Application Research of Artificial Intelligence in the Field of Nuclear Power Non-destructive Testing

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Abstract. The discipline of nuclear power non-destructive testing (NDT) has made a great deal use artificial intelligence technologies recently in an effort to produce safer, more effective, automated, and smarter NDT, to ensure the operational safety of nuclear power plants and to save costs. This paper introduces the relevant AI technologies regarding the domain of nuclear power NDT, and summarizes the typical applications of AI technologies in three aspects: metal supervision of conventional islands, in-service inspection of nuclear islands and improvement of NDT technology. Concludes by summarizing and suggesting possibilities for the advancement of AI in the domain of nuclear power NDT.

Keywords: Artificial intelligence; machine learning; nuclear power; non-destructive testing

1 Introduction

The advent of the Internet and the digital age of big data, artificial intelligence(AI) technology is developing at a high speed and has become a key leading technology for future development[1]. Countries all throughout the world set a high value on it and have successively formulated various policies to promote the development and application of AI. Germany was one of the country to implement the idea of Industry 4.0[2] in 2011, aiming at applying emerging Internet technologies to the field of industrial manufacturing; other countries such as the European Union, the United States, Japan, India, and so on have also put forward a variety of strategies for artificial intelligence. Since 2015, China has put forward a "National Big Data Strategy", and successively released other documents, aiming to comprehensively develop AI technology and promote industrial transformation and upgrading.

As a clean energy source, an essential component of China's new energy is nuclear power, which is also the most efficient option under the goal of "double carbon". Applying artificial intelligence in the nuclear power industry has a very high development prospect and social benefits. Pre-service and in-service tests are indispensable for the substantial expense of nuclear power installation and its operating safety. Non-destructive testing (NDT) technology, which is capable of detecting the existence of defects in the inspected object without damaging any materials, workpieces, and equipment, is very common in nuclear power inspection. Unlike other industries, nuclear power nondestructive testing in addition to meeting the task of conventional island metal supervision, also needs to carry out in-service inspection of the nuclear island, while the nuclear island environment is harsh, high-radiation environment on the

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personnel and equipment requirements are higher. At present, nuclear NDT has no unified standards for data acquisition, storage, management and analysis, which limits the advancement of AI, and AI in nuclear NDT is presently in its early stages of development [3]. Combining artificial intelligence with NDT to achieve safer, more efficient, automated and intelligent nuclear power NDT is the direction of future growth and faces many difficulties.

This paper firstly briefly describes AI-related technology, this provides an overview of the use and state for study for AI in nuclear power NDT from three angles, namely, metal supervision of conventional islands, in-service inspection of nuclear islands and improvement of NDT technology, and finally presents ideas and recommendations for the advancement of AI in nuclear power NDT techniques for the years to come.

2 Overview of artificial intelligence

In recent years, technologies like the web, automation, virtual simulation, and others are evolving quickly, providing a broader application space for AI.

2.1 Machine learning

Many applications exist for machine learning, which is the present network's hot topic. ChatGPT [4] uses a variety of algorithms to achieve natural language processing tasks, these algorithms can be convolutional neural networks[5], transformer model [6], etc., to realize the chat robots and information retrieval and other functions. Face recognition[7], autonomous driving[8], etc. use computer vision technology, and the medical field[9] such as medical disease diagnosis, medical testing technology enhancement, etc. use machine learning technology to achieve assisted diagnosis. Nuclear non-destructive testing will produce a lot of data, and there is potential for this method to be used in the real-world application of nuclear nondestructive testing.

2.2 Digital twin

Digital twin technology is the establishment of a virtual model to reflect real-world objects or processes through technical means such as data acquisition and monitoring, and this model is synchronized with all aspects of the real object and can be interacted with in real time and information feedback. Digital twin technology is widely used in the industrial field[10], which can help companies to simulate and optimize the manufacturing process, test and debug in a virtual environment, and reduce the waste of production resources. It is also widely used in aerospace, medical field[11] and urban planning.

2.3 Industrial robots

Industrial robots[12] are extensively employed in industrial domains, which can automatically perform some tasks, can work according to a predetermined program, and can also formulate a plan of action based on artificial intelligence technology, including the main body, the drive system and the control system of the three parts of the composition. Industrial robots are characterized by intelligence, high productivity, high safety and significant economic benefits, and can operate in high-risk environments. With the development of artificial intelligence, industrial robots are becoming more and more intelligent, efficient, compact and flexible.

3 Typical applications in the nuclear power industry

China is currently pushing artificial intelligence technology very hard. With the nuclear power sector's digital revolution, artificial intelligence has been initially applied to nuclear power nondestructive testing[13], which greatly improves the efficiency of nondestructive testing of nuclear power plants and the usefulness of intelligent maintenance. The section will introduce the typical applications of AI technology in the field of nuclear power NDT from three aspects: conventional island metal supervision, nuclear island in-service inspection and NDT technology improvement.

3.1 Metal supervision of conventional islands

The safe functioning of the conventional island is crucial in nuclear power facilities. Yi et al[14] evaluate sensor data from different nuclear power facility device varieties using the deep learning Transformer model, to intelligently monitor the abnormalities of the equipment in nuclear power plants. The artificial intelligence model, which is depicted in Fig. 1, includes the Transformer model to execute the reconstructed version of the input signal and predicts historical data from sensors corresponding to the chemical and volume control system of the nuclear power plant's charging circulates using a correlation entropy as function that is based on the maximum correlation entropy requirements. The results illustrate the model's capacity to spot faults early on and that the time stamps of the issues that are identified match the actual issues' certain points. The timestamps of the detected faults are basically consistent with the actual fault occurrence time; Liu et al[15] construct a dataset using the Geant4 tool and use CNN neural network training and prediction, to nondestructively detect the nuclear waste casks, thus facilitating further nuclear safety management; Han et al. which facilitates further nuclear safety management; Han et al[16] classified and predicted marine organisms jellyfish based on deep learning GoogLeNet network, thereby guaranteeing that the nuclear power facility can handle the marine biological invasion; Li et al[17] created a revolutionary OSR fault detection framework utilizing the an convolutional neural network CPL, to assist with fault identification and enables more precise identification of the wide range of problems in nuclear energy plants; Zhang et al[18] created a remote testing and evaluation system for nuclear power plant' thermal efficiency using digital twins and AI. This system simulates the real-life condition of the plant, which is crucial for fault detection and operation.

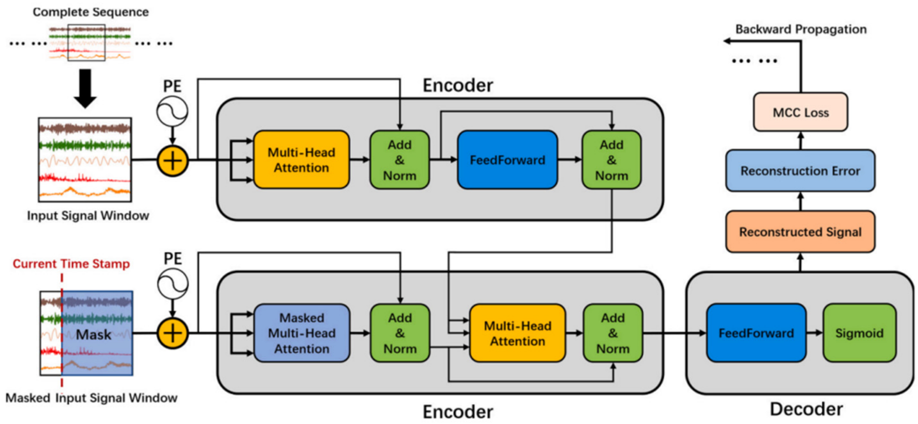


Fig. 1. Transformer-based detection of anomalies model's structural diagram.

In addition to ensuring the secure functioning of nuclear power facilities, the conventional island welding process and non-destructive testing (NDT) of equipment are also very important. Liu et al[19] based on the random forest algorithm, combined with the welding process data, to improve the quality of molding inside the automated welding of nuclear pipelines; Sumesh et al[20] based on the decision tree algorithm to classify weld defects, to automate the judgment of the quality of welds; Jin et al[21] based on the artificial intelligence algorithm and phased array ultrasonic inspection technology to evaluate defects in PAUT of welded structures, which improves the accuracy of defect discrimination. Considering the complexity of PAUT data, the two components of the neural network framework are designed as shown in Fig. 2, the first part uses CNN and learns the A-scan signals, and the other part is the feature processing, which advances the features from the domain knowledge (advanced experience, etc.), a the experimental findings demonstrate that every sub-dataset has a classification accuracy of greater than 0.98, and that the results of the AI diagnosis are almost the same as the results of the expert evaluation , which can be used as an auxiliary diagnostic tool; Benammar et al[22] performed turbine problem detection in real time using fault tree(FT) and ANN neural network for rapid maintenance and discovery of possible faults; Zhang et al[23]developed an automated inspection system, which incorporates eddy modern technology to finish the nuclear electricity turbine rotors weld automatic examination, the detection results are more accurate and efficient; Zhou et al[24] based on optimized CNN convolutional neural network for gas turbine fault diagnosis, the diagnosis results are more accurate and reliable.

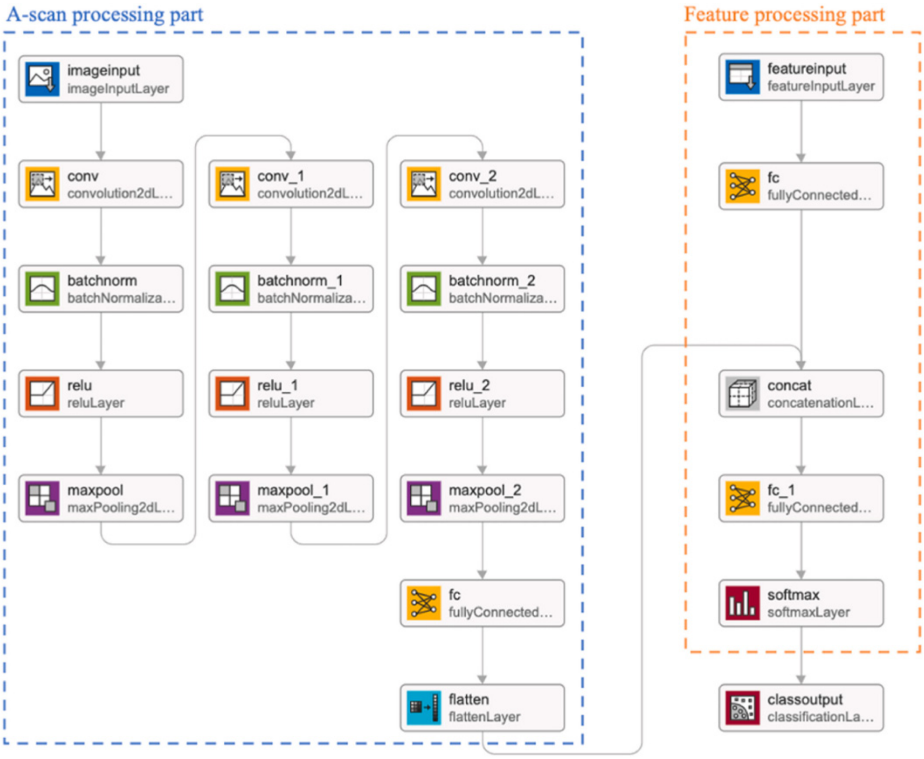


Fig. 2. Neural network architecture in parallel for processing A-scan signals and features input at one time.

3.2In-service inspection of nuclear islands

In the nuclear island environment, it is important to intelligently monitor the safe operating status of the nuclear island and nuclear island equipment. Zhang et al[25] developed an unsupervised intelligent condition monitoring model based on methods such as AI algorithm, which can enable the monitoring and localization of early anomalies in the pumping machines of a nuclear island. The DDAE model is depicted in Fig. 3. The massive centrifugal pumps in a power plant are utilized to test for unforeseen events, and a variety of monitoring metrics are employed to identify the improper states of the devices rapidly. The experimental findings indicate that the monitoring model may effectively rearrange the complex tracking parameters of the typical scenario while lowering the quantity of false alarms that are raised before deviations are noticed. In the end, the monitoring model can pinpoint the isolation and major anomalous factors with accuracy, which can help with fault forecasting and intelligent diagnosis;

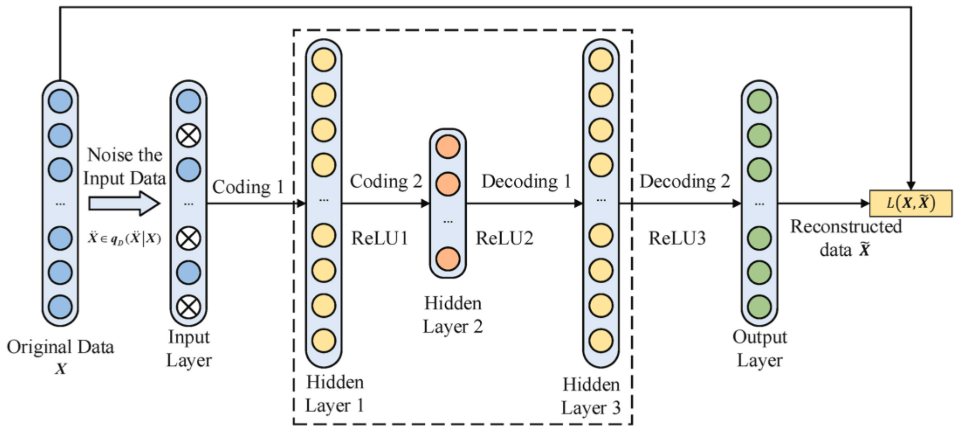


Fig. 3. Transformer-based detection of anomalies model's structure.

Szalóki et al[26] used MATLAB and a database to quickly calculate the activation reaction in a loop that produces the isotope radioactivity to monitor radioactivity levels in the reactor coolant; Zubair et al[27] collected hydraulic parameter data from a pressurized water reactor simulator and used MATLAB to process the data and a neural network classifier (NNC) to predict instantaneous states of affairs to monitor reactor status and diagnose malfunctions; Rataj et al[28] designed and developed a VR-2 reactors the urgency management system that control identification of neutron levels and stop the reactor neutron production if necessary, thus ensuring the nuclear generation plant's safety functioning; zhang et al[29] optimized based on reinforcement learning (DRL) to intelligently detect and control the overheating or saturation of the thermal steam of the nuclear power plant, to guarantee the nuclear power tree's generating power's stability and security; He et al[30] optimized based on AI and orthogonal decomposition, the two thermal-hydraulic of the steam generator parameters are quickly estimated to offer some assistance for the repair of digital twin and for online, real-time steam generator monitoring; Liao et al[31] created a smart system to monitor data and analyze results in immediate time for the pressure vessel inside the reactor for the cold operation test, ensuring the nuclear power plant's safety at work.

In addition to intelligent monitoring of nuclear power plants, the control system and control software of various types of NDT automation equipment are also typical applications of artificial intelligence in NDT on nuclear islands. Zhou et al[32] designed and developed an ultrasonic inspection system for main pump flange screws in nuclear power plants, based on the LabVIEW2013 development platform, the control software is flexible and stable, and the system satisfies the AP1000 during service examination field standards; Yu et al[33] developed the inspection system for the butt joints between steam generators and main pumps, and realized the functions of positional calibration, motion control, and system monitoring through the control software to improve the inspection accuracy and inspection efficiency; Vasiljević et al[34] designed an inspection robot for reactor pressure vessel shells based on computer vision technology for nonlinear motion during equipment scanning and remote control through visualization control software; Seo et al[35] proposed a mobile robot for inspection and maintenance of steam generators (SGs), with a control system architecture that is flexible enough to easily monitor and move the robot remotely. The control has a GUI for the human-machine interface and a 3D graphic module, thus realizing remote control of the inspection. Fig. 4 shows the graphic user control interfaces of the user program while the process of inspection is being performed; Cao et al[36] established a fault diagnosis system based on PAC-SVM technology, which simulates and detects faults through the data from nondestructive testing and assists the operator in determining fault information.

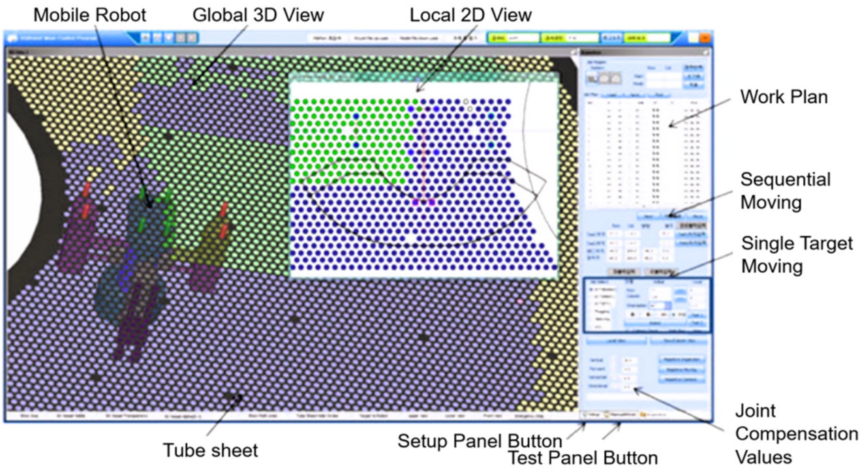


Fig. 4. User interface in graphics for the client program.

3.3 Improvement of NDT technology

Commonly used nondestructive testing includes eddy current, ultrasound, radiography, visualization, leakage, etc. The principles of various testing methods are different, and technology based on AI has become extensively utilized recently in various nondestructive testing methods[37], to improve the testing accuracy or efficiency.

For ultrasonic detection technology, Yao et al[38] combined BP neural network, Dempster Shafer theory and ultrasonic pulse reflection method to further optimize the ultrasonic signal, which lays the foundation for the subsequent detection; Qi et al[39] combined artificial intelligence and phased-array guided-wave technology (PAGW), which was applied to the curved surface version of the damage assessment, and the results were more accurate and efficient; Munir et al[40] used a CNN network to eliminate the autoencoder's noise and fuse faulty signals, which made the ultrasonic detection defect classification accuracy improve. Fig. 5 depicts the CNN and Tensorflow-based self-encoder model. Experimental findings indicate that, even in the presence of noise, the self-encoder's average defect classification accuracy surpasses 98%.; Li et al[41] to enhance the high-frequency ultrasound detecting a flaw echo signals there is a noise problem, based on the improvement of the multiplexed matching tracking algorithm to sparse denoising of high-frequency ultrasound signals, which improves the clarity of the ultrasonic detection of the B-scan image; Granados et al[42] used a deep learning model U-net neural network to simulate the reproduction of field detection to solve the high-dimensional ultrasound detection problem.

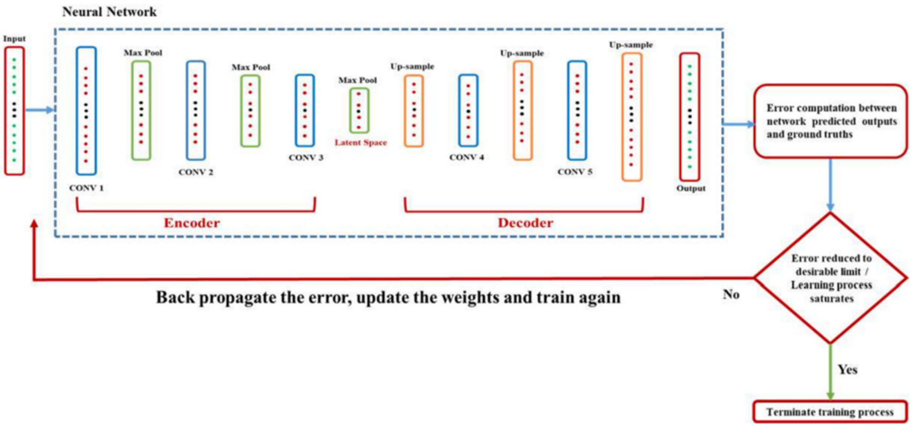
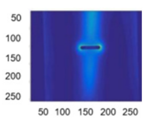
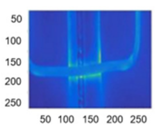
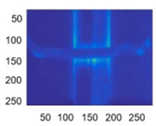
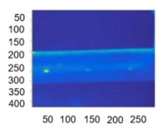
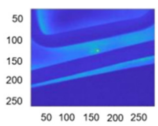


Fig. 5. Flow diagram for the training process of autoencoder.

For eddy current detection techniques, Ren et al[43] suggested an image computing method for replicating corrosion imaging and creating corrosion depth profile data that incorporates sparse denoising and sparse Bayesian learning (SBL), thus obtaining a well-focused corrosion image; Liao et al[44] proposed a multi-frequency eddy current signal based on the NTT algorithm by using steam generator calibration tube data mixing method to detect defects, this algorithm is more stable and the results are more satisfactory; Hampton et al[45] utilized a limited algorithm for optimization to adjust the finite components, which is faster and has less impact on the detection accuracy, which is very important for NDT in the nuclear power industry; Liang et al[46] enhanced the detection effect by applying tensor decomposition to the image recognition of ECPT(eddy current pulsed thermography) image episodes, thus applied to industrial scenes using ECPT detection technology. According to Table 1, compared with the traditional methods, EPCT representative method EJSLRMD[47] and WIASDMD[48] method, the defect separation effect using SNN- TRPCA and TNN- TRPCA methods is better, eliminating most of the noise; The F-score index for each of the four approaches is displayed in Table 2. The bigger the F-score, the more information it includes, and the higher the success rate of the inspected parts is, which can be seen that the inspection accuracy is enhanced when compared to conventional procedures following the addition of AI algorithm models; Song et al[49] in order to improve the pulsed eddy current signal in the strong background noise interference problems and non-smoothness characteristics, can effectively eliminate the noise interference, for the subsequent signal characteristics of the accurate advance and non-destructive detection to lay the foundation.

Table 1. The samples results of experiments.

Method	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
Original					

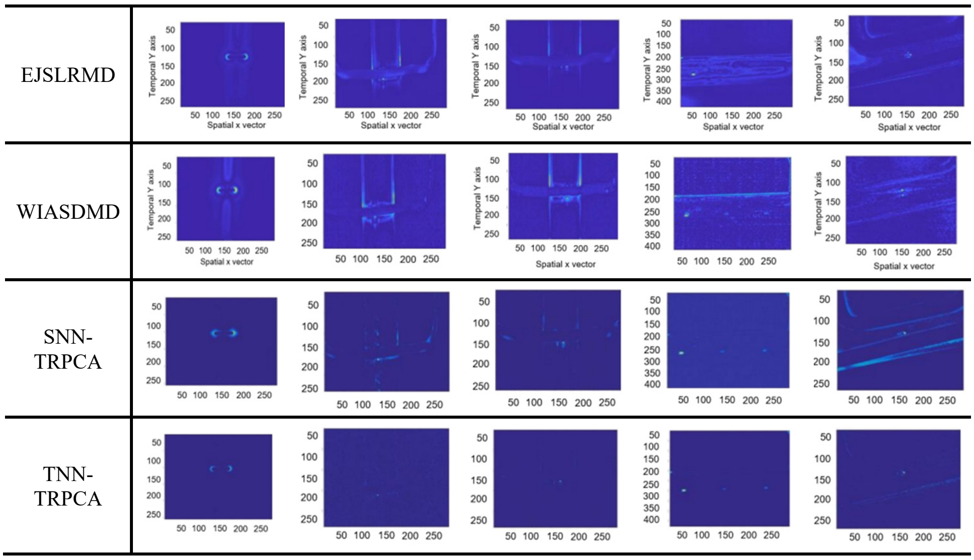


Table 2. Methods in simulations of F-score.

Method	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
EJSLRMD	1.	0.5	0.4	0.4	1.
WIASDMD	1.	0.5	0.5	0.71	1.
SNN-TRPCA	1.	0.67	1.	0.86	1.
TNN-TRPCA	1.	0.67	1.	0.86	1.

In addition, computer vision technology[50] is also widely used in various non-destructive testing techniques that require image recognition and processing. Huang et al.[51] suggested a method for merging panoramic pictures to increase inspection reliability and efficiency and set the stage for later automated surface inspection; Sha et al[52] suggested a technique to improve the underwater detecting photos' quality in order to enhance the efficiency of underwater nondestructive testing in view of the restricted field of view and insufficient illumination of images captured by nuclear power underwater equipment; Lu et al[53] to address the issue of NDT image quality degradation in high radiation environments, suggested a multiple scales morphological decomposition-based adaptive filtering methods, optimized the mixed noise, and utilized the visual adaptive fusing technique to improve the picture detail information; Guo et al[54] enhanced neutron radiography utilizing the YOLO structure to improve its capacity to identify minute flaws and to create a semi-automated fault detection procedure to lessen the effect of inspector inexperience. As illustrated in Fig. 6, the YOLOv5 model is enhanced with the addition of Adaptive Spatial Feature Fusion (ASFF) and Attention Based Mechanism Model (CBAM) to increase the model's performance and enhance its capacity to detect small size defects. Based on the results of experiments shown in Table 3, the model proposed in the paper performs best in Precision and mAP@0.5:0.95 with 98.1% and 80.1% respectively compared to YOLOv5s model ,YOLOv7-tiny model[55], Faster R-CNN model[56] and DETR model[57], which proves that the model can improve the detection accuracy, and also shows good performance in terms of parameters, with promising applications; Zhang et al[58] for the nuclear power weld DR image contrast details are poor, easy to miss detection, combined with Gaussian smoothing filter and decimation algorithm to enhance the image detail contrast, thus improving the defect recognition ability.

Table 3. Performance of Yolov5s, Yolov7-tiny, Faster R–CNN, DETR and our proposed model.

Methods Metrics	Backbone	Precision	mAP @0.5:0.95	Parameters	FPS (batchsize= 1)
YOLOv5s	-	0.81	0.593	7,020,913	103.124
YOLOv7-tiny	-	0.869	0.653	6,022,129	114.943
Faster R-CNN	VGG	0.913	0.768	136,750,479	36.572
DETR	R50	0.807	0.583	41,280,266	64.516
Proposed model	-	0.981	0.801	11,457,530	85.985

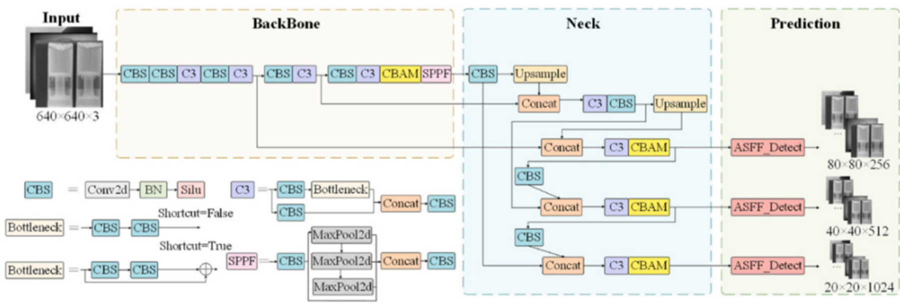


Fig. 6. The suggested fault detection method framework.

4 Summary and outlook

At present, the nuclear power industry is developing at a high speed, and vigorously promoting the use of AI technologies in non-destructive nuclear power testing can improve the efficiency and accuracy of the nondestructive testing of nuclear power equipment, so as to maintain the nuclear power plant safe functioning, and to save lots of human resources and operating costs. This paper summarizes the research ideas of artificial intelligence technology in the area of nuclear power sector NDT by describing the common uses of AI in the three areas of improving NDT technology, in-service inspection of nuclear islands, and metal supervision of conventional islands, which has a broad application prospect. Nonetheless, the following issues continue to be properly resolved:

(1) Currently, the kinds of nuclear energy NDT data are complex and diverse, and there is no unified standard for collection, storage, management and analysis, which makes the application of big data direction limited.

(2) Nuclear NDT application scenarios are complex and rely on operator experience, and when building data set samples, there may be different data sets organized by different professionals, thus affecting the final test results.

(3) Safe inspection by inspection robots is critical when performing non-destructive testing of nuclear power equipment, but duo to the non-interpretability of deep learning, potential bugs in the control software, and the uncertainty of the field environment, the equipment may suffer from problems such as fly-by-night, which can affect the nuclear power plant operational safety.

Consequently, creating a nuclear power NDT data sharing platform and a single norm in this space are crucial research directions. At the same time, it is also very important for the interpretability of big data models, systems and other applications to realize the safety and efficiency of nuclear power nondestructive testing equipment work site. Regarding guaranteeing the functioning safety of nuclear power facilities, the use of artificial intelligence technology to continuously improve the iterative nuclear power nondestructive testing technology, helping the digital transformation and leapfrog development regarding nuclear energy NDT.

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