, and Y. M. Wang, Multi-feature fusion multi-step state prediction of nuclear power sensor based on LSTM, (in Chinese), *Nucl. Power Eng.*, vol. 42, no. 3, pp. 208–213, 2021.

[127] S. Mandal, B. Santhi, S. Sridhar, K. Vinolia, and P. Swaminathan, Nuclear power plant thermocouple sensor-fault detection and classification using deep learning and generalized likelihood ratio test, *IEEE Trans. Nucl. Sci.*, vol. 64, no. 6, pp. 1526–1534, 2017.

[128] G. J. Liu, S. Yang, G. X. Wang, F. L. Li, and D. D. You, A decision-making method for machinery abnormalities based on neural network prediction and Bayesian hypothesis testing, *Electronics*, vol. 10, no. 14, p. 1610, 2021.

[129] D. Wang, Z. H. Wei, H. Li, J. M. Li, and W. Y. Huang, Real-time calculation of nuclear critical safety data based on bp neural network, (in Chinese), *Nucl. Sci. Technol.*, vol. 8, no. 4, pp. 220–228, 2020.

[130] M. Mendoza, P. V. Tsvetkov, and M. Lewis, Multi-modal global surveillance methodology for predictive and on-demand characterization of localized processes using cube satellite platforms and deep learning techniques, *Remote Sens. Appl.*: *Soc. Environ.*, vol. 22, p. 100518, 2021.

[131] Y. Feldman, M. Arno, C. Carrano, B. Ng, and B. Chen, Toward a multimodal-deep learning retrieval system for monitoring nuclear proliferation activities, *J. Nucl. Mater. Manage.*, vol. 46, no. 3, 2018.

[132] K. Kim, D. F. Wu, K. Gong, J. Dutta, J. H. Kim, Y. D. Son, H. K. Kim, G. El Fakhri, and Q. Z. Li, Penalized PET reconstruction using deep learning prior and local linear fitting, *IEEE Trans. Med. Imaging*, vol. 37, no. 6, pp. 1478–1487, 2018.

[133] D. Nie, X. H. Cao, Y. Z. Gao, L. Wang, and D. G. Shen, Estimating CT image from MRI data using 3D fully convolutional networks, in *Proc. 1st Int. Workshop on Deep Learning in Medical Image Analysis*, Athens, Greece, 2016, pp. 170–178.

[134] A. Torrado-Carvajal, J. Vera-Olmos, D. Izquierdo-Garcia, O. A. Catalano, M. A. Morales, J. Margolin, A. Soricelli, M. Salvatore, N. Malpica, and C. Catana, Dixon-VIBE

deep learning (DIVIDE) pseudo-CT synthesis for pelvis PET/MR attenuation correction, *J. Nucl. Med.*, vol. 60, no. 3, pp. 429–435, 2019.

[135] D. Hwang, S. K. Kang, K. Y. Kim, S. Seo, J. C. Paeng, D. S. Lee, and J. S. Lee, Generation of pet attenuation map for whole-body time-of-flight 18F-FDG PET/MRI using a deep neural network trained with simultaneously reconstructed activity and attenuation maps, *J. Nucl. Med.*, vol. 60, no. 8, pp. 1183–1189, 2019.

[136] S. Kaplan and Y. M. Zhu, Full-dose PET image estimation from low-dose PET image using deep learning: A pilot study, *J. Digit. Imaging*, vol. 32, no. 5, pp. 773–778, 2019.

[137] H. Choi and K. H. Jin, Fast and robust segmentation of the striatum using deep convolutional neural networks, *J. Neurosci. Methods*, vol. 274, pp. 146–153, 2016.

[138] W. Shen, M. Zhou, F. Yang, C. Y. Yang, and J. Tian, Multi-scale convolutional neural networks for lung nodule classification, in *Proc. 24th Int. Conf. Information Processing in Medical Imaging*, Isle of Skye, UK, 2015, pp. 588–599.

[139] A. A. A. Setio, F. Ciompi, G. Litjens, P. Gerke, C. Jacobs, S. J. Van Riel, M. M. W. Wille, M. Naqibullah, C. I. Sánchez, and B. Van Ginneken, Pulmonary nodule detection in CT images: False positive reduction using multi-view convolutional networks, *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1160–1169, 2016.

[140] H. K. Wang, Z. W. Zhou, Y. C. Li, Z. H. Chen, P. O. Lu, W. Z. Wang, W. Y. Liu, and L. J. Yu, Comparison of machine learning methods for classifying mediastinal lymph node metastasis of non-small cell lung cancer from 18F-FDG PET/CT images, *EJNMMI Res.*, vol. 7, no. 1, p. 11, 2017.

[141] A. Krizhevsky, I. Sutskever, and G. E. Hinton, Imagenet classification with deep convolutional neural networks, in *Proc. 26th Advances in Neural Information Processing Systems*, Lake Tahoe, NV, USA, 2012, pp. 1106–1114.

[142] P. Blanc-Durand, A. Van Der Gucht, N. Schaefer, E. Itti, and J. O. Prior, Automatic lesion detection and segmentation of 18F-FET PET in gliomas: A full 3D U-Net convolutional neural network study, *PLoS One*, vol. 13, no. 4, p. e0195798, 2018.

[143] Z. Guo, X. Li, H. Huang, N. Guo, and Q. Z. Li, Deep learning-based image segmentation on multimodal medical imaging, *IEEE Trans. Radiat. Plasma Med. Sci.*, vol. 3, no. 2, pp. 162–169, 2019.

[144] J. Y. Choi, Radiomics and deep learning in clinical imaging: What should we do? *Nucl. Med. Mol. Imaging*, vol. 52, no. 2, pp. 89–90, 2018.

[145] D. B. Liu, Z. N. He, D. D. Chen, and J. C. Lv, A network framework for small-sample learning, *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 10, pp. 4049–4062, 2019.

[146] D. B. Liu, Z. N. He, D. D. Chen, and J. C. Lv, An improved dual-channel network to eliminate catastrophic forgetting, *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 52, no. 1, pp. 415–425, 2022.

[147] R. R. Ade and P. R. Deshmukh, Methods for incremental learning: A survey, *Int. J. Data Min. Knowl. Manage. Process*, vol. 3, no. 4, pp. 119–125, 2013.

Chenwei Tang received the PhD degree in computer science and technology from Sichuan University, Chengdu, China in 2020. She is currently a postdoctoral researcher at the College of Computer Science, Sichuan University, Chengdu, China. Her research focuses on the neural network methods for zero-shot learning, computer vision, and industrial intelligence.

Caiyang Yu received the MEng degree in computer architecture from Wenzhou University, Wenzhou, China in 2018. He is currently a PhD candidate at the College of Computer Science, Sichuan University, Chengdu, China. His research focuses on the neural network search and evolutionary computation.

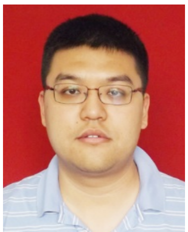
Yi Gao received the BEng degree from Sichuan University, Chengdu, China in 2020. He is currently a master student at the College of Computer Science, Sichuan University, Chengdu, China. His research focuses on the edge detection and zero-shot learning.

Jianming Chen received the BEng degree in software engineering from Sichuan University, Chengdu, China in 2018. He is currently a master student at the College of Computer Science, Sichuan University, Chengdu, China. His research interests include deep learning, open set recognition, and signal processing.

Jiaming Yang received the BEng degree from Chengdu University of Information Technology, Chengdu, China in 2020. He is currently a master student at the College of Computer Science, Sichuan University, Chengdu, China. His research focuses on industrial intelligence and medical intelligence.

Jiulin Lang received the BEng degree in computer science and technology from Southwest Petroleum University, Chengdu, China in 2019. He is currently a master student at the College of Computer Science, Sichuan University, Chengdu, China. His research interests include neural architecture search and computer vision.

Chuan Liu received the BEng degree from Sichuan University, Chengdu, China in 2019. He is currently a master student at the College of Computer Science, Sichuan University, Chengdu, China. His research focuses on the computer vision, neural network architecture search, and neural network quantization.



Zhenan He received the PhD degree in electrical and computer engineering from Oklahoma State University, Stillwater, USA in 2014. Before that, he got the BEng degree in automation from the University of Science and Technology Beijing, China in 2008, and MEng degree from Oklahoma State University, Stillwater, USA in 2011. He is currently an associate professor at the College of Computer Science, Sichuan University, Chengdu, China. His research focuses on intelligent optimization and learning using evolutionary computation approaches.

Jiancheng Lv received the PhD degree in computer science and engineering from the University of Electronic Science and Technology of China, Chengdu, China in 2006. He was a research fellow at the Department of Electrical and Computer Engineering, National University of Singapore, Singapore. He is currently a professor at the Data Intelligence and Computing Art Laboratory, College of Computer Science, Sichuan University, Chengdu, China. His research interests include neural networks, machine learning, and big data.

Ling Zhong received the BS degree in Japanese from Sichuan International Studies University, Chongqing, China in 2011. She is currently a master student at the College of Computer Science, Sichuan University, Chengdu, China. Her main research interest is deep learning.