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Artificial Intelligence Empowering Digital Tokamak Systems: Research Progress, Challenges and Prospects

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ABSTRACT

This study focuses on the application of artificial intelligence (AI) technologies in digital tokamak systems. Through systematic literature review and analysis, it expounds the application status, system construction, technical roadmap, and integration pathways of AI technologies in this field. The research shows that AI technologies have demonstrated significant advantages in plasma control, disruption prediction, and state recognition, effectively enhancing the performance and efficiency of digital tokamak systems. Meanwhile, this study constructs an architectural framework for AI-empowered digital tokamaks, and sorts out the technical roadmap covering multidisciplinary fields such as plasma physics, materials science, and control engineering, and proposes a full-process integration pathway from data fusion and model construction to application deployment. Although certain achievements have been made, challenges remain in model interpretability, data quality and scale, real-time requirements, and multi-scenario adaptability. In the future, deepening the application of AI in digital tokamak systems and advancing controlled nuclear fusion research to new heights will require interdisciplinary collaboration, algorithmic innovation, and data governance.

1. Introduction

Tokamak devices, as key equipment for achieving magnetically confined nuclear fusion, involve extremely complex physical processes, including the confinement, heating, transport of high-temperature plasmas, and interactions with device materials. Realizing controlled nuclear fusion means that humanity can master an almost inexhaustible and clean energy source, which is of far-reaching significance for alleviating global energy crises and addressing climate change. However, the operation of tokamak devices faces many challenges, such as plasma instability, disruption risks, and

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precise control problems, and traditional research and control methods have gradually revealed limitations in handling these complex issues [1-3].

With the rapid development of information technology, AI technologies, with their powerful data processing, pattern recognition, and autonomous learning capabilities, provide a new perspective and methods for solving complex problems in tokamak devices. In the past few decades, AI technologies have made breakthroughs in various fields, from image recognition and natural language processing to robot control, with their application scope continuously expanding. In the field of tokamak research, AI technologies have gradually emerged and begun to penetrate into multiple key links such as plasma control, diagnosis, and prediction. For example, analyzing plasma operation data through machine learning algorithms can achieve precise identification and prediction of plasma states, providing strong support for the stable operation of devices; using reinforcement learning methods to optimize the magnetic field control strategy of tokamaks can effectively improve plasma confinement performance.

However, current research on the application of AI in digital tokamak systems still has certain gaps. On the one hand, most existing studies focus on the application of AI in specific links of tokamaks, lacking research on the systematic integration and optimization of AI technologies from the perspective of the overall system architecture. This leads to problems such as poor data circulation and model incompatibility between various application links, making it difficult to give full play to the collaborative advantages of AI technologies. On the other hand, although some studies have attempted to construct models combining AI and tokamak physical processes, these models are often too simplified to fully consider the complex physical mechanisms inside tokamaks, resulting in the need to improve the prediction accuracy and reliability of the models. In addition, in practical applications, AI models face challenges such as low data quality, difficult-to-meet real-time requirements, and insufficient adaptability to complex and changeable tokamak operation scenarios, which seriously restrict the widespread application and promotion of AI technologies in digital tokamak systems.

Based on the above research status and gaps, this study aims to deeply explore the application prospects and challenges of AI technologies in digital tokamak systems. By constructing a comprehensive and systematic architectural framework for AI-empowered digital tokamaks, combing the relevant technical roadmap, and exploring practical integration pathways, it provides theoretical support and technical guidance for further improving the performance and efficiency of digital tokamak systems. Specifically, the objectives of this study include: first, clarifying the key application scenarios and requirements of AI in digital tokamak systems and constructing a complete architectural framework covering data collection, processing, model training, and application; second, systematically combing the multidisciplinary technical roadmap involved in the integration of AI technologies and digital tokamak systems to provide a clear roadmap for technological research and innovation; third, deeply studying the integration pathway of AI and digital tokamak systems, proposing a full-process solution from data fusion and model construction to application deployment, and verifying its effectiveness through case studies; fourth, comprehensively analyzing the challenges faced by AI in the application of digital tokamak systems, proposing targeted countermeasures and future research directions, and promoting the sustainable development of AI technologies in this field.

2. Methodology

2.1 System Construction of AI-empowered Digital Tokamak

Constructing an AI-empowered digital tokamak system requires consideration from multiple levels. First, at the data level, digital tokamaks generate massive multi-source heterogeneous data during operation, including physical parameters such as plasma temperature, density, and magnetic field strength, as well as operation status data of device components. The efficient collection, storage, and preprocessing of these data are the basis for subsequent analysis and modeling. Therefore, a distributed data collection system needs to be established to ensure the accuracy and real-time of data, and big data storage technologies such as Hadoop Distributed File System (HDFS) should be adopted to store data reliably. In the preprocessing stage, data preprocessing are used to remove noise and outliers, and data standardization and normalization processing are carried out to make different types of data comparable [4,5].

At the model level, various AI models are constructed according to different application requirements. In plasma control, reinforcement learning models can learn optimal control strategies through continuous interaction with the tokamak environment to achieve precise control of plasma position, shape, and temperature. Taking the research of the DeepMind team in tokamak magnetic control as an example, the RL agent interacts with the FGE tokamak simulator to learn to control tokamak configuration variables, effectively improving plasma control accuracy [6]. For plasma disruption prediction, recurrent neural networks (RNNs) and their variant long short-term memory networks (LSTMs) in deep learning are more suitable, as they can capture long-term dependencies in time-series data and accurately predict the possibility of disruptions in advance [7,8]. In plasma state recognition tasks, convolutional neural networks (CNNs) can perform feature extraction and classification on complex plasma image data to achieve rapid recognition of different confinement states (such as L-mode and H-mode) [9,10].

At the application level, trained models are integrated into the digital tokamak control system to achieve real-time monitoring and control. A visualization interface is established to intuitively present the real-time state of the plasma, model prediction results, and the execution status of control commands to operators, facilitating timely adjustment of control strategies. Meanwhile, a remote monitoring and diagnosis platform is built, using cloud computing and edge computing technologies to achieve remote management and fault diagnosis of tokamak devices and improve operation and maintenance efficiency [11].

2.2 Technical Roadmap

According to research fields, the technical roadmap for the integration of AI and digital tokamaks covers multiple key areas. In the field of plasma physics, it involves basic theories such as plasma dynamics and magnetohydrodynamics, as well as applied research such as plasma confinement, heating, and transport. The application of AI technologies in this field mainly reveals the internal laws of plasma behavior through the analysis of a large number of plasma experimental data, optimizes plasma operation parameters, and improves confinement performance. For example, machine learning algorithms are used to study the triggering mechanisms and evolution processes of plasma instabilities, providing a basis for developing effective control strategies [12,13].

In the field of materials science, the key for tokamak devices is to develop high-performance materials that can withstand high-temperature, high-pressure, and strong radiation environments. AI technologies can quickly screen and design new materials through materials genomics methods. By establishing a relationship model between material composition, structure, and properties, and using data mining and machine learning algorithms, potential high-quality materials are searched from massive material data to accelerate the material research and development process. For example, the Oak Ridge National Laboratory in the United States constructed an AI model to screen new alloy materials for nuclear fusion facilities, providing important support for extending the service life of the first wall of fusion reactors [14,15].

In the field of control engineering, the focus is on achieving precise control of tokamak devices. Traditional control methods such as Proportional-Integral-Derivative (PID) control have certain limitations in handling complex and changeable plasma systems. After the introduction of AI technologies, adaptive control and intelligent control can be realized. For example, control strategies based on reinforcement learning can automatically adjust control parameters according to the real-time state of the plasma, improving the flexibility and accuracy of control [16,17].

The field of computer science provides technical support for the application of AI in digital tokamaks, including big data processing technologies for storing, managing, and analyzing the massive data generated by tokamak operations; cloud computing and edge computing technologies for realizing distributed training and real-time inference of models to meet the system's requirements for computing resources and real-time inference of models; and high-performance computing technologies for accelerating the simulation of complex physical models and assisting in the training and verification of AI models [18,19].

2.3 Exploration of Integration Pathways

Data fusion is the first step to achieve effective integration of AI and digital tokamaks. Integrate tokamak experimental data, physical model data, and external related field data to construct a unified data platform. Data fusion algorithms, such as Bayesian network-based fusion methods, are used to associate and integrate data from different sources and formats, improve data integrity and accuracy, and provide high-quality data support for subsequent model training. For example, fusing plasma diagnostic data with device operation status data can more comprehensively reflect the operation status of tokamaks, helping to improve the model's understanding and prediction capabilities for complex working conditions [20,21].

In the model construction stage, suitable AI algorithms are selected for different application scenarios, and customized development is carried out in combination with tokamak physical principles. Taking the plasma disruption prediction model as an example, first, a large amount of historical data containing disruption events is collected, preprocessed, and subjected to feature engineering to extract key features related to disruptions, such as plasma current and temperature gradient. Then, an LSTM network is selected to construct the prediction model. By adjusting the network structure and training parameters, supervised learning is performed using labeled data so that the model can accurately learn the feature patterns before disruptions and achieve accurate prediction of disruption events [22,23].

In the application deployment process, trained models are integrated into the actual control system of digital tokamaks. A model deployment framework such as TensorFlow Serving is adopted to ensure that the model can operate stably in the production environment and provide efficient inference services. At the same time, a model monitoring and updating mechanism is established to real-time monitor the performance indicators of the model, such as prediction accuracy and false alarm rate. When the model performance declines or the tokamak operation conditions change significantly, new data is timely collected, and the model is retrained and updated to ensure the adaptability and reliability of the model [24,25].

3. Results

3.1 Application Achievements of AI in Plasma Control

In the field of plasma control, AI technologies have achieved remarkable results. Taking reinforcement learning as an example, many research teams have successfully achieved precise control of multiple plasma parameters by developing agents to interact and train with tokamak simulators. For example, in a project collaborated by the DeepMind team and the Swiss Plasma Center (SPC), deep reinforcement learning algorithms were used to control the plasma in a nuclear fusion reactor. Through experimental simulation, the accuracy of plasma shape was increased by 65%, and the training time required for new task learning was significantly shortened by more than 3 times compared with before [6]. This achievement provides a new and effective path for complex magnetic field regulation, enabling more precise control of plasma shape in actual tokamak devices, improving plasma confinement performance, and thus enhancing the efficiency of nuclear fusion reactions.

Next Step Fusion collaborated with the University of California, San Diego, to conduct experiments on the DIII-D National Fusion Facility tokamak. They used a machine learning model that directly takes the original magnetic diagnostic data detected by sensors as input to optimize the magnetic field performance. By conducting millions of simulation experiments in the digital twin replica, learning the optimal control strategy, and applying it in the real device, the experimental results showed that this method performed excellently in setting plasma control, effectively optimizing plasma performance. After comparison and verification with real experimental data and local simulators, the model maintained high precision and accuracy at each step, significantly improving the reliability and efficiency of plasma control [26].

3.2 Model Performance in Disruption Prediction and State Recognition

In the field of plasma disruption prediction, AI models developed by multiple research teams have shown excellent performance. The research team of the Institute of Plasma Physics, Chinese Academy of Sciences, adopted a "pre-interpretability" machine learning method for the EAST device and developed an "interpretable prediction model" using a decision tree model, which achieved an area under the receiver operating characteristic curve (AUC) of 0.997 on the test set, successfully revealing the key physical quantities leading to locked mode disruptions. On this basis, the further developed "real-time prediction model" achieved a 94% successful early warning rate and an average early warning time of 137 milliseconds, fully meeting the strict requirements of ITER for disruption early warning [27]. This achievement provides a reliable disruption early warning guarantee for the safe operation of EAST devices and future large fusion devices such as ITER. By predicting disruptions in advance, measures can be taken in a timely manner to avoid serious damage to the device and reduce operation risks.

In plasma state recognition, important progress has also been made. The team from the Institute of Plasma Physics, Chinese Academy of Sciences, innovatively adopted a multi-task learning neural network (MTL-NN) to integrate two closely related physical tasks: operation mode recognition (judging L-mode or H-mode) and edge local mode (ELM) detection, for collaborative learning in one model. The model uses scalar parameters in physical scaling laws as input features, effectively reducing signal noise interference. The experimental results show that its recognition accuracy is as high as 96.7%, which is 3.6% higher than that of the single-task model under the same database [28]. This efficient and precise real-time "diagnostic instrument" provides strong support for the monitoring and control of tokamak plasma operation states, helping to achieve high-performance steady-state operation, because accurate plasma state recognition is the basis for formulating reasonable control strategies, and control parameters can be adjusted in a timely manner according to different states to maintain the stable operation of the plasma.

3.3 System Application Effects in Practical Cases

In practical cases, the AI-empowered digital tokamak system has shown good application effects. For example, the Southwestern Institute of Physics, China National Nuclear Corporation, deployed an AI disruption prediction module in the "China Circulator No. 3" and successfully achieved a plasma "soft landing" with a 1.6MA discharge, with a false alarm rate of less than 5.3% [29]. This application shows that by integrating the AI disruption prediction model into the tokamak control system, the risk of plasma disruption can be accurately predicted during actual operation, and corresponding measures can be taken to achieve a smooth transition, avoiding damage to the device caused by plasma disruption, ensuring the safe and stable operation of the device, and verifying the feasibility and effectiveness of AI technologies in actual tokamak devices.

The "Xuanlong-50U" device of ENN Group uses AI technologies to achieve control of plasma configuration and developed a digital twin system of the device based on neural operator methods. The digital twin system has made significant progress in multi-physics field coupling simulation, with a speed increase of 4 orders of magnitude compared with traditional commercial software [30]. By establishing a digital twin system, real-time simulation and prediction of the operation of tokamak devices can be achieved, providing a basis for optimizing control strategies. In actual operation, the AI-based plasma configuration control technology can quickly adjust control parameters according to real-time monitoring data, achieve precise control of plasma configuration, improve the operation efficiency and performance of the device, and further reflect the application value of AI technologies in digital tokamak systems.

4. Conclusions

4.1 Summary of Research Achievements

This study deeply explores the application of AI technologies in digital tokamak systems and has made a series of important achievements through constructing a comprehensive system architecture, combing the technical roadmap, and exploring integration pathways. In terms of system construction, a complete architecture covering three levels of data, model, and application has been established. At the data level, efficient collection, storage, and preprocessing of multi-source heterogeneous data have been realized; at the model level, various AI models have been developed for different application scenarios, such as reinforcement learning models for plasma control, RNN/LSTM models for disruption prediction, and CNN models for state recognition; at the application level, models have been integrated into the control system to achieve real-time monitoring and control, and visualization and remote monitoring platforms have been built.

The technical roadmap combing results show that the integration of AI and digital tokamaks involves multiple fields such as plasma physics, materials science, control engineering, and computer science. In the field of plasma physics, AI helps reveal the laws of plasma behavior; in the field of materials science, it accelerates the research and development of new materials; in the field of control engineering, it realizes more precise and flexible control; and in the field of computer science, it provides strong technical support.

The exploration of integration pathways proposes a full-process solution from data fusion, model construction to application deployment. Data fusion improves data quality by integrating multi-source data; model construction customizes AI algorithms in combination with physical principles;

application deployment ensures that models can operate stably in actual systems and be updated in real-time.

In terms of practical application achievements, AI has significantly improved control accuracy and efficiency in plasma control, such as the research results of the DeepMind team and Next Step Fusion Company; in disruption prediction and state recognition, related models have shown high accuracy and early warning rate, such as the research of the Institute of Plasma Physics, Chinese Academy of Sciences; in practical cases, the "China Circulator No. 3" and "Xuanlong-50U" devices have successfully applied AI technologies, improving the operation performance and safety of the devices.

4.2 Analysis of Application Challenges

Despite the above achievements, the application of AI in digital tokamak systems still faces many challenges. Model interpretability is a key issue. Many complex AI models, such as deep neural networks, have decision-making processes like "black boxes", making it difficult to understand their internal logic. In a system like tokamaks that requires extremely high safety and reliability, unexplainable model decisions may lead to operators' lack of trust in model prediction results, affecting their practical application. For example, in a plasma disruption prediction model, although it can accurately predict disruption events, it cannot clearly explain which key factors the model relies on to make judgments, which brings difficulties for operators to further optimize control strategies.

Data quality and scale also have an important impact on AI applications. Tokamak operation data often have problems such as noise, missing values, and data imbalance, which will reduce the accuracy and stability of model training. At the same time, due to the high cost of tokamak experiments, it is difficult to obtain large-scale high-quality data, and limited data volume may lead to model overfitting, making it impossible to generalize to different operation conditions. Taking plasma state recognition as an example, if the data volume of a certain state in the training data is too small, the model may not be able to accurately recognize that state.

Real-time requirements are another challenge. During the operation of tokamak devices, the plasma state changes rapidly, requiring AI models to respond in a very short time. However, some complex AI algorithms, such as deep reinforcement learning algorithms, have high computational complexity and long model inference time, making it difficult to meet the real-time control requirements of tokamaks. In the plasma control scenario, if the model cannot output control commands in a timely manner, it may lead to plasma instability and affect device operation.

In addition, the operation scenarios of tokamaks are complex and changeable. Different experimental conditions, device parameters, and operation stages put forward high requirements for the adaptability of AI models. Existing models often perform well under specific conditions, but when the operation scenario changes significantly, the model performance may decline significantly. For example, after the device is upgraded and transformed, the range of some plasma parameters changes, and the original control model may not be able to effectively adapt to the new parameter range and needs to be retrained and optimized.

4.3 Outlook on Future Research Directions

Aiming at the above challenges, future research can be carried out from the following directions. In terms of model interpretability, develop explainable artificial intelligence (XAI) technologies, such as methods based on model visualization, feature importance analysis, and rule extraction, to deeply analyze the model decision-making process, enable operators to understand the basis of model prediction, and enhance trust in the model. For example, by developing visualization tools for tokamak applications, the feature mapping relationships in deep learning models are intuitively presented to help researchers gain insight into how the model understands plasma data [31,32].

To solve the problems of data quality and scale, on the one hand, strengthen data governance, adopt advanced data cleaning, denoising, and completion algorithms to improve data quality; on the other hand, explore data enhancement technologies such as generative adversarial networks (GANs) to generate more effective training data on the basis of limited real data, expand the data scale, and improve model generalization ability. Taking plasma disruption prediction data as an example, use GAN to generate more data samples containing different disruption scenarios to assist model training.

In terms of real-time improvement, on the one hand, optimize the hardware architecture, adopt high-performance computing chips, and combine cloud computing and edge computing to accelerate model inference; on the other hand, develop lightweight and efficient AI algorithms to reduce computational complexity and meet the real-time control requirements of tokamaks. For example, design a dedicated neural network architecture for tokamak plasma control to reduce computation and improve response speed while ensuring control accuracy.

For the problem of model adaptability, carry out research on meta-learning and transfer learning to enable the model to quickly adapt to different tokamak operation scenarios. Meta-learning allows the model to learn how to learn and quickly master knowledge in new scenarios; transfer learning transfers the knowledge of the model trained in one scenario to other similar scenarios, reducing the retraining cost. For example, the plasma state recognition model trained on one tokamak device can be quickly adapted to the similar operation scenarios of another device through transfer learning methods.

In addition, interdisciplinary cooperation is crucial. Strengthen the communication and collaboration among experts in plasma physics, artificial intelligence, materials science, control engineering, and other disciplines to jointly tackle the challenges in the application of AI in digital tokamak systems. Establish interdisciplinary research teams, consider the physical processes of tokamaks, AI algorithm design, and engineering implementation from different disciplinary perspectives, and promote the collaborative innovation and development of related technologies.

AI technologies show broad application prospects in digital tokamak systems. Although facing many challenges, through continuous technological innovation, interdisciplinary cooperation, and in-depth research on key issues, it is expected to provide strong support for the optimization control and performance improvement of tokamak devices and the realization of the ultimate goal of controlled nuclear fusion, promoting humanity to take an important step in the field of clean energy.

Conflicts of Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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