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Innovative Application of AI in Medical Decision Support System and Implementation of Precision Medicine

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Abstract: With the deepening of the concept of precision medicine, the practicability of clinical decision support systems in hospitals has become increasingly significant. The powerful data processing and individualized prompts brought by AI applications have enabled it to transform from an auxiliary tool to an intelligent and precise platform. This article mainly focuses on the innovative application of AI in clinical decision support systems and explores the implementation process of its application in aspects such as the establishment of diagnostic models, treatment selection, and risk prediction. For the current obstacles existing in the process of precision medicine, such as low acceptance of usage, weak interpretability of the model, data heterogeneity, and insufficient generalization ability of the model, an optimization path is proposed, providing theoretical guidance and practical reference for high-quality precision medicine empowered by AI.

Keywords: AI; innovation; medical decision support system; precision medicine; diagnostic model; treatment recommendation

1. Introduction

The medical decision support system is an important auxiliary device for improving the diagnostic accuracy and working efficiency of medical institutions, and plays a significant role in the diagnosis and treatment of many diseases. However, traditional systems rely on hard rules and limited data resources, making it difficult to cope with the differentiated needs of patients and the complex data environment. The development of AI technology has injected a strong driving force into it, enabling it to obtain information from the system and discover information patterns to make predictions, providing the possibility for achieving individualized and precise medical care. At present, the application of this system is not perfect, including insufficient willingness of medical staff to use it, lack of interpretability of the model, absence of data standardization and limited adaptability of the model, etc. This article aims to reveal the application of AI in the medical decision support system, analyze the technical and application obstacles in the promotion process of precision medicine at the present stage, and propose corresponding solutions.

2. AI Innovative Applications in Medical Decision Support Systems

2.1. Construction of AI Diagnostic Models Based on Clinical Data

The main contribution of AI diagnostic models in medical diagnosis lies in their deep learning and self-thinking capabilities. They are mainly based on various structured or unstructured clinical information from patients, such as electronic medical records, examination reports, and images. Through deep learning, they identify the key features of diseases and conduct corresponding predictive analysis and identification models. Common methods include support vector machines, random forests, convolutional neural networks, etc. These techniques have high accuracy and sensitivity in the early identification of many other diseases such as diabetes, lung tumors, and breast cancer [1].

Model training often relies on massive labeled data to identify the discriminative features of specific diseases in a supervised learning manner and continuously iterate and update in real scenarios. Furthermore, NLP technology can process medical record texts into computable features, greatly enriching the information sources and diagnostic scope of the model. Figure 1 below is the flowchart for building an AI diagnostic model based on clinical data.

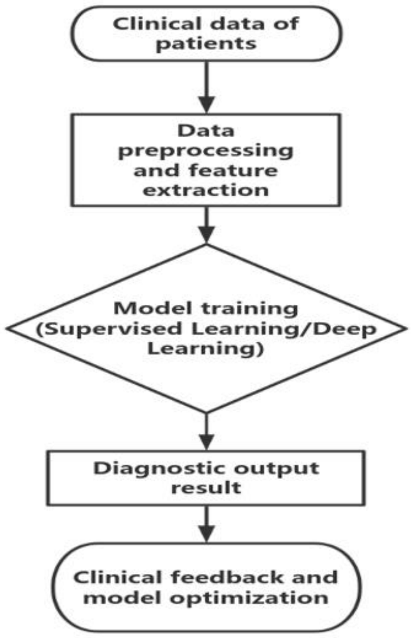

Figure 1. Flowchart of the construction of an AI diagnostic model based on clinical data.

2.2. AI Recommendation of Treatment Plans Based on Individual Characteristics

The traditional treatment model is that doctors, based on their own professional knowledge and experience, find it difficult to provide precise treatment for each patient's particularity and response changes. However, the application of AI makes it possible to establish a patient model based on the patient's age, gender, genetic characteristics, accompanying symptoms, and living habits, etc. The intelligent recommendation system can determine the best treatment path and list the priority in the research on the diagnosis, treatment and effect of a large number of similar cases [2].

The commonly used models at present cover methods such as collaborative filtering, deep learning, and reinforcement learning, which can achieve multi-scheme comparison, dynamic adjustment and real-time update in different environments. In cancer treatment, AI can provide personalized drug plan suggestions and intervention measures based on the cancer stage, genetic map and previous treatment results [3].

This system not only further enhances the targeting of treatment decisions, but also provides doctors with valuable suggestions and support for reference, further improving the effect and rate of clinical intervention. In addition to recommending treatment plans, AI can also combine multiple types of information to predict the development of diseases and provide clinical early warning functions, as shown in Figure 2.

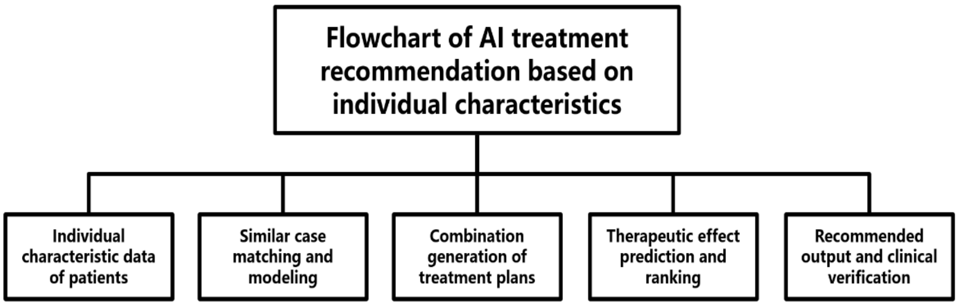

Figure 2. Flowchart of AI treatment recommendation based on individual characteristics.

2.3. Risk Prediction and Decision Early Warning Driven by Multi-Source Information Fusion

During the medical diagnosis and treatment process, patient data often come from diverse sources. It may include organized medical examination reports, vital signs and other data, as well as unorganized data such as image files, written records and monitoring data. AI technology has the ability to analyze high-dimensional data and extract features, which can break down information barriers, integrate different types of data and improve the accuracy of disease risk assessment and early warning [4].

During the development of diseases, AI prediction technology can track the changing trends of key parameters and compare them with the records of past patients and the historical records of similar patients to predict the trend of disease deterioration and potential concurrent risks. For instance, in the care of severely ill patients, major risks such as infection and shock can be detected through constantly changing information like respiratory rate, blood pressure and blood oxygen saturation, and it can also assist medical staff in conducting timely intervention [5].

3. The Current Situation of AI Innovation and Precise Application of Medical Decision-Making Systems

3.1. Medical Staff Have Insufficient Willingness to Use the System

At the stage when AI-assisted medical decision-making systems are widely used, the willingness of medical staff to use the systems has become an important factor restricting the depth of their clinical application. Some medical staff are not familiar with the overall functions and benefits of the system, and are worried about whether "intelligent diagnosis is reliable" and "whether it will affect the existing diagnosis and treatment process", etc. If its operation mode does not conform to one's own daily working habits, it may become an additional burden. The following Table 1 classifies the influencing factors of medical staff's willingness to use:

Table 1. Classification Table of Influencing Factors of Medical Staff's Willingness to Use.

Influence dimension	Specific manifestations
Cognitive impairment	Not understanding the system functions, it is believed that intelligent recommendation lacks practical value
Operating resistance	The usage process is complex, the interface is unfriendly, and it takes up the diagnosis and treatment time
Risk perception	There is concern that the misjudgment of responsibility may lead to unclear attribution and affect medical safety
Technical trust degree	Lack of trust in the source of algorithms and the reliability of data
Individual differences	The acceptance of the system varies among different ages, professional titles and departments

As can be seen from Table 1, there are many factors affecting the willingness of medical staff to use it. The main usage limitations are the cognitive gap and the difference in practical operation experience, etc. The second is the lack of risk awareness and trust, which makes it difficult for the system to be truly integrated into the daily clinical operation process, further affecting the breadth and depth of its promotion.

3.2. The Interpretability of AI Medical Decision-Making Models Is Relatively Weak

Although AI models have relatively high computational efficiency and accuracy in clinical decision-making, the "black box feature" of AI models also makes it difficult for doctors to understand and track the reasoning process, thereby reducing doctors' trust in AI models in clinical decision-making. Many models only output results without providing any diagnostic strategies, reference standards, weights, etc., making it difficult for doctors to determine whether the results are reasonable. When it comes to more difficult diseases, the prediction logic of the model becomes increasingly opaque, further intensifying the sense of uncertainty in the clinical application process. The following Table 2 classifies the manifestations of the lack of interpretability in AI medical models:

Table 2. Classification Table of Manifestation Types of Lack of interpretability in AI Medical Models.

Performance dimension	Description of specific problems
The reasoning process is opaque	The model output does not contain the intermediate inference process and lacks the causal chain explanation
The variable weight is unknown.	The proportion of the influence of the input variables on the prediction results was not presented
Medical logic break	The output results lack the support of medical rules and it is difficult to verify their rationality
The result is not traceable.	The model has difficulty repeatedly outputting consistent conclusions for the same input
Communication barrier	Doctors were unable to convey the model recommendations reasonably to patients and their families

It can be seen from Table 2 that the lack of interpretability mainly focuses on the invisibility of the internal logic of the model, the unknowability of the result mechanism, and the risk of interruption in doctor-patient communication. If doctors cannot know the reasons for the decision-making of the algorithm, they are likely to question the clinical decision-making based on the algorithm, and thus cannot improve physicians' trust in the application of precision medicine and the application ratio.

3.3. Heterogeneity of Medical Data and Lack of Standards

The application of AI in medical decision support systems requires the integration and modeling of information and data from multiple channels. However, the current characteristics of medical information are obvious heterogeneity, and the data structures, codes and collection methods of different hospitals and departments are not exactly the same. Some data are presented in a structured form, such as examination reports and vital sign values. However, a large amount of data is in unstructured forms, such as image data, disease condition information and physician orders, etc., which makes it rather difficult to extract these data. The following Table 3 shows the specific manifestations and classifications of medical data heterogeneity and the absence of standards:

Table 3. Classification Table of Specific Manifestations of Medical Data Heterogeneity and Missing Standards.

Data dimension	Description of the main problem
Data type differences	Structured and unstructured data coexist, and the processing path is complex

The encoding rules are different.	The same diagnostic item has multiple naming conventions in different hospitals
The field content is missing	The absence of key variables and the non-standard format affect the accuracy of modeling
The system interfaces are incompatible	Data cannot be directly shared among systems such as HIS, LIS, and PACS
The time span is chaotic.	The data records are not uniform, and there are phenomena of time omissions and repetitions

As can be seen from Table 3, data heterogeneity is reflected in every link of the data collection, data processing and modeling process. It not only reduces the reliability of model training, but also reduces the portability of the system in a cross-institutional environment. This is largely related to the lack of a unified data standard.

3.4. Insufficient Generalization and Transfer Capabilities of the Model

The performance of AI models in medical decision support systems is highly dependent on the quality and coverage of training data. However, at present, the vast majority of models are trained only relying on the data of a single institution or a specific population, lacking the applicability of cross-regional population coverage. After being removed from the initial training environment, there is usually a sharp performance deterioration, manifested as decreased accuracy, inconsistent results and instability, etc. The differences in disease composition, diagnosis and treatment processes, and working habits among different institutions make it difficult to maintain the matching during the transfer process. The following Table 4 shows the specific manifestations of the insufficient generalization and migration capabilities of medical AI models:

Table 4. Classification Table of Specific Manifestations of Insufficient generalization and migration Capabilities of Medical AI Models.

Problem dimension.	Main manifestations
Strong data dependence	The model is highly dependent on the original training data and has poor cross-hospital adaptability
Weak scene adaptability	The clinical processes in different hospitals vary greatly, and the stability of the model output is affected
Differences among patient groups	The differences in age, race and underlying disease structure lead to the decrease in prediction accuracy
The disease phenotype is complex.	Different manifestations of the same disease have not been comprehensively modeled, and the recognition ability is limited
Insufficient migration verification	There is a lack of a systematic cross-regional model transfer testing and effect evaluation mechanism

As shown in Table 4, the insufficient generalization ability of the model not only affects its horizontal replication among different institutions, but also limits its adaptability to individuals in the precise medical environment with large individual differences, as well as its coverage of real and complex clinical situations and the stability of decision-making.

4. The Path for AI to Facilitate the Precise Realization of Medical Decision-Making Systems

4.1. Optimize the System Interaction and the Training Mechanism for Medical Staff

The most important user group of the medical decision support system is medical staff. The frequent use and proficiency of users will significantly affect the performance of the system and the realization of the goal of precise treatment. Therefore, in the design process, it is necessary to consider whether the system can integrate and adapt to the clinical process to the greatest extent, and reduce and simplify the click frequency and path length of the interface interaction. At the same time, for different roles, functional teaching materials with gradients should also be prepared for them, including the use and processing of basic information, data interpretation, potential risk early warning, etc., to enhance their confidence in mastering the system principles and operations. To evaluate the relationship between the willingness of medical staff to use and the friendliness of the system, the following functional relationship model can be introduced:

$$U = \alpha I + \beta T + \gamma F \tag{1}$$

Among them, U represents the total application requirement score of the system. I is the user's satisfaction with the interaction design. T represents the coverage of training sessions. F represents the proficiency in the application of various functions. α、β、γ are their respective weight and intensity factors, and need to be adjusted and optimized accordingly in combination with the actual situation.

4.2. Introduce Interpretable Modeling and Visualization Techniques for Reasoning Results

Interpretability is a key requirement for the model, as it directly affects physicians' trust and willingness to use it. To further enhance the model's practical applicability, more transparent construction approaches should be adopted-such as decision trees, point-of-interest models, or regression methods capable of assigning feature weights. These techniques allow medical staff to clearly understand the relative influence of each input variable on the final recommendation, thereby supporting more reliable clinical decision-making.

The interpretable reasoning process is also crucial for the understanding and transmission of information. By visually presenting the results, such as using images, event points, cause-related relationships or graphs and other processing methods that can directly reflect the model's reasoning, users will quickly understand the main framework of the model and determine whether it is suitable for the rules in the medical field and the real world.

4.3. Develop Unified Data Standards and Build a Multi-Source Integration Platform

The realization of precision medicine requires high-quality and diverse clinical information data as a prerequisite. But in fact, the data faced by most medical institutions generally have problems such as scattered structure, inconsistent standards and heterogeneous sources, which hinders the efficient operation of AI models in decision support systems. To enhance data availability and model adaptability, it is necessary to unify structured templates, standardize coding rules and normalize data interfaces, and establish an integrated data platform that horizontally connects different systems (such as HIS, LIS, PACS) and vertically covers pre-diagnosis, diagnosis and post-diagnosis.

During the process of platform construction, the data standard coverage function can be defined:

$$S = \frac{n_s}{n_t} \times 100\% \tag{2}$$

Among them, S represents the level of data standardization, n_s represents the number of fields that comply with the unified standard, and n_t is the total number of fields. This index can represent the degree of data standardization of the entire platform and serves as the prerequisite for the accuracy of future model training.

4.4. Carry Out Multi-Center Joint Modeling and Adaptive Algorithm Design

The promotion of AI models in medical decision-making systems often faces problems such as poor adaptability and weak generalization ability due to excessive reliance on data from a single institution. To improve its stable performance in different clinical environments, joint modeling should be carried out relying on multi-center data resources. Data from different regions, departments and various types of patients should be incorporated into the training process to enhance the model's inclusiveness towards group differences. By sharing high-quality, labeled data samples, it helps to enhance the robustness of the model structure and the stability of the prediction results.

Meanwhile, according to the interface requirements, workflow and disease distribution characteristics of different types of organizational systems, an adaptive algorithm design with flexible parameter configuration and variable modules is adopted. The model can be dynamically changed in combination with the characteristics of local data during the actual operation process, so that the output accuracy and consistency of the model remain effective in different complex scenarios.

5. Conclusion

The continuous advancement of AI technology is bringing about profound changes to medical decision support systems, effectively promoting the implementation of precision medicine. Focusing on key links such as intelligent diagnosis, individualized recommendation and risk early warning, this paper explores their core application value, deeply analyzes the main obstacles faced in current practice, and proposes corresponding optimization paths. To achieve the deep integration of artificial intelligence and healthcare, it is necessary to continuously enhance the interpretability of models, the standardization of data, and the adaptability to clinical practice, and promote the implementation and sustainable development of intelligent and precise medical services.

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